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AMYR BORGES FORTES NETO

GIVING EMOTIONAL CONTAGION ABILITY TO VIRTUAL AGENTS IN CROWDS

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Giving emotional contagion ability to virtual agents in crowds

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To my parents, who taught me moral values, encouraged me on following my dreams, and always believed and invested in my character.

If I have seen farther than others,
it is because I stood on the shoulders of giants.
— Sir Isaac Newton

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RESUMO

Modelos de simulação de multidões têm tido um papel importante em ciências da computação já há algumas décadas desde os trabalhos pioneiros. No início, agentes simulados em multidões comportavam-se todos da mesma maneira, e tal comportamento era controlado pelas mesmas regras em todos os agentes. Com o tempo, os modelos de simulação evoluiram, e começaram a agregar uma maior variedade de comportamentos nos agentes. Modelos de simulação de multidões que implementam diferentes comportamentos nos agentes são chamados modelos de Multidões Heterogêneas, em oposição aos modelos de Multidões Homogêneas precedentes. Modelos de simulação de multidões que buscam criar agentes com comportamentos humanos realistas exploram heterogeneidade nos comportamentos dos agentes, na tentativa de atingir tal realismo. Em geral, estudos em psicologia e comportamento humano são usados como conhecimento de base, e os comportamentos observados nestes estudos são simulados em agentes virtuais. Nesta direção, trabalhos recentes em simulação de multidões exploram características de personalidade e modelos de emoções. No campo de emoções em agentes virtuais, pesquisadores estão tentando recriar fenômenos de contágio de emoções em pequenos grupos de agentes, ou mesmo estudar o impacto de contágio de emoção entre agentes virtuais e participantes humanos. Sob a crença de que contágio de emoção em agentes virtuais possa levar a comportamentos mais realistas em multiões, este trabalho foca em recriar modelos computacionais de contágio de emoções destinados a pequenos grupos de agentes, adaptando estes modelos para um contexto de simulação de multidões.

Palavras-chave: modelos de simulação de multidões, modelos de personalidade, modelos de emoções, modelos de comportamento.

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ABSTRACT

Crowd simulation models have been playing an important role in computer sciences for a few decades now, since pioneer works. At the beginning, agents simulated on crowds behaved all the same way, such behaviour being controlled by the same set of rules. In time, simulation models evolved and began to incorporate greater variety of behaviours. Crowd simulation models that implement different agent behaviours are so-called Heterogeneous Crowd models, opposing to former Homogeneous Crowd models. Advances in crowd simulation models that attempt to make agents with more realistic human-like behaviours explore heterogeneity of agent behaviours in order to achieve overall simulation realism. In general, human behavioural and psychological studies are used as base of knowledge to simulate observed human behaviours within virtual agents. Toward this direction, later crowd simulation works explore personality traits and emotion models. Some other work in the field of emotional virtual agents, researchers are attempting to recreate emotion contagion phenomena in small groups of agents, and even studying emotion contagion impact between virtual agents and human participants. Under the belief that emotion contagion in virtual agents might lead to more realistic behaviours on crowds, this work is focused on recreating emotion contagion computational models designed for small groups of agents, and adapting it for crowd simulation context.

Keywords: crowd simulation models, personality models, emotion models, behavioural models.

FIGURE LIST

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1. INTRODUCTION

Models of crowd simulation have been used for applications in films and video games, architecture, security and contingency plans. Films and video games usually present crowds for visual effects, generating great number of actors for epic war tales or cheering crowd background. Applications for architecture and contingency plan are usually meant to measure the security of a building project in terms of evacuation routes, corridor and stairway width, doors and passages that might result in bottlenecks. But, whatever the application is, it is always desirable to have the most realistic simulation possible, to obtain reliable results that support serious decision making.

Since pioneer approaches in crowd simulation, more effective mathematical models were developed by scientific community. At the same time, machines' computational power have significantly improved. These advances have allowed creation of even more complex crowd simulation models. Naturally, agents began to behave differently from each other, not only in terms of basic parameters, such as goal and speed, but in terms of decision-making, many times influenced by surrounding environment and agents' status. Crowd simulation models that implement different agent behaviours are so-called Heterogeneous Crowds. Also, agents have gained many abilities: they interact with each other and the environment, they react to environment events and even user triggered events. In recent works, agents of a crowd are actually programmed to live and evolve in the environment, and they decide on their own what the next task will be, based on their own needs or desires. This opposes to former crowd simulation models where agents, instead, just perform a well defined task such as finding the closest exit. These models are also known as Homogeneous Crowd models.

The problem of crowd simulation have been approached by different manners. Many hypothesis have been explored in order to achieve realism in agents' behaviour, movement and appearance. Some of those rely on personality models from psychology literature. Others use well defined roles to drive agents behaviour in each given situation. Those are also referred as rule-based approaches [54][48]. Results from computer vision systems and motion capture approaches have been used as well to estimate crowd behaviours. Those approaches are called data-driven approaches. Many aspects of crowd simulation using videos of real crowds are depicted in the works of Jacques Junior et. al [39], Bandini et. al[4] and Lerner et. al [45]. Surveillance videos and video databases are analysed to estimate people's trajectories and velocities. Latter, a proper adjustment of parameters in crowd simulator is performed to make simulated agents match estimated velocities and trajectories present in the analysed videos. On the other way around, videos generated by crowd simulation models are used to validate computer video systems designed to estimate crowd aspects. The advantage in those techniques is that, in simulated crowds, the numbers, velocities and densities of agents are known, so there is ground-truth to validate surveillance computer vision systems output.

Ultimately, psychosocial studies in personality, emotions and emotion contagion are taking place in computer based crowd simulation. The human behaviour is object of study for many years in human sciences, such as sociology and psychology. Psychology researchers, such as Goldberg

[30] and Eysenck & Eysenck [27], have mapped traits of human personality that rule individual behaviour and decision-making in many daily situations. Computer science groups have mapped these human studies to computer system parameters in order to simulate more realistic and complex crowd behaviours. We can name th work of Durupinar et. al [25] and Guy et. al [31] that uses the models of Goldberg and Eysenck & Eysenck, respectively. Usually, the goal is to achieve high level lexical input, such as adjectives or well specified characteristics, and use them to make automatic fine agent parameter adjustment. This allows simulation of very diverse agent behaviours within the same scenario using minimum input. This way, agents can be described by their personality profile such as "shy" or "tense"[31], or by their role such as "protester" or "police"[24]. The fine tuning of parameters lies under each profile or trait, which makes easier to configure (or procedurally generate) great number of agents within a crowd with realistic parameters. Since the development of emotional agents into the crowds, one interesting aspect is how such agents interact among them and change their own emotional parameters. This can be considered as a function of an emotional contagion method.

The present work focuses on the introducing an emotional contagion model in the context of crowd simulation. The *BioCrowds* steering model proposed by Bicho et. al [18][19] is extended to accommodate the emotion contagion model proposed by Bosse et. al[11]. With an emotion contagion model, we expect to observe a change of behaviour in crowd agents. As change of behaviour, in the context of *BioCrowds*, we understand to be changes in agent' trajectories. We propose to develop mechanisms to promote an impact in agents' behaviour due to agents' current emotional state. Also, by means of contagion, we expect to observe a spreading of such a behaviour in the crowd, emerging behaviours similar to those observed in real crowds, as described by LeBon[9]. The challenge of introducing an emotional contagion model in crowd context must consider characteristics of crowds such as i) great number of agents (hundreds to thousands), ii) crowds composed of multiple groups and individuals, iii) spatio-temporal information of agents, and iv) agents' goals and trajectories.

1.1 Objectives of the present work

This work's main objective is to introduce emotional contagion feature in crowd simulation context, more specifically in *BioCrowds* [18][19]. The model proposed by Bosse et. al[11] reveals to have flexibility to control important aspects of emotion contagion, which are: i) the individual susceptibility, or disposition to catch others emotions; ii) the individual expressiveness, or ability to express their own emotions to others; iii) the strength of the contagion channel, or contagion influence existent between two persons which allows them to have strong contagion experience of low emotional levels, or weak contagion experience of high emotional levels; and iv) it also has means for generating both positive and negative energy in emotions. The model proposed by Bosse and colleagues is designed for one unspecified emotion within one group. Some limitations in the model must be addressed to enable its use within crowds with many groups and individuals, as well as enabling work with multiple emotions at the same time.

With the ability to feel and promote contagion of emotions, we propose to create mechanisms to impact agents' behaviour according to their emotional state. By means of contagion, we expect to have agents changing their emotional state during simulation scenarios, to match surrounding emotional tendency. By changing agents' emotional state, we also expect to observe changing of behaviour in agents, potentially resulting in realistic emergent behaviours in the crowd.

1.1.1 Specific Objectives

Specifically, the objectives of the present work are:

- Integrate an emotional contagion model with a crowd simulation model, with the ability to promote emotional contagion between crowd agents;

- Integrate mechanisms to enable agents' reaction for emotional contagion, promoting emerging behavioural outcomes;

- Experiment with model's parameters to analyse the impact of parameter changes in agents' behaviour;

- Analyse emotional contagion in agents both quantitatively, using graphical and numerical results, and qualitatively, by commenting emergent behaviours in agents; and

- Improve *BioCrowds* to increase flexibility for agents' behaviour and enrich the possibilities of simulation scenarios.

1.2 Work Organization

This section explains the general organization of this work. It is organized in six chapters: Chapter 1, this chapter; Chapter 2, where the theory from psychology is approached; Chapter 3, where related work on crowd simulation using models of emotions and emotional contagion are depicted; Chapter 4, where we explain the model we are proposing; Chapter 5, where we present the results obtained; and Chapter 6, where we point out some conclusions and possible directions for the research field.

In Chapter 2 emotions and emotional contagion are defined according to the works of Ekman [26] and Hatfield, Cacioppo & Rapson [33] . Section 2.1 presents the definition of emotions and some their physiological aspects. Section 2.2 presents the model developed by Hatfield, Cacioppo & Rapson, and Section 2.2 explains the process of emotional contagion[33]. In Section 2.3 the OCEAN and PEN models of personality are depicted to cover better understanding of related works on crowd simulation, like the work of Durupinar[23], that uses such personality traits. Finally, Section 2.4 depicts some psychological aspects of crowds according to LeBon [9] findings.

In Chapter 3 relevant precedent works are depicted, starting by related work on crowd simulation models depicted in Section 3.2. Then, Section 3.1 discusses some work on emotions and emotional contagion both in crowds [14] and interactive agents [55]. Reminding that we have chosen specifically to adopt the *BioCrowds* [18][19] model and elected the emotional contagion model proposed by Bosse et. al[11] to introduce in its context, we dedicate one section for each one of those particular models, i.e. Section 3.3 is dedicated to explain the *BioCrowds* model and Section 3.4 depicts the emotion contagion model proposed by Bosse et. al.

In Chapter 4, the model proposed by this work is presented, showing how a contagion model for small groups can fit crowd simulation context. In Section 4.2.1 we explain how agents' position information is used to impact emotional contagion. Section 4.2.2 shows a major simplification for the model of Bosse et. al to work using only dyadic interaction (i.e., interaction between two persons). In Section 4.2.3 we show how we extended Bosse's model so it can handle multiple emotions in one scenario. This is useful to create more emotional state options in agents, thus increasing simulation possibilities. Finally, Section 4.2.4 describes how goals are associated with emotions to create a behavioural impact in agents due to emotion contagion.

Chapter 5 explains the performed tests and their objectives, showing scenarios and model parameters chosen for each experiment. We propose three distinct experiments: one with standing agents (i.e, agents do not move) explained in Section 5.1. One experiment with agents moving in opposite directions, described In Section 5.2. And Chapter 5 ends with the experiment with agents moving in the same direction, explained in Section 5.3. Finally, in Chapter 6 directions for the continuity of the research are given.

2. Theoretical foundation

This chapter will cover some theoretical foundation needed to fully understand the concepts that guided our methodology, by reviewing information originated from psychology on emotional contagion and personality. In Section 2.1 we define emotions according to the work of Ekman [26]. In Section 2.2 human emotional contagion process is defined and briefly explained according to Hatfield, Caioppo & Rapson[33]. In Section 2.3 a review on human personality traits is made, more specifically, the OCEAN model (Big-Five) is defined and briefly explained [30]. Personality models are used in works from literature to estimate parameters for heterogeneous behaviour of the agents in the crowd [23][31]. Finally, we make a brief review on crowd behaviour as defined by Le Bon [9].

2.1 Models of Emotions

Emotions are viewed as having adaptive value and thus evolved in dealing with fundamental life tasks. Each emotion has unique features. They can signal eminent life danger (fear) or poisoning danger (disgust). They also have social interaction purposes like love, or anger that might approach people or drive them appart. Each emotion, according to Ekman [26], also has characteristics in common with other emotions: rapid onset, short duration, unbidden occurrence, automatic appraisal, and coherence among responses. These shared and unique characteristics are the product of human evolution, and distinguish emotions from other phenomena.

According to Ekman [26] one of the strongest evidence to distinguish one emotion to another comes from research on facial expression. The author states that there is strong, consistent evidence of a distinctive, universal facial expression for five basic emotions: anger, fear, enjoyment, sadness and disgust. This evidence is not based just on high agreement across literate and preliterate cultures in the labelling of these expressions meanings, but also from studies on actual expression of emotions, both deliberate and spontaneous, and the association of the expressions with social interactive context. In the physiological level, there is evidence for distinctive patterns of automatic nervous system (ANS) activity for anger, fear and disgust, and, according to Ekman, it appears that there may also be distinctive pattern for sadness [26].

A number of separate, discrete, emotional states, such as fear, anger and enjoyment can be identified, which differ not only in expression but probably in other important aspects, such as appraisal, antecedent events, probable behavioural response, physiology, among other. The nine (9) characteristics that distinguish basic emotions from one another, and from other affective phenomena are[26]:

- Distinctive universal signals;
- Presence in other primates;
- Distinctive physiology;

- Distinctive universals in antecedent events;
- Coherence among emotional response;
- Quick onset;
- Brief duration;
- Automatic appraisal;
- Unbidden occurrence.

Ekman [26] describes this nine characteristics of the emotions of anger, fear, sadness, enjoyment, disgust and surprise. He also discuss the possibility that contempt, shame, guilt, embarrassment, and awe may also be found to share these nine characteristics. There are also other models of emotions like the OCC model [56], which threats emotions in the cognitive perspective. The authors believe that all emotions are related to cognitive aspects that are responsible for triggering such emotions. They also believe that physiological, behavioural and expressive aspects of emotions presuppose that first, the cognitive experience have taken place.

2.2 Emotion Contagion: Theoretical Psychology background

Many works can be found in psychology field regarding emotions and emotional contagion. The process known as emotion contagion is a phenomenon observed in some groups of people. This process deals with human affective experience. According to Barsade [5], the three most basic types of affective experience are emotions, moods and dispositional affect. Although those terms are used to describe how people feel, they differ in intensity and duration. Emotions refers to intense, relatively short-term affective reactions to a specific environmental event, while moods, as compared to emotions, are weaker, more diffuse affective reactions to general environmental stimuli, leading to relatively unstable short-term intra-individual changes, and can change readily. Lazarus [44] describes moods as "a transient reaction to specific encounters with the environment, one that comes and goes depending on particular transitions". Finally, dispositional affect is a stable, long-term variable [70] which is, by definition, not prone to emotion contagion but can influence it.

The work of Hatfield and Cacioppo [33] provides evidence to support Primitive Emotional Contagion as a strong contributor for emotional contagion. This is an automatic mechanism that promotes emotional contagion in an unconscious level, where people are influenced without even realizing it. The authors define Primitive Emotion Contagion as: "the tendency to automatically mimic and synchronize expressions, vocalizations, postures and movements with those of another person's and, consequently, converge emotionally." This statement is supported by three psychological mechanisms: i) mimicry, which is the tendency to synchronize vocalizations, postures and movements, ii) feedback, which affects subjective emotional experience from such mimicry, and iii) contagion, which makes people "catch" others emotions from moment to moment. These mechanisms are mostly primitive in the sense that they are unconsciously controlled.

2.2.1 Emotional Contagion Process

According to Hatfield, Caioppo & Rapson [33], one's emotional contagion may be experienced by a continuous process of mimicry, emotional feedback and self-perception, which drives the emotion in the affected subject. Those three processes are visceral, automatic, unconscious psychological mechanisms, and are defined as follows.

- *Mimicry:* is the process of mimicking and synchronizing interlocutors expressed emotions. This process is mainly induced by facial expression interpretation, but is also influenced by voice pitch and posture. This synchrony is automatic and almost instantaneous. During this process, interlocutor unconsciously imitates posture and facial expressions.

- *Emotional Feedback:* addresses the fact that, as proven by subject studies, one tends to have visceral feedback on expressed emotions. Studies designed to prove this hypothesis tested human subjects while watching a comedy video. Some subjects were forced to hold a pencil with their teeth in a way the mouth is kept open like a smile, thus the smiley-group. Other group was asked to hold the pencil with their lips, like a straw, making the subject almost unable to smile, thus no-smile group. The third group was given a pencil, but no instructions were given regarding the pencil, so they mostly just held the pencil in their hands, and this is the neutral or control group. The subjects were then asked to answer a questionnaire to evaluate how funny they perceived the movie. The results of this study showed significant higher fun perception in the smiley group scoring much higher (funnier) than the no-smile group. And yet a difference between the smiley-group with significant higher score than the control group, which in turn scored higher than the no-smile group. This and other studies proof evidence that forcing a facial expression of certain emotion may actually drive such emotion.

- *Self-perception:* is the process of perceiving one's own self. This means that individuals draw inferences about their own emotional states based on the emotional expressions and behaviours evoked in them by the emotional states of others. In other words, by perceiving their own facial expression and posture, individuals tend to catch those emotions moment to moment.

Another observed phenomenon is emotion amplification, or emotion spirals [28]. In these cases, other group members are affected by the emotions of one particular sender, and start expressing the same emotion themselves. That results in the first person to be further **contaged** by his/her own emotion. It is also noticed that this spiral or amplification can have, both positive or negative, influence on the group and its goals [59]. Studies that support those claims can also be found on the work by Hatfield & Cacioppo [33].

According to Dezecache et. al [20], there is evidence of emotional contagion beyond *dyads*. A *dyadic* interaction refers to interaction between two people, thus *dyads*. This means that a person A might experience emotional contagion by observing a person B, which in turn is experiencing emotional contagion by observing a third person C. For their experiments, Dezecache and colleagues chose female participants to represent individuals B in the transmission chain because, as they point out based on numerous studies, women are facially more expressive than men. It is important to remark that this study supports contagion of a third party. This means that, once one person has suffered contagion, she/he is now also a promoter of contagion too, spreading that emotional energy through the members of the crowd. This contributes for homogeneity of crowds, as posted by Le Bon [9] (see Section 2.4).

Beyond the individual inherent susceptibility, external factors such as interpersonal relationship, and the level in which the emotion is expressed by others influence emotional contagion process. Given the definitions of mimicry, emotional feedback and self-perception, the emotional contagion process is defined by i) one subject, either a person or virtual agent, expressing one particular emotion, on a given level of expressiveness, to another subject or group of subjects, ii) the group of subjects exposed to the emotion, each one perceives the emotion at its own perception level, and start mimicking and to synchronize with the perceived emotion, and iii) self-awareness on the influenced subjects drives visceral emotion into them. This process happens continuously each moment of a social interaction.

2.2.2 Some important consequences of emotions and emotion contagion on individual and group behaviour

In order to properly simulate emotional contagion, it is also important to understand the conditions that may strengthen or weaken the contagion process, as well as expected behaviour of a person or a group regarding their emotional state. In order to give basic background and organize a (small) literature review on the subject, this section presents some theories on psychology that deals with emotions and behaviour.

Primitive emotional contagion as defined by Hatfield & Cacioppo [33] leads to convergence in mood and emotions across group members. Emotions and moods helps to coordinate an individual's behaviour and responses [16]. Spoor & Kelly [65] suggests that emotions may play a similar role in a group, through their ability to coordinate group members' activities and actions. In particular, shared affect may facilitate a group's activity by helping group members to work together in the pursuit of shared desired outcomes or goals. Furthermore, shared affect may also serve to prevent group dissolution by facilitating the development of bonds between group members.

Emotions, in particular, operate to quickly signal to oneself important information about the environment, including general valence information regarding whether the environment is relatively safe or potentially dangerous. At the group level, according to Spoor & Kelly[65], this means that group members would have benefited from the development of a mechanism for the rapid transmission of emotional states throughout the group, and emotional contagion may have evolved to serve this communicative function. Groups may also have benefited from the use of mechanisms for controlling the moods and emotions of specific group members, as well as the emotional tone of the group as a whole. By emotional tone we mean emotional harmony (or monotonicity) that can collaborate to strengthen group bonding. In terms of group formation, there is evidence that groups are likely to form when individuals develop shared feelings. Additionally, there is extensive evidence that positively toned affective ties serve several positive functions for the group, including binding group members to one another, to operate in a more group centered manner, to better coordinate efforts, and to better enforce group norms and procedures. Similarly, Turner [69] suggested that human emotions may have evolved in order to facilitate the development of affective ties between individuals, and thus increase group solidarity. The vast majority of research demonstrating these effects has focused on the constructs of group cohesiveness [53] and group rapport [67].

Heerdink et. al [34] propose that deviant individuals (i.e., the ones with tendency to be isolated from the group or feel rejected by the group) interpret the majority's emotional reaction to their behaviour (i.e., emotion expressions of disapproval against one's behaviour) to estimate their position in the group, which may motivate them to change their behaviour. More specifically, Heerdink and colleagues argue that happiness and anger, if expressed toward a deviant individual in a group, may be interpreted as information about the deviant individual's inclusionary status. In other words, these emotional expressions influence the degree to which the deviant individual feel accepted or rejected by the group.

Feelings of rejection may drive the member away from the group, and she/he may not be part of the group anymore. On the other hand, feelings of acceptance may include, or maintain a member inside the group. This claim is supported by studies that relate emotional states, specially concerning positive emotions, as a natural way for people to socialize, and thus group with others. Barsade [5] makes experiments on positive emotions and positive emotional contagion, that is, an increase in positive mood. She concludes that this will lead to greater cooperativeness on both an individual and group level. Positive emotional contagion will also lead to less group conflict and will lead people to rate their own task performance and that of others in the group more highly. Fredrickson [28] also presents a study supporting that positive emotions trigger upward spirals toward emotional well-being.

According to Kessler & Hollbach [42] group-based emotions play an important role in intergroup behaviour. Positive emotions, like joy, directed towards a member of the group makes him/her feel more accepted by the group. Also, negative emotions, such as anger, makes the member feels rejected. Moreover, emotions include motivating components that may lead to specific intergroup behaviours[12]. If one feels he/she is a part of the group (i.e., identifies him/herself with the group) there is an impact on group overall cooperation while performing some task.

Besides performing tasks, interpersonal relatioships are also linked to group emotional experiences. Emotions provide a more differentiated evaluation of a salient intergroup relation than the single dimension of positive and negative affect [62]. Not only emotions directed toward an ingroup may influence identification but also emotions directed toward an outgroup. For instance, Mackie, Devos & Smith [49] showed the mediating role of group-based emotions between intergroup perception and action tendencies. In particular, the action tendency to move against an outgroup is mediated by group-based anger. Group members that engage aggressive behaviour along with the group tend to fell more accepted by the group, strengthening interpersonal bonds with other group members.

