Updating strategies in the Internet of Things by
taking advantage of correlated sources

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Abstract—The success of the Internet of Things (IoT) strongly depends on the development of efficient strategies for gathering and processing large amounts of data while saving energy and increasing device lifetime. This work investigates the use of correlated sources of information to improve the timeliness of data collected from sensing devices in the IoT. We consider information sources that transmit periodic updates to a gateway regarding the status of an observed process and determine the optimal update strategy for these sources. We show that there is an optimal waiting time for the first update to be sent by a secondary, correlated source such that estimation error is the lowest.

Keywords—Internet of Things (IoT), energy efficiency, Age of Information, status updates

I. INTRODUCTION

Our work investigates the use of correlated sources of information to improve the lifetime of low-power sensing devices in the Internet of Things (IoT). We consider sensor nodes as information sources that transmit periodic updates to a gateway regarding the status of an observed process. Status updates contain the value of the process observed, and a timestamp to indicate when the observation was made. We focus on the benefits of using a second information source, possibly one of reduced cost, in order to deliver timely information.

In areas where sensor nodes, i.e. information sources, are densely deployed, information sent from neighbouring sensor nodes observing the same phenomenon (e.g. weather, vehicular traffic, etc.) often exhibits high correlation in time and space. Hence, the information gathered at a given time or location can be used to predict the phenomenon at a different position and at a future time instant. By taking advantage of correlation in such a way, it is possible to decrease the rate at which information sources send status updates to a gateway. Such an approach is desirable when information sources have a limited energy source (e.g. a battery), as fewer updates lead to a longer lifetime. We investigate how frequently the correlated sources should send updates, i.e. their updating strategy, to minimise energy consumption.

We model one information source of interest and one secondary correlated source. The secondary source’s role in the network may be to collect information of its own, and the correlation between information collected by multiple sources allows usage of those updates to benefit the source of interest. Alternatively, the correlated source may be present because it was installed in the network with the sole intention of assisting the source of interest. An example of the first scenario is vehicular traffic monitoring sensors installed at selected sites in a city. While the main purpose of each sensor is to collect information from its site, the correlation between the information collected by all sensors can be leveraged to reduce their update rates. An example of the second scenario would be the installation of a second sensor that is capable of providing data that is strongly correlated to the data collected by the sensor of interest but can operate at a lower cost. Regardless of the reason for the presence of the secondary source, it is always possible to use it to improve the timeliness of updates from the source of interest.

Timeliness of sensing updates depends on the time elapsed since the last update from the source, calculated through metrics that characterise the Age of Information (AoI) [1]. The concept of AoI is useful for modelling communication systems in which the receiver has an interest in fresh information. In [2], authors studied optimal strategies to transmit status updates: they consider the level of dissatisfaction with outdated information to decide how long the source should wait before transmitting the next update. Status updating strategies have also been considered in [3] in the context of information sources performing energy harvesting, where the authors proved that the optimal updating strategy might deviate from a zero-wait policy that transmits updates as soon as energy and server are both available. In our work, we examine how information sent from one correlated source influences the timeliness of the information collected from the main source.

The use of correlated information to improve energy efficiency was first proposed in the context of sensor networks [4]. The main idea in [4] is to use information from only a fraction of all available information sources to fully reconstruct the physical phenomenon. As opposed to determining an appropriate node density to reconstruct the observed phenomenon, we propose an update strategy which reduces the number of transmissions from the information sources.

Alternative ways to save energy relying on the correlation between sources include data prediction and model-based active sampling as described in [5]. Data prediction schemes rely on models, residing on sinks and sensor nodes, to estimate the current status of the phenomenon under observation. Sensors update information about the phenomena of interest only to correct the previous prediction made by the model. The scheme saves energy by sending information only when needed. The model at the source is used to estimate the error made by the model at the sink and takes into account information sent.
from correlated nodes, as presented in [6]. Similarly, in model-based active sampling, the model resides only at the sink and describes sensing of the physical phenomenon carried out by the sources. The sink dictates when the sources should send updates. As demonstrated in [7], the nodes may save energy by reducing both the number of acquired samples and the number of transmissions. In contrast to this work carried out in wireless sensor networks (WSN), we aim to prolong the lifetime of the source of interest by setting up an update strategy based on AoI.

