PKF-ST: A Communication Cost Reduction Scheme Using Spatial and Temporal Correlation for Wireless Sensor Networks

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Abstract

One of the most energy-intensive processes in wireless sensor networks (WSNs) is radio communication, which can be minimized with data compression techniques by using the inherent existence of spatial and temporal correlations in the physical phenomena. Exploiting the two correlation types with low algorithmic overhead in a distributed scenario is challenging. This work proposes PKF-ST, a technique that uses a predictor combined with Kalman filter (KF) to reduce the transmission rate for cluster-based WSNs. Each leaf node uses a reduced-order state space model to independently compress its own data based on temporal correlation. To improve the reconstruction quality, the cluster head uses a KF with the full-order model. Without any intra-communication, the energy cost of each node is further reduced with the help of the spatial correlation. Compared to traditional temporal compression algorithms, PKF-ST maximizes the utilization of temporal correlation; compared with the techniques using spatial correlation, PKF-ST works independently of the networks size and without any coordinator. The simulation results with both artificial signals and real temperature values demonstrate the efficiency of PKF-ST. Compared with a previous technique using spatial-temporal compression, it reduces the reconstruction error by 75.8 %.

Categories and Subject Descriptors

H.3.3 [**Spatial-temporal systems**]: Sensor networks; C.4.1 [**Dependable and fault-tolerant systems and networks**]: Reliability; D.7 [**Network services**]: In-network processing

General Terms

Algorithms, Performance, Reliability

Keywords

Wireless sensor networks, enery efficiency, data compression, spatial and temporal correlation, Kalman filter

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1 Introduction

In almost any application of WSNs, energy efficiency is a primary concern. As widely recognized, one of the most energy-intensive processes of a sensor node is the wireless communication [13]. In a classical architecture for instance, a single bit transmission can consume over 1000 times more energy than a single 32-bit computation [13]. In addition to the energy consumption of data packets transmission, extra energy is also required by overhead activities, such as radio start-up, channel accessing, control packets, turnaround, idle listening, overhearing, and collision as analyzed in [5]. Thus, most of the WSN research focuses on developing energy efficient schemes for reducing the communication cost.

Data compression techniques are very attractive due to the inherent existence of spatial and temporal correlations in the physical phenomena [16]. They aim to reduce either the packet size or the transmission rate. The existing algorithms for packet size compression typically refer to dictionary-based compression [12], [14] or predictive coding [9]. Even if these techniques are able to compress the data size with a high compression ratio, they are incapable of reducing the overheads of each transaction which can dominate the energy consumption in some cases [5]. In contrast, the schemes for transmission rate compression can decrease the total communication energy cost during the transaction [11], [3], [8], and are therefore preferred.

Upon temporal compression, some techniques further exploit spatial correlation to decrease communication cost. For example, in [18], the node intercepts the information from its neighbors to compress its own data. Similarly, in [2], the node receives the model parameters from its neighbors to decide whether to transmit its own parameters to the head. However, these methods require intra-communication among nodes. Without this communication, an energy-efficient data collection framework, EEDC, is proposed in [11]. Each node stores the latest sampling values until its buffer is full and calculates the line segments approximating the original time series. The transmission rate is reduced by only transmitting the end points of every line segment. To further reduce communication cost, the cluster head selects an appropriate number of nodes to be active to satisfy the requirement of reconstruction quality. A similar approach by using spatial correlation can also be found in [15]. Although these approaches do not require intra-communication, they need to store enough samples and need a coordinator to exploit spatial correlation. Those processes are expensive. In contrast, a novel sensing theory, compressive sensing (CS) [1], achieves temporal and spatial compression without any intra-communication and additional coordinator. It promises a reconstruction of a sparse signal by using a sampling rate significantly below the Nyquist rate. The sparser the signal is, the less sampling rate CS requires. However, the density of the network and the data points that it randomly selects in temporal and spatial domain affect the quality of the reconstructed signals.