In addition, these studies demonstrate a positive relation between ingroup identification and group-based emotions (e.g., anger about a relative disadvantage) suggesting that higher identification with a group leads to more intense group-based emotions. Although it is known that personal identification with the group is related with group-based emotions, it is impossible to determine causal priority of one variable over another. Hence, ingroup identification may not only be a determinant but also a consequence of group-based emotions. In particular, ingroup identification may be enhanced or reduced depending on which group-based emotion an individual experienced. If group-based emotions affected ingroup identification then this might provide an explanation for the processes of approaching or distancing oneself from a social group.

Generally, certain emotions may tend to increase ingroup identification whereas others may decrease identification with an ingroup. There are two interesting phenomenon that exemplifyes clrearly this statement. They are: BIRGing and CORFing. BIRG stands for Basking in Reflected Glory and refers to behaviour where someone that identifies him/herself as a member of a particular group recognizes the victory of a group as being his/her own achievement, even if the individual in evidence has taken no part in the execution of such deed. CORF stands for Cutting off Reflected Failure and refers to behaviour where someone tends to lose identification with a group one is a member when the group is somehow defeated, even if the individual is not to blame on the failure. An example to illustrate both behaviours is a supporter of a sports team. There are people who played no role in the sports match that they happen to be celebrating the victory as if they have scored the decisive goal. On an opposite scenario, some supporters may repress demonstrations of affiliation once his team has been defeated. Research on BIRGing showed that a positive performance of a group with which one identifies leads to an enhanced identification and, in particular, an increased public demonstration of group membership[15]. In addition, this finding was complemented by research showing that after group failure individuals distance themselves from an ingroup (cutting off reflected failure, CORFing)[63].

2.3 Personality Traits: Theoretical Psychology background

Although we do not apply personality traits in this work, relevant work in the area does. Personality traits are related to a individual disposition affect, which is the most time invariable characteristic of emotions and emotional contagion. There is more than one personality model in psychology literature. Just to name a few that has already being used in computer sciences works we can cite the PEN personality model proposed by Eysenck & Eysenck [27], and there is also the OCEAN personality model (also known as Big-Five) proposed by Goldberg[30], both originated in psychology and adopted in computer sciences as basis for creating heterogenous crowd behaviour. Works like Durupinar [23], using OCEAN, and Guy [31], using Eysenck's PEN, are examples of computer sciences works that adopts psychological models. The model PEN proposed by Eysenck & Eysenck maps human personality in three dymensions being:

- Psychoticism, measuring the tendency to act impulsively. It is associated not only with the liability to have a psychotic episode (or break with reality), but also with aggression. The research that has been done has indicated that Psychoticism too has a biological basis: increased testosterone levels.

- Extraversion is based on cortical arousal, which can be measured by skin conductance, brain waves, or sweating. While theoretically introverts are chronically overaroused and jittery, theoretically extraverts are chronically underaroused and bored. The theory presupposes that there is an optimal level of arousal, and that performance deteriorates as one becomes more or less aroused than this optimal level. The finding that arousal is related to performance as an inverted U-shaped curve is called the Yerkes-Dodson Law. Extraversion is related to social interest and positive affect.

- Neuroticism is based on activation thresholds in the sympathetic nervous system or visceral brain. This is the part of the brain that is responsible for the *fight-or-flight* response in the face of danger. Activation can be measured by heart rate, blood pressure, cold hands, sweating, and muscular tension (especially in the forehead). Neurotic people, who have a low activation threshold, experience negative affect (fight-or-flight) in the face of very minor stressors. They are easily upset. Emotionally stable people, who have a high activation threshold, experience negative affect only in the face of very major stressors. They are calm under pressure.

It is interesting to note that measures of activation are not highly correlated. That is, people differ in which responses are influenced by stress: some sweat, others get headaches. This is called individual response specificity. It is also interesting to note that stressors differ in the responses they elicit. This is called stimulus response specificity.

Through the parameters given by those models, one can estimate different instant decision making, such as taking right or left in order to avoid collision. Another possible triggered behaviour is the act of pushing other agents to open way [57]. Those decisions are usually based on agents tendency to follow rules, or being assertive to others, which in turn are mapped by personality characteristics.

2.3.1 OCEAN Personality Model: The Big-Five

Also known as The Big-Five, this model claims that human personality can be mapped into 5-dimensions. One can find the history of OCEAN personality traits on the work of John and Srivastava [40]. This document starts from the early efforts of lexical approaches, in which personality researchers turned to the natural language as a source of attributes for a scientific taxonomy, and finishes by presenting an instrument for measuring ones OCEAN personality scores based on a 44-item self-reporting characteristics. Here, we focus on giving a brief introduction to the lexical origin of the OCEAN personality trait model, and the definitions of the five dimensions.

The lexical hypothesis posits that most of the socially relevant and salient personality characteristics have become encoded in the natural language[2]. Thus, the personality vocabulary contained in the dictionaries of a natural language provides an extensive, yet finite, set of attributes that the people speaking that language have found important and useful in their daily interactions [29].

> Rather than replacing all previous systems, the Big Five taxonomy serves an integrative function because it can represent the various and diverse systems of personality description in a common framework.

The acronym OCEAN stands for the description of each one of the five dimensions: *Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism*, defined as follows.

- *Openness* to Experience (vs. closed-mindedness) describes the breadth, depth, originality, and complexity of an individual's mental and experiential life. It is also commonly associated with intellect.
- *Conscientiousness* describes socially prescribed impulse control that facilitates task- and goal-directed behaviour, such as thinking before acting, delaying gratification, following norms and rules, and planning, organizing, and prioritizing tasks.
- *Extraversion* implies an energetic approach toward the social and material world and includes traits such as sociability, activity, assertiveness, and positive emotionality.
- *Agreeableness* contrasts a pro-social and communal orientation towards others with antagonism and includes traits such as altruism, tender-mindedness, trust, and modesty.
- *Neuroticism*: Neuroticism contrasts emotional stability and even-temperedness with negative emotionality, such as feeling anxious, nervous, sad, and tense.

2.4 The Psychology of Crowds

Gustave Le Bon was a pioneer in the study of crowds [9]. He defines crowds as a gathering of individuals of whatever nationality, profession, or sex, and whatever be the chances that have brought them together. Under certain given circumstances, and only under those circumstances, a crowd presents new characteristics very different from those of the individuals composing it. There he defines a psychological crowd, which is not just an agglomerate of people, but rather a single being, subjected to the law of the mental unity of the crowd. Under these circumstances, the sentiments and ideas of all the persons in the gathering take one and the same direction, and their conscious personality vanishes.

Different causes determine the appearance of these characteristics peculiar to crowds, and not possessed by isolated individuals. The first is that the individual forming part of a crowd acquires, solely from numerical considerations, a sentiment of invincible power which allows him to be carried away by instincts which, had he been alone, he would have kept under restraint. He will be less disposed to check him/herself from the considerations as the sentiment of responsibility, which always controls individuals, disappears entirely. This results from the fact of a crowd being anonymous, and in consequence irresponsible for its actions.

The second cause, which is contagion, also intervenes to determine the manifestation of special characteristics in crowds. Contagion is a phenomenon of which it is easy to establish the presence, but that it is not easy to explain. This is sometimes related to the concept of Social Contagion, which in turn is divided in Behavioural Contagion, referring contagion of actions (hysterical contagion, contagion of aggressive behaviour, rule violation contagion) and Emotional Contagion[50]. We defined emotional contagion as Hatfield & Cacioppo proposed [33], and emotions indeed spread through the crowd. Perhaps mimicking plays an important role in the contagion mentioned by Le Bon, but he classes it among those phenomena of a hypnotic order. In a crowd every sentiment and act is contagious, not only emotions. And those are contagious to such a degree that an individual readily sacrifices his personal interest to the collective interest. This is an aptitude very contrary to his nature, and of which a man is hardly capable, except when he makes part of a crowd.

A third cause, and by far the most important, determines special characteristics in the individuals of a crowd which are quite contrary at times to those presented by the isolated individual. Le Bon refers to that suggestibility of which the contagion mentioned before is neither more nor less than an effect, according to him. To understand this phenomenon it is necessary to have in mind certain physiological discoveries. It is known today that an individual may be brought into such a condition that, having entirely lost his conscious personality, he obeys all the suggestions of the hypnotist, and commits acts in contradiction with his character and habits. The most careful observations seem to prove that an individual immersed for enough time in a crowd in action soon finds himself in a special state, which much resembles the state of fascination in which the hypnotized individual finds himself in the hands of the hypnotist. The conscious personality has entirely vanished, will and discernment are lost.

Such also is approximately the state of the individual forming part of a psychological crowd. He is no longer conscious of his acts. In his case, as in the case of the hypnotised subject, at the same time that certain faculties are destroyed, others may be brought to a high degree of exaltation. Under the influence of a suggestion, he will undertake the accomplishment of certain acts with irresistible impetuosity. This impetuosity is more irresistible in the case of crowds than in that of the hypnotised subject, from the fact that, the suggestion being the same for all the individuals of the crowd, it gains in strength by reciprocity. Some experiments performed in Chapter 5 shows that as the number of agents rises, it will take longer time to change the emotional state of the group. This is noticeable in simulation scenarios presented on Section 5.2, as the number of agents in the group rises, the time it takes to change their states to escaping also rises.

We see, then, that the disappearance of the conscious personality, the predominance of the unconscious personality, the turning by means of suggestion and contagion of feelings and ideas in an identical direction, the tendency to immediately transform the suggested ideas into acts are the principal characteristics of the individual forming part of a crowd. He is no longer himself, but has become an automaton who has ceased to be guided by his will. In the next chapter we present some works on crowd simulation and virtual agents, developed by computer sciences research groups, that aims to simulate some of the psychological aspects presented here.

3. Related work

This chapter focuses on related works in computer sciences area. In Section 3.1 we discuss some recent important works that attempt to simulate emotion, emotion contagion and personality traits in virtual agents. Some of those models were not yet applied to crowds, but rather to single agents interacting with humans or small groups of agents. Those models aim to enable emotional expression in agents in a way that a human observer is able to correctly perceive the emotions. To accomplish emotional expression, some models focus on gestures [7], or facial animation characteristic of emotions (such as a smile with hand gestures commonly used to express joy). Those gestures and faces are driven by the emotional state of the agent with the objective to express agent's emotions. In Section 3.2, we discuss pioneer and recent works on Crowd Simulation Models, and since the core of this work is emotional contagion applied to crowds, we dedicated Section 3.2.1 to discuss works on emotional contagion in crowds.

With the objective of highlighting both models (model of crowds and model of emotion contagion) used in this work for integrating crowd simulation and emotion contagion, we depict the details of each model in separated sections. With that in mind, in Section 3.3 we present the crowd simulation model, proposed by Bicho et. al [18][19]. We use this crowd simulation model as starting point for introducing emotional contagion. And finally, in Section 3.4 we depict the emotional contagion model adopted, proposed by Bosse et. al [11].

3.1 Related Work on Computational Models of Emotion and Emotion Contagion

Out of crowd context, psychological models are also being used to compute the emotion that is defined by nonverbal behaviour, such as facial expressions and gestures, and also verbal behaviour such as voice pitch (used in voice synthesis) of interactive agents. The objective of this section is to present computational models of emotion designed to cope with virtual agents. Costa & Feijó [17] published pioneer work in the area where the reactive nature of emotion is explored and a Reactive Emotional Response Architecture is proposed. In this work, the authors start by considering that the question of emotion in computer animation can be tackled from two points of view: (i) the reactive nature of the virtual environment and (ii) the cognitive aspects of the mental models of emotion. By focusing on the first viewpoint, the principles underlying the Reactive Agent Model proposed by the authors are the following: cognition, emergence, situatedness, recursion and cooperation.In this context, the emotional state is generated by procedures rather than by logical deductions from a formal representation of the world. These straightforward procedures render computational efficiency to the implementation of the proposed model. It is important to notice that Costa & Feijï¿½ [17] mentions that a formal model of emotion is not within their scope and, in fact, a very simple mechanism for emotion generation is used. However, the architecture permits one to plug an emotion generator or procedures to the agents in order to test more complete models of emotion.

Bispo & Paiva [8] propose a model of emotion contagion based on the Emotion Contagion Scale (ECS)[21], which measures individual susceptibility to emotional contagion, across five different basic emotions (Love, Happiness, Fear, Anger, and Sadness). The model presented by Bispo & Paiva focuses on unconscious aspects of emotion contagion, and uses the NetLogo environment for implementation. Each agent is modelled by a set of variables to record the current score for each emotion. The higher the score, the more likely will be the emotion to be expressed. This set of variables is labelled by the authors as "Current Mood". Each time an agent is influenced by one emotion, the value of this emotion's variable rises, while the value on the other emotions lowers. As the emotion with highest score is chosen, when two or more emotions are tied in the same value, the emotion which comes first is chosen in the order: Happiness, Love, Anger, Fear, an Sadness. The variables in the "Current Mood" are arranged so that the sum of all values of all Current Emotions will always be 0. Finally, there is a limit for the highest values of an emotion variable, but there is no limit for how low it can be.

The work conducted by Lhommet et. al [47] is designed to simulate crisis situation that shows the emergence of crowd behaviour from individual behaviour, based on the emotion contagion phenomenon. A key contribution of this work is mapping OCEAN personality traits into the strength and susceptibility of emotional contagion. Each individual in the crowd is represented by a cognitive, emotive and social agent. They are modelled with a personality given by $P_A = [P_O, P_C, P_E, P_A, P_N]$ and the authors proposes a formulation to calculate agent's Contagion Power (CP) and Susceptibility to Contagion (SC) from those parameters. Later, CP and SC are used to calculate the amount of contagion in a given time window, according to surrounding agents' parameters.

Pereira & Dimas [58] proposes a computational model designed for emotional contagion simulation for multiple agents. The level of emotion contagion is biased by agent relationship and emotional expression and susceptibility. The work is based on the model proposed by Bispo & Paiva [8]. In this work, the authors model the emotional contagion process in individual agent level, and group emotional contagion behaviour emerge from interactions between agents. The agent can capture en "Emotional Expression" (EE) from the environment, and filter it on the "Contagion Filter" to create a "Received Emotion" (RE) that is used to update agents' "Current Mood" (CM) by the "Mood Updater". When given a chance to express, the agent decides on it with its "Emotional Expression Filter" and uses its "Current Emotion" to create a new "Emotional Expression" (EE). An emotional expression is the way the agents interact with others in the same environment, and is the basis of the model's dynamics. It is represented by a tuple $< t, io >$ where t represents a type of emotion and can be one of the five emotions used by the model (love, happiness, sadness, fear and anger), i represents the intensity of the associated emotions and is a positive real value, and o identifies the transmitter of the expression. In the "Contagion Filter", a captured EE is transformed into a RE using two kinds of perception bias: susceptibility and contagion. The "Susceptibility Bias" probabilistically determines, based on agents "Emotion Contagion Scale" (ECS) score and type of EE, if the agent is affected or not. Each agent has its own ECS score for each emotion given by the probabilistic function $ECS(t)$, where t is an emotion type. The Susceptibility process is represented by the function $Suscept(t)$, where t is an emotion type and the value returned is a real number in the range [0, 1]. If $Suscept(t) < ECS(t)$, contagion occurs.

Bevacqua et. al [7] presents a computational model that generates listening behaviour for an Embodied Conversational Agents (ECA). It triggers backchannel signals according to the user's visual and acoustic behaviour. The authors understand as possible backchannels gestures like head movements or wavening. Actions can be a mix of several backchannels if there are no conflicts on the same modality. Only one action can be displayed by the ECA at a given time and the Action Selection module receives continuously candidate backchannels. The backchannel algorithm has been evaluated by naive participants using an user-agent scenario of storytelling. The participants judged the algorithm-ruled timing of backchannels more positively than a random timing. The system can generate different types of backchannels. The choice of the type and the frequency of the backchannels to be displayed is performed considering the agent's personality traits. The personality of the agent is defined in terms of two dimensions: extraversion and neuroticism. The authors link agents with a higher level of extraversion to a higher tendency to perform more backchannels than introverted ones, and they link neuroticism to less mimicry production and more response and reactive signals sent. A perception study to test these relations in agent-user interactions was conducted by the authors. It was found that the selection of the frequency of backchannels performed by their algorithm contributes to the correct interpretation of the agent's behaviour in terms of personality traits.

There are also works that focuses on studing emotional contagion in the interaction between human users and virtual agents as in the work conducted by Tsai and collegues [68]. Since studies are being conducted in psychotherapy and military training using virtual agents in simulations, the impact of such emotional interactions must be considered in order to avoid undesirable repercussions. According to the authors, while many works addresses the subject of emotional contagion, few addresses the subject regarding the interaction between human and virtual agents. The effects are assumed to either be non-existent, and therefore overlooked entirely, or to mimic human-to-human emotional influences. However, the authors shows those are both poor assumptions and most likely to be harmful to users in sensitive domains. In order to attempt the confirmation of those statements, three sets of studies are conducted by the authors in this work[68]. The first study examines pure contagion case, by simply showing a still image of a virtual agent either showing happy or neutral expression, and afterwards, assessing the subjects mood. The second study adds the presentation of game-theoretic situation known as a Stag-Hunt along with the character image to assess both the contagion and the behavioural impact of the virtual character in a strategic setting. Although the authors always tell subjects to be trusting, for example, this may not result in any meaningful impact on behaviour in a strategic situation. So, it is attempted to examine whether behavioural impacts arise in strategic situation from agent-human contagion. Finally, the third study examines the post-hoc hypothesis that the presentation of a decision to the user dampens the emotional contagion effect. Specifically, the same strategic situation in the second study is presented to the subject, but with the decision already made.

Seeking to achieve socially aware virtual characters, Ochs & Pelachaud proposes the study of the smile in the context of social signals[55]. Meaningful gestures like facial expressions showing emotions, head nod showing agreement, and other verbal and non-verbal body and facial expressions are considered as social signals. To respond in a social manner, in synchrony with the user, a virtual character should be able to display, in a timely manner, social signals that can be perceived by the user. For instance, to communicate disagreement, a raise of eyebrows may be shown. In this context, Ochs & Pelachaud study the social signal of a smile. A smile may convey totally different meanings – such as amusement, embarrassment, or politeness – depending on subtle characteristics of the face. Moreover, one's smiling behaviour may affect the another's perception, his/her motivation, enthusiasm, and even the realization of a task. Also, a virtual character should be aware of the impact that its social signals have on the users, thus they must have a repertoire of expressions with their corresponding meaning. They focused their efforts on three types of a smile: an amused smile (or genuine smile), a polite smile (also called false, social, masking, or controlled smile) and an embarrassed smile. As result, the authors create socially aware virtual characters, a repertoire of smiles with different meanings that has been produced starting from a user-created corpus of virtual smiles. The latter has been integrated in virtual characters and evaluated at different levels of interaction.

The model proposed by Soleimani & Kobti [64] uses fuzzy apprisal approach to analyze the influence of applying different regulation strategies as direct pro-regulation intervention to the system. The model is based on Emotional Response Level (ERL) and Neutral-Emotional-Neutral (NEN) approach, which in turn is similar to disease contagion Susceptible-Infected-Susceptible (SIS) model [1]. The emotional contagion is function of ERL on each agent and the emotional value that is transmitted in the contagion process. In the process, neutral agents transit to emotional agents and vice-versa.

3.2 Related Work on Crowd Simulation Models

In pioneer approaches, agents behave the same way: they all shared the same decision-making algorithm. Usually, the only behaviour of agents used to be goal seeking. Different approaches for navigation or collision avoidance were proposed, but all agents basically did the same thing: navigate in the scenario in a collision free manner, and seek a predefined goal. The differences relied only on agents' speeds and goals, but no other significant difference between agents occurred. With different behavioural algorithms, agents gain flexibility to behave differently from each other when facing the same situation. An example of this different behaviour is *taking right* decision to avoid potential collision. Depending on cultural plurality, people might agree to walk to their right to deviate from another person coming in the opposite direction in order to avoid bumping into them. But, although this might be the common sense, thus the rule in some crowd simulation models, it might not be applicable to everyone in real life. Somebody may take the left side instead for some personal reason. To have this kind of behaviour emerging in the crowd, agents must be able to make different decisions, so more specific decision-making algorithms are required. For the given example, the algorithm should be able to make some agents take right, others take left, depending on simulation state (i.e., internal agent's parameters or surrounding environment). The objective of this chapter is to picture the evolution of crowd simulation models, from pioneer works to later state-of-the-art, some of which make use of psychology models to improve realism.

The pioneer work in crowd simulation is Reynolds' flocks, herds and schools [60]. Based on a particle approach, all agents have attraction (velocity matching) and repulsion forces (collision avoidance), combined with a goal force (flock centring). This gives the observer a sense of group, since all the individuals move together. The model was applied to flocks of birds, schools of fishes and herds of land animals (by constraining the third dimension). The agents are all *bird-oids*, most commonly called *boids*. Attractive forces drive the individuals to the average position of their neighbours, keeping the group together. Each *boid* feels forces to align their velocity with their neighbours' velocity. To avoid collision, repulsive forces are used to drive individuals apart from their neighbours. The combination of those three forces (attraction, alignment and repulsion forces) results in desired velocity for each individual at each simulation frame. The emergent behaviour from this simulation resembles the movement of flocks and herds. Despite the fact that there is a sense of group in Reynolds' simulations, according to the authors, the agents do not behave in a human-like form, and thus they do not suggest simulation of human agents. Human-like behaviour can be defined as the emergence of crowd behaviours consistent with real observed human crowds. Reynolds' crowds behaviour resembles schools of fishes or flocks of birds, but not human crowds.

Another classic pioneer work is Helbing empirical Social Force Model [37]. In his work, Helbing defines that agents should respond to three basic forces: (i) desire to reach a specific location or goal in the environment pulling the agent towards it, (ii) presence of other pedestrians in their surroundings forcing the agent to keep minimal distance, and (iii) attraction to other correlated pedestrians (family and friends) or interest points in the environment. This references previous other Helbing's works which implement a pedestrian specific gas-kinetic (Boltzman-like) model[36][35]. The authors make use of *social forces* concept, which was first introduced by Lewin [46]. In Lewin's idea, behavioural changes are guided by *social forces* or *social fields*. According to the proposed process, a sensory stimulus causes a behavioural reaction that depends on the personal aims and interests, but also on the perception of the situation and the environment. Proper reactions are chosen from a set of behavioural alternatives with the objective of utility maximization. *Social forces* must not be confused with forces originating from the environment applied over the pedestrian body. Rather, they are quantities that describe *motivation to act*. Also, *social forces* are mathematically modelled as monotonic increasing potential lines, and can be modelled as attraction forces, pulling the individual toward an objective or a friend, or they can be modelled as repulsion forces, which drive the individual away from obstacles, walls or other unknown individuals that may cause discomfort due to physical proximity.

Later, Musse and Thallman [54] developed an approach based on group hierarchy. The agents behaviours are defined in three basic ways: (i) by using innate scrip behaviour; (ii) by defining behavioural rules through a script; and (iii) by defining external control to guide crowd behaviours in real time. Although agents in the same group are programmed to follow a leader, the group does not behave as a unique flow. Instead, they have individual behaviour inherited by the script behaviour set for that particular group. Thus, this approach is based on group hierarchy. The complexity of scripts may define different decision making and interaction behaviours on most complex scenarios.

Pelechano et. al proposes an approach for controlling individual agents in high density crowds (HiDAC)[57]. The model focuses on the problem of simulating the local motion and global path finding behaviours of crowds moving in a natural manner within dynamically changing virtual environments. The solution to the problem of realistically simulating local motion under different situations and agent personalities uses psychological, physiological and geometrical rules combined with physical forces. Since applying the same rules to all agents leads to homogeneous behaviour, the authors gave agents different psychological (e.g., impatience, panic, personality attributes) and physiological (e.g., locomotion, energy level) traits that trigger individual heterogeneous behaviour. Each agent is also endowed with perception and reacts to static and dynamic objects and other agents within the nearby space. Agents' behaviour is determined by a high-level algorithm (including: navigation in complex virtual environments, learning, communicating and decision making) and low-level motion controllers. The model was used to simulate a situation of evacuation, modifying agent behaviour based on personality and perception of other agents' level of panic.

