34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Fault Detection and Isolation in Motion Monitoring System

Duk-Jin Kim, Myoung Hoon Suk, and B Prabhakaran, *Member, IEEE*

Abstract— **Pervasive computing becomes very active research field these days. A watch that can trace human movement to record motion boundary as well as to study of finding social life pattern by one's localized visiting area. Pervasive computing also helps patient monitoring. A daily monitoring system helps longitudinal study of patient monitoring such as Alzheimer's and Parkinson's or obesity monitoring. Due to the nature of monitoring sensor (on-body wireless sensor), however, signal noise or faulty sensors errors can be present at any time. Many research works have addressed these problems any with a large amount of sensor deployment. In this paper, we present the faulty sensor detection and isolation using only two on-body sensors. We have been investigating three different types of sensor errors: the SHORT error, the CONSTANT error, and the NOISY SENSOR error (see more details on section V). Our experimental results show that the success rate of isolating faulty signals are an average of over 91.5% on fault type 1, over 92% on fault type 2, and over 99% on fault type 3 with the fault prior of 30% sensor errors.**

I. INTRODUCTION

The technical advance on sensor technology and mobile device over the past few decades has changed the whole paradigm of the motion monitoring system. For the combination of sophisticated inertial sensing, wireless communication and signal processing technologies have made such a pervasive and remote monitoring possible [1]-[3].

In order to obtain accurate motion monitoring, the monitoring system should provide many factors such as the compactness in size, the long last battery life, the durability of sensors, and so on. However, due to the nature of the sensing and communication mechanisms, these monitoring sensors are susceptible to errors and failures.

In this paper, we focus on the problem of identifying and isolating faulty sensor(s) in a network of two on-body inertial sensors. First, we introduce the related works on the fault detection and isolation problems in wireless sensor networks. Next, we outline the three types of fault sensor data. Then, we proposed our fault detection scheme using history based approaches that can facilitate this process without the need for a larger number of sensors for redundancy or fault tolerance. Our experimental results show over 90% of accuracy with 30% of sensor error rate. The proposed approach cannot identify and isolate all sensor faults, especially if the errors are marginal or the noise on the signal is minor. However, our experimental results show that our approach can provide good confidence in the pervasive monitoring system with only two sensor deployments that is being used for interpreting activities of daily living.

Contributions: In [6], we carried out studies on fault detection and isolation problems among larger number (9 or more) on-body sensors. Considering the difficulty in wearing multiple on-body sensors, in this paper, we have focused on reducing the number of sensors to just two. Conducting a study with 9 sensor locations, we come up with recommendation for the locations of two sensors that would facilitate pervasive monitoring. Then, we contribute by facilitating fault detection and isolation in these two sensors.

II. RELATED STUDY

Motion monitoring sensors in the Pervasive Healthcare Systems consist of small and low-cost sensors. These sensors are exposed in harsh environments that node failure or faulty sensor reading becomes inevitable. Therefore the fault tolerance system in wireless sensor networks have been studied for many years [8]-[10].

Most algorithms like [8] have high fault detection accuracy with a relatively low fault probability, whereas the performance terribly degrades as the number of nodes increase. In order to solve such a low scalability problem, authors present a distributed adaptive scheme for fault detection in WSNs in [9]. Dynamically by adjusting the parameters such as thresholds in each node, the scheme can keep up high performance even with increased number of faulty nodes. In the proposed approach of [10], the network is divided into four disjoint zones until the suspected faulty node is identified. In each zone, there is a master in charge of finding the suspected faulty node and identifying the faulty nodes. The approach is shown that faulty node detection accuracy is considerably high when the number of faulty nodes is relatively small to the number of sleeping nodes.

In summary, many existing fault detection schemes require two basic assumptions: (1) a large amount of sensor deployments; and (2) a similar or the same sensed value between the sensor and its neighbor sensors. These aspects cannot be fulfilled in Pervasive healthcare system with on-body sensors for monitoring activities of daily living for reasons such as: different body joints produce different data; and the number of deplored sensors must be small such that it does not restrict daily activities. Our proposed approach focuses on these problems.

