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Robust Hierarchical Data Fusion Scheme for Large-Scale Sensor Network

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Abstract

The advanced driver assistant system (ADAS) requires the collection of a large amount of information including road conditions, environment, vehicle status, condition of the driver, and other useful data. In this regard, large-scale sensor networks can be an appropriate solution since they have been designed for this purpose. Recent advances in sensor network technology have enabled the management and monitoring of large-scale tasks such as the monitoring of road surface temperature on a highway. In this paper, we consider the estimation and fusion problems of the large-scale sensor networks used in the ADAS. Hierarchical fusion architecture is proposed for an arbitrary topology of the large-scale sensor network. A robust cluster estimator is proposed to achieve robustness of the network against outliers or failure of sensors. Lastly, a robust hierarchical data fusion scheme is proposed for the communication channel between the clusters and fusion center, considering the non-Gaussian channel noise, which is typical in communication systems.

Keywords: Advanced driver assistant system, Data fusion, Sensor network

1. INTRODUCTION

In order to construct the advanced driver assistant system (ADAS), it is important to gather useful data such as traffic flows, traffic control, accidental circumstances, road conditions, conditions of drivers and cars, and other environmental factors to determine the circumstances, which can cause accidents and provide drivers with a more convenient and safer ambiance. Gathering the data and transforming it into useful information requires the integration of information technology with the ADAS. In this regard, a large-scale sensor network can offer a well-suited solution for this purpose.

It is important to monitor the road surface temperatures because it can fluctuate significantly depending on the time of day, extent of cloud cover, sub-surface conditions (e.g., frost penetration, moisture presence, and thermal retention properties), and type of road surface. A variety of sensors and equipment has been developed to measure and monitor road and weather conditions. They provide monitoring of road temperature, wet/dry status, freeze point of the solution on the road, presence of chemicals and concentration, and subsurface temperatures. These sensors report the road surface as being wet, dry, or frozen, and further report the road surface temperature. The sensors are embedded flush in the road and the sub-surface; moreover, they generate data that can be used to identify trends.

A common approach used in the road surface sensors is the monitoring of road surface conductivity, which changes as the surface conditions of the road change. Passive road sensors (see Fig. 1) are embedded in the road without any heat energy being transferred to or from the sensor. They attempt to measure the road surface conditions and the residual salt using conductivity, capacitance, vibration, radar, or other methods. The monitoring of the relative parameters of the road surface is equally important to improve the efficiency and effectiveness of the winter maintenance

Fig. 1. Two examples of road sensors

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operations and to better inform motorists of the driving conditions. The amount of highway salt used in de-icing roads is largely dependent upon the mass of snow or ice on the road surface and the pavement temperature. The accurate knowledge of pavement surface temperature assists in determining the suitable salt application rates and reduces salt waste for fiscal and environmental reasons; moreover, it reduces structural degradation such as chloride-induced corrosion of reinforced concrete structures, etc.

The recent advances in large-scale sensor network technologies have enabled the deployment of a large number of sensors in the surrounding environment. Each sensor consists of a small node with sensing, computing, and communication capabilities. Owing to the limited processing capabilities of the sensor nodes, sensor readings are minimally processed at the sensor network level. Subsequently, the sensor data is transmitted through a multi-hop communication route to a centralized sensor database system for further processing. An important task of a sensor network is the ability to detect, track, and classify objects. As objects move around the sensor field, they affect the observations at nearby nodes. The key to collaboration across nodes is to determine the possible relations between the observations at different nodes, and subsequently use these related observations to generate more accurate estimates of the existence, track, and type of object.

