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On the Trade-off between Power Consumption and Time Synchronization Quality for Moving Targets under Large-Scale Fading Effects in Wireless Sensor Networks

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ABSTRACT

In this work we find a lower bound on the energy required for synchronizing moving sensor nodes in a Wireless Sensor Network (WSN) affected by large-scale fading, based on clock estimation techniques. The energy required for synchronizing a WSN within a desired estimation error level is specified by both the transmit power and the required number of messages. In this paper we extend our previous work introducing nodes' movement and the average message delay in the total energy, including a comprehensive analysis on how the distance between nodes impacts on the energy and synchronization quality trade-off under large-scale fading effects.

Keywords: Wireless Sensor Networks; Clock Offset Estimation; Time Synchronization; Wireless Channel Fading; Moving Targets

1. Introduction

With the advent of wireless technologies over the last decade, Wireless Sensor Networks (WSN's) are overtaking wired networks in the field of sensing [1]. A WSN typically consists of low cost battery-powered or self-powered sensor nodes. Thus, energy management becomes a substantial matter in order to guarantee reasonable sensors' lifetime values. Time synchronization algorithms aim to provide mechanisms for nodes to obtain an estimate of their internal clocks with respect to the other nodes, aiming to reach a consensus on the concept of time among all the nodes. For each node *i*, its internal clock c_i can be modeled as a linear equation with a corresponding skew α_i and offset β_i [2,3], namely $c_i(t) = \alpha_i + \beta_i$. In order to achieve a target synchronization quality, parameter estimation techniques can be applied, being the estimation error ϵ a function of the estimator and the number of samples employed. Time synchronization can be energy-consuming since it involves wireless messages exchange, however, when achieved, it allows significant energy savings through network power management. In all, WSN synchronization remains amongst the most challenging open topics in WSN's [4]. In our previous work [5] we had introduced the existing tradeoff between time synchronization accuracy and synchronization energy, although we did not contemplate nodes' movement in our analysis. In this paper we introduce this important feature under large-scale fading, a situation that is present in a realistic environment where nodes change their relative distance within a network.

2. Related Work

There is a number of clock synchronization techniques that exploit the number of received messages from a given sensor node to produce their clock estimation.. Examples of these are Reference-Broadcast Synchronization (RBS) [6], Timing-Sync Protocol for Sensor Networks (TPSN) [7] and Pairwise Broadcast Synchronization (PBS) [8]. In RBS, a reference node broadcasts reference beacons that serve the nodes in the network to perform receiver-receiver pairwise synchronization. TPSN creates a hierarchical structure in which each node synchronizes to its parent in a sender-receiver fashion. Yet, in PBS, a pair of supernodes *A* and *P* exchange messages that are overheard by all nodes in the network, allowing each node to construct their local estimate of the clock offset and skew with respect to the supernodes based on reception time stamps. Thus, for a given node *B* the quality of offset estimation with respect to reference node *P* can be obtained as follows [8]:

$$\operatorname{var}(\hat{\theta}_{offset}^{(BP)}) \geq \frac{\sigma^2 \sum_{i=1}^{\tilde{m}} D_i^2}{\tilde{m}\sum_{i=1}^{\tilde{m}} D_i^2 - (\sum_{i=1}^{\tilde{m}} D_i)^2} \quad (1)$$