In this paper, we study two temporally and spatially correlated information sources which send updates to a sink. Our main contribution is in determining the optimal update strategy for the two correlated sources. We prove that there is an optimal waiting time for the first update from the correlated source such that estimation error is the lowest. We conclude the paper by deriving the maximum possible gain the correlated source can provide to the system.

II. SYSTEM MODEL

The purpose of a sensing system is to observe a physical phenomenon \( Z(x, t) \) evolving in time (\( t \)) and space (\( x \)). We consider a data gathering system consisting of two correlated nodes in the IoT, as represented in Figure 1. We are interested in the value of \( Z(x_1, t) \), where \( x_1 \) is the position of information source \( S_1 \). With a correlation model, we can predict the value of \( Z(x_1, t) \) using outdated information \( Z(x_1, \Delta_1(t)) \), or using information from another source \( S_2 \) \( Z(x_2, \Delta_2(t)) \), where \( \Delta_i(t) \) denotes the AoI [8] obtained from \( S_i \) available at time \( t \), i.e.

\[
\Delta_i(t) := t - t_i,
\]

where \( i \in \{1, 2\} \), and \( t_i \) represents the time of the last update generated by source \( S_i \).

Each sensor node in our system represents an information source sending information to a sink, where information from the two sources is gathered and processed. In this work, we assume that the transmission of updates is periodic with rate \( \lambda_i \), i.e. the interval between consecutive updates is deterministic, given by \( 1/\lambda_i \). The frequency of updates determines the energy consumed in transmissions and, for battery-powered sensors, has a direct effect on the lifetime of the sensors.

Both the information sent by \( S_1 \), which is the sensor of interest, as well as information sent by another sensor \( S_2 \), located at a distance \( h \) from \( S_1 \), improve the knowledge about the physical phenomenon. We consider that the observed phenomenon can be represented by a stationary Gaussian process. Therefore, the observations are assumed to be jointly Gaussian. When trying to estimate the value of \( Z(x_1, t) \) given the most recent observation available, the estimator which minimises the mean square error is the conditional expectation

\[
\hat{Z}_i = E[Z(x_1, t)|Z(x_i, \Delta_i(t))], \quad i \in \{1, 2\}.
\]

The conditional variance is proportional to \( 1 - \rho_i^2 \), where \( \rho_i \) is the correlation coefficient, defined assuming unit variance as

\[
\rho_i := \text{cov}(Z(x_1, t), Z(x_i, \Delta_i(t))),
\]

which is a function of the age, i.e. the time separation, and the spatial separation between the selected sources.

Finally, we define a measure of estimation error:

\[
\varepsilon_i(|x_1 - x_i|, t) = 1 - \rho_i^2.
\]

We model the correlation between sources using an exponential separable covariance model [9]. Under the assumption of unit variance, we have the correlation between two measurements taken by \( S_1 \) as follows:

\[
\rho_1(0, t|\theta) = \exp(-a\Delta_1(t)),
\]

while, due to spatial separation \( h := |x_1 - x_2| \) between the two sources, the correlation between two measurements taken by \( S_2 \) is:

\[
\rho_2(h, t|\theta) = \exp(-bh) \exp(-a\Delta_2(t))
\]

with:

\[
\theta = (a, b).
\]

A separable covariance model enables us to observe how the process of interest varies across space at a given time, or how the process at a given location varies over time. The first term in (6) describes spatial variation, where \( h \) is the distance between the information sources and \( b \geq 0 \) is the spatial scaling parameter. The second term describes the temporal variation of the process, with \( a \geq 0 \) as a scaling parameter of time. The use of separable covariance functions enables tractable mathematical modelling for observing the spatial or temporal variation of a natural process. For example, in [9]...
the author applied a separable covariance model to wind data collected in Ireland, indicating that such model is adequate to describe the covariance in certain data gathering scenarios.