Graphical modeling techniques such as Kalman filtering and *hidden Markov model*s have been employed very successfully in sensor networks [1,2]. In terms of the network topology, we study large-scale sensor networks that lie within a two-dimensional plane and a two-dimensional strip. The placement of sensors can vary significantly in different applications. In a “structured” sensor network application (e.g., video surveillance system), the sensors are placed at specific locations. However, in an “unstructured” sensor network application (e.g., battlefield surveillance), the sensors may be randomly placed. In this work, we focus on the latter case wherein sensors are randomly placed in a field. The arbitrary networks are inherently robust and time efficient [3-5]. First, they are surprisingly fault tolerant against random node failures. Second, they usually exhibit a *small-world* phenomenon [5], i.e., the average link length (in hops) scales logarithmically (or polylogarithmically) with the network size, resulting in considerable time efficiency. In addition, empirical studies [6] show that arbitrary topologies have a positive impact on the performance (through fewer messages and smaller latency) of gossiping algorithms in static sensor networks. It is conceivable that nodes group together in large-scale sensor networks to form arbitrary networks.

The deployment of a sensor network in the ADAS presents challenges. The first challenge is the design and implementation of an arbitrary topology of a large-scale sensor network. This includes the selection of both an arbitrary topology and an adequate set of communication protocols capable of providing the necessary autonomy. Secondly, the stringent restriction (i.e., non-Gaussian channel noise which is typical in communication systems) of sensor network nodes strongly influences the task of decision-making in the network architecture. Considering these premises, we address the estimation and fusion problems in large-scale sensor networks with the aim of obtaining an optimal performance in the monitoring of road surface temperature. The surface temperature monitoring system of the road using a robust cluster estimator demonstrates the robustness of its network against outliers or failure of sensors,

This paper is organized as follows. The problem is formulated in Section 2. In Section 3, we propose a robust hierarchical estimate fusion algorithm within the link failure between the sensors and cluster heads in sensor networks. Hence, the fusion estimate of the fusion center is a linear combination of the fused estimates of each cluster head, and the fusion estimate of the cluster heads is a linear combination of the local estimate. Therefore, the estimates fused in the cluster heads are computed through a local filter in each sensor node. In Section 4, the local filter is designed to be robust to measurement uncertainty. In Section 5, we present the simulation results of estimation of road surface temperature with brief concluding remarks in Section 6.

2. PROBLEM FORMULATIION

As explained in the previous section, the aim of this research is to estimate and fuse the road surface temperature data in the sensor networks. In our research scenario, numerous temperature sensors are deployed widely in the ADAS to measure the road surface temperature. A dynamic system is required to achieve global data fusion based on the sensor measurements. The temperature can be modeled as a dynamic system; moreover, the measurement system represents the temperature sensors. Hence, the following dynamic system can be briefly explained as [7]

k : Discrete time instance, $k = 0, 1, 2, ..., t_k = k\Delta t$
$T_{s,k}$: Current road surface temperature
$T_{a,k}$: Current air temperature
D_k : Current dew point
h_k : Current relative humidity

$W_{a,k}$: Average wind speed
$W_{m,k}$: Maximum wind speed
v_k : Environmental noise
$y_k^{(i)}$: Temperature measurement obtained from i^{th} sensor
$\xi_k^{(i)}$: Measurement noise in i^{th} sensor
$\theta^{(i)}$: Uncertainty for i^{th} sensor
N: total number of sensors in sensor networks

The dynamic system model for state x_k is of the following form:

$$x_{k+1} = F_k x_k + C_k v_k \,, \qquad x_k = [T_{s,k} \;\; T_{a,k} \;\; D_k \;\; h_k \;\; W_{a,k} \;\; W_{m,k}]^T, \qquad (1)$$

The multi-sensor measurement model containing N sensors is given as

$$y_k^{(i)} = \theta^{(i)} H_k^{(i)} x_k + \xi_k^{(i)}, \quad i = 1, \ldots, N, \quad k = 0, 1, 2, \ldots, \qquad (2)$$

where $x_k \in R^6$, $y_k \in R^{m_i}$.

The environmental noise v_k and the measurement error $\xi_k^{(1)}, \ldots, \xi_k^{(N)}$ are uncorrelated white Gaussian noise $v_k \in R^r \sim N(0, Q_k)$, $\xi_k^{(i)} \in R^r \sim N(0, \eta_k^{(i)})$, $i = 1, \ldots, N$. The initial state x_0 is normal, $x_0 \sim N(\bar{x}_0, P_0)$. $N(\cdot, \cdot)$ is the normal Gaussian density. Notably, all the sensors (local filters) are working on the same state vector x_k.

