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A neural approach to synchronization in wireless networks with heterogeneous sources of noise

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ABSTRACT

The paper addresses state estimation for clock synchronization in the presence of factors affecting the quality of synchronization. Examples are temperature variations and delay asymmetry. These working conditions make synchronization a challenging problem in many wireless environments, such as Wireless Sensor Networks or WiFi. Dynamic state estimation is investigated as it is essential to overcome non-stationary noises. The two-way timing message exchange synchronization protocol has been taken as a reference. No a-priori assumptions are made on the stochastic environments and no temperature measurement is executed. The algorithms are unequivocally specified offline, without the need of tuning some parameters in dependence of the working conditions. The presented approach reveals to be robust to a large set of temperature variations, different delay distributions and levels of asymmetry in the transmission path.

1. Introduction

Clock Synchronization Protocols (CSPs) have a fundamental role in many technological contexts in which a common time reference is required [1]. For example, synchronization is used in Wireless Sensor Networks (WSNs) [2], localization [3,4], home automation [5], industrial networks [6], traffic scheduling [7,8], and in a number of other contexts in which actuation and/or sensing must be synchronous. The quantities measuring the asynchronism between the clocks of two nodes in a network are: the *offset*, i.e., the difference between the two clocks and the *skew*, i.e., the normalized difference between the Crystal Oscillator (XO) oscillation frequency and its nominal frequency. The variable component of the skew is the *drift*. Their precise estimation defines the target of the CSP and they are jointly optimized [9]. They typically represent the state of the synchronization problem, when it is formulated under dynamic state equations.

The estimation process may be severely compromised by a number of factors. The most important are: the random delays affecting the communication path between nodes, including software or hardware delays inside them, the precision of nodes in timestamping events, and changes in the environment conditions. Estimation of offset and skew may be driven by signal processing techniques, which assume a time-fixed state (see, e.g., [10] for WSNs) or by dynamic state tracking, e.g., through Kalman filtering (as an example, see [11] for IEEE 1588 protocol). Addressing time-varying conditions means to follow instantaneous fluctuations due to non-stationary noises, such as temperature variations of XOs [12–14].

1.1. Background and objectives

In the present paper, we study how to compensate with a single technique all the possible factors affecting synchronization. The idea to analyze and compensate a number of causes together is not new. Algorithms derived from machine learning (e.g., neural networks, support vector machines, …) are typically exploited to model complex processes; in particular, in the case a theoretical model is not known or it cannot be parameterized because too many measurements of the real system are needed for a satisfactory characterization. The latter is the case of synchronization protocols. The oscillation frequency of an XO is influenced by several environmental factors: temperature, supply voltage, vibrations, age, etc. All these factors, well documented in the scientific literature [12], have not the same influence on the behavior of different types of XOs, and even the same type of XOs differently reacts to environmental conditions, depending on the manufacturing process. To compensate all these factors, each XO must be experimentally characterized with respect to the physical phenomena that can modify its behavior. Such a kind of analysis can be performed

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only during the manufacturing process because XOs are usually soldered on the mother-board. Physical quantities must then be sensed at runtime for their relevant compensation. This last step is not easy or feasible at all; for example, XOs do not usually include temperature sensors. In this case, the estimation must be derived by using sensors in the proximity of the XO. On the other hand, XOs that automatically compensate some external factors exist, but they are integrated in commercial devices at increasing manufactoring costs. The same difficulties in finding a correct model apply also to other quantities such as the timestamps precision and accuracy, and asymmetric delays. They depend on the hardware, but in the case of software timestamps also on the interference caused by other processes executed in the operating system of the node. For these reasons, we decide to focus on an algorithm that compensates all these aspects together. Delay assymetry is addressed jointly with temperature variations.

The algorithm we pursue should be capable to work with minimal online adjustment of the parameters, thus avoiding the need of reconfigurations on the basis of the actual behavior of the noises.