From (1), the estimation quality (variance of the clock offset estimator) depends on the number of received messages $\tilde{m}$ and the time stamps differences D_i. Increasing $\tilde{m}$ will enhance estimation quality in detriment of the energy consumed. While many authors expose this energy-synchronization quality balance as a known open topic (such as [9,10]), to the best of our knowledge, previous contributions in the field of clock synchronization focus on the algorithmic aspect of the timing mechanism with little concern on the energy and delay required to attain such a goal. In [11], authors propose a mechanism for synchronizing a WSN by means of constructive interference in order to achieve low duty cycles in radio operation, thus minimizing the energy spent, although they do not mention the existing trade-off between energy and synchronization accuracy. In [12], the authors expose the trade-off of energy consumption and synchronization quality from a local sleep-time perspective, without contemplating the energy spent in nodes interaction. Also, [13] aims to minimize the energy for maximum accuracy but from a local node's perspective, with low duty cycle and low frequency crystal oscillators hardware. More recent works such as [11,14] approach the energy efficiency problem from a protocol perspective, without detailing the physical phenomena involved in wireless channels. For example, [14] proposes a new algorithm, the Recursive Time Synchronization Protocol (RTSP), which aims to minimize the number of transmitted messages in a WSN, although the authors do not include in their analysis either transmit or receive power in each sensor node as part of the minimization problem. Therefore, the tradeoff "power consumption-clock synchronization quality" is a critical issue for wireless embedded systems that requires finding an optimal solution.

3. One-Way Message Clock Offset Estimation Quality as a Function of Transmit Power

3.1. Motivation

We will use one-way message mechanism as the starting point for exposing the underlying issues associated with clock synchronization by means of wireless messages. The Flooding Time Synchronization Protocol [15] uses this technique to estimate the sender's clock offset through a linear regression of the received samples.

3.2. Model Statement

Transmit power and clock synchronization quality operate on different layers: the first one is a physical magnitude whereas the latter belongs to the application layer. However, prior to estimation, physical layer reception occurs with a given probability of failure as a function of the transmit power *S*, given by the channel's outage probability P_{out}, defined as the probability that the received signal falls under a minimum acceptable threshold [16]. Let's consider each node's clock offset θ is estimated with an unbiased estimator $\hat{\theta}$ and let $\sigma_{\hat{\theta}}^2$ be the variance of the clock offset estimator. Consider sender node A sends m packets while receiver node B receives $\tilde{m} = E[M] = m \cdot (1 - P_{out})$ successful messages, where M is a binomial random variable, *i.e.* $M \sim b(m, 1 - P_{out})$. The average delay per message can also be derived as a function of the outage probability as follows:

$$\delta = T_M \cdot \frac{m}{\tilde{m}} = \frac{T_M}{1 - P_{out}} \quad (2)$$

where T_M is the message transmission time. Thus, reducing the outage probability will also enhance the synchronization time. However, this must be balanced with the application's energy budget, since in order to reduce P_{out}, the transmit power S must be increased. Since the estimation quality depends on the number of successfully received packet $\tilde{m}$, the interesting relation $\sigma_{\hat{\theta}}^2 = f(S)$ is sought. It will be necessary then to relate the estimation quality's dependence on the number of received messages, namely $\sigma_{\hat{\theta}}^2(\tilde{m})$, and the number of received messages dependence on the transmit power, *i.e.* $\tilde{m}(S)$. We will approach the synchronization problem from the local perspective of a node that is synchronizing with a neighbor, irrespective of the network size and topology. The analysis presented in this work is not tied to a particular procedure but it represents a universal lower bound on the "energy-synchronization quality" trade-off.

3.3. Definitions

3.3.1. Estimators and Theoretical Limits

The trade-off studied in this work can be stated as an estimation problem. Both expected value and variance of the offset's unbiased estimator are defined as shown below:

$$E[\hat{\theta}] = \theta \quad (3)$$

$$\sigma_{\hat{\theta}}^2 = E[(\hat{\theta} - E[\theta])^2] = E[(\theta - \theta)^2] = \sigma_{\theta}^2(\tilde{m}) \quad (4)$$

In order to formulate a general problem, the Cramer-Rao lower bound [17] can be used for delimiting the best performance an estimator can afford. Thus, the estimation quality relates with the Fisher Information function $I(\theta)$ as follows:

$$\sigma_{\hat{\theta}}^2 \geq \frac{1}{I(\theta)} \quad (5)$$

with the Fisher Information's expression as shown below [17]:

$$I(\theta,\tilde{m}) \triangleq -E\left[\frac{\partial^2}{\partial\theta^2}\ln f(\theta,\tilde{m})\right] \quad (6)$$

where f is the likelihood function of the parameter θ.