There are a number of applications where the probability that the measurements contain only noise is non-zero. Hence, we assume that the unknown parameters $\theta^{(i)}$, i = 1,..., N are derived from the set {0, 1}. If the i^{th} sensor is out of order, such that the unknown parameter $\theta^{(i)}$ equals "0", then $y_k^{(i)} = \xi_k^{(i)}$. If the i^{th} sensor normally obtains data with a noise measurement error, such that $\theta^{(i)}$ equals "1", then $y_k^{(i)} = H_k^{(i)} x_k + \xi_k^{(i)}$.

The aim is to estimate the current state x_k in (1) considering the observations in (2). In order to optimally estimate the current state of road surface temperature, in Section 3, we propose a robust estimate fusion algorithm. Subsequently, we describe a local estimator to tackle the measurement uncertainty problem in Section 4, i.e., the Laniotis Kalman filter (LKF) [8,9].

3. ROBUST HIERARCHICAL DATA FUSION WITHIN LINK FAILURE IN SENSOR NETWORKS

3.1 Architecture for Decentralizwd Estimate Fusion Algorithm

A hierarchical architecture in Fig. 2 is selected for the large-scale sensor networks. In Fig. 2, the sensor nodes are connected to the nearest cluster and each cluster transmits the local fused estimate to the fusion center. The advantage of this topology is the reduction of the computation complexity of the decentralized data fusion algorithm. The sensor networks based on the hierarchical architecture consists of three layers. The first layer is the sensor system (sensor and node), which obtains the road surface temperature data (measurement value) and possesses a computational ability to estimate the state of the object based on the measurement value. The second layer, called a cluster head, obtains the information, which can be the measurement value or the estimate and its covariance, from the first layer, and subsequently fuses all the information. The third layer is the base station or the fusion center that fuses all the fused information obtained from the clusters to compute widely fused information [10].

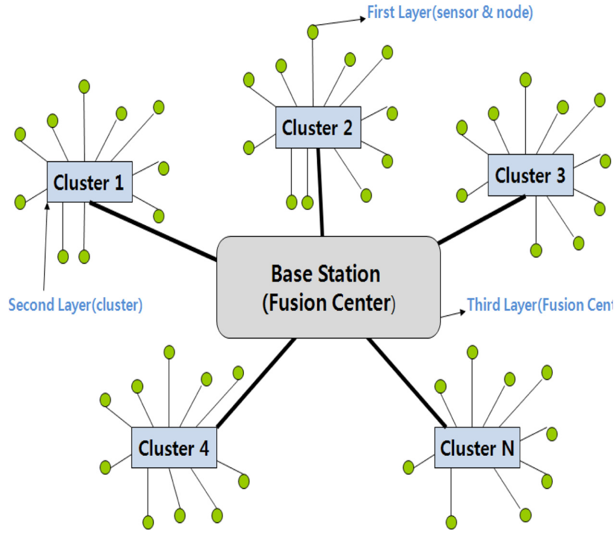

Fig. 2. A Hierarchical Data Fusion in Sensor Networks

3.2 Estiamate Fusion within Link Failure betweeen Cluster Heads and Nodes

In most applications, the information used in the sensor networks is converted into a form that determines the estimated state of the target objects. In numerous cases, especially in industrial applications, the information can be represented as means and variances that can be combined within the framework of Kalman-type filters. A decentralized sensor network for the determination of the position of an unmanned aerial vehicle, for instance, can combine the acceleration, fusing the estimates from a node measuring the pressure of engines with those of the angle sensors attached to each wings. If each independent node provides the mean and variance of its estimate of each sensor, fusing the estimates to obtain a better filtered estimate is relatively easy [11].

The most serious problem in the decentralized data fusion of sensor networks is the effect of redundant information. Covariance information must be maintained to avoid this problem. However, maintaining consistent cross covariances in arbitrary decentralized networks is not possible. The only reasonable way to achieve robustness and consistency in a general decentralized network is by exploiting a data fusion mechanism that does not require independence assumptions such as Covariance Intersection (CI) [11].