III. FUNDAMENTAL EQUATIONS

In this section, we explain the fundamental methods that are used through the paper: the Power Spectral Density (PSD) and the Singular Value Decomposition (SVD). SVD is one method of the dimension reduction techniques without losing much of the signal patterns. PSD is another important metrics

D. Kim is with the University of Texas at Dallas, Richardson, TX 80305 USA (e-mail: dxk051000@ utdallas.edu).

M. Suk is with the University of Texas at Dallas, Richardson, TX 80305 USA (e-mail: mhsuk@utdallas.edu).

B. Prabhakaran with the University of Texas at Dallas, Richardson, TX 80305 USA (e-mail: praba@utdallas.edu).

978-1-4577-1787-1/12/$26.00 ©2012 IEEE

for detecting unusual motion behavior or faulty sensor reading. We assume many human motions generate very low frequency that its power spectrum has high reading on a low frequency zone. We, also, assume that any constant sensor reading generate very low power spectrum. We mainly use the SVD for the motion classification and the PSD for checking a faulty sensor reading.

A. Singular Value Decomposition (SVD)

Sliding windows of the sensor node has been used for dimension reduction which preserves the pattern of data. Consider the sliding window of a matrix M with m number of time frames where *k* is *x, y, z*-axis. For each m x 3 matrix with m >= 3, there is an m x 3 unitary matrix U, an m x 3 diagonal matrix Σ with nonnegative real numbers on the diagonal, and V^T a conjugate transpose of an *3* x *3* unitary matrix V. The diagonal values of Σ are the singular values of matrix M_i (eq. 1). These extracted the singular values $\{\sigma_x^i, \sigma_y^i, \sigma_z^i\}$ of matrix M_i represents the SVD_i of sensor location i (eq. 2.)

$$M_i = U\Sigma_i V^T, \; M_i \nu = \sigma_k^i \mu, \; M_i^T \mu = \sigma_k^i \nu \tag{1}$$

$$SVD_i = \{\sigma_x^i, \sigma_y^i, \sigma_z^i\} \tag{2}$$

B. Power Spectral Density (PSD)

The PSD simply transform the time dependent data into the frequency dependent data such that any unusual sensor reading (e.g., a sequence of data tweaking) can be easily observed. For the PSD transformation we use the Cooley-Tukey algorithm. The Cooley-Tukey algorithm [4] subdivides size N points into smaller Discrete Fourier Transforms (DFT) of sizes N_1 and N_2 recursively (where $N=N_1N_2$). The DFT algorithm transforms the sequence of N complex number vector $T=\{\chi_0, \chi_1, \chi_2, \ldots, \chi_{N-1}\}$ into T' = $\{X_0, X_1, X_2, \ldots, X_{N-1}\}$. The DFT is defined by eq. 3.

$$F(T) = \{X_\kappa \mid X_\kappa = \sum_{n=0}^{N-1} \chi_n \, e^{\frac{-2\pi i}{N} n\kappa}\} \tag{3}$$

where $e^{\frac{2\pi i}{N}}$ is a primitive N'th root of unit; an integer κ is ranging from 0 to N-1; i is the imaginary unit; and the X_κ can be viewed as coefficients of T in an orthonormal basis.

PSD values are highly dependent on the pattern of their time domain value. Actual acceleration values of faulty node may not be so much different from those of high energy motions. Notice that the pattern, however, will be preserved regardless of any motion values on time domain. Hence, what we are interested in is not an actual value of power spectral density (PSD) but rather its pattern for a particular motion sensor node or a collection of sensor nodes. We use Fast Fourier transform algorithm to transform acceleration data of each sensor axis $\{ g_i^x(t), g_i^y(t), g_i^z(t) \}$ into the power spectrum $\{PSD_i^x(h), PSD_i^y(h), PSD_i^z(h)\}$ (eq. 4).

$$PSD_i^j(h) = F\left(\{g_i^j(t)\}_{t=0}^{N-1}\right) \tag{4}$$

where t is time(sec), h is frequency (Hz), i is a sensor location and j∈{x,y,z axis}.

IV. Fault Isolations

In this section, we explain a flow of our proposed fault detection scheme in detail. We separate the motion signal pair (right pocket signal and hand signal) with six motion groups (walking; running; jumping; sitting down and standing up; stair walking; and hand waving motions) based on their motion activeness. For the fault detection and isolation, the two step detection method is used. The first step is to detect unusual sensor readings by using the Gaussian Mixture Model clustering and the second step is to isolate the faulty sensor location by using the Bayesian Probability.

A. Gaussian Mixture Model Clustering

In order to separate the faulty sensor data and the non-faulty sensor data, the *Gaussian Mixture Model Clustering* technique [8] is used. Our GMM clustering base approach has two steps of divided processes: 1) defining the membership of input sensor data; 2) separating the input data and the selected motion data group into two data groups. We simply deploy all the data including faulty node reading as well as normal motion reading and separate them by two sensor data groups: a faulty group G_F and a non-faulty group G_T.