III. OPTIMAL UPDATING STRATEGIES

In our system, $S_1$ is the information source of interest. Updates sent by $S_2$ serve to reduce the estimation error caused by outdated information from $S_1$. The estimation error from information sent from $S_1$ depends only on temporal separation, i.e. on the age of the last received update. The estimation error from information originating from $S_2$ has to account for temporal and spatial separation. Denoting the spatial separation between sources by $h$ and making use of the definition in (4), the estimation errors for information gathered from $S_1$ and $S_2$ are:

$$\varepsilon_1(0, t) = 1 - \exp(-2a\Delta_1(t))$$

(8)

$$\varepsilon_2(h, t) = 1 - \exp(-2bh - 2a\Delta_2(t)).$$

(9)

Let $T_1$ denote the period of updates from source $S_1$, i.e. $T_1 = 1/\lambda_1$. Every time that $S_1$ transmits an update, the estimation error $\varepsilon_1$ drops to zero, as shown in Figure 2. As information becomes more outdated, the estimation error slowly rises according to the expression in (8). Let $T_2$ be the period of updates from $S_2$. Updates are transmitted at time instants $\tau_\Delta + jT_2, j \in \{1, 2, \ldots\}$, at which times $\Delta_2(t) = 0$, and the estimation error based on information received from $S_2$ becomes $\varepsilon_2(h, 0) = 1 - \exp(-2bh)$. The sink in our system always uses information from the source which provides the smallest expected estimation error. Therefore, the system estimation error at any given time is:

$$\varepsilon_{sys}(h, t) = \min\{\varepsilon_1(0, t), \varepsilon_2(h, t)\}.$$  

(10)

In this section, we analyse the system to determine the optimal updating strategies for the two sources. In the first subsection, we analyse the system when sources have the same update rate, i.e. $\lambda_1 = \lambda_2$. We explain how a time offset between the sources’ updates affects the system estimation error. In the second subsection, we investigate a case in which $S_2$ updates more frequently than $S_1$, i.e. $\lambda_2 > \lambda_1$, to determine the influence of different update rates on system estimation error.

A. Equal Update Rates

When sources update with equal update rate, i.e. $\lambda_1 = \lambda_2$, the system estimation error depends on the time shift $\tau_\Delta$ between the sources’ updates. We define $\tau_\Delta$ as time between an update from $S_1$ and the next update from $S_2$ as shown in Figure 2. Later in this section, we show there is an optimal time shift $\tau_\Delta = \tau^*$ for which the average system estimation error is the lowest possible.

The update from $S_2$ can reduce the system estimation error only if the estimation error caused by the outdated $S_1$ update is higher than $\varepsilon_2(h, 0)$, at the time of $S_2$’s update. We define $\tau_p$ as the minimal time shift between the two sources’ updates for which an update from $S_2$ will lower the system estimation error. When $S_2$ updates with time shift $\tau_p$, the estimation error from $S_2$ at $\Delta_2(t) = 0$ equals the error from the $S_1$ at time $\tau_p$. Hence, we can calculate $\tau_p$ the following way:

$$\varepsilon_2(h, 0) = \varepsilon_1(0, \tau_p),$$

(11)

$$1 - \exp(-2bh) = 1 - \exp(-2a\tau_p).$$

(12)

Simplifying the above expression yields the following result for $\tau_p$:

$$\tau_p = \frac{bh}{a}.$$  

(13)

$\tau_p$ is independent of update rates and depends only on the scaling parameters and the spatial separation between sources.

The average system estimation error can be calculated by integrating $\varepsilon_{sys}(h, t)$ over one period $T_1$. The dashed area in Figure 2 represents the average system error, which can be expressed as

$$\tau_{sys} = \frac{1}{T_1} \left( \int_0^{\tau_\Delta} \varepsilon_1(0, t)dt + \int_{\tau_\Delta}^{T_1} \varepsilon_2(h, t)dt \right).$$

(14)

where, for $0 \leq t \leq T_1$:

$$\Delta_1(t) = t$$ and $\Delta_2(t) = t - \tau_\Delta$,

and with the condition:

$$\tau_\Delta > \tau_p.$$  

The result of the integral is:
The maximum benefit, in terms of estimation error, due to information received from the correlated source decreases with increasing distance $h$. This behaviour is seen in Figure 3, which indicates that when sources are further apart, the optimum time lag between consecutive updates from the two sources is longer.