In subsection (3.2.1), the global network estimate is explained, which is the final fused estimate $\hat{x}_k$. In order to achieve the final estimate $\hat{x}_k$, the fused estimates $\hat{z}_k^{(j)}$ in the cluster head are required, along with their variances $\Gamma_k^{(j)}$. The estimates and their covariance in the cluster head are derived in subsection (3.2.2). In order to calculate $\hat{z}_k^{(j)}$ and $\Gamma_k^{(j)}$, the local estimate $\hat{x}_{k|k}^{(i)}$ and its variance $P_{k|k}^{(i)}$ should be provided to each cluster head. Thus, in Section 4, a robust local estimator under measurement uncertainty is described to obtain $\hat{x}_{k|k}^{(i)}$ and $P_{k|k}^{(i)}$ for each sensor node.

3.2.1 Global Network Estimate

In the base station, the widely fused estimate $\hat{X}_{k|k}$ is calculated. Further, $\hat{X}_{k|k}^{(j)}$ and $(\Gamma_{k|k}^{(j)})^{-1}$ indicate the fused estimates and the information form of covariances in each cluster head, respectively. Furthermore, L is the number of cluster heads linked to the fusion station. Based on the information from each cluster head, the global estimates are obtained as

$$\Gamma_k^{-1}\hat{x}_k = \sum_{j=1}^{L} \tilde{w}_k^{(j)} \Gamma_k^{(j)^{-1}} \hat{z}_k^{(j)}, \quad \Gamma_k^{-1} = \sum_{j=1}^{L} \tilde{w}_k^{(j)} \Gamma_k^{(j)^{-1}}, \tag{3}$$

where the weights are calculated [12],

$$\tilde{w}_k^{(j)} = \frac{\det(\Phi_k) - \det(\Phi_k - \Gamma_k^{(j)^{-1}}) + \det(\Gamma_k^{(j)^{-1}})}{L \times \det(\Phi_k) + \sum_{j=1}^{L}\left[\det(\Gamma_k^{(j)^{-1}}) - \det(\Phi_k - \Gamma_k^{(j)^{-1}})\right]}, \tag{4}$$

$$\Phi_k = \sum_{j=1}^{L} \Gamma_k^{(j)^{-1}}, \quad k = 0, 1, 2, \ldots, \quad j = 1, \ldots, L. \tag{5}$$

Finally, the global estimate takes the form,

$$\hat{x}_k = (\Gamma_k)\sum_{j=1}^{L} \tilde{w}_k^{(j)} \Gamma_k^{(j)^{-1}} \hat{z}_k^{(j)} \tag{6}$$

As derived above, to achieve the final fused estimate $\hat{x}_k$, the fused estimates $\hat{z}_k^{(j)}$ in the cluster head are required, along with their variance $\Gamma_k^{(j)^{-1}}$. In order to calculate $\hat{z}_k^{(j)}$ and $\Gamma_k^{(j)^{-1}}$, the local estimate $\hat{x}_{k|k}^{(i)}$ and its variance $P_{k|k}^{(i)}$ should be provided to each cluster head. Thus, in Section 4, a robust local estimator under measurement uncertainty is described to obtain $\hat{x}_{k|k}^{(i)}$ and $P_{k|k}^{(i)}$ for each sensor node.

3.2.2 Local Fusion Estimate in Cluster Heads

Using the CI algorithm, it is possible to fuse estimates from each cluster, despite a link failure between the nodes and clusters or the clusters and base station owing to an unreliable communication system.