The frequency domain of the acceleration data of the normal motions cannot be easily classified unless there are noticeable signal changes. Many of PSD values are similar among different motions. Therefore, it is not a very good feature to classify motion groups. On the other hand SVD values have much better motion separation than the PSD.

To find the motion group membership of input signal, the Euclidian distance is used. Every time a new sensor input is received, the Euclidian distance (eq 5) is computed from the input feature vector (V_i) of the current motion segment to the centroid (C_k) of the each motion group where $v_i^m \in V_m, c_i^k \in C_k$, and the nearest distanced group is selected as a reference set for fault detection.

$$d(V_m, C_k) = \sum_{i=1}^{n} \sqrt{\left(v_i^m - c_i^k\right)^2} \tag{5}$$

We use the Gaussian Mixture Model to estimate and generate normal and abnormal sensor groups. Each set of sensor group consists of similar power spectral density and singular value of the particular window. Each clustered set G^i $G^i = G_T^i \cup G_F^i$, $G_T^i \cap G_F^i = \emptyset$, G_T^i is non-faulty set, and G_F^i is faulty set

B. Fault Probability

After dividing two groups of sensor data cluster sets $G_F^j = \{x_1^j, x_2^j, \ldots, x_n^j\}$ and $G_T^j = \{x_{n+1}^j, x_{n+2}^j, \ldots, x_{n+z}^j\}$ of the sensor j, select each member $x_l^i \in G_F^j$ to the selected motion group set $G_n^j = \{y_1^j, y_2^j, \ldots, y_{m-1}^j\}$ of sensor j from the motion database to the set X^j such that it becomes $X^j = \{y_1^j, y_2^j, \ldots, y_{m-1}^j, x_l^j\}$. The normal probability $p(x_l^j)$ can be computed using eq. 6 with mean μ and standard deviation σ of the set X^j. From the fault group G_F^j, we estimate a possible number of fault sensor reading k (eq. 7) for computations of conditional probabilities of current signal reading x_l^j being fault or not (eq. 8 for fault probability and eq. 9 for not being fault probability.) The Bayesian fault probability for current node reading $p(f|x_l^j)$ can be computed using eq. 10.

$$p(x_l^j) = p(x_l^j|\mu^j, \sigma^j) = \frac{1}{\sigma^j\sqrt{2\pi}} e^{\frac{-(x_l^j-\mu^j)^2}{2\sigma^{j^2}}} \quad (6)$$

$$k = \mathrm{round}(|X^j| \times \frac{|G_F^j|}{|G_F^j|+|G_T^j|}) \quad (7)$$

$$p(x_l^j|f) = \binom{n}{k} p(x_l^j)^k(1-p(x_l^j))^{n-k} \quad (8)$$

$$p(x_l^j|t) = \binom{n}{k} p(x_l^j)^{n-k}(1-p(x_l^j))^k \quad (9)$$

$$p(f|x_l^j) = \frac{p(x_l^j|f)p(f)}{p(x_l^j|f)p(f)+p(x_l^j|t)p(t)} \quad (10)$$

Example:

Let's assume that a selected motion group set $\{X_j = \{13,12,22,11,14,13,12\}$, $G_F^H = \{34, 40, 35\}$ and $G_T^H = \{13,12,22,11,14,13,12\}$, then $|G_F^H| = 3$ and $|G_T^H| = 7$. The prior fault probability of $\frac{|G_F^H|}{|G_F^H|+|G_T^H|}$ is 0.3. Let's assume that one of node reading value in the set G_F^H is 34 which is an unusual value for node H. We can simply compute k that is 0.3*8 (size of X_j with a new value 34) = 2. Mean and sigma of X^H are 13.6 and 3.39 respectively. Likelihood probability p(34) is 0.0031. Then

$p(34|f) = \binom{8}{2}\ (0.0031)^2(1-0.0031)^6 = 2.64*10^{-4}$, and

$p(34|t) = \binom{8}{6}\ (0.0031)^6(1-0.0031)^2 = 2.469*10^{-14}$.

With all these values we can compute Bayesian probability of input 34 being fault. That is

$$p(f|34) = \frac{2.64*10^{-4}*0.3}{(2.64*10^{-4}*0.3+2.469*10^{-14}*(0.7)} = 1$$

Since p(f|34) is 1 that it can be categorized as an unusual node reading.