In a case when $\epsilon_2(h,0)$ is larger than the maximum $\epsilon_1(0,t)$ possible, updates from $S_2$ do not decrease the system estimation error, as the spatial separation between sources is too large.

The optimal update strategy for $S_2$ is to update with a time shift $\tau^*$ after $S_1$ updates. This result holds for a system with sources with equal update rate; system dynamics change when sources have different update rates.

### B. Different Update Rates

When sources have different update rates, e.g. $\lambda_2 > \lambda_1$, the system estimation error depends on the update rate of $S_2$ and the time shift $\tau_\Delta$. An underlying assumption is that $S_2$ can transmit more frequent updates because its cost of transmission is lower (e.g. it may rely on a more stable energy source). We assume that the update rates are related through an integer factor $k$ as follows:

$$k \frac{1}{\lambda_2} = \frac{1}{\lambda_1} \quad (19)$$

where:

$$k \in \{1, 2, 3, \ldots\}.$$

Figure 4 illustrates the system behaviour when $S_2$ updates more frequently than $S_1$. In the depicted case, $S_2$ updates seven times more often than $S_1$. It is noticeable that the first two updates from $S_2$ do not lower the system estimation error. Only $S_2$ updates with time shift greater than $\tau_p$ reduce the system estimation error. $\tau'$ represents the time shift between an update from $S_1$ and the first update from $S_2$ which reduces

$$\tau' = \frac{\tau_p + T_1}{2}. \quad (18)$$
the system estimation error. Note that \( \tau_p \) is independent of update rates and is calculated as shown in (13).

To calculate the average system estimation error, we again integrate \( \varepsilon_{sys}(h, t) \) over one period of \( T_1 \) as expressed in equation (20). Until the first update from \( S_2 \) after \( \tau_p \), i.e. at time \( \tau' \), only information from \( S_1 \) contributes to the system estimation error. After that we integrate \( \varepsilon_2(h, t) \) \( n \) times over one period of \( T_2 \). The number \( n \) represents the number of full transmissions \( S_2 \) sends between \( \tau_p \) and the next update from \( S_1 \); for example in Figure 4 \( n = 4 \). What remains is only an \( S_2 \) update before a new update from \( S_1 \) intervenes.

\[
\varepsilon_{sys}(h, t) = \frac{1}{T_1} \left( \int_0^{\tau'} \varepsilon_1(0, t) dt + n \int_0^{T_2} \varepsilon_2(h, t) dt \right) + \int_{T_2 - \tau}^T \varepsilon_2(h, t) dt \tag{20}
\]

where:

\[
n = \left\lfloor \frac{T_1 - \tau'}{T_2} \right\rfloor \tag{21}
\]

\[
\tau' = \tau + \left\lceil m \right\rceil T_2 \tag{22}
\]

with

\[
m = (\tau_p - \tau\lambda_2). \tag{23}\]

The integral (20) reveals that the average system estimation error depends greatly on the update rate \( \lambda_2 \). The reduced error gain represents the impact multiple updates from \( S_2 \) have on reducing the system estimation error. We define this gain as the ratio of the estimation error if \( S_1 \) would transmit on its own to the average system estimation error:

\[
G(h, t) = \frac{\varepsilon_1(0, t)}{\varepsilon_{sys}(h, t)}. \tag{24}\]

Figure 5 shows the rise in gain as the \( k \) factor changes from 1 to 50, for three different distances \( h \). At first, the gain rises sharply but then eventually reaches saturation. To compare fairly different update rates, we plot the gain considering the optimal value of \( \tau_\Delta = \tau^* \) for each \( k \). Unfortunately, because of the floor functions in expressions (21) and (22), the derivative of integral (20) does not admit a closed-form solution. To plot the graph, we numerically calculated \( \tau^* \). The reduced gain reveals that the \( S_2 \) update rate does not have to be much higher than that of \( S_1 \) to make a noticeable difference.