There are many ways to explore different agent behaviours within a crowd. Some works explore Personality Models found on psychology literature[23][31]. Some other works like Li [48] use role playing to determine agents' behaviour in the crowd. In those cases, a number of different roles to be played by each agent is programmed. At run time, those roles are attributed to each agent, according to a schedule or an expected behaviour in a given situation. The agents usually change more than one time their role during a simulation.

Some research groups have been trying to model pedestrian behaviours in crowds by making use of computer vision models. A lot of information on video techniques to model and analyze crowds can be found in the work of Jacques Junior et. al [39]. To model virtual crowds based on video data, computer vision techniques are used to extract from video images the trajectories of real life pedestrians. The parameters of the crowd model (agents' velocity, goals and paths) are then adjusted to make simulated agents take trajectories that resembles the ones captured in video. To validate crowd simulation models, an inverse process is taken, i.e. first the model's parameters are set, later, data captured from video is used to validate agent's trajectories.

3.2.1 Emotional Contagion in Models of Crowds

Later works on crowd simulation have integrated models derived from psychology studies to imitate human social interaction outcomes. Mathematical models that imitate phenomena related to personality, moods and emotions are being developed and integrated on virtual agents to drive their interaction, both with humans and other virtual agents. Behaviours like group formation, fight picking, goal and/or speed changing are all being mapped to some psychological state of the virtual agents in crowds[23][24]. These approaches aim to achieve crowd behaviour specification in more automatic manner. They map high level personality trait parameter, such as *shy* or *extroverted* into lower level computational model parameters. The user does not have everything in control, and agent's behaviour arise from their personality's parameters as a function of agent's status, surrounding environment and interaction with other agents. Personality models are relevant to this work because they can be related to the agent's emotional tendency. The difference between emotion and personality is that emotion is a temporary status and personality is a concept much more constant, i.e., invariant in time.

Durupinar et. al presented an approach [23]to incorporate OCEAN personality model into HiDAC simulation system[57]. The objective of this work is to easily create different personalities. To do so, the parameters of the HiDAC simulation system were mapped into individual OCEAN traits and its polarities. Also, simple adjectives such as "leadership", "impatience", "panic", among others, are mapped to the same traits. This way, agents' behaviours are easily specified through adjectives, which in turn are translated to OCEAN traits, and then to lower level HiDAC parameters. The model enables simulation of heterogeneous crowds, where each subgroup is composed of individuals with similar personality traits. The model also frees the user from understanding underlying methodologies of HiDAC, and allows the use of higher-level concepts related to human psychology. Later, Durupinar et. al evaluated their model within a user study[25]. According to authors results, the traits designed were perceived by the participants as expected.

Another personality model used in crowd simulation models and originated from psychology studies is Eysenck's PEN [27]. Guy et. al conducts a work that applies PEN on crowd simulation scenario [31]. The authors conduct two user studies: one to correlate simulation parameters with personality model parameters, and the other to validate the correlations found. To perform the study, two videos were presented to participants by the authors: one presenting a scenario configured with the parameter setting to be tested, and the other with default parameters to be used as control reference. The work presents linear regression matrices for mapping PEN personality model into simulation parameters. As input to QR decomposition with column pivoting, the authors use difference between the given agent's parameters and those of the agents in reference video. This removes the need to compute an offset as part of the regression. The input is also normalized to increase numerical stability of the linear regression. After defining appropriate regression matrices, the authors subject their result to a behaviour perception user study, where they validate the parameter mapping found. Finally, by performing Principal Component Analysis (PCA), and because the PEN factor dimensions are not completely orthogonal, the authors summarize their data analysis into two Principal Components, leading to a bi-dimensional personality mapping. By the end, the authors accomplish a high level parameter choice, based on PEN personality trait adjectives, and are able to remap those high level parameter into lower level agent parameters.

In the work by Carretero et. al[14] a simple emotion model is developed and applied in crowd simulation context. Opposing to personality models, which makes agents personalities constant, emotions can vary during simulation. Emotions are driven basically by the agent's mood, which is an emotion tendency for every agent. Moods have very slow variation in time, taking hours or even days to change, in opposing to emotions that lasts from few minutes to hours. Here we make notice that emotional models might implement decay functions that adjust agent's emotional state to match its inner mood tendency while in absence of external events. This way, even when an agent has a sad mood, is it possible for this agent to become happy for a short period of time, when he or she meets a friend with good news, for example. To enable this, an emotion contagion model is also created, and agents are given the ability to express their moods (or emotions). On the other end, agents are also able to perceive other agents' emotions. To decide what agent infects the others, a power on agents relationships is modelled in a way that agents with more emotional contagion power over the others will have their counterparts infected with their own emotion. When the interaction between agents cease, agents tend to return to their initial moods. The authors models three moods: sadness, happiness and neutral. The model of contagion is still too simple, but rather the work focuses on body animation and body expression of the moods to be very convincing. The body expression gives the ability for the agents not only to express their moods towards one another, but to express their moods towards a human observer.

Much has been done so far to achieve realistic crowd behaviour, and state-of-the-art approaches makes use of psychological models, including personality and emotions, to estimate agents' behaviours. Situations of panic and fight picking were simulated on HiDAC[57]. Personalities were applied to the same model to easily configure agents' variations on behaviour, and emotion contagion has been made avaliable [23][24], applying a contagion model derived form spreading of diseases. It uses a threshold model, which means that contagion only occurs after a certain threshold if contagion is achieved. Furthermore, work by Tsai et. al [68] performs a comparison of the model proposed by Bosse et. al [10] (to be further explained in Section 3.4) with the model proposed by Durupiar [22] (which used the same contagion model as in [24]) and shows slightly better performance of the first over the later, according to Tsai et al. metrics. The authors suggests that the primary cause of the statistically significantly worse performance found with the epidemiological/social contagion model of [22] is in the mechanism of contagion itself, which is probabilistic and uses a binary representation of the effect. Other models like [14] also shows emotion contagion in crowds, but both their emotion and contagion model are far too simple to address different aspects of contagion such as stronger or weaker contagion and emotional spirals.

3.3 The BioCrowds

Inspired in algorithms for simulating plant growth, the *BioCrowds* model [18][19] incorporates an interesting collision avoidance methodology. The authors adapted an algorithm for space competition applied to vegetal growth simulation on the work by Runions et. al [61]. On the later, the authors objective is to create leaves and branches of trees. For that, they fill the space with auxins – or, as they call, attraction points – that will stimulate branches to grow their way. They also initialize tree nodes. Directional vectors are calculated from each node that has attraction points close enough to it. Those nodes will grow to the resulting directional vector by creating new nodes in the pointed direction. Finally, the algorithm removes every attraction point that has tree nodes too close to it. By changing parameter setting (i.e., marker's positions and density, initial tree nodes, distances for activating attraction of nodes and triggering deletion of markers) different shapes of trees and bushes are generated by Runions algorithm. But, what is the relationship between plants and crowds?

The key idea of *BioCrowds* for crowd simulation is to use markers in the scenario to represent free spaces, just like Runions's attraction points. Those markers are threated as resources for which agents in crowd compete. Agents will take ownership of free markers close to it. As the agent moves in the scenario, it will release ownership of markers that are left behind and got far from it. The distance where markers should be taken or released by the agent is based on its social space, as defined by Edward Hall [32]. This way, in the model proposed by Bicho, the evaluation of agent's neighbourhood is possible through the quantity of markers associated to the agent at a given moment. In other words, the agents are blind, and they only see the environment through markers. A perception area that surrounds the agent is then marked as owned, allowing the agent to recognize its proxemics.

The BioCrowds approach preserves most of the space competition algorithm characteristics. The key elements adopted by Bicho et. al to support the original algorithm modifications to crowd simulation problem are:

- **Markers space restriction**: In the geometric model for generation of tree branches, a tree node can be influenced by any attraction point marker (or *auxin*) present in the leave/tree space. At each simulation iteration, each marker is associated to the closest node. On the crowd simulation model, just markers that are present in the personal space of the agent (or its proxemics) are able to influence it, rather than being influenced by all markers in the scenario.

- **Markers Persistence**: As the tree branches grows and occupy the space, the attraction point markers are removed from the space. The condition to remove is that there must be nodes close enough to the marker in order to trigger deletion. In the crowd simulation model the markers are never removed, so they keep in the virtual environment during all simulation. Instead of being removed, they are just marked as taken, or owned by some agent. Agents claim ownership of markers inside its personal space. Once an agent claims ownership of a set of markers, those markers are available only for that agent. The only way for the agent to move is claiming new markers for its own personal space. At the same time, markers left behind are released by the agent. Those markers, now released, are discrete representation of free space and can be disputed by other agents so they can also move in the virtual environment by occupying free space.

- **Goal Seeking**: The growth of tree branches is guided simply by space availability, represented by the existence of attraction point markers. However, in crowd simulation, people movement is guided not only by availability of space, but also by the intention of reaching a destiny. The navigation, in terms of goal seeking, is also computed through markers in the environment. The ones that leads to positions closer to the objective are strongly weighted. The weighting function has mainly three properties: (i) reach its maximum when the angle θ between orientation vector and goal is $\theta = 0°$ (ii) reach its minimum when $\theta = 180°$, and (iii) decrease monotonically while θ increases from $0°$ to $180°$. This way, agents can reach their goal, while respecting obstacles and other agents' spaces.

- **Velocity Adjustment**: In the space colonization algorithm, trees branches grows in constant rate, which implies constant speed. In the crowd simulation context, agents vary their velocity according to space availability. The desired speed for each agent is an input to the model.

To initialize the crowd simulation model, some considerations were taken in order to incorporate crowd related parameters and features. For starters, a scenario must be described. This is done using an input file with the coordiantes describing a set of blocks representing obstacles, or unwalkable area. The number of agents and its initial positions are also inputs for the model. Also, the goals for agents are defined in a group hierarchy, i.e., agents inherit group's goal. To initialize the scenario, the density of markers must also be set. The more markers in the scenario the better is the resolution of discrete free space description and results in smoother agent's trajectories. On the other hand, too much markers can increase significantly the algorithm's computational cost. Another input parameter is the agents proxemics, or, in other words, the ray (R) of agents personal space. Finally, every agent must have the module of desired speed initialized to s_{max}. This is the maximum movement speed of the agent input parameter. To compute agent's translation an instantaneous speed is computed as $s'_{max} = s_{max}/FPS$, where FPS is a given number of frames-per-second (time resolution) of the output.

3.3.1 Computing Agent's Velocity

In order to make agents evolve in the scenario towards their goals, the movement of each agent i is calculated iteratively. In each iteraction cycle, both agent's position $p(t)$ and and the objective vector $g(t)$ indicating agent's destination are updated. A set of markers $S_i(t)$ is generated containing all markers in agent's i personal space, which are closer to agent i than to any other agent in the scenario. Implicitly, this division of space represents a decomposition of space according to the distance relative to preset points, those points being agents' positions. This decomposition is also known as Voronoi diagram [3].

Considering an instant $t = t_0$ and omitting the variable t, given a size N set of markers associated to agent i denoted by $S_i = \{a_1, a_2, ..., a_N\}$, to compute the agent's position in time $t = t_0 + 1$, firstly a set of vectors must be calculated in the form:

$$S'_i = \{d_1, d_2, ..., d_N\}, \text{ where } d_k = a_k - p, \tag{3.1}$$

given that p represents the current position of the agent. Put in words, d_k are vectors starting in the agent's position, and pointing to each marker in S. Having computed this set of vectors, the algorithm for plant growth would simply calculate the resultant vector and grow the plant in the given direction. For crowd simulation, the agent's goal must be considered. For that, the vectors in S' must be weighted, in order to guide the agent towards its goal. As explained before, the weight of those vectors are dependent on the angle θ between the agent's goal vector g and each vector d_k in S'. Considering this aspect, the movement vector m can be written as follows:

$$m = \sum_{k=1}^{N} \omega_k d_k, \tag{3.2}$$

where the coefficients ω_k are given by

$$\omega_k = \frac{f(g, d_k)}{\sum\limits_{l=1}^{N} f(g, d_l)}. \tag{3.3}$$

Finally function $f(g, d)$ must be defined. In order to accomplish its goal, function $f(g, d)$ must have the following characteristics:

1. Output its maximum value when angle θ between goal vector g and marker vector d equals $0°$.

2. Output its minimum value when angle θ between goal vector g and marker vector d equals $180°$.

3. Monotonically decrease as angle θ rises from $0°$ to $180°$.

4. Output values equal or higher than zero.

Another aspect considered by Bicho et. al [18][19] is the distance of markers from the agent. Markers with smaller distances $||d_k||$ are considered more relevant than markers farther away. Thus, a possible choice for function f could be:

$$f(g, d_k) = \begin{cases} \dfrac{1 + cos\theta}{1 + \parallel d_k \parallel} = \dfrac{1}{1 + \parallel d_k \parallel} \left(1 + \dfrac{\langle g, d_k \rangle}{\parallel g \parallel \parallel d_k \parallel} \right) & \text{, if } \parallel d_k \parallel > 0 \\ 0 & \text{, if } \parallel d_k \parallel = 0 \end{cases} \tag{3.4}$$

where $\langle \cdot, \cdot \rangle$ denotes internal product.

With f function defined, it is possible to solve Equation 3.2 and calculate movement direction m. If there is enough space, the agent should be able to navigate in the virtual environment with s_{max} velocity. However, in dense crowds, available space is sometimes scarce, reducing agent's speed. On the model proposed by Bicho, availability of space can be estimated through available markers in the agent's surrounding. The model adjusts agent's velocity according to vector m module and s_{max}. The solution proposed by Bicho et. al to calculate the instant movement vector v is given by

$$v = s_{min}\frac{m}{\parallel m \parallel}, \text{ where } s_{min} = min\{\parallel m \parallel, s_{max}\}. \tag{3.5}$$

Equation 3.5 implies that, if $||m|| > s_{max}$, maximum agent's translation is limited by s_{max}. Otherwise, movement is given by $||m||$. It must be noted that there must exist markers in the agent's proxemics (i.e., S is not empty), and some of those markers lead to the goal's direction. Otherwise, markers with $\theta = 180°$ and an empty set S both result in $f(g, d_k) = 0$), implying in a zero denominator in Equation 3.3.

Further details on tests and results of the *BioCrowds* model can be found in the work of Bicho et. al [18][19]. There, the author shows some limitations of the model, such as in cases where obstacles are too thin and valid markers beyond the obstacle gets inside agent's proxemics. In those cases, the agents ignored the obstacle, "jumping"over it. Hocevar [38] created group organization features for the model. On this work, Hocevar implements social behaviour on walking groups so that groups up to three agents are able to walk side-by-side, using v-formation or in a straight line[52]. Commonly behaviours observed in real crowds, like lane formation and arc formation, can be observed in *BioCrowds* simulation results. Those results are not programmed, but rather emergent due to the model's conception.

3.4 Emotion Contagion Computational Model

The work adopted as starting point for integrating emotion contagion in the *BioCrowds* model is the one proposed by Bosse et. al [11], where the authors proposes a mathematical model for emotional contagion process. It focuses on the contagion of emotion itself, therefore Bosse's agents do not have the need for spacial coordinates of position. The model does not consider agents mood or emotional personality. Instead, it only models agent's emotional influence over the group it is inserted, and also the influence of the group over the agent. This implies that agents do not change their behaviour concerning emotional contagion during the simulation. In other words, one agent that begins the simulation being very susceptible to contagion, will remain susceptible during all simulation. To change that it would be necessary a model of emotions that controls dynamically such parameters. Also, such model could cope with decay functions to change agent's emotional state according to individual mood or some other cognitive reason, which is not in the scope of the work by Bosse et. al presented in this Section.

To model emotional contagion, some aspects that might control level of emotion and intensity of contagion are defined within the model. One characteristic that influences strength of contagion is the relationship between people. For instance, two strangers might have much less emotional contagion experience than a mother playing with her son. Also, there are people who are more expressive than others, resulting in more clear and sometimes exagerated emotional expression [43] which, in turn, can promote stronger contagion than shy or repressed expressions of emotions. It is also known that there are people more susceptible to emotional contagion than others [21]. These people tend to catch much easier emotions of others and, by primitive empathy, they tend to experience the same feelings much easier. This may be related not only to primitive empathy, but also to a more cognitive, sophisticated and socially beneficial process of empathy or sympathy[33]. Finally, there is a personal emotional tendency, driven by one's mood. Considering this, Bosse and colleagues developed two basic models within their model: an absorption model, responsible for contagion through (primitive) empathy imitating the average group emotion; and an amplification model, responsible for strengthening emotional spirals both upwards and downwards, depending on agent's personal bias. This enables the model to simulate oberved emotional contagion spirals, where emotions tend to increase, or decrease, in intensity due to diadic interaction. One limitation of the model addressed herein is that it treats only one non-specifyed emotion. This could be any emotion, like those proposed by Ekman [26], which distinguishes anger, disgust, fear, joy, sadness and surprise, according to facial expressions. Results shows that upward and downward spiral can be simulated, as well as agents emotional influences over each other. The strength of contagion can also be balanced, making agents very susceptible and/or very expressive. It is also possible to turn of expression or susceptibility by setting the parameters to zero. This is useful to make one or more agents immune to contagion, but able to promote contagion on other, or vice-versa.

Mathematically, Bosse defines the emotion of an agent as a value q in the range $[0, 1]$, that represents the intensity of an unspecified emotion. The only restriction about emotional specification is that it should be the same emotion for all agents in the simulation. Each agent expresses its own emotional level to the group at a given expression level ε also in the range $[0, 1]$. This way extroverted, expressive, active persons will induce stronger contagion of emotion than a shy person would. On the other side, another agent will have to be able to perceive emotional expressions. The authors propose to represent the susceptibility of catching the emotions of others by the variable δ, which also lies in the range $[0, 1]$, and defines how much a person allows other people's emotions to affect his own emotional state. Finally, the relationship between agents is taken under consideration. Depending on people's relational links, emotional contagion may be stronger or weaker. This interpersonal relationship link is represented in this model by a variable α_{kl}, which represents the relationship between agents k and l. Notice that α_{kl} can be different from α_{lk}, as the influence of the mother over the son may be different from the influence of the son over the mother during a particular emotional contagion experience. This leads to a matrix containing all α_{kl} parameters, with k and l in the range $[1, G]$ where G is the number of agents in the group. The dimension of this matrix is NxN where N is the number of agents in the group.

In order to address emotional spirals, two variables where proposed by the authors: i) a bias represented by the variable η to define the agents tendency to either absorb, meaning that group members converge to some average emotional level, or amplify emotions, meaning that group members catch others emotion in a way they generate higher or lower overall emotional level; and ii) a bias represented by the variable β to decide whether the amplification model tendency is upwards or downwards. Considering a group of two agents: S being the agents sending a particular emotion, and R being the agent receiving such emotion, all those definitions can be summarized in the Table 3.1.

Tabela 3.1 – Variables to be considered on the emotional contagion process

Variable	**Purpose**
q_j	Represents instantaneous emotion level of agent j.
ε_S	Represents the S agents expressiveness.
δ_R	Represents R agents emotional susceptibility.
α_{SR}	Represents the influence S has over R, notice that α_{RS} can be different from α_{SR}.
η_j	Bias to determine the models tendency to amplify or absorb emotions on agent j.
β_j	Bias tendency to amplify emotions upward or downward on agent j.

Bosse et. al[11]

To compute the variation of emotion in each agent at each simulation frame, first it is needed to compute the strength in which a particular emotion is transferred from agent S to agent R. The strength of emotional contagion from agent S to agent R is given by γ_{SR} and calculated as the product:

$$\gamma_{SR} = \varepsilon_S \alpha_{SR} \delta_R. \tag{3.6}$$

With all γ_{SR} is possible to compute the overall strength by which emotions from all other agents in the group are received by R in group G, indicated by γ_R, and defined as:

$$\gamma_R = \sum_{S \in G \backslash \{R\}} \gamma_{SR}. \tag{3.7}$$

That represents the sum of $\gamma_(SR)$ for all $S \in G$ except for the case when $S = R$.

As stated before, the model can simulate upwards and downwards emotional spirals, starting from an initial given q_A for every agent A in the scenario. Through spirals mechanisms, not only individual agents, but the whole group can get to a higher or lower level of emotion, even enabling the group to create an overall higher (or lower) emotional energy that was not there before. Each agent will reach its own emotional equilibrium within the group. Suppose A is an agent in group G, being G defined as the set $G = \{A_1, A_2, ..., A_G\}$, the dynamic of A's emotion level is given by:

$$dq_A/dt = \gamma_A \left[\eta_A \left(\beta_A PI + (1 - \beta_A) NI\right) + (1 - \eta_A) q_A^* - q_A\right]. \tag{3.8}$$

The overall group's emotional influence over agent A is denoted by q_A^*. This represents an emotional average of the group and can be computed by:

$$q_A^* = \sum_{S \in G \backslash \{A\}} \omega_{SA} q_S. \tag{3.9}$$

A weighted sum with weights ω_{SA} computed by:

$$\omega_{SA} = \frac{\varepsilon_S \alpha_{SA}}{\sum_{C \in G \setminus \{A\}} \varepsilon_C \alpha_{CA}}. \tag{3.10}$$

Equation 3.10 considers the strength of contagion of each agent S over agent A and that depends on senders' expressiveness ε_S and their attachment with agent A denoted by α_{SA}. Each weight ω_{SA} represents the influence of agent S over agent A, normalized to the total group influence. Or, in other words, the fraction of the group emotional impact over A relative to agent S. This product is normalized by the sum of the total contagion strength of the group, excluding agent A.

The group emotion q_A^* is in fact the reference level to which the absorption model tries to reach. It represents a sort of group emotional average, and in a pure absorption situation ($\eta_A = 0$) the agents emotion will try to follow this reference. Notice that it varies in time as the emotions q_S in the agents also changes every iteration. Values of η_A in between 0 and 1 combines both amplification and absorption phenomena. For the pure amplification scenario ($\eta_A = 1$), the model brings an upward and a downward factor, represented respectively by PI, standing for *Positive Influence* and NI, standing for *Negative Influence*. Basically the positive influence normalizes q_A^* to fit the range $[q_A, 1]$, and the negative influence normalizes it to fit in the range $[0, q_A]$. This way, the higher the emotion level of the group, the higher will be PI and the lower will be NI, and vice-versa. The formulation of both influences is given by:

$$PI = 1 - (1 - q_A^*)(1 - q_A). \tag{3.11}$$

$$NI = q_A^* q_A. \tag{3.12}$$

This summaries the formulation on work of Bosse et. al. The results published by the authors confirm the ability of the model in simulating desired emotional behaviours, such as spirals[11]. For such reasons, it was adopted to continue in the crowd simulation scenario.

4. Methodology of Proposed Model

This Chapter presents the current proposed model for the integration of emotional contagion in crowd simulation context. It is based on a series of modifications on the model of Bosse et. al[11], with the objective to adhere this emotional contagion model in crowd context, most specifically the *BioCrowds* model[18][19]. A main challenge in this fusion is related to contextualizing agents in a virtual environment. As opposed to the model of Bosse et. al, we propose now to endow agents with a position in space and the ability to navigate in the scenario, as a function of time. This should be able to somehow impact the emotional contagion model.