Because of the manageable complexity and low memory requirement, the Kalman filter (KF) has been widely used in WSNs (in applications, e.g., target tracking, outlier detection, data fusion, etc); it makes KF an ideal candidate for a hardware accelerator and encourages its use for data compression as well. A recent approach [4] based on KF selects the transmission points employing an error bound in the time domain instead of random sampling. The technique, called PKF (predictor combined with Kalman filter), provides an energy efficient communication cost reduction scheme for cluster-based WSNs. However, it does not take full advantage of the spatial correlation.

This work, called PKF-ST, improves the original PKF scheme, by efficiently utilizing the spatial temporal correlation among nodes and provides two major innovations:

- In contrast to existing techniques, it maximizes the utilization of temporal correlation by transmitting the data-points violating the threshold in the time domain.
- It exploits the spatial correlation in the cluster head (instead of the leaf nodes) without any intra-communication, without any coordinator, and independent of the network size.

The rest of this paper is organized as follows. Section 2 introduces the PKF approach and presents the proposed PKF-ST scheme. Section 3 estimates the efficiency of PKF-ST by using both artificial and real signals. In Section 4, we conclude our work and present future research directions.

2 PKF-ST Approach based on Multivariate Temporal and Spatial Correlations

PKF-ST is based on PKF. In this section, we briefly review the PKF scheme and its underlying philosophy. The interested reader is referred to [4] and [6] for a more detailed explanation. Afterwards we improve it using multivariate temporal and spatial correlations.

2.1 PKF Approach

PKF aims to reduce the communication cost between leaf node and cluster head for cluster-based WSNs. The main idea behind PKF is to suppress the transmission of a leaf node at a time step, if the cluster head is able to predict the current data with a tolerable error using the previously received data.

Fig. 1 depicts the block diagram of PKF. Each node is required to firstly execute a KF to filter the noise of the measurement, $z(k)$, and produce Kalman-optimal values, $\hat{x}(k)$. In order to reduce the communication energy cost, the cluster head uses a simple predictor, P_{kf}, to predict the Kalman-optimal values, $\tilde{x}(k)$. To guarantee the prediction quality, the leaf node synchronously runs this predictor to follow the prediction of the cluster head and compare the forecast with its optimal value. If the prediction error, $\varepsilon(k)$, exceeds a given threshold, τ, the current optimal value is transmitted to the cluster head. Note that this predictor is equivalent to a k-step ahead Kalman predictor.

The value of the threshold τ provides a trade-off between communication energy cost and the reconstruction quality, which can be adapted to the requirement of a specific application. Observe that this scheme guarantees a maximum-error bound.

2.2 PKF-ST Approach

The spatial and temporal correlation between multi-nodes can be modeled as a multivariate state space. If the measurements of each node are correlated, a PKF approach using this multivariate model (full-order) produces better predictions than using a univaritate one. However, the approach would require each node to communicate with its neighbors or transmit more states than needed. This drastically reduces the energy savings. To avoid the intra-communication and extra transmission while keeping the advantages of PKF, we present our PKF-ST approach. The basic idea is: each node uses a reduced order model to execute the standard PKF approach; afterwards, a full order KF is executed in the cluster head by utilizing the spatial correlation to improve the prediction quality. Key for this idea to work is the precise analysis of the requirements for the full order KF which is executed in the cluster head.

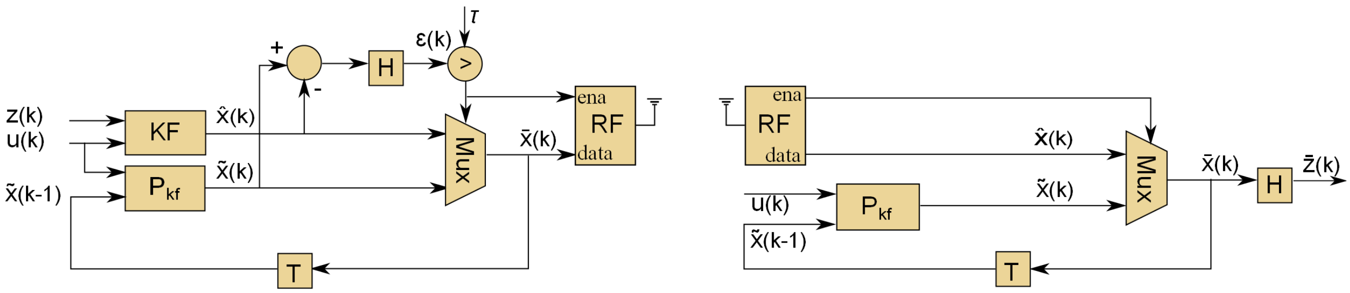
To characterize the spatial and temporal correlation between n nodes, we model the dynamics of their processes using a multivariate stochastic full model $\mathbf{m_f}$ as follows:

$$\begin{aligned} X(k) &= FX(k-1) + BU(k) + W(k) \\ Z(k) &= HX(k) + V(k) \end{aligned} \tag{1}$$

where $X(k)$ and $Z(k)$ are the real values and noisy observations of n nodes at time k, respectively. F is the full transition matrix, which represents the correlation structure among nodes; B is the control matrix and $U(k)$ is the control input; H is a identity matrix; $W(k)$ and $V(k)$ are vectors of the process noise and measurement noise of each node.

Similar to PKF, the system parameters, e.g., F, B and H, in PKF-ST can be both time variant and invariant. For time invariant systems, these parameters can be found offline by analyzing the historical data as done in Section 3, while for time variant systems, they can be updated using offline or online methods, e.g., an approach in [17].

The maximal compression of a PKF-like approach can be achieved by considering one ideal element (i.e., an oracle), which knows all measurements from each node and uses a full-order model. Although this is unpractical, it is useful to characterize how close a real approach to the ideal case is. We call it **PKF-ideal**. Taking a cluster with three neighboring nodes, N_1, N_2 and N_3, and a cluster head for example. The oracle knows all data from these three nodes as shown in Fig. 2. It controls the transmission of each node by using PKF encoder and produces the optimal values $\hat{X}(k)$. For those elements whose predictions are not accurate, the corresponding elements in $\hat{X}(k)$ are transmitted. For example,



The diagram of PKF-en in slave node   The diagram of PKF-de in the cluster head

Figure 1: The block diagram of PKF.

the prediction error of N_1 exceeds the threshold at time k, the first element in vector $\hat{X}(k)$ is transmitted. The cluster head predicts the multivariate optimal values and updates the predictions with the corresponding PKF decoder.

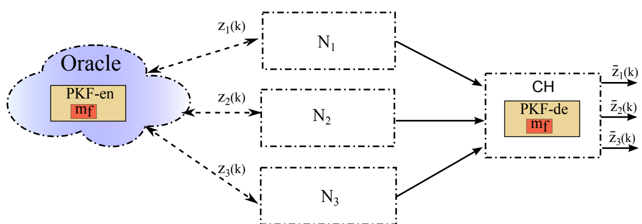


Figure 2: The architecture of PKF-ideal using spatial correlation in an oracle.

A direct implementation of PKF-ideal is too inefficient. Each node needs to either receive the measurements from its neighbors with more intra-communication cost or update the multivariate predictions using its own measurements with more inaccuracy. But in both cases, the node needs to transmit n variables if the prediction is inaccurate. To solve this problem, PKF can be executed independently using a reduced-order model. This scheme is called **PKF-idp**. The order of the model can be selected depending on the overhead of the communication. If the overhead is large, the transmission bits have less impact on the communication cost, then we can use a larger order model and vice versa.

For example, the reduced-order model of N_1, denoted as $\mathbf{m_r}$, is formulated as:

$$x_1(k) = a_1x_1(k) + b_1U(k) + \bar{w}(k)$$
$$z_1(k) = h_1x_1(k) + v_1(k) \quad (2)$$

where $\bar{w}(k) \sim N(0, \bar{q})$.

Each node uses m_r to execute PKF encoder independently. When the prediction of the cluster head using the corresponding PKF decoder is not accurate, the states with less variables are transmitted. PKF-idp avoids the transmission of all states while the prediction quality is decreased due to the unused spatial correlation.

