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Monitoring processes using sensor networks and an extended Kalman filter

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Abstract: - Two main difficulties in process monitoring are lack of reliable measurements of key process variables and difficulty in defining quantitative relationships between state variables. In this study sensor networks are used to demonstrate an approach based on Kalman filtering to model the specific monitoring systems. Kalman filtering at both local nodes and fusion center are the covariance matrices of tracking errors. Performance analysis is dedicated to the distributed Kalman filtering fusion for distributed recursive state estimators of dynamic systems under consideration.

Key-Words: - Distributed processing, performance, sensors, Kalman filtering

1 Introduction

Many current control systems make use of a large number of various sensors in practical applications ranging from robotics and automation systems and defence, to the monitoring and control of plant processes. An important practical problem in such systems is to find an optimal state estimator. Kalman filtering is the best-known recursive algorithm to optimally estimate the unknown state of a dynamic system. When the processing center can receive all measurements from the local sensors in time, the centralized Kalman filtering can be carried out, and the resulting state estimates are optimal. Unfortunately, due to limited communication bandwidth, or to increase survivability of the system in a poor environment, every local sensor has to carry out Kalman filtering upon its own observations first for local requirement, and then transmit the processed data–local state estimate to a fusion center. Therefore, the fusion center needs to fuse all received local estimates to yield a globally optimal state estimate (see [7, 21]). Grime, Durrant-Whyte, and Ho [5]) considered sensor networks in which there is no central fusion center and each sensor communicates to its nearest neighbors. A more general decentralized Kalman filter was considered in [6], it requires no fusion center and no explicit knowledge of the transformations between the estimators, and minimizes communication with respect to message size and topology.

2 Monitoring with Sensor networks

Natural environments are typically extremely dynamic and therefore sensors will need to continuously adjust to dynamic systems. The challenge is to represent an accurate picture of the changes in the environmental variables. This can only be achieved if the physical phenomenon is sensed or sampled from the environment at an accurate rate. The physical phenomena measured ultimately dictates spatial and temporal sampling scale. A very well-known scenario for sensor network applications is habitat monitoring, and a first concrete experiment in this field was carried out on the Great Duck Island. Sensors were deployed in burrows of seabirds for monitoring purposes. During the day time, the burrows were expected to be empty, as thus a low sampling rate should be suffcient to avoid idle listening. However, if some unusual measurements are recorded at some burrows, it would be desirable to collect samples from them more frequently than from other burrows.

Generally, we assume that each node in a wireless sensor network has certain constraints with respect to its energy source, power, memory, storage, and computational capabilities. Not only the resources of the single sensor nodes are limited, but also those of the network as a whole. Especially in wireless sensor networks, which have one shared medium and therefore have to deal with packet collisions, the network capacity is strongly limited. Multisensor data fusion has found widespread application in diverse areas ranging from local robot guidance to military etc. (see [17]). The use of sensory data from a range of disparate, multiple sensors are to automatically extract the maximum amount of information possible about the sensed environment under all operating conditions. Increased performance, reliability, data rates, and autonomy, coupled with increased complexity, diverse uncertain operating environments, requires the automated intelligent combination of data from multiple sensors to derive less ambiguous/uncertain information about the desired state. In recent years there has been increasing awareness that a variety of sensors/platforms owned and operated by different agencies can be fruitfully integrated for better intelligence gathering, situation awareness, tactical missile defence, etc. For this purpose, efficient algorithms for data fusion and track-to-track association must be derived so that existing systems can be easily upgraded without imposing undue burdens on system operators, using existing hardware and software. While the concept of data fusion is not new, the emergence of new sensors, advanced processing techniques, and improved processing hardware make real-time fusion of data increasingly possible. Despite advances in electronic components, however, developing data processing applications such as automatic guidance systems has proved difficult. Systems that are in direct contact and interact with the real world require reliable and accurate information about their environment. This information is acquired using sensors that are devices that collect data about the world around them. The ability of one isolated device to provide accurate reliable data of its environment is extremely limited as the environment is usually not very well defined in addition to sensors generally not being a very reliable interface. Sensor fusion seeks to overcome the drawbacks of current sensor technology by combining information from many independent sources of limited accuracy and reliability to give information of better accuracy and reliability. This makes the system less vulnerable to failures of a single component and generally provide more accurate information. In addition several readings from the same sensor are combined, making the system less sensitive to noise and anomalous observations. The objective of this paper is to derive new Kalman based fusion model to give a better, state estimate at each step.

Resources in sensor networks are strongly limited and thus resource consumption (energy, network bandwidth) must be minimized. Adaptive sampling handles this issue by making the rate of sensing dynamic and adaptable to the signal complexity of the environment. Since sensor networks differ from traditional distributed systems, hardware (sensor nodes) and software (algorithms) must be adapted and take some special properties of sensor networks into account. In future applications sensor networks are envisioned to consist of hundreds or even thousands of single nodes, which all communicate with each other through an ad-hoc wireless network.