For the minimum threshold value of the fault probability, the difference of the hand sensor and the right pocket senor is computed. We compute the difference $\Delta\delta_l$ of two sensor H and RP such that $\Delta\delta_l = |\ x_l^H - x_l^{RP}\ |$ where $1 \leq l \leq n + z$. Different motion defines different $\Delta\delta_l$. We use equation (10)-(14) to compute fault probability of each $\Delta\delta_l$ and set the minimum threshold of fault probability as fallow (eq. 11).

$$\theta = \min(\{p(f|\Delta\delta_i\ )\})) \quad (11)$$

$$\text{where } 1 \leq i \leq |G_F^j|$$

Repeat these processes for all sensor readings in the faulty sensor group of both the hand sensor data and the right pocket sensor data; and compare the fault probability of both the hand and the right pocket to isolate faulty sensors. Fault decision flows are shown in Algorithm 1.

V. Experimental Results

We assume that conventional threshold based tests should filter out faults causing constant reading or no sensor reading as well as higher threshold. Also, minor noise can be easily collected by using the low pass filter or the Kalman filter. Therefore, we examine only high volumes of noisy sensor readings and unusual sensor readings with the marginal errors. The sample set was collected six different motions (walking, running, jumping, walking on the stairs, sitting down and standing up, and hand waving) from 12 people using the iPhone 4G and the iPod touch 3G. In this study, we are not focusing on the hand dominance of the participants. For experiment implementation, Matlab 7.9 was used to program fault detection algorism. Faulty nodes and faulty motions were simulated in a random manner.

Algorithm 1. Algorithm for fault detection

Input: Let input data set G_{input} and the selected motion group set G_{motion} from the motion database using the equation 9.
  Let a set $G_0 = [G_{input}\ G_{motion}]$
  $G_{new\ motion} = G_{motion}$
Output: [Fault sensor location, G_{new_motion}]
Step 1 From the given set G_0, separate two sets G_F^H, G_F^{RP} using GMM
  if $|x_l^j - \mu_{motion}^j| > \pm\, \sigma_{motion}^j$
    goto step 2
  else
    choose next input data $x_{l+1}^j \in G_F^j$
    where $x_l^j \in G_F^j$, $j \in \{H, RP\}$
  endif
Step 2: Count the number of data sets that are bigger than probability threshold θ from the eq. 11.
  If $(p(f|x_l^H) \geq \theta)$ H += 1
  If $(p(f|x_l^{RT}) \geq \theta)$ RT += 1
  Where θ from the eq. 11
Step 3: If x_l^H is the last element of the set G_F^H
  goto Step 4
  else
  goto step 2
  endif
Step 4: If (H>$\frac{|G_F^H|}{2}$ and RT>$\frac{|G_F^{RT}|}{2}$)
    {both sensors are faulty}
  else if (RT>$\frac{|G_F^{RT}|}{2}$)
    {the right pocket sensor is faulty}
  else if (H>$\frac{|G_F^H|}{2}$)
    {the hand sensor is faulty}
  else {need a visual inspection to add x_l^j
    $x_l^j \in G_{new\_motion}$, $j \in \{H,RT\}$ }
  endif

A. Simulation Parameters

Three faulty signals were injected for faulty node readings:

- Fault Type 1: CONSTANT [5] sensor error is a series of data with zero or near zero variation for a period of time.
- Fault Type 2: SHORT [5] sensor error generates data significantly deviated from expected sensor temporal models of the data.
- Fault Type 3: NOISY sensor data that may be caused by communication noise or unstable sensors.

We used prior probability $p(x) = \{x|\ x = 5*k,\ 1 \leq k \leq 19,$ and $k \in \mathbb{Z}\}$ such that we can compare detection accuracies.

TABLE I. The experimental results of average faulty sensor detection

	(a) Fault Type 1						(b) Fault Type 2						(c) Fault Type 3					
P(x)	***5***	***10***	***15***	***20***	***25***	***30***	***5***	***10***	***15***	***20***	***25***	***30***	***5***	***10***	***15***	***20***	***25***	***30***
Accuracy(%)	97.7	85.7	73.7	85.4	86.2	91.5	99.4	97.9	97.4	96.4	93.8	92.0	100	100	100	100	99.8	100
Precision(%)	69.1	66.1	73.7	79.1	76.1	71.3	89.0	79.7	82.3	82.0	74.9	73.0	100	100	100	100	99.4	100
Recall(%)	96.2	100	100	98.6	97.2	100	100	100	100	100	100	100	100	100	100	100	100	100

**p(x)* indicates fault probability (%)

For each fault type error, three faulty sensor detection cases were tested:

1) Only the hand sensor is faulty.
2) Only the right pocket sensor is faulty.
3) Both the hand and the right pocket sensor are faulty.