Since the cluster head has all information of each node, it can utilize the spatial correlation to improve the quality of the reconstructions produced by PKF-idp. Then the computational complexity is shifted from the leaf node to the cluster head. Here we use a full-order KF as shown in Fig. 3. After using PKF-idp to produce the reconstructions of each node $\bar{z}_i(k)$, the KF treats these reconstructions as noisy measurements but with time variant noise $\bar{R}_i(k)$ which is related to n_i, the number of step ahead that $\bar{z}_i(k)$ comes from. This technique is called **PKF-ST**.

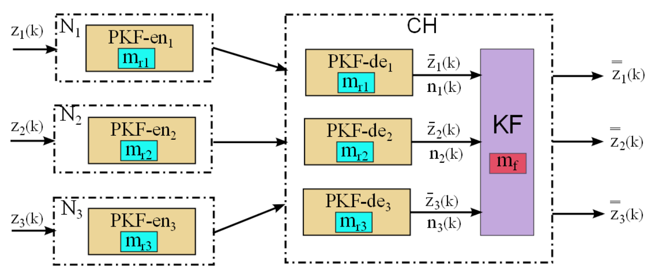


Figure 3: The architecture of PKF-ST using spatial correlation in cluster head without intra-communication.

More specifically, let us start the analysis after a transmission, so that $\tilde{x}_i(0) = \hat{x}_i(0)$ and the prediction error is zero. The k-step ahead prediction, $\tilde{x}_i(k) = a_i^k\hat{x}_i(0)$ evolves from the optimal value with a random error $\varepsilon_i(k) = h_i\left[\tilde{x}_i(k) - \hat{x}_i(k)\right]$, where $\varepsilon_i(k)$ is distributed normally with zero mean and variance σ_k^2. If $\bar{z}_i(k)$ is from $k-$step ahead, the error comparing with the real states, $e_i(k) = \bar{z}_i(k) - h_ix_i(k)$, can be approximated as a normal distribution with a time **variant** variance $\bar{R}_i(k)$ in each step as analyzed in [6]. In a naive way, we can take all errors together to get a time **invariant** measurement noise $\bar{R}_i$. However, all errors together do not have Gaussian distribution. The data produced by KF using $\bar{R}_i$ should be worse than using the time variant $\bar{R}_i(k)$ for each time step. Thus, we use an indicator n_i to indicate which step ahead $\bar{z}_i(k)$ comes from and adjust the corresponding variance $\bar{R}_i(k)$ in KF. Then the full order KF becomes to be time variant with a variant $\bar{R}_i(k)$ for each node at different time step. It produces the final reconstructions, $\bar{\bar{z}}_i(k)$, using neighbors' information.

3 Simulation results

In this section, we aim to estimate the efficiency of PKF-ST through the trade-off between transmission rate and reconstruction accuracy. Since it is a model based approach, its performance is affected by the accuracy of the model. In order to avoid the estimation bias caused by the uncertainty of the system model, we firstly generate an artificial system. Then we use real temperatures to demonstrate that even if the model is not perfect, PKF-ST still works more efficiently than other techniques.

3.1 Artificial System

We construct a representative 3-variate system without control input and simulate it to generate 2^{16} samples per node. The transition matrix $F = \begin{bmatrix} 0.9 & 0.02 & 0.1 \\ 0.02 & 0.6 & 0.4 \\ 0.1 & 0.4 & 0.4 \end{bmatrix}$ is constructed on the basis that N_1 has strong temporal correlation and small spatial correlation with its two neighbors, while N_2 and N_3 are affected a lot by each other, especially N_3. Thus we cover those cases when only temporal correlation can be used, and those when both correlations can be used. The pseudo-random values of the noise are drawn from the standard normal distribution. The process noise of each node is independent with the same variance $Q_i = 0.36$, while the independent measurement noise have variances $R_1 = 0.01$, $R_2 = 0.04$ and $R_3 = 0.09$.