In each cluster head, the fused estimate $\hat{z}_k^{(j)}$ of the state x_k and its covariance $\Gamma_k^{(j)}$ are computed, where i and j represent the sensor index and the cluster index, respectively. Further, $(i \in V_j)$ represents i[th] node linked to the j[th] cluster head and N_j is the number of sensors linked to the j[th] cluster head. For example, $V_1 = \{1, 4, 5, 10\}$ indicates that 1[st], 4[th], 5[th] and 10[th] sensors are connected to 1[st] cluster head, and N_1 equals 4. Further, $\hat{x}_{k|k}^{(i)}$ and $P_{k|k}^{(i)}$ are the local estimate and the covariance computed from the i[th] sensor node, respectively. The local estimator is described in Section 4. The data fusion in the cluster heads is computed as

$$\Gamma_k^{(j)^{-1}} \hat{z}_k^{(j)} = \sum_{i \in V_j} w_k^{(i)} P_{k|k}^{(i)^{-1}} \hat{x}_{k|k}^{(i)}, \quad \Gamma_k^{(j)^{-1}} = \sum_{i \in V_j} w_k^{(i)} P_{k|k}^{(i)^{-1}}, \tag{7}$$

where the weights $w_k^{(i)}, i \in V_j$ are calculated [12],

$$w_k^{(i)} = \frac{\det(\Psi_k^{(j)}) - \det(\Psi_k^{(j)} - P_{k|k}^{(i)^{-1}}) + \det(P_{k|k}^{(i)^{-1}})}{N_j \times \det(\Psi_k^{(j)}) + \sum_{i \in V_j}\left[\det(P_{k|k}^{(i)^{-1}}) - \det(\Psi_k^{(j)} - P_{k|k}^{(i)^{-1}})\right]}, \tag{8}$$

$$\Psi_k^{(j)} = \sum_{i \in V_j} P_{k|k}^{(i)^{-1}}, \quad k = 0, 1, 2, \ldots, \quad i = 1, \ldots, N. \tag{9}$$

4. LOCAL ESTIMATE USING LKF

The local estimate is denoted as $\hat{x}_{k|k}^{(i)}$ and its variance is denoted as $P_{k|k}^{(i)}$ under measurement uncertainty [8,9]. The Bayesian approach forms the basis of the LKF in which the unknown parameter $\theta^{(i)}$ is assumed to be random with prior probabilities. Moreover $\theta^{(i)}$ is initially selected randomly and does not change.

$$\begin{aligned} \hat{x}_{k|k}^{(i)} &= p(\theta_1^{(i)}|y_k^{(i)})\hat{x}_{k|k}^{(i,1)} + p(\theta_2^{(i)}|y_k^{(i)})\hat{x}_{k|k}^{(i,2)} \\ P_{k|k}^{(i)} &= p(\theta_1^{(i)}|y_k^{(i)})P_{k|k}^{(i,1)} + p(\theta_2^{(i)}|y_k^{(i)})P_{k|k}^{(i,2)} \\ i &= 1, \ldots, N, \quad k = 0, 1, 2, \ldots, \end{aligned} \tag{10}$$

correspond to the posterior probabilities of $\theta_j^{(i)}$, if $y_k^{(i)}$ is known, and are calculated through the recursive Bayesian formula [10], where

$$\hat{x}^{(i,1)}_{k|k} = \hat{x}^{(i)}_{k|k}(\theta^{(i)}_1), \quad \hat{x}^{(i,2)}_{k|k} = \hat{x}^{(i)}_{k|k}(\theta^{(i)}_2)$$
$$P^{(i,1)}_{k|k} = P^{(i)}_{k|k}(\theta^{(i)}_1), \quad P^{(i,2)}_{k|k} = P^{(i)}_{k|k}(\theta^{(i)}_2) \tag{11}$$

$\hat{x}^{(i,1)}_k$ and $\hat{x}^{(i,2)}_k$ are the standard local Kalman estimates matched to the state system (1) and measurement system (14).

$$y^{(i)}_k = \tilde{H}^{(i,j)}_k x_k + w^{(i)}_k, \quad \tilde{H}^{(i,j)}_k = \theta^{(i)}_j H^{(i)}_k,$$
$$k = 0, 1, 2, ..., \quad i = 1, ..., N, \quad j = 1, 2 \tag{12}$$

where *i* represents the i[th] sensor and *j* represents the index of the unknown parameter, under the condition that the unknown parameter $\theta^{(i)}$ belongs to the discrete space, i.e., $\theta^{(i)} = \theta^{(i)}_j$, j = 1, 2.