Synchronization is formulated as a dynamic state tracking problem beyond regular LQG hypoteses[3] because temperature measurement noise may not always be Gaussian in practical systems [13–15]. The inherent optimal estimation filter may be hardly derived in closed form. This approach typically has consequences in terms of numerical analysis with complex operations (see, e.g., the Particle Filtering in [10]), which are not easily applicable in devices in which computational power or energy are scarce resources. Since the investigated suboptimal filter is based upon neural approximation, the approach may lead to a heavy computational effort in the offline phase (during which the training of the neural network is provided), but synchronization corrections are provided online almost instantly.

1.2. Contribution

The method firstly outlined in [15] for *receiver-receiver* CSPs [6], is now applied in the sender-receiver context, more used in practice, and under realistic conditions of WSN and WiFi networks, including delay asymmetry. Despite the considered CSP drives delay compensation, we show how no knowledge of delay is necessary for the used estimation techniques. An enhancement of the method is proposed to cope with exponentially distributed delays, a condition not often detectable in practice, but analyzed in some scientific works [16]. The method provides good generalization capabilities to different delays distributions (i.e., Gaussian and exponential delays). The multi-hop context is also addressed to limit computational cost and simplify the applicability of the method.

1.3. Organization of the paper

The paper is organized as follows. The next section deals with the analysis of the state of the art and highlights the position of the present paper. Section 3 addresses the mathematical formulation of the estimation problem. The subsequent sections enter in the details of the estimation techniques proposed, including computational and implementation aspects. Section 9 defines the setting of the experiments and Section 10 discusses the results. Conclusions and future work are finally outlined at the end of the paper.

[3] Linear dynamics of the system, quadratic cost function and Gaussian noises.

2. Related literature

2.1. State estimation

Dynamic state estimation for synchronization is an open issue for environments with non-Gaussian and non-stationary noises [13,14]. An example for WSN has been reported in [10], by introducing Particle Filtering (PF). Wu et al. [10] shows how addressing time-varying conditions may considerably improve the synchronization gain over signal processing techniques. PF is able to adapt to Gamma distributed delays better than signal processing, which works well under Gaussian or exponential delays. PF belongs to the optimal Bayesian framework for dynamic state estimation. This is exactly the research line we want to pursue here, without incurring in the computational burden involved by PF.

As far as signalling processing techniques are concerned, our approach has been compared with [17], which is a reference target in this field (see, e.g., [16]), since it presents a computationally light approach, which is also robust to the underlying network delay density function and asymmetry. More refined techniques are available as well, for example, in the presence of exponentially distributed delays [16].

2.2. Parameters setting

Online adaptation may be critical if the statistical parameters of the noises cannot be known in advance. More specifically, the covariance matrix of the noises is typically used as a parameter of the mentioned algorithms (Kalman [11], signal processing as in [16] and Particle Filtering (PF) in [10]). How parameters setting may be a critical task in Kalman is evidenced by [18], in which practical guidelines are provided. This critical aspect has been also registered by [14], in which the parameters of the estimation algorithm are tuned online and by [13], in which the parameters of the temperature-skew mapping are supposed to be known in advance. Synchronization solutions with self-learning capabilities may be hardly found in the literature. Prez-Solano and Felici-Castell [19] has recently investigated how to adapt the time window of linear regression. The approach has been tested in stationary Gaussian conditions.

2.3. Temperature noise

Recent works address synchronization in WSNs by overcoming the temperature noise. In [13], the thermal drift is removed in advance, by exploiting the relationship between XO frequency and the temperature. A multi-model Kalman filter is studied in [14] to obtain the model likelihood for the skew, based on the measured temperature. The main advantage of the two approaches relies on the possibility to reduce the sending rate of synchronization messages, by keeping unchanged the synchronization quality since the temperature is locally compensated. An ARMAX model is studied in [20] to compensate temperature and aging effects. An upper bound of the error is derived in closed-form under Gaussian assumptions. The mentioned works rely on a mapping table from temperatures to clock skews [21]. Xu et al. [21] models the correlation between clock skews and temperature variations through the least squares method, thus achieving more flexibility, still relying on temperature measurements. The approach presented here does not exploit any measurement of the temperature. Yang et al. [22] deals with high latency networks by introducing a new message exchange in two steps: in the first one the delay is estimated and, in the second one, Kalman is applied. The refined procedure reveals to be robust to noise, including temperature changes.