In order to apply PKF-ST, we calculate a reduced order model, m_r, for each node. The parameter a of each system is the corresponding diagonal element of matrix F. The system noise $\bar{q}$ is obtained by taking neighbors' information as unknown elements (noise). The example is selected to cover different possibilities for a which ranges from 0.4 to 0.9, and $\bar{q}$ which ranges from 0.4 to 1.5.

Firstly we analyze the efficiency of PKF-ST in reducing the communication cost and improving prediction quality. As depicted in Fig. 4a, 4b and 4c, the covariance of reconstruction errors increases along with the transmission rate decreases. PKF-ideal compresses maximally the transmission rate under the same reconstruction quality constraints. The larger the spatial correlation is, the better performance PKF-ideal achieves. Due to model reduction, PKF-idp has larger reconstruction errors using the same transmission rate. Compared to PKF-ideal, the performance of PKF-idp decreases as the spatial correlation increases. There is no big difference between them in node 1 who has small correlation with its neighbors, while in node 2 and node 3, especially node 3, PKF-idp performs much worse.

In contrast, by using spatial correlation in the cluster head, PKF-ST improves the reconstruction quality of PKF-idp without any intra-communication. The efficiency of PKF-ST lies between that of PKF-idp and PKF-ideal. For example, a maximum transmission rate in node 3 of 20% would allow a reconstruction error around $0.4C^2$ for PKF-ST, while PFK-idp produces errors larger than $0.8C^2$. The best achievable reconstruction is around $0.2C^2$.

Next we analyze the impact of time variant KF on the quality of reconstructions. Firstly, we study the distribution of the errors. As an example, we consider node 2 when $\tau = 0.4$. The distribution of all errors, $\bar{z}_2 - h_2 x_2$, has a variance $\bar{R}_2 = 0.0549$. They are produced by 11 different steps ahead predictions. The noise from the first 2 steps ahead have the variance 0.0386 and 0.0928 respectively. Clearly the values are very different. Now we measure the improvements in reconstruction achieved when the differences in the variance are considered. Compared to the naive method that uses a time invariant variance, $\bar{R}_2$, our PKF-ST achieves better reconstruction quality as illustrated in Fig. 5a, 5b and 5c. The improvements increase as the spatial correlation increases. For example, a maximum transmission rate in node 3 of 20% would allow a reconstruction error around $0.4C^2$ for PKF-ST, while the invariant approaches produces errors larger than $0.7C^2$, very close to the $0.8C^2$ of PKF-idp. The results are reasonable: by using more information of the signal, more accurate data can be reconstructed.

3.2 Real temperature values

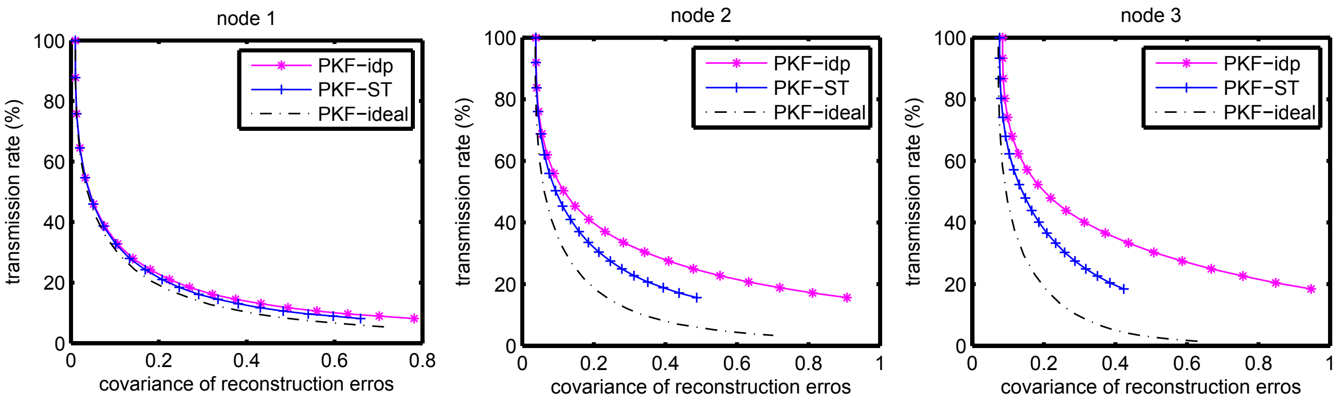
In this study we use the temperature values from LUCE [7] to further illustrate the efficiency of PKF-ST and compare it with EEDC [10]. The data is collected by Shockfish TinyNode at intervals of 30 seconds across the EPFL campus. We use the data between 15:20, 2nd, November and 8:26, 3rd, November from node 3, node 5, node 44 and node 45 as our datasets since these traces have less packet loss and the measurements are more precise.