It is an estimate matched to the linear system (4) with a fixed *i*. The Kalman estimate $\hat{x}^{(i,j)}_k$ can subsequently be determined using the standard Kalman filter equations [13], [14]. In this equation, the sensor index *i* is fixed.

$$\hat{x}^{(i,j)}_{k|k-1} = F_k \hat{x}^{(i,j)}_{k-1|k-1}, \quad \hat{x}^{(i,j)}_{0|0} = \bar{x}_0,$$
$$P^{(i,j)}_{k|k-1} = F_k P^{(i,j)}_{k-1|k-1} F^T_k + G_k Q_k G^T_k, \quad P^{(i,j)}_{0|0} = P_0,$$
$$K^{(i,j)}_k = P^{(i,j)}_{k|k-1} \tilde{H}^{(i,j)T}_k \left[\tilde{H}^{(i,j)T}_k P^{(i,j)}_{k|k-1} \tilde{H}^{(i,j)}_k + \eta^{(i)}_k \right]^{-1}, \tag{13}$$
$$\hat{x}^{(i,j)}_{k|k} = \hat{x}^{(i,j)}_{k|k-1} + K^{(i,j)}_k (y^{(i)}_k - \tilde{H}^{(i,j)}_k \hat{x}^{(i,j)}_{k|k-1}),$$
$$P^{(i,j)}_{k|k} = (I_n - K^{(i,j)}_k \tilde{H}^{(i,j)}_k) P^{(i,j)}_{k|k-1}, \quad j = 1, 2,$$

As discussed above, the efficiency of the LKF (12)-(15) depends on the dimensions of the system (1), (2), since it requires the calculation of a large number of posterior probabilities $p(\theta^{(i)}_j | y^{(i)}_k)$ at each time instance, though the filtering algorithm considerably reduces the computational burden and further aids in achieving online computational requirements.

5. SIMULATION

In this section, the algorithm explained in previous sections is applied to the widely estimated pavement temperature. In order to create a dynamic system model of pavement temperature, linear regression analysis was used based on the data on metrological parameters—air temperature, dew point, relative humidity, average wind speed, wind gust, and other parameters [7].

Based on the data, the state parameter and measurement system is same as (1) and (2) in Section 2. All the assumptions described in Section 2 are applied in this simulation. The time index *k* represents the hour. The system model was constructed as

$$x_{k+1} = \begin{bmatrix} T_{s,k+1} \\ T_{a,k+1} \\ D_{k+1} \\ h_{k+1} \\ W_{a,k+1} \\ W_{m,k+1} \end{bmatrix}$$
$$= \begin{bmatrix} 1.1091 & -0.4197 & 0.2644 & 0.0042 & -0.0223 & 0.0156 \\ 0.2204 & 0.5912 & 0.2 & 0.0012 & -0.0037 & 0.0076 \\ 0.1188 & -0.2199 & 1.0948 & 0.0002 & -0.0227 & 0.0105 \\ -0.2681 & 0.4987 & -0.2532 & 0.9989 & 0.011 & -0.0288 \\ 0.1904 & -0.1817 & -0.0028 & 0 & 0.3562 & 0.4448 \\ 0.2559 & -0.2002 & -0.0198 & 0.0072 & 0.1698 & 0.8046 \end{bmatrix} \begin{bmatrix} T_{s,k} \\ T_{a,k} \\ D_k \\ h_k \\ W_{a,k} \\ W_{m,k} \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} v_k \tag{14}$$

The initial state mean value is $\bar{x}_0 = [-4\ -4\ -7.9\ 74\ 14.04\ 14.4]^T$, $P_0 = \mathrm{diag}[18\ 19\ 24\ 68\ 50\ 78]$, $y^{(i)}_k = \theta^{(i)}[1\ 0\ 0\ 0\ 0\ 0]x_k + \xi^{(i)}_k$, $i = 1, \ldots, N$, $k = 0, 1, 2, \ldots$, where $\theta^{(i)}$ assumes two values $\theta^{(i)}_1 = 1$, $\theta^{(i)}_2 = 0$; scalar v_k and $\xi^{(i)}_k$ are uncorrelated zero-mean