The process of adapting an emotional contagion model in crowd context must aim to benefit from both models. The model of emotional contagion carries emotion related information and also the ability to spread this information (e.g., instantaneous emotional levels, expressiveness, susceptibility, etc.) in other agents. Since it is known that emotions have impact on peoples behaviour, it should be natural to use this information to impact on agents' behaviour as well. The model of crowd simulation carries spatio-temporal information, since agents are instantiated in a virtual environment, and navigate in this environment as a function of time. The *BioCrowds* model also brings agent's goal information. The agent's goal determines its trajectory (considering obstacles and other agents in the scenario), and since navigation is the observable behaviour of agents in *BioCrowds*, we propose that emotional information should impact on agents' goals. Also, the process of emotional contagion between agents can be designed to be impacted by agents' positions. We propose that the strength of contagion can be impacted with distance, since it might be harder to identify people's facial, gestural and vocal expressions with increasing distance. It is expected to observe emergent behaviour in crowd agents in function of emotion information exchange between agents and the impact of that information in their goals.

Beyond the challenge to integrate the model of Bosse et. al[11] and BioCrowds[18][19] in an extended version, some aspects of original model of Bosse et. al should be adapted in order to work in crowds. The model proposed by Bosse et. al is designed to deal with one emotion in the context of one group of agents. In crowds there are many groups and also individual agents. And they all, at some point, must have the ability to trigger emotional contagion from any other agent in the crowd, independently of their group status (i.e., whether they belong to the same group or not). It is desired that the contagion is possible to occur with ungrouped agents, as well as within one group and in between groups. In Chapter 3 we discussed about some of the many emotions aspects and its behavioural outcomes individually and in groups. Since Bosse et. al only deals with one emotion, it would be desirable that one agent have the ability to feel more than one emotion at a time. An extension to the model of Bosse et. al was made to accommodate more than one emotion in each agent.

In Section 4.1, we present the re-definition of agents in our extended version of Bosse-BioCrowds. This is important because agents in extended version incorporates parameters needed to contagion model. Section 4.2 details all modifications proposed in the extension concerning specifically the model proposed by Bosse et. al to be integrated with BioCrowds. Notice that the modifications presented could apply to another steering model.

4.1 Agent parameter definition

This section defines the parameters of an agent integrating both *BioCrowds* and emotional contagion model in our proposed extension Bosse-BioCrowds. Consider a crowd C with two or more agents where $C = \{A_0, A_1, ..., A_{N-1}\}$, being N the number of agents in the crowd. Each agent A_n, where $n = [0; N-1]$ and $A_n \in C$, in a given simulation instant t, is defined by the parameters $A_n(t) =< q_{A_n}(t), \varepsilon_{A_n}, \delta_{A_n}, \eta_{A_n}, \beta_{A_n}, og_{A_n}, \vec{x}_{A_n}, p_{A_n}, \vec{g}_{A_n}(t) >$. The parameter $q_{A_n}(t)$ is the instantaneous emotional level of agent A_n in time t. Some parameters are not denoted in function of t because they are constants. Parameter ε_{A_n} is the expressiveness of agent A_n, δ_{A_n} is the susceptibility, η_{A_n} is the bias of amplification and absorption model in agent A_n, and β_{A_n} is the bias between positive impact PI and negative impact NI on the amplification model. The parameter og_{A_n} denotes the disposition of agent A_n to be emotionally influenced by agents who does not belong to agent's A_n group. This parameter lies in range [0;1] and is multiplied by α to obtain α' according to Equation 4.7. When $og_{A_n} < 1$ this will result in smaller values of α attenuating contagion channel. The position of the agent A_n at time t is given by parameters $\vec{x}_{A_n}(t)$, which represent world coordinates in the virtual environment. The proxemics p_{A_n} is the minimum distance required for two agents to be able to interact with each other. Finally, $\vec{g}_{A_n}(t)$ is a position in the environment where the agent is supposed to reach, as long as it has space to navigate. The goal is a function of t because it can change anytime according to agents' emotional state.

Considering that one of the proposed extensions to perform in Bosse-BioCrowds method is to include multiple emotions, we define a set of emotions as $\Psi = \{e_0, e_1, ...e_{M-1}\}$, where M is the number of emotions defined for a specific scenario, and $e_m \in \Psi$ is the label of a specific emotion which can be any unspecified emotion. For each emotion, it is possible to define one emotion profile, denoted by $E_{A_n}^{e_m}$ and defined in Equation 4.1

$$E_{A_n}^{e_m} =< q_{A_n}^{e_m}, \varepsilon_{A_n}^{e_m}, \delta_{A_n}^{e_m}, \eta_{A_n}^{e_m}, \beta_{A_n}^{e_m}, og_{A_n}^{e_m}, \vec{g}_{A_n}^{e_m} > . \tag{4.1}$$

Where each parameter related to the contagion model is defined for emotion e_m, and the variable t is omitted to simplify reading. This is motivated by the fact that emotions are different in nature, and so may have different parameters depending on emotion's nature. For a scenario with multiple emotions, the set of all emotion profiles in one agent A_n, denoted by E_{A_n}, can be defined as in Equation 4.2.

$$E_{A_n} = \{E_{A_n}^{e_0}, E_{A_n}^{e_1}, ..., E_{A_n}^{e_{M-1}}\}. \tag{4.2}$$

Finally, the current emotional state of agent A_n, denoted by ψ_{A_n}, can be defined as in Equation

Tabela 4.1 – Variables of the extended model

Variable	Purpose
$q_{A_n}(t)$	is the instantaneous emotional level of agent A_n in time frame t.
ε_{A_n}	is the expressiveness of the agent A_n. It strengthen the contagion channel when A_n is the sender of emotion.
δ_{A_n}	Is the susceptibility of agent A_n. It strengthen the contagion channel when A_n is the receiver of emotion.
η_{A_n}	Is the bias that controls the amplification model and the absorption model in agent A_n, according to Equation 4.15.
β_{A_n}	Bias the positive impact (PI) and negative impact (NI) in the amplification model in A_n defined in Equation 4.15.
og_{A_n}	determines the attenuation in the emotion contagion channel promoted by that fact that A_n does not belong to the same group as the sender.
$\vec{x}_{A_n}(t)$	determines the position of agent A_n in instant t.
$\vec{g}_{A_n}$	Denote the direction pointing to agent's A_n goal.

4.3.

$$\psi_{A_n} = e_m \implies q_{A_n}^{e_m} = max(q_{A_n}^{e_0}, q_{A_n}^{e_1}, ..., q_{A_n}^{e_{M-1}}). \tag{4.3}$$

The emotional state ψ_{A_n} is the label of the emotion denoted by e_m which has higher emotional level $q_{A_n}^{e_m}$ than any other emotion in Ψ. So, the emotion that the agent actually behaves according to (the goal he/she pursuits) is the one pointed by ψ_{A_n}. The priority is given by declaration order (e_0 has priority over e_1 and so forth).

Now agent A_n can be re-defined for multiple emotions as in Equation 4.4.

$$A_n =< E_{A_n}, \vec{x}_{A_n}, p_{A_n}, \vec{g}_{A_n} > . \tag{4.4}$$

Notice that the parameter $\vec{g}_{A_n}$ seems redundant with the parameters $\vec{g}_{A_n}^{e_m}$ contained within each $E_{A_n}^{e_m} \in E_{A_n}$ (see Equation 4.1), but that is on purpose. The objective with apparent redundancy is to allow the agent to overwrite its original goal with the goal defined by its current emotional state ψ_{A_n}. This way, agents can change goals as they change emotional state. Also, goals associated to emotions are optional. If one particular emotion profile $E_{A_n}^{e_k}$ does not have a goal defined, whenever $\psi_{A_n} = e_k$ the original agent's goal $\vec{g}_{A_n}$ is used. The new variables used in the model for contagion in crowds are listed in Table 4.1.

4.2 Adapting emotion contagion model to crowd simulation context

This section describes the changing made in Bosse's model to achieve emotional contagion in crowd context. Here we aim to present, motivate and justify the decisions that resulted in the formulation presented in Section 4.1. Section 4.2.1 explains in further details how spatial and group information is used to resolve emotional contagion strength, most specifically referred to the relationship attachment between agents, denoted by α. Following, in Section 4.2.2, a simplification in the model is proposed, with the justification of removing matrices overhead and simplifying contagion between groups and between individual agents. In Section 4.2.3, the extension made in Bosse's model to accommodate more than one emotion is explained. And finally, in Section 4.2.4 we explain how emotions impact agents behavioural outcomes. With the proposed modifications it is expected that the emotion contagion model enables emotion contagion in crowd context. Using the advantages of an emotion contagion model already proven efficient in controlling aspects of emotion contagion such as contagion levels, contagion strength in a continuous contagion process. On top of that, the disposition of agents in the virtual scenario and their trajectories also influences the contagion of emotions.

4.2.1 Replacing Relationship Matrix with Space and Group Information

Interpersonal relationship refers to bonds that people create with each other. Family bonds, like mother and son, love affections, friendship bonds, colleagues, neighbours, those are all examples of social bonds people may want to create and maintain in their lives. Some of those relations might strengthen emotional contagion experience, while others might weaken it. But, these relationships can be linked to emotional contagion, and, just as in the model of Bosse et. al, this must be somehow present in the current model. As described in Section 3.4, the model of Bosse et. al designs this feature with the variable α_{SR}, denoting the impact of the relationship, or social bond, existent between agents S (the sender of emotions) and R (the receiver of emotion), and translates it to a number in the interval $[0, 1]$. So, a matrix must be declared as input data, containing all α_{ij} where A_i and A_j are agents. Considering that $\{A_i, A_j\} \in G$, and G is a group of N agents, this matrix must have dimensions $N \times N$ to accommodate all α_{ij} terms.

The relationship between people is an information that can not be calculated, it is known *a priori*. In crowd context, agents have no information about parenthood or friendship bonds. Although these information could be added, there is the problem of initializing such data. For numerous crowds (hundreds or thousands of agents), it is interesting that the relationship of agents could be estimated, or entering these data manually might lead to unnecessary overload of work.

One feature that the context of crowd has over the approach of Bosse et. al it that agents are placed in a virtual space. Taking advantage of spatiality now enabled on agents, we propose to estimate α_{SR} simply by measuring the distance between agents. Actually, we speculate that contagion should decrease while distance increases. That assumptions lies in the fact that, with increasing distance, it becomes harder to listen to someone's speech, or to correctly visualize and interpret gestures and facial expressions. Also, Bosse et. al [11] [10] states that α_{SR} must be function of attachment and distance. Furthermore, for our experiments, we decided to create a cut-off distance, i.e., a distance beyond which contagion becomes impossible. Here we introduce agent's proxemics, defined by p_{A_i}, where $A_i \in G$. If the distance between A_i and A_j is greater than the receiver's p_{A_i}, then it is considered that agents are two far away to perceive gestures, facial expressions or voice pitch, and contagion will not occur. Also, since in our model it is the receiver agent that trigger contagion, it is the receiver's proxemics that decides whether other agents are within range. Equation 4.5 shows how to compute alpha in the present scenario.

$$\alpha_{A_jA_i} = \begin{cases} min(1, 1/d) & d \leq p_{A_i} \\ 0 & d > p_{A_i} \end{cases}. \tag{4.5}$$

Where d is the Euclidean distance between agents A_i and A_j, defined by equation 4.6.

$$d = \sqrt{(x_{A_i} - x_{A_j})^2 + (y_{A_i} - y_{A_j})^2 + (z_{A_i} - z_{A_j})^2}. \tag{4.6}$$

In Equation 4.5 there are two conditions. If the distance d, computed by Equation 4.6, is smaller or equal to the proxemics of agent A_i, denoted by p_{A_i}, then $\alpha_{A_jA_i}$ equals the inverse of the distance d, which is $1/d$, because contagion strength must decay if distance increases. Also, if the distance d is smaller than $1m$ (since distances in *BioCrowds* are given in metric standard), this could lead to $\alpha_{A_jA_i}$ greater than 1, which is illegal according to the model of Bosse et. al. So, the function $min(1, 1/d)$ ensures that $\alpha_{A_jA_i}$ remains in the range [0,1]. Finally, according to Equation 4.5, if the distance between the two agents is greater than agent's A_i proxemics, then the contagion must stop so, $\alpha_{A_jA_i} = 0$.

By calculating $\alpha_{A_jA_i}$ with equation 4.5, we remove the need for a matrix containing all $\alpha_{A_jA_i}$ for all agents A_i and A_j belonging to group G. This matrix is now replaced by the module of the distance between agents that are interacting with each other. The advantage of doing this is that makes input data easier to be computed, since it is not necessary to initialize agents' relationships. But this also implies a limitation in our model. In Bosse's model it is possible to have any $\alpha_{A_jA_i}$ different from $\alpha_{A_iA_j}$, reflecting the fact that the contagion influence of A_i over A_j can be different of the contagion influence of agent A_j over agent A_i. In other words, the contagion channel strength of a mother over a son might be different of the contagion strength of the son over the mother. Since our model is simply the distance, and physically the distance of A_j to A_i is obviously the same of A_i to A_j, the result is that we can not model this difference in contagion channel. Some possibilities have been considered here e.g. use the distance together with other parameter (for example the expressiveness ε_A) to provide different values for α, however we chosen to do not provide any other change in α computation since for contagion model, ε_A and other parameters are already considered. Another option is to control agents' interactions in a frame-by-frame basis. By doing so, one can skip some interactions of one agent, weakening the contagion strength of such agent in relation to others that interact every frame. This approach has the advantage to introduce unbalanced contagion strength between two agents, even if they belong to the same group. The disadvantage is that it is only possible to weaken contagion strength, one can not strengthen the contagion channel using this approach.

A crowd is usually composed by many groups of agents and also by individual agents. Furthermore, crowd groups can contain many agents. At the same time, contagion must occur between all agents independently of their group status. To accommodate group information in an interaction, we focused on intra-group contagion, i.e., contagion between agents of different groups, or individuals. Moreover, we assume that agents from the same group will have full contagion, and agents from different groups may have full contagion, but they may also have the contagion strength reduced by some factor. This factor, denoted by og_{A_n} (which stands for Out Group of agent A_n) and lying in the range $[0, 1]$, measures the openness of agent A_n to exchange emotional contagion experience with members of other groups. To produce impact on contagion channel, og_{A_n} is multiplied by $\alpha_{A_jA_i}$, reducing contagion strength if $og_{A_i} < 1$, as in Equation 4.7, resulting in $\alpha'_{A_jA_i}$. In the case where the agents in a dyadic interaction are from the same group, the parameter og_{A_i} will be overwritten by its maximum value 1, so that contagion strength depends only on the value of $\alpha_{A_jA_i}$.

$$\alpha'_{A_jA_i} = og_{A_i}\alpha_{A_jA_i}. \tag{4.7}$$

This parameter also permits to disable contagion of a given emotion beyond the group. This can be done for any agents that require such limitation, and also this can be different from one emotion to another. For example, fear is very likely to spread beyond groups, but joy is most likely to remain within one particular group.

4.2.2 Simplifying for dyadic interactions

One issue in the model proposed by Bosse et. al that might potentially increases the model's complexity, when integrating it into crowd context, is that it predicts interaction within only one group of agents. Crowds usually contains a number of groups and individuals, and all of them should be able to suffer and promote contagion with each other. By instantiating a number of groups using replication of Bosse's model it could be achieved a scenario with a crowd and its many groups, but contagion would be limited to the boundaries of each group. Those boundaries would be resultant of the fact that one instance of the model (or group) cannot interchange messages with the other. A mechanism could be created to communicate the emotion of one group to the other, but this represents an increase on model's complexity, and thus misleading to computationally costly model.

Now, consider a group G with N agents. For this group, the model of Bosse et. al demands an input matrix that we denote matrix **A** from now on, containing all $\alpha_{A_jA_i}$ that represents the impact of agents' relationship status (are they friends, family or strangers?) in the strength of the contagion channel between them[1]. More specifically, $\alpha_{A_jA_i}$ represents the impact of the relationship status existent between agents A_j and A_i over the contagion strength of A_j over A_i. The Equation 3.6 permits to calculate all γ_{SR} for every two agents $\{S, R\} \in G$, where, at this instant, S is the sender of emotion and R is the receiver of emotion. The set of all γ_{SR} can also be seen as a matrix, that we call $\mathbf{\Gamma}$ from now on, with dimensions $N \times N$, where N is the number of agents in G. And finally there is also the computation of ω_{SR} in Equation 3.10 that generates another matrix, that

[1] See table 3.1 for details on Bosse's parameters.

we call $\mathbf{\Omega}$ from now on, also with dimensions $N \times N$.

Resolving both $\mathbf{\Gamma}$ and $\mathbf{\Omega}$ matrices results in an algorithm $2\Theta(N^2)$ for calculating the weights that will be latter used for resolving dq_A/dt in Equation 3.8. In Bosse's model this is not an issue, because α_{SR} does not change during simulation, so, matrices $\mathbf{\Gamma}$ and $\mathbf{\Omega}$ can be calculated during initialization, and stored for later use. But, since we adopted α_{SR} as the distance between agents (according to Section 4.2.1), matrices **A** , $\mathbf{\Gamma}$ and $\mathbf{\Omega}$ must be recalculated frame-by-frame. For small groups this is not a problem in terms of memory cost or processing time. But within a crowd of 100 (one hundred) agents, matrices **A** , $\mathbf{\Gamma}$ and $\mathbf{\Omega}$ ends up with $10,000$ (ten thousand) calculations each frame, since now α_{SR} might vary from one iteration to another because it is dependant on positions of moving agents. Although creating real-time simulations is not our goal, we believe it is a good practice to keep the model simple and efficient to result in easier implementation and increase application possibilities.

Now, lets further analyse the particular case in the model of Bosse et. al where there is a group with only two agents, thus characterizing a **dyadic interaction**. Consider a group G' composed of just two agents $G' = \{A_i, A_j\}$. Both A_i and A_j will be sender and receiver of emotions, in turns, during each simulation frame. That is the reason why, from now on, we are using terms A_i and A_j, which denotes generic agents, instead of S and R which denotes the sender and receiver respectively.

In the model of Bosse et. al, when dq_{A_i}/dt is calculated for agent A_i using Equation 3.8, at this instant, it is assumed that agent A_i is the receiver (R) and the impact of the senders (S or, in this case A_j) is given by $q^*_{A_i}$, defined in Equation 3.9. Also, the strength of the contagion channel in this case is given by γ_{A_i}, defined in Equation 3.7 and used to resolve Equation 3.8. To compute γ_{A_i}, first it must be calculated $\gamma_{A_iA_j}$ using Equation 3.6. It is possible to rewrite Equation 3.6 as in Equation 4.8, replacing R for A_i and S for A_j, reminding those are now the only two agents in group G, and replacing $\alpha_{A_jA_i}$ by $\alpha'_{A_jA_i}$, according to Equation 4.7.

$$\gamma_{SR} = \varepsilon_S \alpha_{SR} \delta_R = \varepsilon_{A_j} \alpha'_{A_jA_i} \delta_{A_i}, \text{ when } A_i = R \text{ and } A_j = S. \tag{4.8}$$

So far there is nothing new compared to the approach proposed by Bosse and colleagues, but when one analyses Equation 3.7 to compute γ_R (or, in this case, γ_{A_i}), it can be rewritten as in Equation 4.9

$$\gamma_R = \gamma_{A_i} = \sum_{A_j} \gamma_{A_jA_i}, \text{ when } A_i = R \text{ and } A_j = S. \tag{4.9}$$

And since A_j is the only agent in the sum, this results in Equation 4.10

$$\gamma_{A_i} = \gamma_{A_jA_i} = \varepsilon_{A_j} \alpha'_{A_jA_i} \delta_{A_i}. \tag{4.10}$$

The interpretation of Equation 4.10 is that, since the only agent in group G' (that is not A_i, the receiver) is agent A_j, the contagion strength of the group over A_i equals the contagion strength of

A_j over A_i. In other words, the group is represented by just A_j, from the point of view of agent A_i. That claim turns out to be also true when calculating the weights ω_{SA}, as shows Equation 4.11. Reminding that ω_{SR} represents the fraction of the group impact promoted by agent S over agent R when the group has more than one agent, as pictured in Equation 3.10. But, in the case where the group has only two agents and denoting $\omega_{A_jA_i}$ for agents A_i and A_j, it is possible to rewrite Equation 3.10 as in Equation 4.11.

$$\omega_{SA} = \frac{\varepsilon_S \alpha_{SA}}{\sum_{C \in G \setminus \{A\}} \varepsilon_C \alpha_{CA}} = \omega_{A_jA_i} = \frac{\varepsilon_{A_j} \alpha'_{A_jA_i}}{\sum_{A_j} \varepsilon_{A_j} \alpha'_{A_jA_i}} = \frac{\varepsilon_{A_j} \alpha'_{A_jA_i}}{\varepsilon_{A_j} \alpha'_{A_jA_i}} = 1, \tag{4.11}$$

when $A_i = R$ and $A_j = S$. In Equation 4.11 we start comparing with the weights on the original model as proposed by Bosse et. al and defined by Equation 3.10, and denotes the weights of all group senders (S) over the contagion of a specific agent A in the group G, thus ω_{SA}. The weight ω_{SA} is normalized by a sum over all agents in G, excluding agent A, in the original model by Bosse et. al. In our case, the fact that $\omega_{A_jA_i}$ is always 1 means that agent A_j always holds full impact of the group over agent A_i. It also means that there is no need to compute any $\omega_{A_jA_i}$ for the case where G has only two agents. That makes sense, since agent A_i cannot impact himself through this model, remaining only agent A_j responsible to promote contagion over A_i. This property also has an impact on the solution of Equation 3.9, that defines q^*_A, which can be rewritten as in Equation 4.12.

$$q^*_{A_i} = \sum_{S \in G \setminus \{A_i\}} \omega_{SA_i} q_S = \sum_{A_j} \omega_{A_jA_i} q_{A_j} = q_{A_j}, \tag{4.12}$$

because all weights $\omega_{A_jA_i} = 1$ in the case of two agents in the group.

So, it is not necessary to calculate ω_{SA}, as stated before, because it is always 1. Is it also not necessary to compute q^*_R since it will be always equal to sender's emotional level $q^*_R = q_S$ when there is only two agents in the group, thus $q^*_{A_i} = q_{A_j}$. Finally, for the positive impact PI and the negative impact NI in the amplification model, they can be simply rewritten as in Equations 4.13 and 4.14.

$$PI = 1 - (1 - q_{A_j})(1 - q_{A_i}). \tag{4.13}$$

$$NI = q_{A_j} q_{A_i}. \tag{4.14}$$

Reminding Equation 3.8, it is now possible to solve for dq_{A_i}/dt as in Equation 4.15.

$$dq_{A_i}/dt = \gamma_{A_i} \left[\eta_{A_i} \left(\beta_{A_i} PI + (1 - \beta_{A_i}) NI \right) + (1 - \eta_{A_i}) q_{A_j} - q_{A_i} \right], \tag{4.15}$$

where η_{A_i} and β_{A_i} are both parameters of agent A_i, $\gamma_{A_jA_i}$ is given by Equation 4.10, q_{A_i} and q_{A_j} are the current emotional level for agents A_i and A_j respectively. Also, the Positive Impact PI and the Negative Impact NI are computed by Equations 4.13 and 4.14 respectively.