By using Matlab system identification toolbox to fit these 2103 measurements, we can find the system parameters of m_f. The model is constructed on the basis that the matrix H is a 4×4 identity matrix. The a matrix of the reduced order model, m_r, of each node keeps the corresponding diagonal element of F; the system noise $\bar{q}$ is obtained by taking neighbors' states as noise.

We take the optimal values generated by the KF using the full-order model m_f as the real system states, since the temperature values without noise are not available. Using this reference we analyze the trade-off between transmission rate and reconstruction error (see Fig. 6 and Fig. 7 for the different techniques). We use EEDC [10] as a reference: it provides good temporal compression; the spatial correlation method it uses is very common, selecting a node as a representative in one cluster.

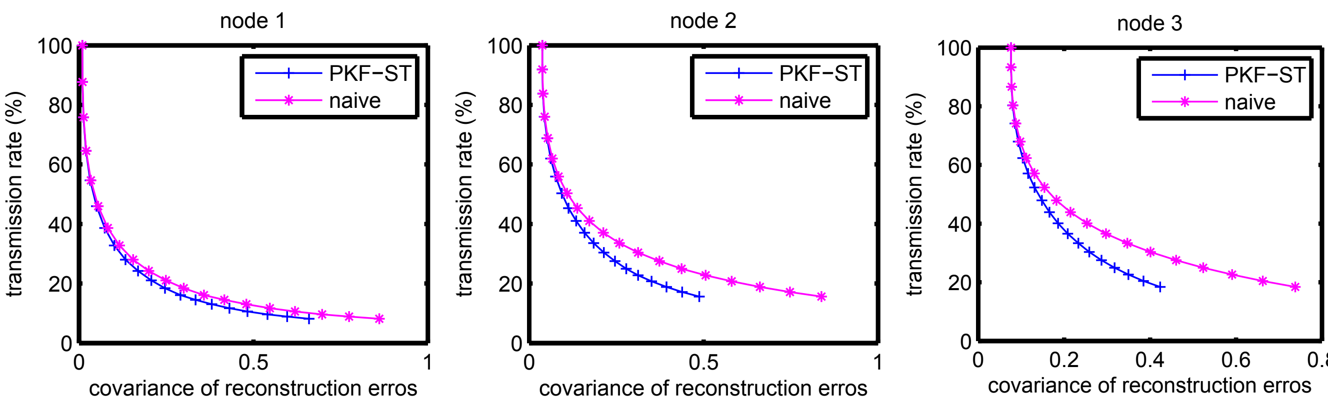
The best reconstruction of EEDC [10] appears when only temporal correlation is used, it is that all the nodes transmit without using any representative. The results, reported in Fig.7 as EEDC-max, are very close to the PKF-ideal. However, after using spatial correlation that each node is uniformly selected as the representative node, EEDC produces significant errors (see line EEDC in Fig. 6). Compared with PKF-ST, it produces 75.8 % more error for node 1 when the transmission rate is 11.6 %. The situation is even worse for the remaining nodes. The covariances of EEDC are so large that they lie outside the range of the axis in Fig. 7.

Further on, the results obtained by PKF-idp, PKF-ST and PKF-ideal are consistent with the results using the artificial system. Taking node 2 in Fig. 7a for example, when PKF-ST and PKF-idp uses the same transmission rate 11.6 %, the variance of reconstruction errors of PKF-idp is reduced by 59.6 % by PKF-ST. In another word, under the same reconstruction quality (variance 0.009), PKF-ST further reduces the transmission rate of PKF-idp by 24 %.