3.3.2. Communication Channel Model

For wireless channels, the received to transmit power ratio S_R / S is dictated by [16]:

$$\frac{S_R}{S}(dB) = 10\log K - 10\gamma\log\frac{d}{d_0} - \psi_{dB} \quad (7)$$

where K is a constant that models the antenna gain, d_0 a reference distance, γ the path loss exponent, d the distance between transmitter and receiver nodes, and $\psi_{dB} = 10\log\psi$, being ψ a random variable that models large-scale (shadowing) effects. A communication is defined to be successful, *i.e.* the receiver can process the transmitted message, when the received Signal-to-Noise Ratio (SNR) γ_s satisfies $\gamma_s > \gamma_0$, being γ_0 the minimum acceptable SNR by the receiver [16]. We will consider that the wireless channel is memory-less and time-invariant, meaning that each channel use will be independent and uncorrelated from each other, *i.e*., they will undergo independent and identically distributed (i.i.d.) fading effects [16], which means that two subsequent messages sent over the wireless channel will present independent and uncorrelated impairments.

3.4. Problem To Solve: Energy Optimization

The number of successfully received packets $\tilde{m}$ is related to the transmit power S as shown below:

$$\tilde{m} = m\cdot[1 - P_{out}(S)] \quad (8)$$

The main challenge is to find the transmit power S that satisfies the following condition:

$$\min(S) \quad \text{s.t.} \quad \sigma_{\hat{\theta}}^2(\tilde{m}) < \epsilon \quad (9)$$

Equation (9) seeks the minimum transmit power S that guarantees the necessary amount of received messages $\tilde{m}$ so that the clock offset estimation error $\sigma_{\hat{\theta}}^2$ is less than a desired level ϵ. For Cramer-Rao efficient estimators, *i.e*. estimators that attain equality in (5), the following inequality can be stated:

$$\sigma_{\hat{\theta}}^2 = \frac{1}{I(\theta,\tilde{m})} < \epsilon \quad (10)$$

where I is the Fisher Information of the estimated parameter θ as a function of the received samples $\tilde{m}$. Thus, the problem can be stated as follows:

$$\text{Find:} \quad \min(S) \quad \text{s.t.} \quad I(\theta,\tilde{m}) > \frac{1}{\epsilon} \quad (11)$$

Equation (11) seeks the minimum transmit power *S* for achieving a desired estimation error ϵ on the clock offset θ by successfully receiving $\tilde{m}$ messages after transmitting *m* messages. In order to account for energy optimization, *both transmitter and receiver energy must be minimized*; the first one depends on the transmit power *S* and the number of transmitted messages *m*, whereas the latter is determined by the total time the receiver circuit is powered-on. Since the transmitter sends *m* messages and the average message delay is δ, the receiver must be turned on for at least $m\cdot\delta$ to successfully receive $\tilde{m}$ messages. Thus, the total energy function for a pair of nodes (i, j), where node *i* is transmitting messages to node j, can be expressed as follows:

$$\begin{aligned} E_{ij}(Total) &= E_i(Tx) + E_j(Rx) \\ &= S\cdot m\cdot T_M + \eta\cdot S\cdot m\cdot\delta \\ &= S\cdot m\cdot\delta\cdot(1+\eta-P_{out}) \end{aligned} \quad (12)$$

where $T_M / \delta = 1 - P_{out}$ as per (2) and $\eta \triangleq S_{Rx}/S$ represents the ratio between the receive power and the transmit power, which typically falls in the range 0.5 ~ 0.8 for commercial transceivers [18]. The term $(1+\eta-P_{out}) \in (\eta, 1+\eta)$ in (12) has a smooth variation with S for which it does not strongly contribute to the overall variation as the rest of the unknowns *S*, *m* and δ do, *i.e*. it is sufficient to minimize the product of *all S*, *m* and δ to find the minimum energy working point. Hence, let

$$A(S,m,\delta) = S\cdot m\cdot\delta \quad (13)$$

be a representative measure of the total energy required for synchronizing a pair of nodes. Thus, the objective is to minimize the $A(S,m,\delta)$ function for large-scale fading effects. This will be the main motivation throughout the rest of this work.