Now that the model of contagion for dyads is defined, it must be applied in a way that promotes contagion for all agents in a crowd, and not only two of them. To do so, we propose to trigger many dyadic interactions each frame (or iteration), promoting contagion in each of the agents, from all the others in the crowd, in a dyadic manner. To illustrate how all agents of a crowd (grouped or not) can suffer and promote contagion with each other in a dyadic manner, lets consider a group G with two or more agents where $G = \{A_0, A_1, ..., A_{N-1}\}$, being N the number of agents in the group. Also, each agent A_i, is defined by the Equation 4.4, in Section 4.1. The Algorithm 1 illustrates the procedure applied to promote contagion in all members of G in a dyadic manner.

$$C(t) = \{A_0(t), A_1(t), ..., A_N(t)\}. \tag{4.16}$$

The Algorithm 1 operates over the data structure called $C(t)$ which contains the crowd state at time instant t, measured in frames or iterations. This means that each algorithm iteration represents one simulation frame. The definition of data structure $C(t)$ is given in Equation 4.16 and equals the set of agents present in the crowd $\{A_0(t), A_1(t), A_N(t)\}$ and their status at instant t. Reminding the definition of agent from Section 4.1, written in Equation 4.4, the Algorithm 1 updates only E_{A_n}, which contains the emotional parameters of agent A_n, according to Equation 4.2. Also, E_{A_n} is defined as the set of all $E_{A_n}^{e_m}$, defined in Equation 4.1. For the present case, $E_{A_n} = \{E_{A_n}^{e_0}\}$ and so we can rewrite E_{A_n} according to Equation 4.17.

$$E_{A_n} =< q_{A_n}, \varepsilon_{A_n}, \delta_{A_n}, \eta_{A_n}, \beta_{A_n}, og_{A_n}, \vec{g}_{A_n} > . \tag{4.17}$$

And since q_{A_n} is the only term variant in time (we omit the goal during estimation of emotional level), Algorithm 1 focuses on updating this value according to contagion process for one emotion. The updated value of q_{A_n} for every agent A_n results in the updated emotional state of the crowd (i.e., the emotional state of agents contained in the crowd) for the next time instant $t + 1$. To do so, the algorithm sweeps all agents in the crowd varying index i, making every agent A_i a receiver of emotion. Then, for every agent A_i, it sweeps the crowd again varying index j. The condition in line 3 ensures that no agent will ever interact with himself.

In line 4 we introduce a variable Δ that simply stores the result of Function `Interaction` (A, B), in line 8, which in turn returns dq_A/dt for time t having agent A as emotion receiver and agent B as emotion sender. This is how much the emotion level of agent A, denoted by q_A, must vary due to contagion. So, in line 5 the emotional level for the current receiver of emotion agent A_i, denoted by q_{A_i}, has its value updated by Δ. This algorithm must be called each instant t to compute the next one, until the simulation ends.

Finally, the Function `Interaction` (A, B) describes the model discussed so far, with the simplifications proposed. To incorporate spacial information existent in crowd context, the distance between the two agents, passed as parameters to Function `Interaction` (A, B), is calculated using the Euclidean distance, defined in Equation 4.6. This distance is stored in d for later access. In line 10, if distance is greater then agent's A proxemics, this means that contagion will not occur.

So the function returns zero, implying in no variation to agent's A_i emotional level q_{A_i}. If d is lesser or equal to p_A, the algorithm continues in line 11 by estimating α_{BA} as the inverse of distance d. And in line 12 we ensure that α_{BA} stays in the range [0,1] even if the distance d is lesser than $1m$.

The remaining of Function `Interaction` in Algorithm 1 processes the contagion of emotion, by computing dq_A/dt. First it computes γ_A, PI_A and NI_A according to Equations 4.10, 4.13 and 4.14 respectively. In line 16, the recently computed values γ_A, PI_A and NI_A, along with agent's A parameters q_A, η_A and β_A, as well as sender's emotional level denoted by q_B are used to resolve dq_A/dt, which is then returned as result.

Algoritmo 1: Applying dyadic approach to crowds.

Data: crowd $C(t) = \{A_0(t), A_1(t), ..., A_N(t)\}$
Result: crowd $C(t+1) = \{A_0(t+1), A_1(t+1), ..., A_N(t+1)\}$
1 **for** $i \leftarrow 0$ **to** $N-1$ **do**
2   **for** $j \leftarrow 0$ **to** $N-1$ **do**
3   **if** $j = i$ **then next** j;
4         $\Delta \longleftarrow$ `Interaction`$(A_i(t), A_j(t))$;
5         $q_{A_i}(t+1) \longleftarrow q_{A_i}(t) + \Delta$;
6   **end**
7 **end**
8 **Function** `Interaction`(A, B) **begin**
9     $d \longleftarrow$`EuclideanDistance`(A, B);
10   **if** $d > p_A$ **then return** 0;
11     $\alpha_{BA} \longleftarrow 1/d$;
12   **if** $\alpha_{BA} > 1$ **then** $\alpha_{BA} \longleftarrow 1$;
13     $\gamma_A \longleftarrow \varepsilon_B * \alpha_{BA} * \delta_A$;
14     $PI_A \longleftarrow 1 - (1 - q_A) * (1 - q_B)$;
15     $NI_A \longleftarrow q_A * q_B$;
16     $dq_A/dt \longleftarrow \gamma_A * [\eta_A * (\beta_A * PI + (1 - \beta_A) * NI) + (1 - \eta_A) * q_B - q_A]$;
17   **return** dq_A/dt;
18 **end**

4.2.3 Extending for multiple emotions

In this section we propose to extrapolate the model proposed by Bosse et. al [11] to enable it to simulate a given number of emotions, denoted by M, being M an integer and $M \geq 1$. Having multiple emotions is an important feature because people are able to feel many emotions, and there are many emotional models in the psychology literature, all of them suggesting more than one emotion. Also, it is known that emotions may have impact on people's behaviours and actions. So, we propose that actions of crowd agents can be driven, or motivated, by agent's emotional status.

Consider a crowd C where $C = \{A_0, A_1, A_{N-1}\}$, being N the number of agents in C. According to the original model proposed by Bosse and colleagues, it is possible to define the emotional profile of an agent $A_n \in C$ at a given simulation instant t according to Equation 4.17 for one emotion, as the set $E_{A_n}(t) =< q_{A_n}(t), \varepsilon_{A_n}, \delta_{A_n}, \eta_{A_n}, \beta_{A_n}, og_{A_n} >$ (the parameters that are not presented in function of t are constants). The descriptions of the variables that compose $E_{A_n}(t)$ are described in Table 4.1.

Once it is considered more than one emotion in the model, the emotional contagion must be remodelled in order to deal with this variety of emotions. Now consider a set of emotions $\Psi =< e_0, e_1, ..., e_{M-1} >$ where M is the number of emotions. It is possible to define a vector $E_{A_n}^{e_m}$ as the emotional profile of agent A_n, regarding emotion e_m, being $e_m \in \Psi$, as in Equation 4.18. Each element addressing one of the scenario's possible emotional profiles in each agent. Emotional profiles describe the way each agent will respond, in term of contagion, for each particular emotion. Factors that impact this parameter are related to agents' personalities, i.e. whether they are shy or expressive. It can also be impacted by emotion nature, since some emotions may spread faster than others.

$$E_{A_n}^{e_m} =< q_{A_n}^{e_m}, \varepsilon_{A_n}^{e_m}, \delta_{A_n}^{e_m}, \eta_{A_n}^{e_m}, \beta_{A_n}^{e_m}, og_{A_n}^{e_m} > . \tag{4.18}$$

Since agents are now able to "feel" more than one emotion, we can also define the emotional state of an agent as the emotion with higher emotional level at a given simulation instant. Suppose an agent A_n, where $A_n \in C$ in a scenario with a set of emotions $\Psi = \{e_0, e_1, ..., e_{M-1}\}$, and M being the number of existing emotions in the current scenario. The emotional level for each emotion on agent A_n is given by the vector $q_{A_n} =< q_{A_n}^{e0}, q_{A_n}^{e1}, ..., q_{A_n}^{e_{M-1}} >$, where $q_{A_n}^{e_m}$ is the instantaneous emotional level in the range $[0, 1]$ of a given emotion e_m in agent A_n. The emotional state of agent A_n, denoted by ψ_{A_n} can be defined as the emotion with maximum emotional level given by Equation 4.19.

$$\psi_{A_n} = e_m \implies q_{A_n}^{e_m} = max(q_{A_n}^{e0}, q_{A_n}^{e1}, ..., q_{A_n}^{e_{M-1}}). \tag{4.19}$$

With emotion profiles, each agent is able to express its own emotions to the group at a given expression level ε. Depending on the agents personality traits, he or she might express every emotion in different ways. A person with a high expressiveness should present stronger expressions of emotions than a shy person with low expressiveness. Also, negative emotions, like fear, tend to spread faster than positive emotions, like joy. This implies that ε can vary from one emotion to another, depending on emotion's nature. From the point of view of the receiver agent, a person has the susceptibility of catching the emotions represented in the model by the variable δ, which also lies in the range $[0, 1]$. Similarly to the expressiveness ε, the susceptibility δ regulates the disposition of an agent to catch one emotion. Using emotion profiles, the susceptibility of agents can vary from one emotion to the other, depending on emotion's nature and agent's personality, analogous to the expressiveness. Same with η and β, which bias the amplification model. Since it is meant to generate emotional both positive and negative energy, the amplification model can force an emotional state in the agent.

The energy one agent presents for a given emotion is related to the situation in a simulation that might trigger such emotion, and depends on emotion nature and the context the agent presents him/herself.

Finally, the relationship between the agents $\alpha_{A_jA_i}$ is calculated in function of distance and group information, as explained in Section 4.2.1. So, there is no need to vectorize $\alpha_{A_jA_i}$ for every emotion, since it will be calculated in a frame-by-frame basis.

4.2.4 Enabling emotions impact on agents' behaviour

Considering one random agent A_n, since q_{A_n} lies in the range $[0, 1]$, agents with only one emotion are able to feel a given level of such emotion every time t instant. With the ability to perceive more than one emotion (according to Section 4.2.3), agents now can change their emotional state. By emotional state, we propose to be the stronger emotion agent feels at a given time instant t, denoted by ψ_{A_n} and defined in Equation 4.3. We propose that, although agents can feel more than one emotion at a time, and are able to promote and suffer contagion from all its emotions, the current emotional state ψ_{A_n} of the agent A_n is the only one that impacts agents' behaviour.

The variable ψ_{A_n} equals the index (or label) that identifies the emotion with higher level $q^{em}_{A_n}$. We propose to endow the agents with the option to associate a goal, denoted by $\vec{g}^{em}_{A_n}$, to each emotional profile $E^{em}_{A_n}$, according to Equation 4.1. Each goal $\vec{g}^{em}_{A_n}$ represents coordinates in the virtual environment where the goal is placed. The index ψ_{A_n} is then used to identify if there is a goal associated to respective emotion profile $E^{em}_{A_n}$. If there is, it will take priority over the original agent's goal $\vec{g}_{A_n}$, associated to them during *BioCrowds* initialization. This way, according to agent's emotional state, the goal of agents can change, allowing the emotional contagion model to impact on the outcomes of *BioCrowds*. This information can be also used to other purposes. In our case, we change agents' colour to identify each agent's emotional state in the scenario. Other application may use this information within totally different contexts like urban signs application, where signs can be static (meaning they won't move in the scenario) expressive-only agents, and pedestrians would be susceptible-only agents looking for directions. We remark that associating a goal to an emotional state $E^{em}_{A_n}$ is an optional feature, i.e., there might be one or more emotions with no goals associated to it. In those cases, the original goal of the agent will not be overwritten, and no behavioural changes will occur when the emotion pointed by ψ_{A_n} has no goals.

With this extension we expect to have behavioural outcomes originated from emotional state changing in agents. As their states changes, their goals might change as well, altering their trajectories, potentially leading them to interact with other agents in the scenario. This can result in a chain-reaction, impacting both emotional state and trajectories of crowd agents.

5. Simulation Experiments and Results

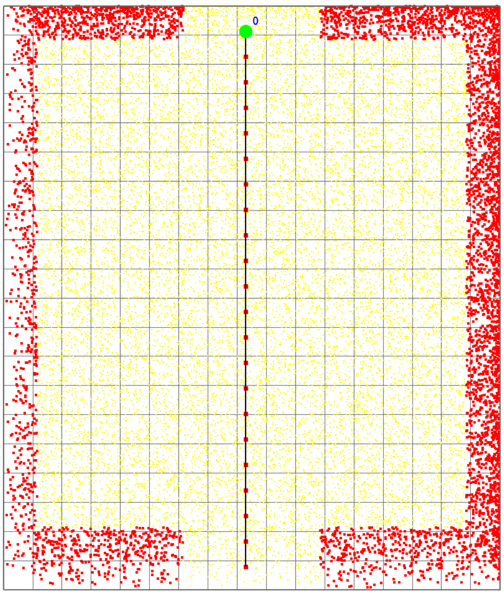
This chapter explains the scenarios used for testing the emotional contagion model in crowd simulation context. In order to explore the many aspects of emotional contagion processes in the ambience of a crowd, a carefull choice of scenarios must be made. At first, it is important to explore spatio temporal impact on the emotional contagion model. This is a key diference between the present work and the work of Bosse et. al [11]. A dyadic situation with **standing agents** (not moving) in our model is identical to a situation in Bosse's model when $\alpha_{ij} = \alpha_{ji}$. So, a scenario with standing agents in the context of a crowd (dozens of agents) is elected to make a first comparison of our model with the model proposed by Bosse et. al.

As depicted in Chapter 4, the strength of contagion between agents A_i and A_j is defined by variable α_{ij}, and decreases as the distance between agents A_i and A_j increases. This is a result of contextualization of agents in a virtual space. If agent's trajectories approach them to each other, it will result in strengthening of contagion, or weakening of contagion, if they wander away from each other, to the point where they cease contagion of emotion due to distance. The distance threshold, as explained in Chapter 4, is defined by agent's proxemics. Having in mind that contagion strength vary during simulation, and that this variation is ruled by agent's movements, it is correct to speculate that agent's mobility is another aspect for testing scenarios design. So two scenarios with **moving agents** are elected: one scenario where agents move in the **same direction**; and another with **counterflow**, where agents move against each other. The variation of contagion strength is another characteristic that differs this model from the model by Bosse et. al.

Finally, emotions are known to drive actions. Furthermore, emotional monotonicity is known to strengthen group bonds if they are positive emotions (such as joy) increasing feelings of acceptance in group members. Knowing this, behavioural aspects should be measured in the scenarios. Moreover, as explained in Chapter 4, behavioural changes in the present model are translated into changes in agents' goals. So, to experiment behavioural changes, goals are associated with emotions in both **moving agents** scenarios. Further details on this implementation are given in the following sections of this chapter. In the scenario with **standing agents** it makes no sense on changing agents' goals, since they are not supposed to move. So, for that scenario, no behavioural outcomes are expected regarding agents' movements. However, in **standing agents** scenario we expect to observe some outcomes concerning emotional level of agents and emotional spreading though the crowd, such as third party contagion and emotional monotonicity over the crowd.

In all scenarios, we make some conventions about colors of agents and markers in the scenario area, which are now briefly explained. For starters, all scenarios have a collection of dots randomly spread in all the scenario area respecting a given density of markers. Those markers, as explained in Section 3.3, stand for walkable area. Agents will compete for space through the ownership taking of those markers. In our experiments, we conventionally used yellow dots to denote walkable area, and red dots to denote obstacles. In Figure 5.1, we can see the representation of a room with two

Figura 5.1 – Simulation scenario example with two entrances/exits: one in the top, and another in the bottom.

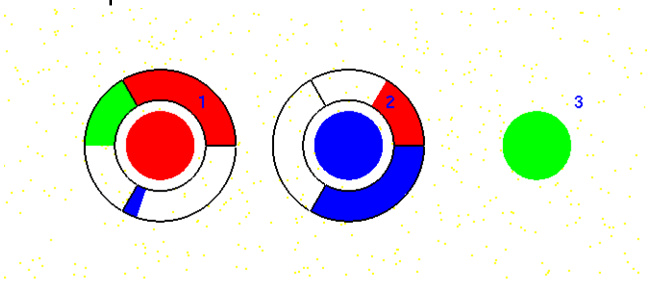


Simulation screenshot.

exits, one in the bottom, and the other in the top. Indeed, in *BioCrowds* computation process, only markers present in walkable areas (yellow ones) are used to calculate agents motion. Red dots, as illustrated in Figure 5.1, are used to visually illustrate walls and obstacles. Also, in the top entrance, we can see one agent represented by a green circle and it is labeled with a 0 on its top right corner, meant to identify it as agent A_0. The black line represents agent's intended trajectory, and every red dot in this line is one checkpoint in the trajectory. Those checkpoints are calculated via A* algorithm, starting in agent's current position and ending in agent's final goal, considering any physical obstacles. Since there are no obstacles in this example along agent's trajectory (represented by red markers) the trajectory is simply a straight line. Finally, the grid shows scenario size. In the example of Figure 5.1, the scenario size is 17×20. This grid is usually hidden for visualization purposes.

The agents appear as coloured circles and their identity number is placed on their top right corner as shown in Figure 5.1. But there are more details about agent's visual representation, and we give further examples. The colors of the agents represent their actual emotional state. Additionally, in some pictures, there might appear a ring containing an instantaneous measure of each emotion and, as convention, the values grows as the coloured slices of the ring fills in counter-clockwise sense. For example, in Figure 5.2 there are three agents depicted. The first two agents, from left to right, have three non-specified emotions each: RED, $GREEN$, and $BLUE$. Observing agent 1, we see $GREEN$ at half-way (0.5), $BLUE$ is almost empty, but not equal zero, and RED is at maximum, thus the agent's color is red. By observing agent 2 we see that there is no $GREEN$, since it is equal zero (notice they occupy the same portion of the ring), RED is at half-way, and $BLUE$ is at its maximum, thus the agent's color is blue. Agent 3 is represented without the emotional ring. Although he has all three emotions they can be hidden for visualization purposes. The only thing

Figura 5.2 – Agent representation example. Agents have three unspecified emotions: RED, $GREEN$, and $BLUE$. Agents are labelled with an identification number. Agent A_1, shows emotion RED at full, emotion $GREEN$ halfway full and emotion $BLUE$ nearly empty (or weak). Agent A_2 presents emotion RED halfway full, emotion $GREEN$ equals zero, and thus it remains blank, and finally emotion $BLUE$ in agent A_2 is completely full. Agent A_3 is represented without the emotional ring, and it can only be inferred that his/her emotion $GREEN$ has higher value than RED and $BLUE$, since the agent is coloured green. This picture is just an example of possible agents' status and their visual representation.



Simulation screenshot

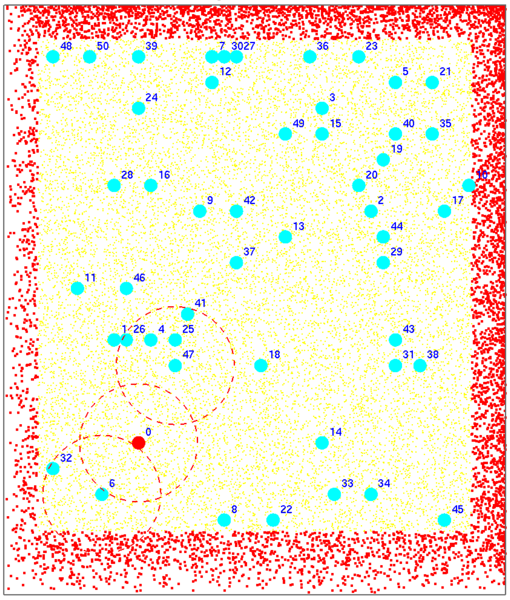
that can be inferred by observing agent 3, in this visualization mode, is that emotion $GREEN$ has higher value compared to RED and $BLUE$, since the agent is coloured green.

The remainder of this Chapter is organized as follows: in Section 5.1 a scenario to measure the impact of spatio temporal context over the emotional contagion model is proposed. This experiment takes away agents' movements, so the emotional spread depends only on agents initial position, agents distance from the Expressive agent, time and the contagion process itself. The scenario depicted in Section 5.2 experiments emotional contagion with agents in movement, with one group moving towards the emotional spreading agent. Finally, in Section 5.3, the impact of an agent spreading emotion moving through a standing crowd is experimented. In this scenario, the contagion also impacts agents' behaviour by making standing agents decide to follow (or not to follow) the emergent leader.

5.1 Standing Agents scenario

As explained before, the trajectories of agents may drive them closest to each other, or away from each other, depending on each situation, during the simulation. In both cases, the variation in agents' distances to each other also impacts in the strength of contagion due to the model explained in Chapter 4. In order to isolate this variable and make a first comparison with the outcomes from the model proposed by Bosse et. al, this experiment takes away agents' movement, so the emotional spread depends only on agents' initial position, agents' distance from each other (that never changes), time and the contagion process itself. We propose a scenario populated by agents in three arbitrary cases: one with 50 agents, one with 80 agents and one with 110 agents. These numbers are chosen based on scenario size. What really matters here is the density of agents, because the distances between agents depends on that, and, in turn, the strength of contagion depends on agents' distance from each other. So, the aim here is to control density of agents, by

Figura 5.3 – Standing Agents experiment with 50 agents in the crowd. One can observe that agent A_0 is not close enough to any other agent in the crowd so, he will not trigger contagion. The red circumferences around agents A_0, A_6 and A_{47} denotes agents' interaction space, beyond which there is no contagion. Those are the closest agents to A_0.



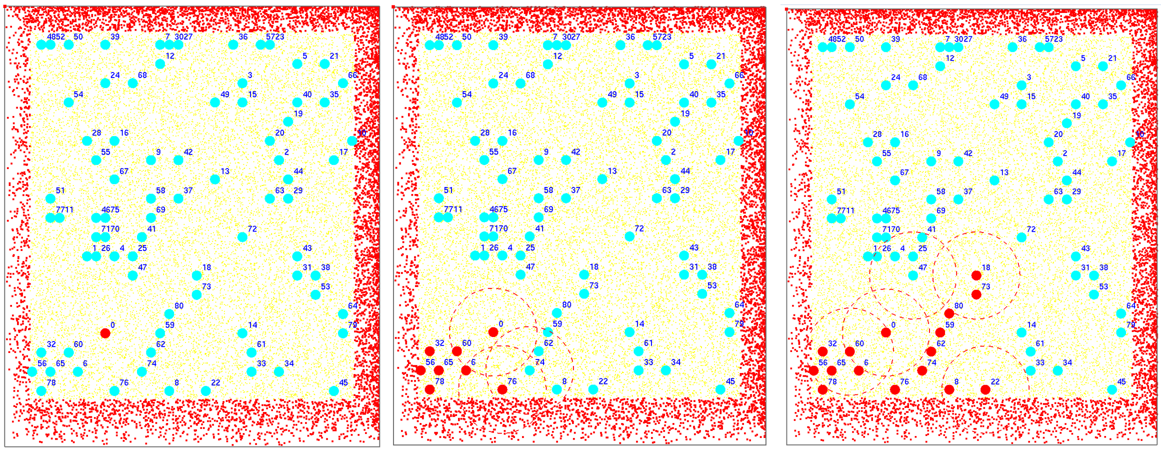
Simulation screenshot

changing absolute agent number and keeping the space area unchanged. In Figure 5.1 it is possible to visualize the map grid, which determines world dimensions in *BioCrowds*. The present scenario uses the same configuration of 17×20 (columns vs. lines) map cells, where each cell has $1m^2$.

Now consider a crowd denoted by C where $C = \{A_0, A_1, ..., A_{N-1}\}$ is a set of N agents A_i being $i = [0..N-1]$. To measure the contagion in crowd C, one agent is arbitrarily elected to be the *emotional leader*, or, in other words, the one that generates emotional energy and promotes change of emotional state in others. By convention, the *emotional leader* is always agent A_0. To create the experiment, the scenario must be set with two emotions. One emotion to be tested, represented in Figures 5.3, 5.4 and 5.5 in red, that represents one unspecified emotion (i.e., an emotion of unspecified nature), and labelled as RED, from now on. The other emotion serve as control variable on the experiment, represented in the Figures 5.3, 5.4 and 5.5 in blue, and we will reference this emotion as $BLUE$, from now on. This does not spread in the crowd and its values does not vary in time. Figures 5.3, 5.4 and 5.5 omits the emotion ring for visualization purposes so, in these figures, agents painted in red have the condition $q_i^{RED} > q_i^{BLUE}$, and agents painted in blue, otherwise.