(a) (b) (c)

Figure 4: Performance comparison of PKF-idp, PKF-ST and PKF-ideal using an artificial system with three nodes.



(a) (b) (c)

Figure 5: The superiority of PKF-ST by using time variant variance.

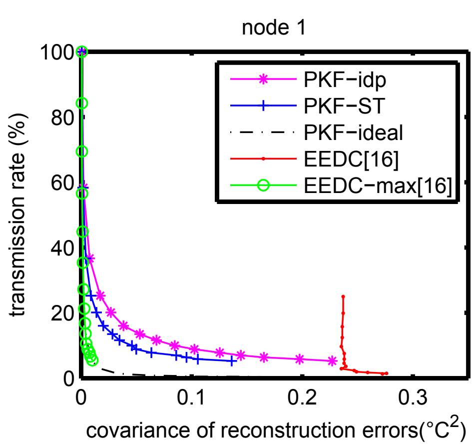


Figure 6: Performance comparison of PKF-idp, PKF-ST, PKF-ideal, and EEDC using real temperature values from four nodes. Comparison for node 1.

4 Conclusion and Future Work

This work combines temporal and spatial correlation to reduce communication energy cost for wireless sensor networks. The technique, called PKF-ST, is simpler and more accurate than previous techniques. It reduces the transmission rate of each node using a reduced order model with a guaranteed reconstruction quality and low complexity. The leaf nodes operate independently and do not require a coordinator. By using neighbors' information, the accuracy is further improved in the cluster head without any extra communication. The precise analysis of the distribution of the errors makes the reconstructions be close to the ideal one.

In contrast to previous approaches, PKF-ST is not restricted to network size. For a small size network, it works efficiently as illustrated in the experimental results. For the networks with larger number of nodes, it can work by dividing them into small groups. Compared with EEDC for example, the reconstruction error is several times smaller for low-density networks.

The dynamic optimization of the threshold for each node is currently being investigated.

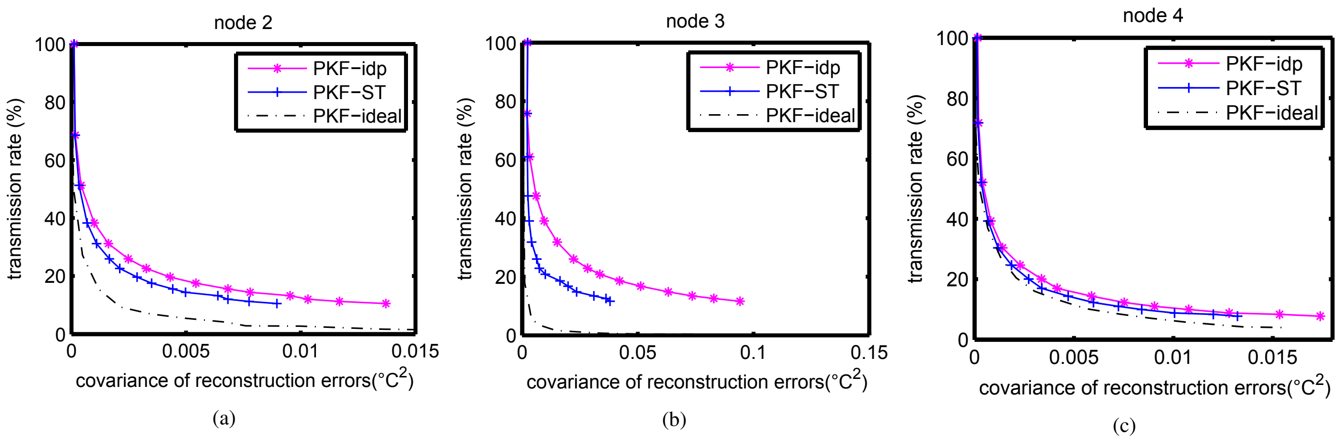


Figure 7: Performance comparison of PKF-idp, PKF-ST and PKF-ideal using real temperature values from four nodes. Comparison for nodes 2, 3, and 4.

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