3.5. Gaussian Observations of the Clock Offset

As per (6), the Fisher Information function requires a likelihood function to be applied. Considering the case of Gaussian distributed likelihood functions, for $\tilde{m}$ Gaussian i.i.d observations of θ, the joint probability distribution function is expressed as:

$$f(\theta,\tilde{m}) = \frac{1}{(2\pi\sigma_V^2)^{\tilde{m}/2}}\exp\left[-\sum_{j=1}^{\tilde{m}}\frac{(\theta_i-\theta)^2}{2\sigma_V^2}\right] \quad (14)$$

where σ_V^2 is the variance of the perturbations that impair the measurements around the real value of the parameter θ to be estimated. Operating with (6), (11) and (14), we obtain:

$$I(\theta,\tilde{m}) = \frac{\tilde{m}}{\sigma_V^2} > \frac{1}{\epsilon} \quad (15)$$

3.6. Large-Scale Effects: Path Loss and Shadowing

Large-scale fading represents the average signal power attenuation or path loss over large areas, a phenomenon affected by prominent terrain contours (billboards, clump of buildings, etc.) between the transmitter and receiver [19]; still, for indoor applications, this phenomenon is also present for distances smaller than 10 meters [16]. Under path loss and shadowing, the outage probability P_{out} is defined as the probability that the received power falls below a given outage threshold S_{Rx} expressed in dBm as found below [16]:

$$Q(z) \triangleq \int_z^{+\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) dx = \frac{1}{2}\operatorname{erfc}\left(\frac{z}{\sqrt{2}}\right)$$
$$z(S) = \frac{S_{Rx} - [S + 10\log K - 10\gamma \log(d/d_0)]}{\sigma_{\psi_{dB}}} \quad (16)$$
$$P_{out}(S) = 1 - Q(z(S))$$

with the unknown transmit power S expressed in dBm. Parameters K, d, d_0, γ, d defined in (7) are assumed known. In this scenario, the random variable ψ_{dB} assumes a Gaussian distribution with zero mean and variance $\sigma_{\psi_{dB}}$ (assumed known). Involving (8), (11), (15) and (16), it can be seen that for a desired estimation precision ϵ, the transmit power S must fulfill the following:

$$Q\left(\frac{S_{Rx} - [S + 10\log K - 10\gamma \log(d/d_0)]}{\sigma_{\psi_{dB}}}\right) > \frac{\sigma_V^2}{m \cdot \epsilon} \quad (17)$$

Equation (17) shows that for decreasing estimation error ϵ, either power S or number of transmitted messages *m* must be increased accordingly. Since *Q* increases with increasing *S*, the minimum transmit power S_{min} will be found on the limit of equality in (17). It is then convenient to rewrite this equation into a function as follows:

$$B(S_{min}, m, d)\big]_{\epsilon} = Q\left(\frac{K_1(d) - S_{min}}{\sigma_{\psi_{dB}}}\right) - \frac{\sigma_V^2}{m \cdot \epsilon} = 0 \quad (18)$$

with

$$K_1(d) = S_{Rx} - 10\log K + 10\gamma \log(d/d_0) \quad (19)$$

For nodes moving at a relative velocity V, the distance d between them at time t is determined by:

$$d = d(t) = d_0 + V \cdot t \quad (20)$$

where d_0 is the initial distance between the nodes exchanging messages. Equation (20) is a scalar expression due to the fact that we study the fundamentals of the energy trade-off problem with two nodes communicating with each other; for the general case of *N* nodes, the expression can be better represented by a vector equation. Furthermore, *V* can be either positive or negative; in case of negative relative velocity (nodes' approaching each other) we will consider that the nodes' instantaneous distance *d* fulfills $d(t) > d_{min} \, \forall t$ in order to remain in the large-scale effects scenario. The minimum distance d_{min} for large-scale effects is typically 10 m for indoor applications and 100 m for outdoor applications.