The emotion under study is RED, and thus must be different in agent A_0 compared to all other agents in the scenario. This is because the *emotional leader* agent A_0 must constantly generate RED energy in order to promote contagion in the surrounding crowd. The other agents must remain neutral, meaning they must not generate additional emotional energy, they should only follow the surrounding agents' emotional influence by (primitive) empathy. For the agent A_0 to be able to generate emotional energy, it is necessary to activate the amplification model in A_0 (Section 3.4).

Figura 5.4 – Standing Agents experiment with 80 agents in the crowd: In Figure 5.4(a) one can observe the first frame of the simulation experiment. There, only agent A_0 is in RED, and all other agents are coloured blue because they have emotion RED level under threshold $BLUE$. In Figure 5.4(b) it is pictured an intermediary frame in the middle of the simulation, showing a number of agents already changed their emotional state from $BLUE$ to RED. In Figure 5.4(c) is pictured the final frame of the simulation. The red circumferences around on agents A_0, A_{18}, A_{22}, A_{47} and A_{60} denotes agents' interaction ray, beyond which there is no contagion.



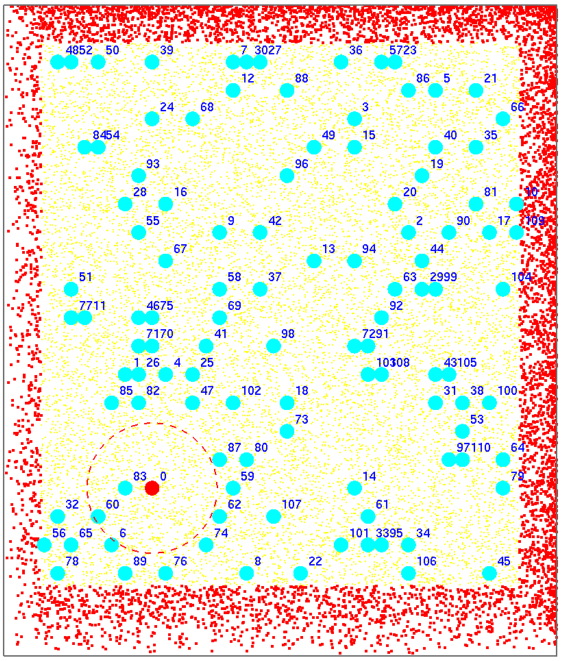
(a) First simulation frame (b) One minute time elapse (c) Last simulation frame

This agent must also suffer influence from the crowd, so the absorption model must also be activated, in order to allow agent A_0 to catch and follow other emotions too. To do so, parameter η_0 in agent A_0 must be $\boldsymbol{\eta_0 = 0.5}$, that will balance absorption and amplification model bias, resulting in half strength of contagion in amplification model, and half strength of contagion in absorption model. This way agent A_0 have both amplification and absorption models active with the same bias during the experiment. Also, to ensure that amplification is positive for emotion RED in agent A_0, the amplification bias β_0 (see Equation 3.8) is set to its maximum $\boldsymbol{\beta_0 = 1}$ for agent A_0, promoting full positive bias in amplification model. It is important to notice that this choice results in agent A_0 also suffering contagion by the crowd as desired. The remaining agents A_k (where $A_k \in C, k \neq 0$) must have $\boldsymbol{\eta_k = 0}$, eliminating influence of the amplification model in those agents, remaining only the absorption model. This way they are not generating any additional emotional energy, and will follow crowd tendency. Since $\eta_k = 0$ for all A_k where $k \neq 0$, the bias β_k does not matter for those agents (see Equation 3.8) and is set to $\boldsymbol{\beta_k = 0}$ for all agent A_k.

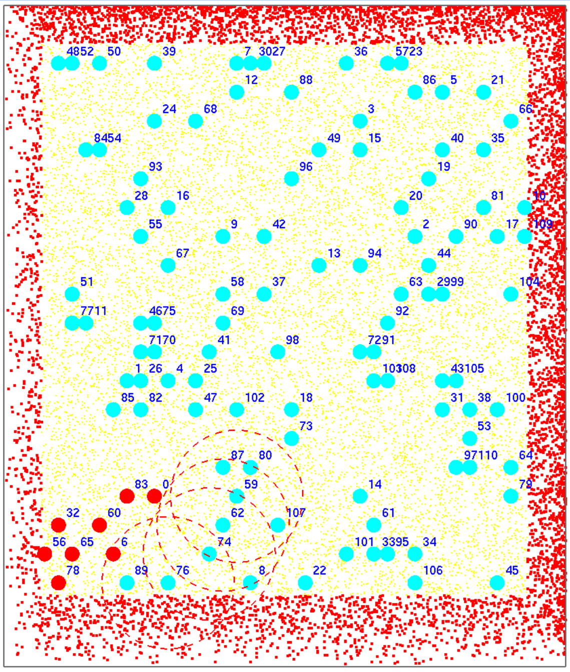
The objective is to observe how the emotional energy of A_0 will spread through the crowd. So, agents must be able to express their emotions, in order to promote contagion in others. They also must suffer contagion, since we want to experiment the impact of the crowd over agent's A_0 emotion as well as agent's A_0 influence over the crowd. For the present experiment, it was decided that $\boldsymbol{\epsilon_i = 0.5}$ and $\boldsymbol{\delta_i = 0.5}$ for all agents $\boldsymbol{A_i \in C}$ where $\boldsymbol{i = [0..N-1]}$. This choice makes both expressiveness and susceptibility of agents active, but not so strong, and not so weak.

Finally, the $BLUE$ emotion is used as control so, we do not want it to vary, and must be the same for all agents $A_i \in C$. Moreover, it must be initialized with the same level for all agents, so

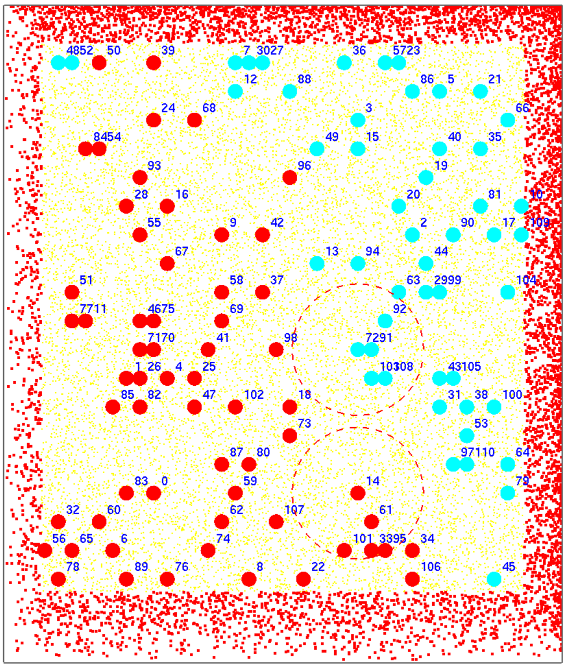
Figura 5.5 – Standing Agents experiment with 110 agents in the crowd: In Figure 5.5(a) one can observe the first frame of the simulation experiment. There, only agent A_0 is in RED, and all other agents have emotion RED level under threshold $BLUE$. The circle around agent A_0 denotes its interaction space, inside which there are only agents A_{60} and A_{83}. In Figure 5.5(b) it is pictured the 125^{th} frame showing a number of agents that form a chain reaction to spread emotion to the remaining agents of the crowd. In Figure 5.5(c) it is pictured frame 700 in the simulation. The circles denotes agents' A_{14} and A_{72} interaction spaces. The distance between agents in this area block the emotion RED to promote contagion in lower left agents, so the contagion spreads to the upper right corner of the scenario. In Figure 5.5(d) it is pictured the final frame of the simulation. Agent A_{45} is the only remaining agent that has not suffered contagion. This is because it is isolated and no other agent is inside its interaction space, denoted by the red circumference around it.



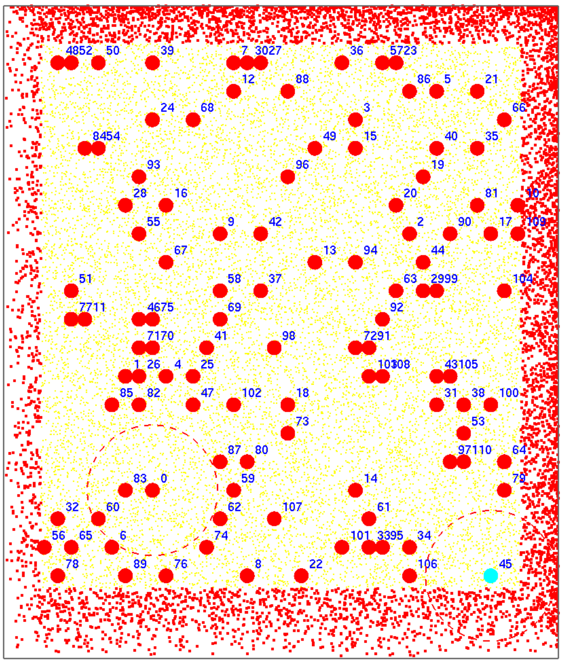
(a) First simulation frame



(b) Frame 125 from the start of simulation.

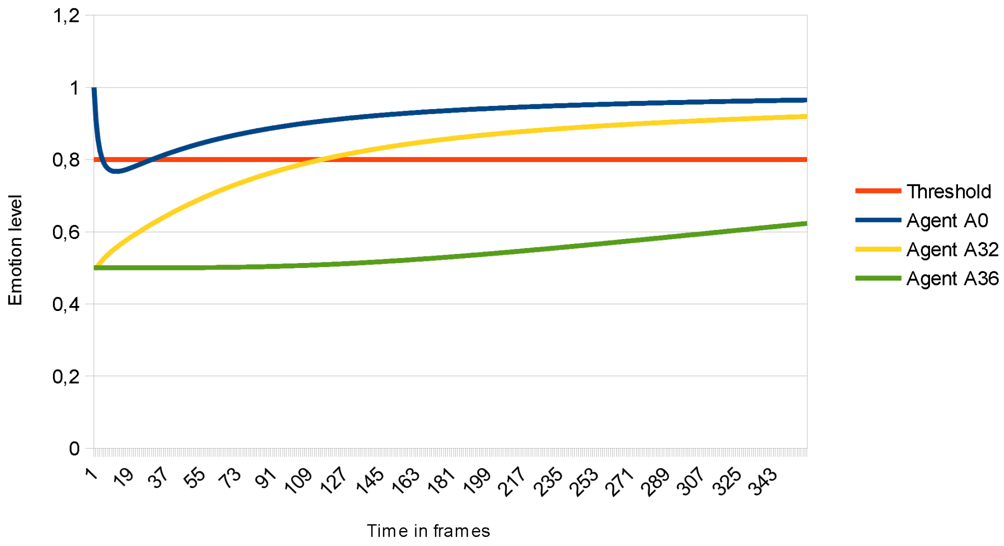


(c) Frame 700 from the start of simulation.



(d) Last simulation frame

Figura 5.6 – Standing Agents emotion levels.



that it is possible to compare the emotion state changes in all agents. Emotion $BLUE$ can also be seen as a *threshold* rather than an emotion, since it does not change. For the present experiment, this threshold is set to $q_i^{BLUE_{initial}} = 0.8$ for all agents A_i where $i = [0..N-1]$. While the agent is coloured blue, it means that RED is below threshold. When emotion RED is above threshold, the agent changes its emotional state from $BLUE$ to RED, changing also its colour. When this happens, it is signal that a change of emotional state in the agent has occured.

In summary, the parameter setting for agent A_0 is $\epsilon_0^{RED} = 0.5$, $\delta_0^{RED} = 0.5$, $\eta_0^{RED} = 0.5$ and $\beta_0^{RED} = 1$, with initial emotion level $q_0^{RED_{initial}} = 1$, to ensure agent A_0 starts with maximum RED emotion level. And for the remaining A_k agents, we have $\epsilon_k^{RED} = 0.5$, $\delta_k^{RED} = 0.5$, $\eta_k^{RED} = 0$ and $\beta_k^{RED} = 0$, with initial emotion level $q_k^{RED_{initial}} = 0.5$, to ensure all agents A_k starts in $BLUE$ emotional state, since $q_i^{BLUE_{initial}} = 0.8$.

As mentioned before, we propose three situations in this scenario with standing agents: one with the *emotional leader* plus 50 agents in the crowd; one with the *emotional leader* plus 80 agents in the crowd, and one last experiment with one *emotional leader* plus 110 agents in the crowd. This will change agents density in the scenario, since for all cases the scenario size is kept unchanged with measures 17×20. Figure 5.3 shows the first frame of the scenario with 51 agents total and the *emotional leader* is identified as agent A_0. The circles around agents A_0 and its closest neighbours A_{47} and A_6 represents the interaction space of the agents, beyond which the contagion is zero. In the Figure 5.3 it is possible to see that no agent lies inside agent's A_0 interaction circle. In this case, A_0 won't be able to promote any contagion to the crowd. This happens because the density is too low and agents got to sparse in the scenario. In other words, the pseudo-random function used to generate agents' initial positions did not place any agent nearby agent A_0 with the seed used here (we initialized the pseudo-random function with seed 321). If the seed of the pseudo-random function were changed, it could eventually result in a configuration where one or more agents would lie nearby A_0, inside its interaction space. But the goal here is to test the impact of densities in contagion, so we decided to further increase number of agents in the scenario instead of using other seed. Also, this results shows that, if one agent is sufficiently isolated from the crowd it will not interact with it, and thus should not be able to suffer or promote contagion, which is the case of agent A_0 for the current scenario. In this case, the time factor also does not promote any contagion change in the emotional state of the agents, since they do not move and will not approach each other entering interaction space.

An experiment with 81 agents was then executed with the objective of increasing agents' density, and check if there is contagion. Some frames of this experiment are pictured in Figure 5.4. Comparing 5.4(a) and 5.4(c) it is possible to observe that the emotion RED spreads through the crowd, since a number of agents changed their colours, signalling they have changed emotional state. In Figure 5.4(b), the interaction space is highlighted for the agents A_0, A_{74} and A_{76} in a particular instant of the simulation. By examining the interaction space of agent A_0, only agent A_{60} is able to suffer contagion from A_0. Also, agent A_{76} has suffered RED contagion from agent A_6, since it is the only agent inside agent's A_{76} interaction space that presents RED state. For the same reason, as the simulation elapses, agent A_{74} will turn red, see Figure 5.4(c), because of agent's A_{76} influence over him. Actually, all those agents are suffering influence of agent's A_0 emotional state (generating emotional with $\eta_0^{RED} = 0.5$ and $\beta_0^{RED} = 1$) directly, or indirectly in a chain reaction. In other words, agent A_0 can only influence agent A_{74} by first influencing agent A_{60}, then agents A_6 and A_{76} in a chain reaction. Finally, in Figure 5.4(c), it is possible to see the interaction circle of some key agents that we enlist: A_0, A_{18}, A_{22}, A_{47}, A_{60}. By looking carefully at those agents, the first thing to notice is that agent A_0 can only reach agent A_{60} directly, because this is the only agent inside agent's A_0 interaction space. And since agent A_0 is the only one capable to promote energy on emotion RED, the obvious conclusion is that A_0 is promoting third party contagion. By looking at the interaction circles of agents A_{18}, A_{22} and A_{47}, it is right to conclude that the spread of emotion RED has stopped because remaining agents are outside the interaction area of the group of agents that now share RED emotional state. Beyond this circle, emotional contagion does not happen because of the distance between the agents. That is why the remaining agents will never catch emotion RED. At this point, the scenario is stable meaning that emotional states will not change anyfurther.

It is noted that by increasing the number of agents from 50 to 80 there was an increase of agents who has suffered a change in emotional state, due to contagion from 0 agents in the first case to 15 agents in the second case. But yet many agents are kept excluded from this process, because they are isolated from the source of emotional energy, the agent A_0. At the same time, agent A_0 is creating an area of emotional influence around itself, its neighbours, and their neighbours in a chain reaction. A further increase in agents number is then promoted, expecting to increase density and, as a result, include more agents in the emotional influence area created by agent A_0.

In Figure 5.5 we picture yet some frames of the experiment with 111 agents in the crowd, the *emotional leader* agent A_0 plus a crowd of 110 agents. In Figure 5.5(a) we picture the first frame of the simulation experiment with only agent A_0 in red state, and the remaining agents in blue state, denoting their initial status, as in the previous cases. It is also pictured the space of interaction of agent A_0, and it is possible to identify agents A_{60} and A_{83} as the only two agents inside A_0 interaction space. These are the only two agents that will suffer contagion directly from agent A_0. In Figure 5.5(b) the 125^{th} simulation frame is pictured. There is also pictured the space of interaction of agents A_{59}, A_{62}, A_{74} and A_{76}. Notice that the only red agent inside this area is agent A_6, and it is also important to notice that agent A_0 is outside this area. From this point on, agent A_0 can only influence emotionally the remainder agents of the crowd through a chain reaction effect by promoting contagion on agents A_{76}, A_{74}, A_{52} and A_{59}. The frame 700 of this experiment is depicted in Figure 5.5(c). The interaction space of agents A_{14} and A_{72} are shown to illustrate a gap that exists in the area between these two agents. This gap blocks emotion contagion from the lower left part of the scenario to the lower right part of the scenario. This is why RED emotion, at this simulation instant, is spreading to the top left corner of the scenario instead of growing equally in all directions. Finally, Figure 5.5(d) shows the last simulation frame. The space of interaction of agent A_{45} shows that this agent is isolated from the crowd, and thus it will never change its emotional state. But all other agents have converge to the same emotion as A_0, resulting in all remaining agents with the same emotional state.

This last scenario illustrates how one single agent generating emotional energy can promote contagion in a whole crowd of agents, depending on space and time. And since agent A_0 proved able to promote indirect contagion, even to far away agents, further investigation is needed to determine how strong this chain reaction can be. In the Figure 5.6 the instantaneous values of emotions are plotted in the graphic for agents A_0, A_{32} and A_{36}, for the experiment with 111 agents. It is also plotted the threshold line (a constant equals to 0.8). The vertical axis measures emotional level, and the horizontal axis measures time in frames. Although agent A_{36} is far from agent A_0 relative to the scenario size, it is possible to see in the graphic that the emotional level in agent A_{36} begins to rise very early in the simulation. Actually, at frame 16 it already presents minor numeric change on the emotion level (it changes from 0.5 to 0.500001). This data suggests that the referred chain reaction is not just present, but seems to be rather fast. Agent A_{32} is close to agent A_0, and as expected, it suffered much stronger contagion if compared with agent A_{36}. By comparing the curves of both agents A_{32} and A_{36} in the graphic it is possible to observe that the curve of the first rises much faster, because contagion is much stronger. Another important information in the graphic is in the curve of agent A_0. In the beginning of the experiments (both with 80 and 110 agents in the crowd) it was noticed that agent A_0 changes to blue, before returning to red in the first frames of simulation. In the graphic of Figure 5.6, the curve of agent A_0 drops below the threshold at frame 6 and returns at frame 30, and then it keep ascending. That is happening because parameter $\eta_0^{RED} = 0.5$, which balances both absorption and amplification models. The absorption model is responsible to allow agent A_0 to suffer contagion from the crowd, as it promotes contagion on the crowd at the same time. Since all agents in the crowd are initialized with $q_0^{RED_{initial}} = 0.5$, they influence agent A_0 with this emotional level in a chain reaction. And they also influence each other promoting some kind of inertia, or resistance of the crowd changing emotional state.

The scenarios experimented showed that, with enough emotional energy, enough proximity between agents, and enought time to accomplish the method, it is possible to promote contagion in all agents of a crowd. Also, if one agent gets isolated it will not be able to suffer contagion, neither promote contagion on its neighbours. We could also observe the phenomena of contagion beyond dyads, which is a phenomena observed in real groups of people according to Dezecache et. al [20]. Furthermore, the crowd achieved the same emotional state, a monotonicity predicted by LeBon [9]. The crowd followed its leader, at least regarding to its emotional state.

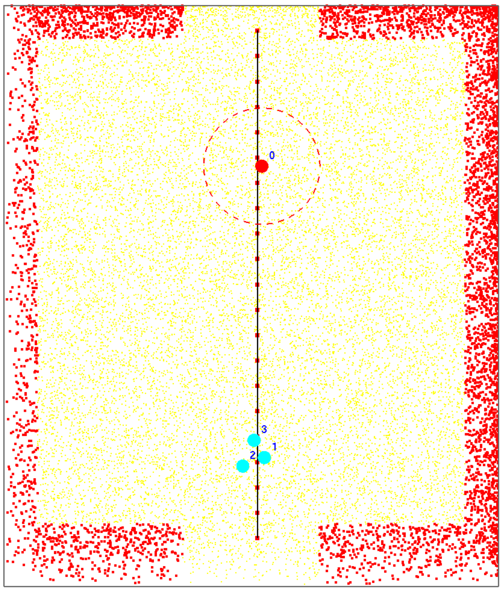
5.2 Counterflow scenario

Since the proposal of this work is to integrate emotional contagion in crowd context, it is now time to allow agents to move in the virtual scenario according to the steering model. And since they are moving, they must have a goal associated to them, so that agents know where they are supposed to move to. Also, it was discussed in Chapter 2 that emotions have impact on peoples actions. With that in mind, In Chapter 4 we proposed to introduce in the model the option of defining a goal associated to each emotion. So, a goal is defined to each one of the possible emotional states in the agents. The same way as in the **standing agents** experiment described in Section 5.1, this scenario is configured with two possible emotional states for the agents. The emotion under study is an unspecified emotion represented in RED, and the threshold represented in $BLUE$ is a constant equals to 0.8.

Figure 5.7 pictures the scenario used for the current experiment. Since the agents are moving they need a goal to pursue. We propose a scenario with two entrances/exits, one in the top, the other in the bottom, each of which represents the goals in the scenario. We then associate one goal for each emotion and, by convention, we determine that agents in state $BLUE$ aim to the top exit, and agents in state RED aim the bottom exit. We also propose to consider one agent A_0 moving from top to bottom, and one group of agents G, moving from bottom to the top. In the example of Figure 5.7 one can observe agent A_0 coloured in red at the top of the scenario, and three other agents members of group G (A_1, A_2 and A_3) at the bottom of the scenario, coloured in blue. By its colours it is conventionally known that agent A_0 is going to the bottom exits, and the remaining agents are going to the top exit. With this configuration, their paths are making them cross with each other. While they are close enough, it is expected to observe emotional contagion in agents.