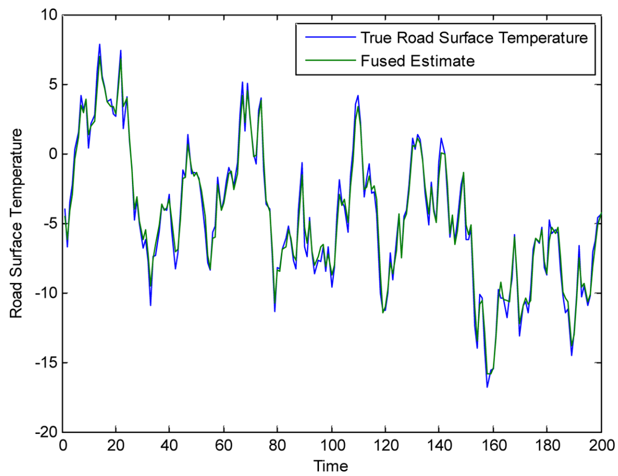

Fig. 3. A Hierarchical Data Fusion in Sensor Networks

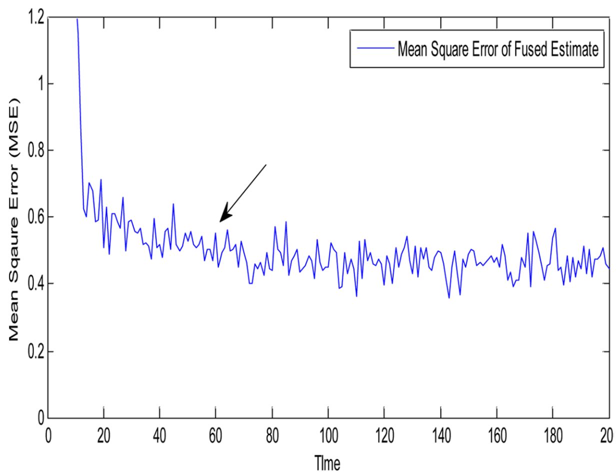

Fig. 4. A Hierarchical Data Fusion in Sensor Networks

Gaussian white noises with intensities Q and $\eta^{(i)}$, respectively. The initial state is subjected to $x_0 \sim N(\bar{x}_0, P_0)$. The prior probabilities were set to $p(\theta_1^{(i)}) = 2/3$, $p(\theta_2^{(i)}) = 1/3$. The values of the system and measurement parameters were set to: Q = 5, $\eta^{(i)} = 0.5 \times i$.

The mean square error of the fused estimate is calculated from $J_k = E[(T_{s,k} - \hat{T}_{s,k})^2]$. In Figs. 3 and 4, the dynamic pavement surface temperature system (14) is adopted to apply and test the accuracy of the proposed algorithm. The result shows that the proposed algorithm is robust to measurement uncertainty and link failure between the nodes and the cluster heads.

6. CONCLUSIONS

Building an advanced driver assistant system requires data such as traffic flows, traffic control, accident circumstances, road conditions, and weather. In this regard, large-scale sensor networks can be an appropriate solution since they were designed for this purpose.

In this paper, hierarchical fusion architecture for an arbitrary topology of the large-scale sensor networks is proposed. The advantage of the hierarchical architecture is the reduction of the computational complexity of the decentralized data fusion algorithm [10]. In sensor networks, apart from the computational complexity, the link failure between the nodes and cluster heads should be addressed [11]; thus, CI is applied to overcome the effect of redundant information.

In large-scale sensor networks, numerous sensors are used to measure the road surface temperature. However, some sensors could be out of order or unable to obtain the temperature data owing to disorders. In this case, we need to isolate those sensors to properly calculate the widely fused estimate of the surface temperature. Thus, the LKF is applied to detect the faulty sensors and to isolate them [8,9].

The result shows that the proposed algorithm is robust to measurement uncertainty and link failure between the nodes and the cluster heads.

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