3.7. Large-Scale Effects: Towards Energy Minimization

From (18), the number of transmitted messages *m* is determined by:

$$\lceil m_{min} \rceil = \frac{\sigma_V^2}{\epsilon \cdot Q\left(\frac{K_1(d) - S_{min}}{\sigma_{\psi_{dB}}}\right)} \quad (21)$$

After combining (2) and (16), the delay δ adopts the following expression under large-scale effects:

$$\delta_{min} = \frac{T_M}{Q\left(\frac{K_1(d) - S_{min}}{\sigma_{\psi_{dB}}}\right)} \quad (22)$$

By substituting (21) and (22) into (13), and expressing S_{min} in dBm, the minimization problem is stated as:

$$\frac{\partial}{\partial S_{min}}\left[\frac{T_M \cdot 10^{0.1 S_{min}} \sigma_V^2}{\epsilon \cdot Q^2\left(\frac{K_1(d) - S_{min}}{\sigma_{\psi_{dB}}}\right)}\right] = 0 \quad (23)$$

A solution to (23) was shown in [5], leading to:

$$Q\left(\frac{K_1(d) - S_{min}}{\sigma_{\psi_{dB}}}\right) - \frac{2 \cdot \exp\left[-\frac{1}{2}\left(\frac{K_1(d) - S_{min}}{\sigma_{\psi_{dB}}}\right)^2\right]}{0.23\sqrt{2\pi}\sigma_{\psi_{dB}}} = 0 \quad (24)$$

which can be graphically solved to find the optimal S_{min} value, provided that $S_{min} \geq K_1(d)$. Equations (21) and (24) represent an energy-efficient solution to the target estimation error ϵ under the effect of large-scale fading.

4. Simulation Results

This section exposes the simulations results for typical WSN parameters as referenced in [16] under one-way message exchange. **Figure 1** shows the dependence of the number of transmitted messages *m* and the required energy $A(S,m,\delta)$ with transmit power S under the influence of large-scale fading for different values of the estimation quality ϵ, for a fixed distance d between transmitter and receiver nodes. **Figure 2** shows the dependence of m with S and d under large-scale fading. It can be seen that for S fixed, as d grows, m has to be increased accordingly.

Since under large-scale effects the dominating factor in signal fading is the distance d between pairs, the nodes' relative velocity is not an independent variable in the energy graphics. However, it is always possible to define a fixed time window, e.g. $\Delta t = 1s$, substitute d with its definition in (20), and analyze the variation of the energy minima as dictated by (24). Hence, although there is a unique relation between d and V, it is more accurate to analyze the variations the energy minima with d under this scenario. The figures in this section have the following simulation parameters:

$$\sigma_V^2 = 1, S_{Rx} = -80\ dBm, K = 7.0146\cdot 10^{-4},$$
$$d/d_0 = 10, \sigma_{\psi_{dB}} = 1\ dB, \gamma = 3.71, T_M = 1\,\mathrm{s}.$$