B. Experimental results

With all three cases of fault detections scenarios, we have been achieved an average of over 91% accuracy with the fault prior probability of 30% (see TABLE I (a)). In our experimental results for the Fault Type 1 indicated that right pocket sensor had much higher accuracy among all three test cases (the hand sensor error, the right pocket sensor error, and both sensor error detection cases).

The precision of the hand sensor error detection, however, was less stable than that of the right pocket sensor error accuracy. It may be caused by the nature of hand motion. Since hand motion is much higher degree of freedom that the obtained signal can be much nosier than that of the right pocket sensor in some motions. The precision of the both sensor error result had lowest rank among three test cases due to the precision of the hand sensor error.

The accuracy result of the Fault type 2 had slightly better than the accuracy result of the Fault type 1. With all three cases of fault detections scenarios, we have been achieved an average of over 92% accuracy with the fault prior probability of 30% (see TABLE I (b)). Our experimental result showed that precision of the Fault Type 2 had more stable than the precision result of the Fault type 1. Overall, the results were very similar to those of the Fault Type 1.

Among all three Fault Types the Fault Type 3 had the highest accuracy. We have been achieved an average of over 99% accuracy with the fault prior probability of 30% for all three test cases (see TABLE I (c)). The Fault Type 1 errors and the Fault Type 2 errors were sharing one common characteristic that is the injected noise is not much different from the original signal. On the other hand, the Fault Type 3 did not share the much of similarity between the original sensor signal and the error injected sensor signal. This indicates that the accuracy of detecting fault sensor becomes less accurate if the noise of the detected sensor is minor.

VI. Conclusion

One of the challenges of the fault detection problems in the pervasive monitoring system is that the sensor reading of one location may not be the same or similar to other sensor readings. More challenging problem is to deal with small number of sensor nodes.

In this paper, we have proposed the fault detection and isolation algorithm in the pervasive motion monitoring with two motion sensors. The proposed approach works with three different types of faulty sensor data. The extracted features (SVD and PSD) help to identify the similar motion group as well as to isolate three different types of sensor errors. The proposed algorithm requires the only two sensor deployment. Our experimental results show over 90% of success rate for all three types of sensor errors. The success rate of isolating faulty signals are an average of over 91.5% on fault type 1, over 92% on fault type 2, and over 99% on fault type 3 with the fault prior of 30% sensor errors.

VII. Future work

One of the potential directions that we can pursue is to be dealing with missing sensor data. In the pervasive monitoring system, missing data caused by communication error or malfunction of the sensor can happens. In our experiment, we assumed that the sensors always generate motion signals, and the base station always obtains the sensor readings. In real life, sensors are not always synchronized perfectly. The poor constructions of the sensors or monitoring program can generate missing data or unsynchronized data. Therefore it is critical to investigate such problem and to propose solutions. The missing data analysis has been studied more than a decade, yet not many research have been focused on the missing data analysis of the pervasive monitoring system. This becomes one the challenging research directions.

References

[1] UP, http://jawbone.com/up/preview

[2] Nike +, http://nikerunning.nike.com/

[3] Garmin, http://www.garmin.com/

[4] J. Cooley and J. Tukey, "An algorithm for the machine calculation of complex Fourier series," *Math. Comput.* 19: 297–301, 1965.

[5] K. Ni et al., “Sensor Network Data Fault Type,” ACM Transactions on Sensor Networks, 5(3):1-29, 2009

[6] D. Kim and B. Pravhakaran, “Motion Fault detection and isolation in Bady Sensor Networks,” Pervasive and Mobile Computing (2011), doi:10.1016/j.pmcj. 2011.09.006

[7] C. Bishop, “Pattern Recognition and Machine Learning”, Springer, 2006.

[8] C. Zhang, et. Al, “Sensor Fault Detection in Wireless Sensor Network”, in Proceedings of the IET International Conference (CCWMC’09), pp66-69

[9] J. Choi, S. Yim, Y. Huh, and Y. Choi, “ A Distributed Adaptive Scheme for Detecting Faults in Wireless Sensor Networks,” WSEAS Trans. Comm. 2(8):269-278, Feb. 2009.

[10] A. Akbari, A. Dana, A. Khademzadeh and N. Beikmahdavi, “Fault detection and recovery in wireless sensor network Using Clustering,” Internaltinal Journal of wireless & Mobile Networks(IJWMN), 3(1):130-138, Feb. 2011.