Diminishing marginal returns in estimation error gain due to the presence of the second source indicate that the influence of the second source has a limit, which can be determined by increasing \( k \) to infinity. The result is the maximum possible reduction in the estimation error from the two sources, as presented in Equation (26). \( G_{max} \) depends only on the scaling parameters and the distance between the sources.

\[
G_{max}(h, t, k) = \frac{\varepsilon_1(0, t)}{\lim_{k \to \infty} \varepsilon(h, t)}, \tag{25}\]

where:

\[
\lim_{k \to \infty} \varepsilon(h, t) = \frac{1}{T_1} \left( \tau_p + \frac{\exp(-2a\tau_p) - 1}{2a} + (T_1 - \tau_p)(1 - \exp(-2hb)) \right). \tag{26}\]

Let us consider a system where \( S_2 \) was deployed with the sole intention of assisting \( S_1 \) in reducing the frequency...
of its updates, thereby increasing $S_1$’s lifetime. For example, $S_1$ can be deployed very close to the centre of the observed phenomenon; however, due to infrastructural limitations it may be only battery powered, while $S_2$ is located further away from the centre of the observation point, but closer to a good infrastructure which provides a reliable power source. From the perspective of $S_1$, $S_2$ should transmit only when updates effectively reduce the system estimation error. Such $S_2$ transmission behaviour would yield results as presented in Figure 6. The temporary rise of $\varepsilon_2(h,t)$ before $\tau^*$ does not influence the system estimation error. We refer to $\tau^*$ as the idle time, as $S_2$ would refrain from sending any updates during that time. Such an approach does not change error gain because $S_2$ sends information only when the system benefits from fresh information.

$S_2$ saves $m$ updates by adopting the idle time updating strategy described above. The strategy may be employed whenever $S_2$’s primary function in the network is to assist $S_1$ in gathering information. However, in a case in which $S_2$ is independent of $S_1$, the idle time strategy is not possible, as another service may depend on those updates. In such a case, our analysis shows a possible schedule for the transmission of periodic updates from $S_1$ and $S_2$, with a time separation $\tau^*$ between updates from the two sources.

IV. Final Remarks and Future Work

In this paper, we analysed two correlated information sources and established the optimal time shift between sources’ updates such that the estimation error is minimal. Furthermore, we analytically calculated the maximum gain from using correlated information. We showed a tradeoff between reduced error gain and update rate, which must be considered when setting the updating strategy for correlated sources.

Using the age of information concept, we were able to quantify which update from two sources is more informative to the system. For correlated sources, an update from any source contains some information regarding the value of the observed physical phenomenon. Therefore, an update from any correlated source decreases the need for a fresh update from other sources. The estimation error indirectly indicates the value of each update. The lower the estimation error resulting from an update, the higher the value of the information in that particular update is. It is reasonable to use the update resulting in the lowest estimation error. The value of information in an update depends on two factors: the age of the last received status update, and the correlation between the information sources. The age of an update always increases linearly, while the correlation depends on a given system.

Our proposed updating strategy may be applied in an IoT network to address the challenge of scaling [10]. A more general network model with more than two sources is of interest and will be part of our future investigations. Furthermore, due to different physical phenomena measured by sensors, we are currently extending the work by using multiple covariance models to describe the correlation between the two sources. With a better representation of the correlation between the sources, we will be able to determine the optimal use of correlated information sources in the IoT.

Different IoT services correspond to different requirements on the timeliness of the information collected. For example, a real-time monitoring application requires a constant flow of fresh updates, i.e. the application needs updates with low estimation error. In contrast, a non-real-time monitoring application has a lower requirement on the timeliness of the information from received updates, meaning that the estimation error resulting from those updates maybe higher. However, the timeliness of updates is not the only objective to be considered in an IoT system design. In our future work, we will explore the joint optimization of the scheduling of updates, contention for the transmission channel, and sensor lifetime (remaining battery life) in a network of multiple information sources.

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