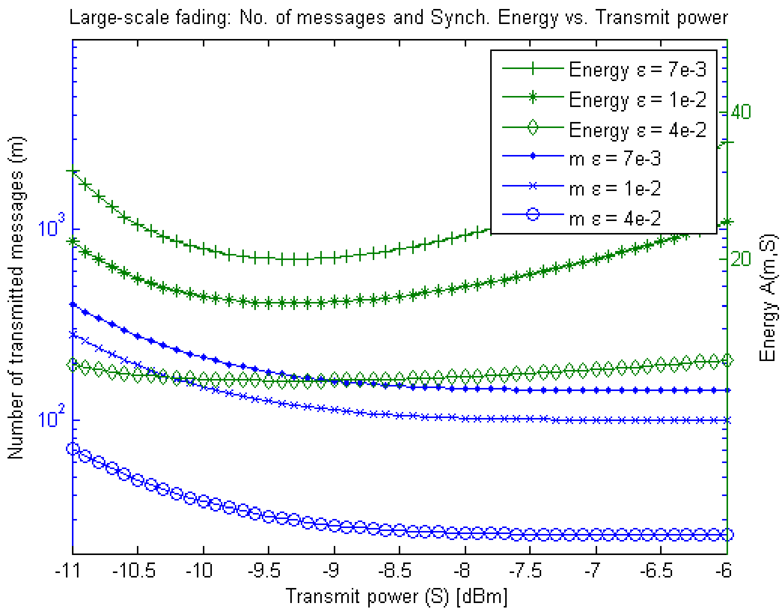

Figure 1. Number of transmitted messages *m* and Energy required *A*(*S*, *m*, *d*) as a function of transmit power *S* for large-scale fading, for different clock offset estimation qualities e using one-way messages.

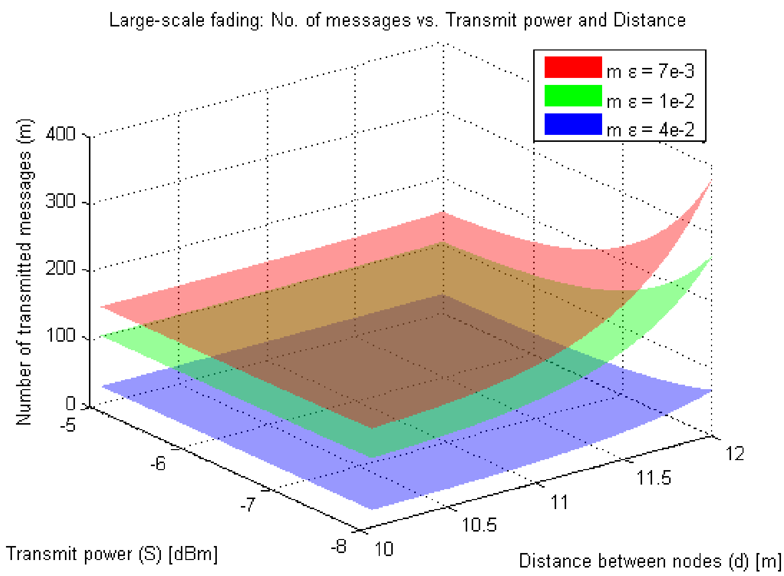

Figure 2. Number of transmitted messages *m* as a function of transmit power *S* and nodes' separation distance *d* for large-scale fading, for different clock offset estimation qualities e using one-way messages.

5. Summary and Discussions

Time synchronization for a WSN can be achieved by means of parameter estimation techniques which require a number of messages to be transmitted from a sender to a receiver node. The minimum amount of total energy required for achieving a desired estimation quality ϵ is represented by the product of the transmit power *S*, number of messages *m* and the average message delay *d*. By introducing the concept of outage probability of the wireless channel for large-scale fading, a minimization problem can be stated for the total energy function. The resolution of the entire system finds the energy-optimal working point which represents a lower bound for the estimation quality. We have also analyzed the effect of distance and relative movement between sensor nodes and presented a set of equations describing their impact on the system's parameters, which constitutes an interesting and realistic problem to real-world applications. The general results obtained in this work have been applied to the particular case of Gaussian perturbations for the Cramer-Rao efficient, unbiased offset estimator $\hat{\theta}$. For other estimators that do not fulfill these conditions, the estimation error $\sigma_{\hat{\theta}}^2$ shall be used instead of the Fisher Information function in order to compute the theoretical limits for that particular case. As part of our future work, we are working on the small-scale effects counterpart when moving targets are synchronizing in a WSN.

Finally, unlike under large-scale effects where the distance between nodes plays a predominant role in the energy minimization problem, under small-scale effects the relative velocity between nodes is a determining factor in the synchronization accuracy, due to the Doppler spread effect [19]. Thus, our aim is to complete a comprehensive analysis of "energy-synchronization quality" tradeoff under both fading scenarios as part of our future work.

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