3 Monitoring with Kalman filters

The Kalman Filter is a mechanism for predicting the multi-dimensional state of a system from a multi-dimensional observable (see [7, 21]). The system is assumed to evolve linearly and the observable is assumed to be linearly related to the state. Denoting for discrete time series the system state $\mathbf{x}$ we have:

$$\mathbf{x}[k] = \mathbf{A} \cdot \mathbf{x}[k-1] + \mathbf{w}[k-1]$$

We assume that the system is influenced by process noise denoted w. The state dynamics determine the linear operator A. The state contributes to the observation y, which also includes a stochastic, additive measurement noise v:

$$\mathbf{y}[k] = \mathbf{C} \cdot \mathbf{x}[k] + \mathbf{v}[k]$$

The process and measurement noises are assumed to be Normal processes with known covariances W and V. Now let us assume that we have an estimate $\hat{\mathbf{x}}[k-1]$ of the state, and also an estimate of the error co-variance $\mathbf{P}[k-1]$ in the estimate, at step k-1. The Kalman filter uses these estimates, the observation $\mathbf{y}[k]$ at sample k, and $\mathbf{A}$, $\mathbf{C}$, $\mathbf{W}$ and $\mathbf{V}$ to form an estimate of the state and its error co-variance at step k:

$$\hat{\mathbf{x}}[k] = \mathbf{K}[k] \cdot \left(\mathbf{y}[k] - \hat{\mathbf{y}}[k]\right)$$

$$\hat{\mathbf{P}}[k] = \left(\mathbf{I} - \mathbf{K}[k] \cdot \mathbf{C}\right) \cdot \tilde{\mathbf{P}}[k] \cdot \left(\mathbf{I} - \mathbf{K}[k] \cdot \mathbf{C}\right)^T$$

where

$$\hat{\mathbf{y}}[k] = \mathbf{C} \cdot \mathbf{A} \cdot \hat{\mathbf{x}}[k-1]$$
$$\mathbf{K}[k] = \tilde{\mathbf{P}}[k] \cdot \mathbf{C}^T / \left(\mathbf{V} + \mathbf{C} \cdot \tilde{\mathbf{P}}[k] \mathbf{C}^T \right)$$
$$\tilde{\mathbf{P}}[k] = \mathbf{A} \cdot \hat{\mathbf{P}}[k-1] \cdot \mathbf{A}^T + \mathbf{W}$$

The estimated system state x[k] is thus completely determined by the observation $\mathbf{y}[k]$, the estimated state at step k-1, the system dynamics, and the statistical properties of the process and measurement noise. The error in the estimate $\mathbf{x}[k]$ falls with k, converging upon a limiting error covariance that is fully determined by {**A**, **C**, **W**, **V**}. Correspondingly, we can choose any initial estimate of **x** and **P** and the filter will, after several iterations, adjust the state estimate and error accordingly.

A Kalman filter uses the known dynamics of the modes to distinguish between the mode "signal" and other contributions to the measured detector output: i.e., it detects modes. This distinguishes it from other methods such as linear notch filters [8] which purport to characterize or remove artifacts, but which in fact simply suppress all contributions to the noise.

From the state estimate at each step we can, through the measurement equation, estimate the contribution of the system to the actual observation. This estimated contribution can be subtractive removed from the actual observation, leaving a residual that is as free from the contaminating influence of the process as we can make it.

4 Simulation Experiment

To explore the effectiveness of the Kalman filter in monitoring with sensor networks we have collected data from multiple sensors: temperature (deg C), light (lumens) humidity (percent), and the voltage level (V) of the batteries at each node. The data was collected in the following format:

Time	NodeID	Temp	Light	Hum	Vol

This is a "real" dataset, with lots of missing data, noise, and failed sensors giving outlier values, especially when battery levels are low. The typical graph of data is shown on Fig. 1. Figures 1 and 2 show the result of a Kalman filter implementation. Fig 1 shows temperature data without Kalman filtering, anf Fig. 2 shows estimation with Kalman filtering.

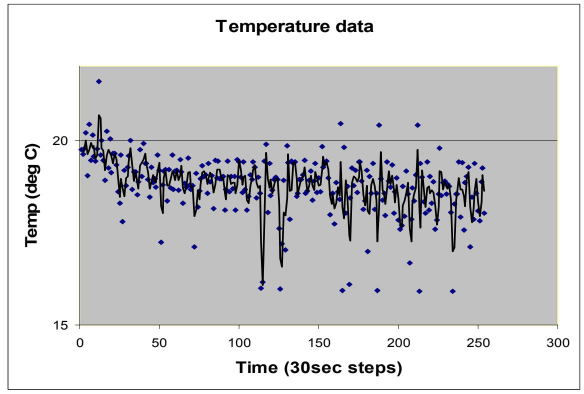

Fig 1. Estimation with moving average (dots represent measurement and solid line moving average)

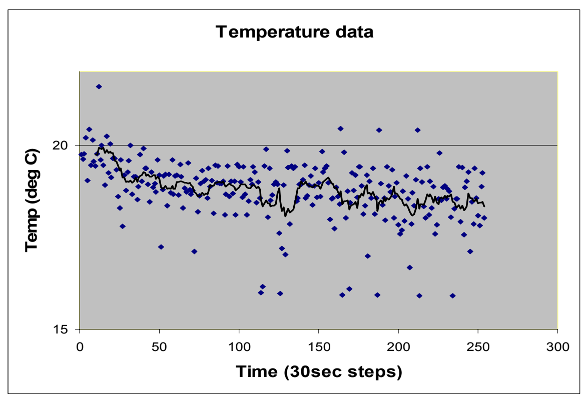

Fig 1. Estimation with Kalman filter (dots represent measurement and solid line estimation with Kalman filtering)

5 Results and Discussion

Given a set of network and environment characteristics and definitions, resource consumption (energy and network bandwidth) should be minimized while maximizing the measurement accuracy. The aim is to produce an accurate spatial picture of a certain physical process, while making an efficient use of resources As events are not uniformly distributed in the environment, not all sensor nodes should collect data samples at a common, fixed rate.

In this paper a preliminary analysis has been presented for the application of Kalman filtering to sensor data fusion. Simulation was used for testing. First, the data collection experiment was set up. Individual sensors were placed in an environment (lab) where the temperature varies. Second, software [20] has been adopted to run simulations. In our experiment we have shown that the data fusion with feedback improves quality of monitoring in sensor based networks.

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