Also, in all cases presented in this section, agent A_0 is elected as the *emotional leader*, or, in other words, the agent that generates emotional energy through the amplification model. We propose to simulate a number of cases here, varying agents' expressiveness, susceptibility, and the number of agents in the group G that is encountering agent A_0. Consider group G as being the set $G = \{A_1, A_2, ..., A_N\}$, where N is the number of agents in G. Notice that agent A_0 does not belong to G, so the total crowd number in this case would be $N + 1$, or the N agents in G plus

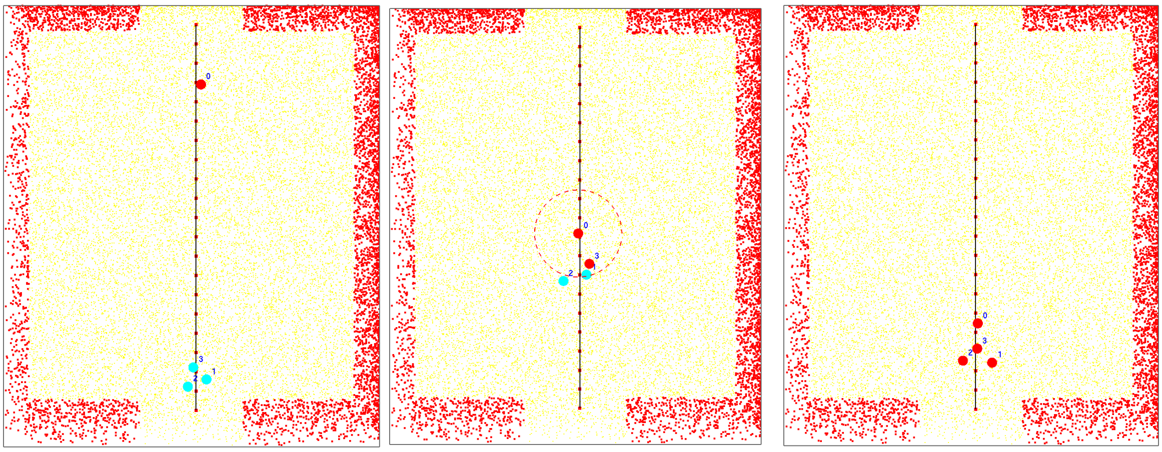
Figura 5.7 – Counter flow Scenario example.



A_0. This group will be simulated with N varying from 1 (one) to 10 (ten) agents. We propose varying the expressiveness (ε) and the susceptibility (δ) of the agents in group G by four manners: i) $\varepsilon_k = 0.1$ and $\delta_k = 0.9$, ii) $\varepsilon_k = 0.1$ and $\delta_k = 0.1$, iii) $\varepsilon_k = 0.9$ and $\delta_k = 0.9$, and iv) $\varepsilon_k = 0.9$ and $\delta_k = 0.1$. These four cases simulates extreme emotional profiles, respectively as follows: i) low expressiveness (or shy, introspective) and high susceptibility (or open to contagion, sociable), ii) low expressiveness and low susceptibility (or closed to contagion), iii) high expressiveness (expressive) and high susceptibility, and iv) high expressiveness and low susceptibility. And for every case, we want to measure the speed in which the emotion spreads in the crowd, by comparing the curves of emotions of some agents in the crowd. All agents in group G initializes its emotional level with $q_{A_n}^{RED_{t0}} = 0.5$ to begin under the threshold, thus in $BLUE$ emotional state. The remainder parameters of the agents belonging to the group G, η and β, are set to zero, so that agents in G have only absorption model active.

Agent A_0 initializes in time $t = t0$ with maximum emotion level $q_{A_0}^{RED_{t0}} = 1$, maximum expressiveness $\varepsilon_{A_0}^{RED_{t0}} = 1$ to enhance agent's strength of emotion contagion, $\delta_{A_0}^{RED_{t0}} = 0.1$ for low susceptibility, making it harder for the group G to promote contagion on A_0. Also, to enable amplification model in agent A_0, its parameter $\eta_{A_0} = 0.1$ creating a weaker amplification than agent A_0 in the **standing agents** experiment, but in the present experiment the number of agents to interact with A_0 is smaller. Furthermore, since agents are moving, the time window for contagion is shorter than in the previous experiment (i.e., while the group G is passing near agent A_0). In this experiment we expect to observe emotional state changing in A_0. That is why agent A_0 has a smaller parameter setting for η_{A_0} than the experiment presented in Section 5.1. Agent's A_0 choices for ε and δ were made to make faster contagion of A_0 over G, and lower contagion in the opposite direction. We expect to see variation of responses as we change the number of agents in G and vary the parameter of agents in G.

Figura 5.8 – Counterflow experiment with 3 agents in the group G: Figure 5.8(a) shows the beginning of the simulation. Agent A_0 is in RED, and moving from top to bottom. All other agents are coloured blue, and move from bottom to the top. In Figure 5.8(b) it is pictured an instant where agents have already reached contagion distance. Only the contagion space of agent A_0 is pictured, but at this moment almost all agents are inside agent's A_0 interaction space, represented by the red circle around the agent. Agent A_5 already changed its emotional state from $BLUE$ to RED. In Figure 5.8(c) is pictured the end of the simulation, where agents are almost reaching the bottom exit. In this case, all agents exits by the bottom door by the end of the simulation.

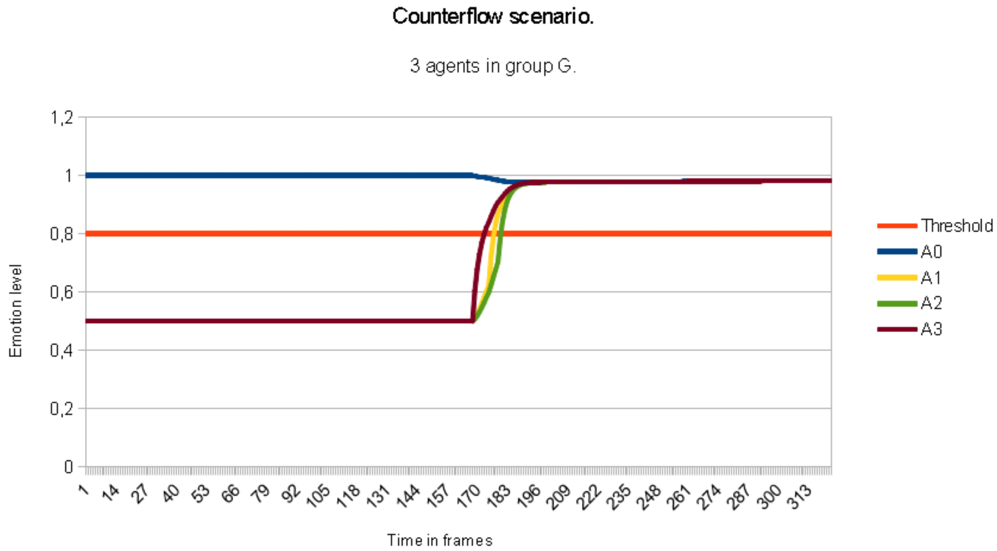


(a) Beginning of simulation. (b) Moment of encounter. (c) Agents reaching bottom exit.

So, for this experiment, there are 4 different emotional profiles E_{A_n} for the scenarios, according to Section 4.1, varying expressiveness and susceptibility parameters of group's G agents, all those scenarios simulated with 1 to 10 agents in the group, adding a total of 40 scenarios. Also, we mentioned that the window of contagion is due to the time agents walk side-by-side, in the moment they are passing by. The time they keep together depends on the length of the path, and agent's speed. So, we decided to experiment with two different scenario sizes: i) a short scenario measuring 17×20, ii) and a long scenario measuring 17×40. This adds up to 80 simulations in total.

In Figure 5.8 it is pictured some frames of the case where the number of members in the group G is $N = 3$, and the agents are set with the emotional profile susceptible (meaning that susceptibility is set to a high level $\delta_{A_n} = 0.9$) and shy (meaning that expressiveness is set to low level $\varepsilon_{A_n} = 0.1$). Figure 5.8(a) shows the beginning of the simulation. Agent A_0 is in the top, coloured in RED, and moving from top to bottom, due to the goal associated to emotion RED, and the fact that agent's A_0 emotional level initialized as $q_{A_0}^{RED} = 1$ is higher than the threshold defined as $q_{A_0}^{BLUE} = 0.8$. All other agents are coloured blue, and move from bottom to the top. In Figure 5.8(b) it is pictured an instant where agents have already reached contagion distance. Only the contagion space of agent A_0 is pictured, but at this moment almost all agents are inside agent's A_0 interaction space and all agents are able to interact with each other. Agent A_3 already changed its emotional state from $BLUE$ to RED, and all other agents will be changing their emotional states in the next frames. In Figure 5.8(c) it is pictured the end of the simulation, where agents are almost reaching the bottom exit. This is not the last frame, because agents are still in the scenario. In this case, all agents have exited through the bottom door by the end of the simulation. This experiment shows a group of

Figura 5.9 – Counterflow scenario graphic picturing instantaneous emotion level of agents plus the threshold line (0.8).



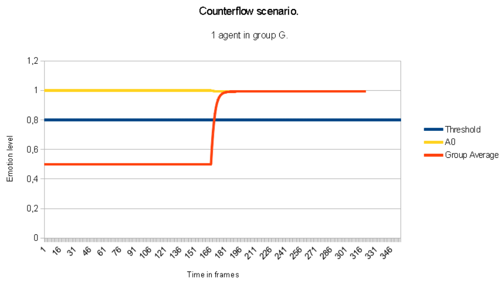
Simulation screenshot

agents (G) changing their goal in function of their emotional status. A similar behaviour may be observed in dangerous situations, where one person warn others about potential danger, and they all run away in fear.

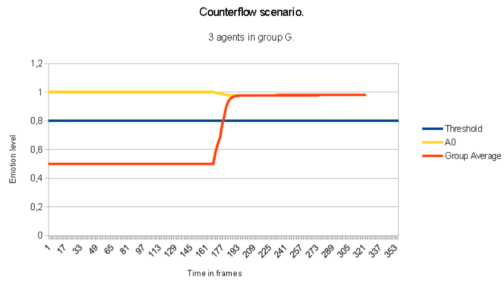
In Figure 5.9, a graphic is pictured showing curves of instantaneous emotional levels of all agents in the simulation. The line at emotional level 0.8 is the threshold above which agents turn their emotional status from $BLUE$ to RED. The threshold is $q_{A_i}^{BLUE} = 0.8$ for all agents in the crowd, including agent A_0. The other curves represent emotional state RED for all agents in the scenario, including agent A_0. For agent A_0, the emotional level is initialized as $q_{A_0}^{RED} = 1$, and when agents get close to each other, around frame 170, q_{A_0} tends to drop a little. That is expected since the susceptibility $\delta {A_0}^{RED} \neq 0$. Notice that before agents get closer, the curves do not change. The agents inside G do interact with each other, but since all are initialized with $q_{A_n}^{RED} = 0.5$ (where $n = [1,3]$) they do not change their status. There is already a monotonicity of emotion in the group. In other words, they all match group's average emotional level. For the group G there is a fast rise of emotional level around frame 170, when agents get closer. That is because the susceptibility of the group was made high. So, as expected, the agents on the group follows the emotional influence of A_0 in this case. When the emotional level of agents in G pass higher 0.8, agents change their goals. Finally, the emotional level of all agents, according to generated data, stabilizes around 0.98.

Now that we pictured one particular case, we compare the many variations of the scenario explained so far. To make easier to read the graphics, from now on, we will plot the arithmetic average of the emotional level of all agents in the group G, instead of plotting each agent's emotional levels individually. In Figure 5.10 there are four graphics showing emotional level curves for different group G sizes, using shy ($\varepsilon_{A_n} = 0.1$ for $A_n \in G$) and susceptible ($\delta_{A_n} = 0.9$ for $A_n \in G$) setting

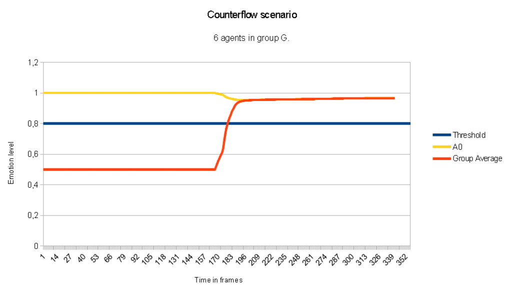
Figura 5.10 – Counterflow experiment varying number of agents in the group G: Figure 5.10(a) shows the emotion level curves of A_0 and A_1, since the group G has only one agent in this case. Figure 5.10(b) shows the emotion level curves of A_0 and the average emotion level of the 3 agents in group G. Figure 5.10(c) shows the emotion level curves of A_0 and the average emotion level of the 6 agents in group G. Figure 5.10(d) shows the emotion level curves of A_0 and the average emotion level of the 10 agents in group G. All figures pictures the threshold line in 0.8 above which agent's are in RED emotional state, moving from top to bottom in this case scenario.



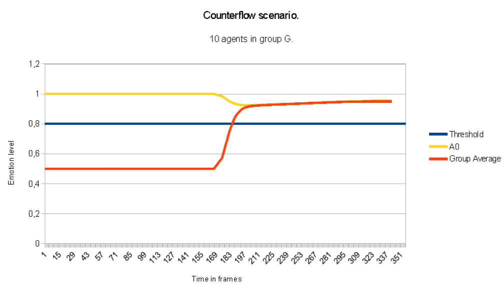
(a) 1 agent in group G.



(b) 3 agents in group G.



(c) 6 agents in group G.



(d) 10 agents in group G.

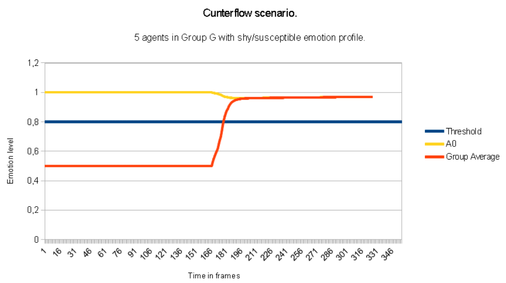
for emotional contagion profile of the agents in group G. Since the agents in group G have low expressiveness, they cannot impact strongly agent A_0 (or each other). That's why the emotional level curve for agent A_0 never drops below threshold. Also, they are very susceptible, so the emotional level of agents in group G rises fast. With this parameter setting the emotional average of the crowd converges to a high emotional level of emotional state RED. Also, it is possible to notice that A_0 emotional level also drops due to contact with agents in group G. Furthermore, as the number of agents in the group G increases, the drop in agent's A_0 curve increases. This suggests that, the more agents in the group, the more resistance (or some sort of emotional inertia) the group presents.

To further explore the results, we now compare the four emotional profiles studied: i) shy/susceptible with parameters set to $\varepsilon_k = 0.1$ and $\delta_k = 0.9$, ii) shy/closed with parameters set to $\varepsilon_k = 0.1$ and $\delta_k = 0.1$, iii) expressive/susceptible with parameters set to $\varepsilon_k = 0.9$ and $\delta_k = 0.9$, and iv) expressive/closed with parameters set to $\varepsilon_k = 0.9$ and $\delta_k = 0.1$. Also, it was elected to use the case with 5 agents in the group to illustrate the differences on each parameter setting. Figure 5.11 shows the four curves resultant from this parameter setting, each one for each emotional profile. In Figure 5.11(a), the emotional profile with agents shy (low expressiveness) and susceptible (high susceptibility) tends to achieve emotional equilibrium above threshold, meaning that the group tends to follow the influence of A_0, which is expected according to previous experiments, and due to the fact that the susceptibility is set high. But Figures 5.11(b) and 5.11(c) suggests that susceptibility does not handle alone the impact of A_0 over the group and vice-versa. Figure 5.11(b) shows the expressive susceptible configuration and, although the susceptibility of group agents have not changed compared to Figure 5.11(a), there is some force that inhibits group G contagion at first, making A_0 drop much below threshold around frame 206. Although the curve rises after frame 206, the simulation ends before emotional level in all agents reach the threshold, so all agents (including A_0) exits by the top exit in $BLUE$ emotional state, in the expressive susceptible case. Despite agent A_0 is generating some emotional energy through its amplification model (agent's $\eta_{A_0}^{RED} = 0.1$), it is not enough to revert agents' emotional state back to RED. Maybe a longer scenario would give time for agents to change emotional state again and exit through the bottom. In Figure 5.11(c) the curves for the shy/closed setting are pictured. Although it is not clear in the graphic, simulation results and data generated shows that agent A_0 lowers its emotional level downto 0.795536 but stabilizes it at 0.803074, which is close to 0.8, but above it. So, agent A_0 briefly changes emotional state during the simulation, but ends the simulation in the bottom exit. The remaining group agents never reach the threshold level, so they keep moving from bottom to top until they exits in the top. In this case scenario, agents just pass through each other, and does not definitely change their emotional status remaining with their original goals. Maybe if agents move slower, they would spend more time in range for contagion and the results could change. Finally, in Figure 5.11(d) the emotion level curves for the expressive/closed are pictured. The emotional level of agent A_0 drops quickly around frame 198 and the group does not change much compared with cases in Figures 5.11(a) and 5.11(c). Actually, in both cases where group expressiveness is high the resistance of the group in changing emotional status rises. Supposedly because group agent's expressiveness is high, giving them more strength to influence each other and A_0.

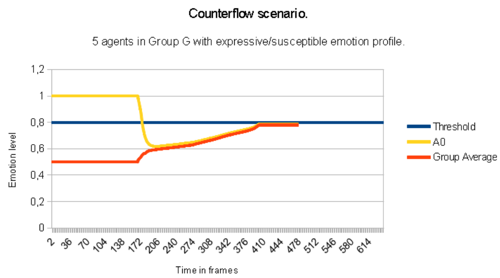
Consider now the case where agents are expressive and susceptible with 5 agents in group G, as showed in Figure 5.11(b). We speculate that a longer scenario might give agents in group G the chance to spend more time close to agent A_0, and potentially result in agent A_0 changing its emotional state back to RED, influencing agents on group G. This hypothesis rises because, although the graphic in Figure 5.11(b) shows that agents' emotional level converge to a value near 0.6 when agent A_0 encounters the group around frame 206, the curve keeps rising. Now we present the same experiment comparing two scenario sizes: 17×20, as in the previous experiment; and 17×40 with twice the length of previous experiment. Figure 5.12 shows three frames of the simulation with in a scenario 17×20 which results are presented graphically in Figure 5.11(b).

In Figure 5.12(a) it is pictured the beginning of the simulation. Agent A_0 is not in contagion range of any agent in group G, that is why in Figure5.11(b) agents' emotional levels does not vary until frame 172. In frame 176, pictured in Figure 5.12(b), agent A_0 changes emotional state from RED to $BLUE$, and also changes moving direction to aim the top exit, just like the other agents. Figure 5.12(c) pictures frame 409 of this experiment, which is the moment agent A_0 is removed from the scenario, since it has reached the top exit. At this instant, agent A_0 stops generating emotional energy, because its contagion model has been disconnected from the scenario when A_0

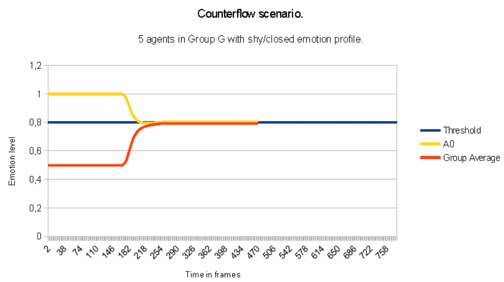
Figura 5.11 – Counterflow experiment with 5 agents in G, varying emotion contagion profile in agents of group G: Figure 5.11(a) shows the emotion level curves of A_0 and the average emotion level of the 5 agents in group G for Shy/Susceptible emotion contagion profile. Figure 5.11(b) shows the emotion level curves of A_0 and the average emotion level of the 5 agents in group G for Expressive/Susceptible emotion contagion profile. Figure 5.11(c) shows the emotion level curves of A_0 and the average emotion level of the 5 agents in group G for Shy/Closed emotion contagion profile. Figure 5.11(d) shows the emotion level curves of A_0 and the average emotion level of the 5 agents in group G for Expressive/Closed emotion contagion profile.



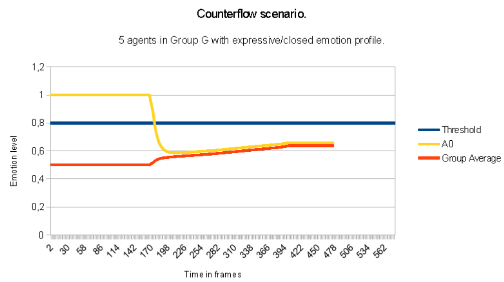
(a) Shy/Susceptible.



(b) Expressive/Susceptible.



(c) Shy/Closed.

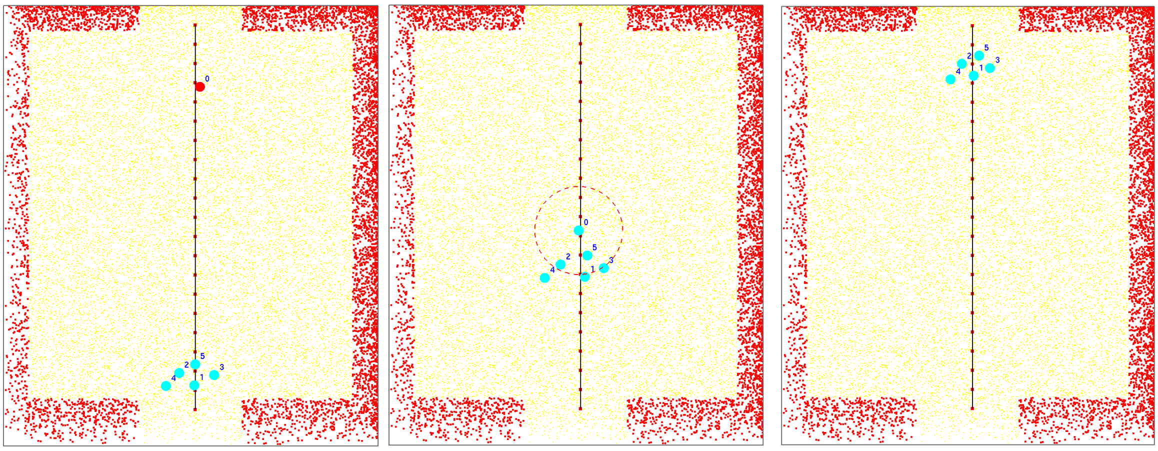


(d) Expressive/Closed.

was removed. That is why agents' emotional levels does not vary after frame 409 in the graphic presented in Figure 5.11(b). The same thing happens in Figure 5.11(d) after agent A_0 is removed (around frame 422 for this case).

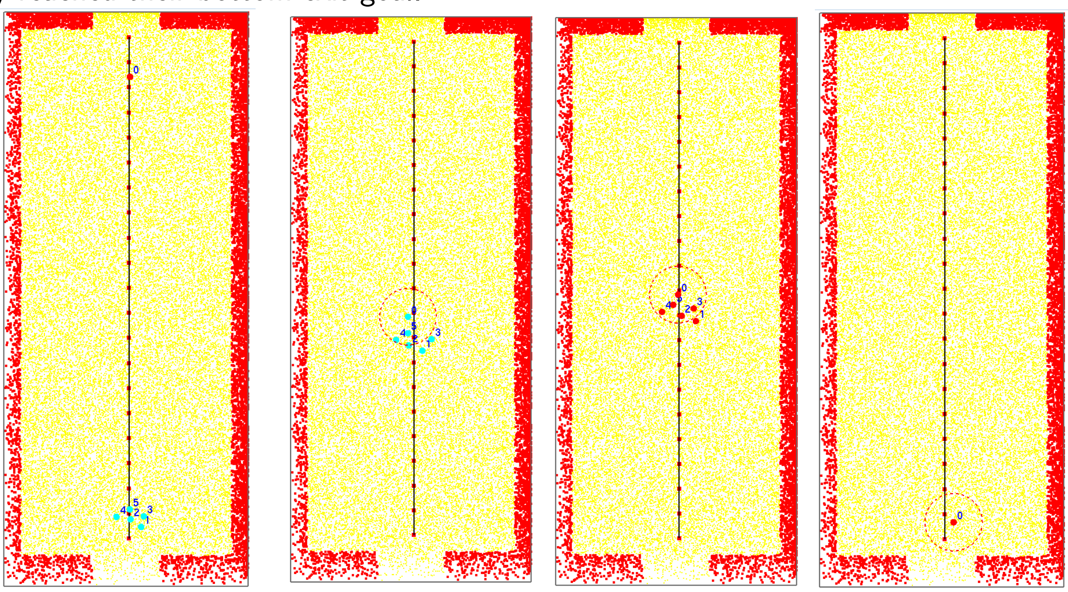
Figure 5.13 shows the last experiment but in a scenario with dimensions 17×40, which is twice the length of the last scenario. In Figure 5.13(a) it is pictured the beginning of the simulation, with agent A_0 in the top, aiming the bottom exit, and the remaining agents in the bottom, aiming the top exit. In Figure 5.13(b), it is pictured the frame 365 when agent A_0 changes its emotional state from RED to $BLUE$ due to the influence of the agents in group G. Since agents in G have high expressiveness and outnumber A_0 (they are five "against" one), their influence is strong enough to pull agent's A_0 emotional energy below threshold. Figure 5.13(c) pictures the frame 452 of the simulation, when agents A_0 have changed its emotional state back to RED, and also the other five agents in group G. At this point, all agents are seeking the bottom exit. Finally, Figure 5.13(d) shows one of the final frames of the simulation, when only agent A_0 has not yet reached the exit and is not removed. Since agent A_0 is the last out, he is able to generate emotional energy until the last instant. Figure 5.14 pictures the numeric emotional level output in a graphic containing the curves for agent's A_0 emotional level, and the average emotional level of the five agents in group G, and also the threshold line in 0.8.

Figura 5.12 – Counterflow experiment with 5 agents in G, with emotion profile expressive susceptible in a 17×20 scenario size: Figure 5.12(a) shows the beginning of the simulation, when group G is not inside agent's A_0 contagion space. Figure 5.12(b) shows the moment when, in frame 176 agent A_0 changes emotional state from RED to $BLUE$. Figure 5.12(c) shows the frame 409 in the end of the simulation when agent A_0 is removed from the scenario. From this instant on no emotion energy is generated, so agent's emotion levels does not vary.



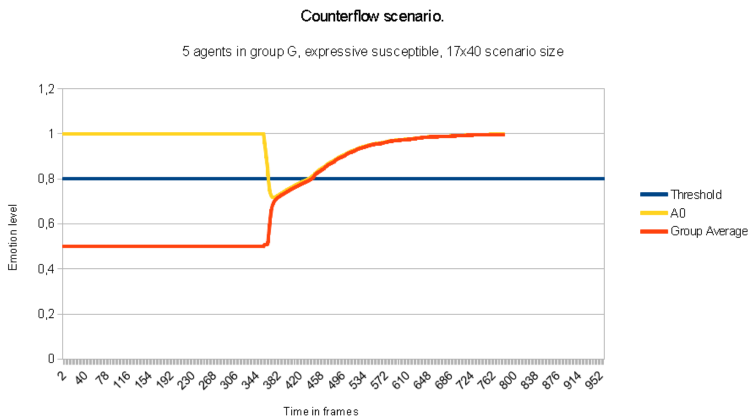
(a) Beginning of simulation. (b) Frame 176. (c) Frame 409.

Figura 5.13 – Counterflow experiment with 5 agents in G, with emotion profile expressive susceptible in a 17×40 scenario size: Figure 5.13(a) shows the beginning of the simulation, when group G is not inside agent's A_0 contagion space. Figure 5.13(b) shows the moment when, in frame 365 agent A_0 changes emotional state from RED to $BLUE$. Figure 5.13(c) shows the moment when, in frame 452 agent A_0, and all other agents in group G, changes their emotional state from $BLUE$ to RED due to emotional energy created by agent's A_0 amplification. Figure 5.13(d) shows the end of the simulation, when only agent A_0 remains in the scenario. All other agents have been removed since they reached their bottom exit goal.



(a) Beginning of simulation. (b) Frame 365. (b) Frame 452. (c) Simulation end.

Figura 5.14 – The curves for emotional level of agent A_0, the arithmetic average of group G emotional level and the threshold line (0.8).



Beginning of simulation.

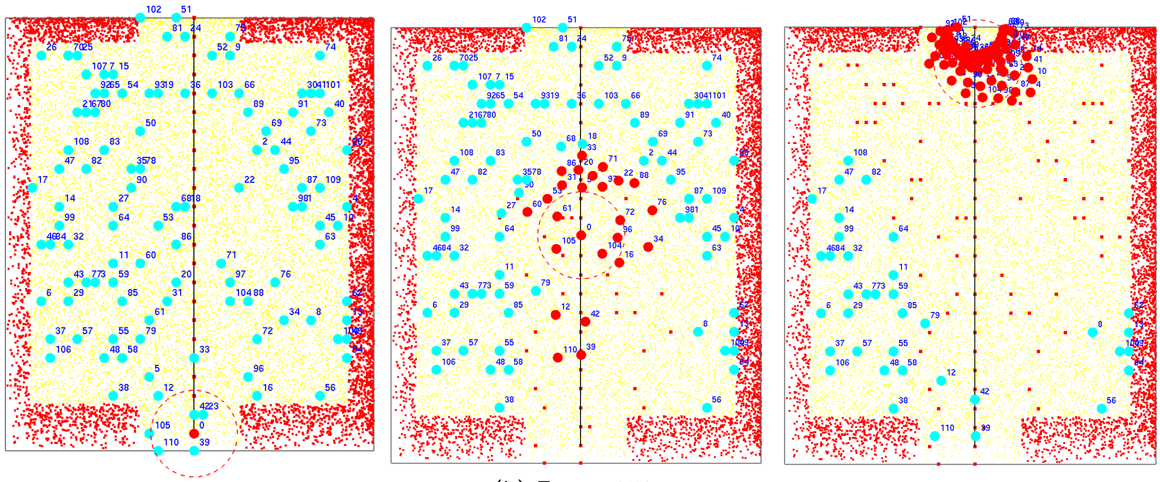
5.3 Same direction scenario

In this section we propose an experiment similar to the **standing agents**, presented in Section 5.1, with the difference that, in the present case, the leader has a goal to pursue. The remaining agents will be standing in the same position, as long as they keep their original emotional state. Analogous to previous experiments, we propose two emotional states: RED and $BLUE$, and we will test the outcomes in emotion state RED. Emotional state $BLUE$ is set as a threshold with constant value 0.8. Since emotional state $BLUE$ is being set as a threshold, all agents have their $BLUE$ emotional state initialized as: $q_{A_i}^{BLUE} = 0.8$, $\varepsilon_{A_i}^{BLUE} = 0$, $\delta_{A_i}^{BLUE} = 0$, $\eta_{A_i}^{BLUE} = 0$, $\beta_{A_i}^{BLUE} = 0$, $og_{A_i}^{BLUE} = 0$, and since there is no goal associated to it, agents in emotional state $BLUE$ tend to remain in (or move back to) their initial position.

The emotional state RED must have two different profiles, one for the crowd, and another for the leader. In the elected leader agent A_0 the emotional state RED is initialized with the objective of generating emotional energy, so the amplification model in A_0 must be active. The parameters for emotional profile RED in A_0 are initialized as follows: $q_{A_0}^{RED} = 1$, $\varepsilon_{A_0}^{RED} = 0.5$, $\delta_{A_0}^{RED} = 0.5$, $\eta_{A_0}^{RED} = 0.5$, $\beta_{A_0}^{RED} = 1$, $og_{A_0}^{RED} = 1$. Also, the top exit is the goal associated to all agents in emotional state RED. Notice that, since $q_{A_0}^{RED} > 0.8$, the motional state of agent A_0 is $\psi_{A_0} = RED$ when the simulation starts.

For the remaining agents in the crowd, the emotional state RED has a different profile compared to agent A_0, because those agents are not supposed to generate emotional energy. The values that initializes remaining agents' parameters are: $q_{A_n}^{RED} = 0.5$, $\varepsilon_{A_n}^{RED} = 0.1$, $\delta_{A_n}^{RED} = 1$, $\eta_{A_n}^{RED} = 0$, $\beta_{A_n}^{RED} = 0$, $og_{A_n}^{RED} = 1$, where $A_n \in C$. Notice that the RED emotional level, denoted by $q_{A_n}^{RED}$ must be initialized with a value lower that 0.8 to set all agents except A_0 to emotional state $\psi_{A_n} = BLUE$ when the simulation starts. The objective is to observe how many agents turn their emotional states from $\psi_{A_n} = BLUE$ to $\psi_{A_n} = RED$ as a result of the impact of agent A_0 emotional influence over the remaining agents.

Figura 5.15 – Agents walking in the same direction: In Figure 5.15(a) one can observe the first frame of the simulation experiment. There, only agent A_0 is in RED, and all other agents are coloured blue. In Figure 5.15(b) it is pictured frame 250 of the simulation, showing a number of agents already changed their emotional state from $BLUE$ to RED and moving to the top exit. In Figure 5.15(c) is pictured the final frame of the simulation.



(a) First simulation frame

(b) Frame 250.

(c) Last simulation frame

We propose to experiment this emotional configuration with agent A_0 plus 110 agents in the scenario. The scenario measures 17×20, and has two exits. In Figure 5.15 some frames of this scenario are pictured. Figure 5.15(a) pictures the first frame of the simulation. There it is possible to observe agent A_0 in red in the bottom entrance of the scenario, and the red circle around it denotes its interaction space. Since A_0 is coloured red, indicating emotional state $\psi_{A_0} = RED$, its current goal is the top exit, according to the goal associated to emotional state RED. The remaining agents have emotional state $\psi_{A_n} = BLUE$, indicated by their colour. No goals are associated to emotional state $BLUE$, so, when each agent is initialized, a goal to its current position is defined automatically. This results in agents seeking to stand in their original position as long as their emotional state is $BLUE$. The vertical line with red dots in the middle of the figure denotes the path planning of agent A_0, tracing the path agent A_0 will follow to get to its goal, which is the top exit. Finally, although there are some agents inside agent's A_0 interaction space, since the simulation is not yet started, they are yet to interact with A_0 to promote and suffer emotional contagion.

Figure 5.15(b) depicts simulation frame 250. In this picture it is possible to observe that many agents have changed their emotional state and have now $\psi_{A_n} = RED$. All those agents are moving towards the top exit, accompanying agent A_0. In their original positions there are red dots, denoting each agent's original starting position, and original goal, which is now being overwritten as a result of agents' emotional state changing. Also, notice agents A_{110} and A_{39} in the bottom, coloured red, are being left behind. This is due to a small random variation in agents' speeds present in *BioCrowds* model. It has three possible speeds: fast, defined as $3.3m/s$; medium, defined as $2.4m/s$; and slow, defined as $1.2m/s$. Simulation data shows that both agents A_{39} and A_{110} had slow velocity setting selected.

In Figure 5.15(c), the last frame of the simulation is pictured. Notice that agents A_{39} and A_{110} have been left behind, eventually changing their emotional state back to $\psi_{A_{39}} = BLUE$ and $\psi_{A_{110}} = BLUE$. This results in both agents returning to their original positions. The same happend with agents A_{12} and A_{42}. At the same time, many other agents have changed their emotion state to RED and moved to the top. It is also important to observe that many of the agents that turned RED were never inside agent's A_0 interaction space, but instead had suffered contagion indirectly from other agents, as a result of contagion beyond dyads.

In this experiment, it was possible to observe the emergence of a group leader. Although the scenario is configured with 111 individuals (110 plus A_0) with no group predefined, as agents interact and converge emotionally, they also approach each other as they converge to common objective.

5.4 Performed Experiments Summary

In Section 5.1 we experimented varying the density of agents in the scenario. It was observed that the higher the density the more agents suffer contagion. Some agents do not suffer contagion because, in low densities, groups of agents get isolated from each other. That happens because we restrained the distance of contagion to $2m$, considering agents' proxemics. Nevertheless, some situations might require different approaches. If we consider big manifestations such as parades, strikes, protests or even sports events or music shows, there might be room to increase this distance limitation.

In the experiment presented in Section 5.2, the agents move against each other. The result is that, since their path cross, they do not spend much time inside their interaction space. That is one of the reasons why in the graphic presented in Figure 5.11(c) agent A_0 is not able to change emotional state in other agents. Other reasons are related to the expressiveness and susceptibility of agents. In this sense, it was observed that great number of agents, with no amplification model, creates a chain reaction, or some sort of inertia to succumb to the emotional energy generated by the one. Also, a crowd with higher expressiveness presented behaviour in a way that increased this inertia, since the curves presented on Figures 5.11(b) and 5.11(d) (on the right side) shows a significant drop in the emotion level of A_0, by the time agents meet, if compared to the figures on the left side. In Figure 5.11(a) the emotional level of agent A_0 is always $q_{A_0} > 0.8$ (even greater than 0.9 according to data), and in Figure 5.11(c) the emotion level q_{A_0} drops slightly below 0.8, as commented in Section 5.2, but stabilizes above threshold. Increasing susceptibility, on the other hand, appears to lower the crowd inertia emergent in this model. By comparing Figure 5.11(a) with Figure 5.11(c), and Figure 5.11(b) with Figure 5.11(d) it is possible to observe that, as the susceptibility rises, the stabilizing point also rises as one would expect.

In Section 5.3 we experimented with one agent generating emotional energy (A_0) and 110 agents, configured with only absorption model, responding to this generated energy. As agents changed their emotional state, they also began to share the same goal of A_0, which resulted in agents moving closer to each other, since their trajectories converge to the same location in the scenario. At the same time, some slower agents were left behind and, by interacting with other agents (not A_0) which have their $q_{A_n}^{RED} < 0.8$, they changed their state back to its original state ($BLUE$) and, because of that, marched back to their original positions. By the end of this simulation, only 37 of the 110 agents remained in the scenario, while all others gathered around the goal point in the top exit. Since agents are not removed from this scenario when they reach their goal, they form a semi-circle around it, as an emergent outcome of *BioCrowds*.

As a result of emotional contagion, it was possible to observe agents changing their emotional state during simulations. Also, this have impact over agents' trajectories, since we associated goals to emotions. This illustrates the impact of emotional contagion over the flow of agents in the crowd. At the same time, while agents navigate in the scenario, they enter interaction space of other agents, changing their emotional status (and goal) as well. This illustrates the impact that agents' movements has over the emotional contagion model. As agents evolve in the scenario, as a function of time, they are also changing their distances and, with that, changing the contagion channel strength with its neighbours. Both impacts from emotional contagion model over crowd trajectories, and the movement of the crowd impact over emotional contagion are desired. The results where agents synchronize their emotional state resemble statements of LeBon [9], who claims that individuals in a crowd tend to have an identity with the crowd, if he or she is immerse in such a crowd for enough time. Also, the emergent behaviour where agents get closer to each other due to a synchrony of their emotional state, as in the experiment showed in Section 5.3, resembles studies of Barsade & Gibson [6], where the authors claims that positive emotions can approach group members, by increasing feelings of acceptance. Although agents in the experiment presented in Section 5.3 are not in the same group (they are actually all individuals), they approach each other due to the fact they share the same goal.

6. Final Considerations

This work presented an emotional contagion model adapted for crowd simulation context. Our main objective was to endow agents in a crowd simulation model with emotional contagion ability. This gave origin to a new Bosse-Biocrowds extension which benefits from both models. The contribution of the crowd simulation model is the ability to instantiate agents in a virtual environment, and allow those agents to navigate towards a goal. The contribution of the emotional contagion model is to carry the emotional information, and endow the agents to exchange this information by means of contagion. To implement those features, the parameters had to be integrated into a new set of parameters, keeping information about agent movement and goal (*BioCrowds*) along with information related to agents' emotional profiles (parameters derived from the model proposed by Bosse et. al). Also, the algorithm was adjusted to enable full contagion of individual agents in the crowd, as well as contagion between different groups in the same crowd.

In Section 1.1 we presented specific goals to be achieved in this work. We believe we have successfully integrate the model of Bosse et. al in *BioCrowds*. To support this claim we presented simulations in Chapter 5 where it is possible to observe agents changing their emotional status through contagion. In Section 5.1 we measured the impact of density of agents over contagion. It was observed that, due to a limitation in contagion distance imposed by our parameter setting, some groups of agents are isolated, and thus they do not suffer contagion from the leader agent. Furthermore, by associating goals with emotions, it was possible to observe agents changing their goals as they changed emotional state, and sometimes it was possible to observe agents switching back to their original goals, as in the experiment presented in Section 5.2. Finally, Section 5.3 pictures agents changing their emotional state and sharing goal with the leader. As a result, agents that suffer emotional state changing due to contagion tend to converge to the same goal, getting physically close to each other. The proximity of agents can be further explored for coping with group formation and group dissolution. This way, group of agents can be dynamically assigned according to the simulation scenario, agents' emotional states and affinities, instead of being determined by input data. The advantage is not only minimizing input data overhead, but mainly increasing possibilities for simulation scenarios. Yet, this allows to create scenarios with emergent leaders both in groups and in the crowd. All this emergent behaviours are result of the emotional energy generated by one single agent, the position and trajectories of remaining agents in the crowd, and the time window agents keep inside each other interaction space.

By integrating an emotion contagion feature in *BioCrowds* we believe the model gained many possibilities. Now, agents are able to carry information about emotions and emotional state, and transmit this information to other agents. Based on this information, it is possible to determine new goals for agents. In this sense, the emotional information can be treated as other nature of information, such as willing to go shopping, or eating. Following this idea, a parallel project was developed using emotion information as direction signs in a city. The signs were designed as agents with expressiveness proportional to the appeal (or size) of the signal and, obviously, signals do not suffer contagion, so their susceptibility was set to zero. Also, signals do not move, their are just objects in the scenario (outdoors, posters or traffic signs giving directions). The agents in the scenario suffer contagion from the signs, depending on their will to pursue the directions the sign point to. The willing to go to a restaurant, or a computer store is given by agents' susceptibility to rise that particular "emotion", or will. For example, if an agent is hungry, and not at all interested in buying computers, its susceptibility to go to a restaurant is high, while the susceptibility go to go a computer store is low (or zero). Reminding that, in this parallel project, emotions became the disposition to go to one of the possible scenario goals.

Beyond improving possibilities in *BioCrowds*, we also extended the emotional contagion model. Besides creating contagion in a crowd of agents based only in dyadic interactions, perhaps the most significant advance in the model by Bosse et. al is the extension for multiple emotions. This allows more realistic simulation of emotions, since real people are able to feel more than one emotion. An important result of this is the ability of changing emotional state that emerges on agents. By changing agents' emotional state it is also possible to change their behaviour, which impact the crowd flow. Also, the contagion of emotions is now function not just of time, but also is function of space, translated to the distances between agents and their trajectories. The model still lacks verification of obstacles for emotion contagion. At the present moment emotions can spread through obstacles, like walls, and a mechanism to control this behaviour is desirable. One possible approach is to use a cone of perception that restricts agents' perception to their sensory space, both visual and/or auditive.

Considering the contagion of multiple emotions, in the work of Hatfield and collegues [33] the authors states that emotional contagion phenomena can occur by one particular emotion driving the same emotion in other subject, in a process known as (primitive) empathy. For example, if someone gets angry at some event or interest object, others, by empathy, might get anger as well at the same event. On the other hand, emotional contagion may occur under *counter-contagion* mechanism which means, for example, that if someone gets angry at another subject, that subject might have fear of an aggression. In this second scenario, we have a *counter-contagion* phenomena, where one expressed emotion drives a different emotion in the perceiver.

To model this characteristic of emotional contagion, a *Perception matrix* denoted by P is proposed as future work, with dimension $M \times M$, where M is the number of emotions. Its elements ρ_{ij} where i and j indicates emotional perception between emotions i and j. Consider a vector containing the emotional level of all emotions e_m in an agent A_n, defined by $\vec{Q}_{A_n} = [q^{e_0}_{A_n}, q^{e_1}_{A_n}, ..., q^{e_{M-1}}_{A_n}]$. Also, consider that the resultant perception vector of emotions is denoted by $\vec{Q'}_{A_n}$. By performing a matrix product as in Equation 6.1 with the emotional level vector of the sender, it is possible to rearrange vector Q_{A_n} in Q'_{A_n} to promote counter-contagion. The resulting vector, denoted as *perception* vector, serves as input for agents emotional model. As a default value for this matrix an identity matrix can be used to model the simple case of direct contagion of emotion, i.e. when fear promotes contagion of fear, and joy promotes contagion of joy. Also, fractions of emotions can be configured by only one stimulus, as in a case where anger triggers a fraction of fear, but also a fraction of anger as well.

Filling the perception matrix P with realistic values is a challenge. Counter-contagion may happen in many ways, and is deeply dependent on the scenario. On behalf of that, a plausible hypothesis is that the values of matrix P are dynamic, and change from time to time. This means that in one situation a person may respond to a threatening anger expression with fear, but in other situation the response might be also anger. Many factors such as the level of threat and emotional condition of the receiver may impact this phenomenon. Another concern is that the nature of emotions matters in this process, in other words, counter-contagion mechanisms for *joy* driving emotions of other nature may work in a different manner than counter-contagion mechanism for *anger* driving emotions of other nature.

$$\vec{Q'}_{A_n} = \vec{Q}_{A_n} \cdot P_{A_n} \tag{6.1}$$

$$\begin{pmatrix} q'^{e_0}_{A_n} \\ q'^{e_1}_{A_n} \\ \vdots \\ q'^{e_{M-1}}_{A_n} \end{pmatrix} = \begin{pmatrix} q^{e_0}_{A_n} & q^{e_1}_{A_n} & \cdots & q^{e_{M-1}}_{A_n} \end{pmatrix} \cdot \begin{pmatrix} \rho^{0,0}_{A_n} & \rho^{0,1}_{A_n} & \cdots & \rho^{0,M-1}_{A_n} \\ \rho^{1,0}_{A_n} & \rho^{1,1}_{A_n} & \cdots & \rho^{1,M-1}_{A_n} \\ \vdots & \vdots & \ddots & \vdots \\ \rho^{M-1,0}_{A_n} & \rho^{M-1,1}_{A_n} & \cdots & \rho^{M-1,M-1}_{A_n} \end{pmatrix} \tag{6.2}$$

Some works like Kapadia et. al [41] have mapped emotional traits and linked them to simulation parameters. For future work, we suggest efforts to translate emotional traits to emotional tendency parameters. The *susceptibility* of agents can be estimated by Emotion Contagion Scale measure for people [21]. The *expressiveness* can be calculated by the Emotion Expressivity Scale [43]. There is also the PANAS scale [70], that measures Positive and Negative affection and could determine the variable β controlling *upward* and *downward* spirals Finally, measures of empathy or neuroticism can estimate η. Furthermore, we believe that β should be dynamically controlled. Sometimes people have reason to be in a particular emotional state, due to cognitive experience or recent events, generating visceral, inner, emotional energy that result in emotional spirals. Sometimes, people change their emotional state. By doing that, they can change their emotional behaviour regardless of a contagion process. By controlling β dynamically, it is possible to keep $\beta = 0.5$, balancing positive and negative impact, resulting in a contagion process similar to $\eta = 0$. An emotion model should be designed to apprise and count for recent events or cognitive reasoning that may drive emotion spiral in the agents. This emotional model then takes control of β rising it above 0.5 for positive emotional spirals, and lowering it below 0.5 for negative emotional spirals. The strength and speed of the spirals are given by β (the farther from 0.5 the stronger the spiral) and also by η. Lower values of η (near zero) results in weaker spirals and higher values of η (near one) results in stronger spirals.

There are still many aspects of emotions to explore in this work. Anyhow, we believe that impacting agents' behaviour by their emotional state, and changing this emotional state by means of contagion create many possibilities to generate more realistic and complex simulation scenarios. It is expected that correct use of such features contribute to more reliable simulation results, improving decision making based on this results. Also, in the field of animation, agents with more flexible behaviour programming (i.e., since now they can decide among more than one goal) can enable creation of more realistic situations.

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