A ROBUST METHOD TO IDENTIFY FAULTS IN CORRELATED SENSORS IN MACHINE CONDITION MONITORING

Zehra Cataltepe, *Chao Yuan, Claus Neubauer, Meltem Demirkus, and Hans-Gerd Brummel*

Istanbul Technical University .... Siemens Corporate Research Inc.
Computer Engineering Dept. Maslak, Sariyer, Turkey .... 755 College Road East, Princeton, NJ 08540, USA
email: zehra@cs.itu.edu.tr .... phone: +1-(609)-734-6500, fax: +1-(609)734-6565

ABSTRACT

We present a robust method to identify and isolate faulty sensors among a set of correlated sensors. For each sensor, we estimate the sensor a number of times, using each of the other correlated sensors separately. We use the median of these estimates as the estimate for the sensor. When up to less than half of the sensors are faulty, this method identifies the faulty sensors accurately. Since the median is used and since estimates for the same sensor as opposed to different original sensor values are used in the median, this method is very robust. The method gives much better spill-over and error recognition rates, compared to the traditional method of using the mean of the actual sensor measurements.

1. INTRODUCTION

In automated monitoring of plants and machines, a model is trained based on sensor data collected during the normal operation of the machine or plant. The new test sensor data are used as input to the trained model and it is checked if the test data are in agreement with the training data. If the residuals (actual data - estimates) are higher than some thresholds for a sensor, then a fault is reported.

Sometimes, a large number of sensors are correlated with each other. They measure the same physical entity (such as temperature or pressure) at the same or similar machine parts. If a sensor behaves unlike others (a drift or a step), it is important to identify that sensor as soon as possible.

If the estimate for a sensor is based on other sensors, as in the case of auto-associative models, when one of the input sensors change, the change affects the estimate for the other sensors, too. If the output sensor is not one of the faulty sensors, then this is known as spillover (of the fault from the faulty sensor). In other words a fault is seen in the estimate of a sensor that is not actually faulty. If the output sensor is faulty, the fault is often underestimated. Although input driven models would not suffer from spillover, sometimes there aren't enough input (independent) sensors to estimate output (dependent) sensors with small enough residuals [5]. [9] is an attempt to overcome this problem by adding the mean of dependent sensors to the list of input sensors. However, the mean is not robust against outliers [8]. Especially when there is a small number of independent sensors, or when the disturbance is big, the mean would be affected significantly from a disturbance in one of the sensors.

There are various methods of dealing with outliers in training data, see, for example [3,6] and [8]. These robust methods reduce the effect of outlier training data points on the model and give similar results to least mean squares method when there are no outliers. In this study we assume clean training data and concentrate on the problem of estimating the amount of faults on the test data as accurately as possible. There have been previous studies to detect and isolate faulty sensors among a set of correlated sensors. [1] used standardized least squares residuals to eliminate faulty variables in an iterative process. [7] used artificial neural networks and fuzzy logic to eliminate faulty sensors. [2,4] investigated different linear and nonlinear methods for detection of sensor faults.

We present a method to identify and isolate faulty sensors in test data among a set of correlated sensors. For each sensor, we use all other sensors to estimate it. We use the median of the estimates given by the other sensors as the estimate for that sensor. Since median is more robust to outliers than mean, this method gives much better results than the traditional method of using the mean of the actual sensor measurements (simple redundancy [7]).

2. MEDIAN OF THE ESTIMATES BY OTHER SENSORS AS THE ESTIMATE FOR THE SENSOR

Assume that sensors $x_1, x_2,\ldots,x_n$ are being monitored and they are correlated. Sensors $x_{n+1},\ldots,x_m=\underline{u}$ are the independent sensors. We do not require the dependent sensors to be linearly correlated, we just require that each dependent sensor x_i can be estimated using each of the other dependent sensors and the independent sensors. In other words $x_i(t) = f_{ij}(x_j(t),\underline{u}(t)) + e_{ij}$ for some function f_{ij} and noise $e_{ij} \sim N(0,\sigma_{ij}^2)$. (Please see figure 1.) One possible candidate for f_{ij} is the degree d polynomial $f_{ij}(x_j(t)) = w_{ij0} + \sum_{k=1}^{d} w_{ijk} x_j^k(t), i \neq j, i, j \leq n$. In this paper we use linear (i.e. degree 1 polynomial) functions for f_{ij}.

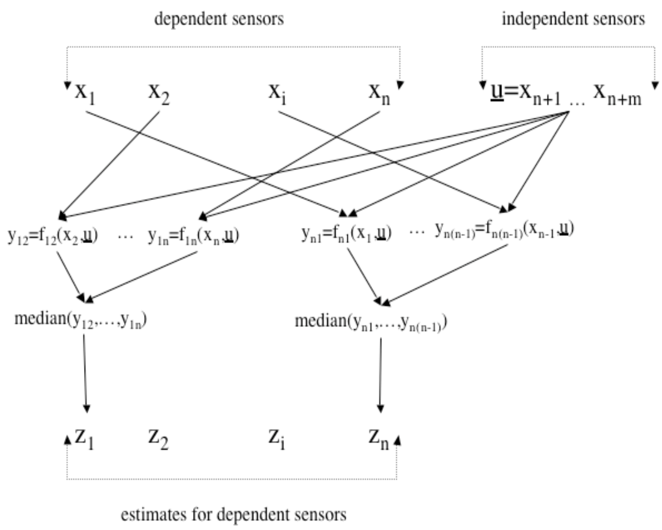

Figure 1. *We first obtain an estimate of each dependent sensor in terms of the independent sensors and another dependent sensor. We use the median of the n-1 such estimates to compute the robust estimate for the sensor.*

We assume that for time t=1,…,T fault-free training data $x_1(t), x_2(t), \dots, x_n(t), x_{n+1}(t), \dots, x_m(t)$ are available. We denote all the training data for the ith sensor by the Tx1 column vector $\underline{x_i} = [x_i(1) \quad x_i(2) \quad \cdots \quad x_i(T)]'$. We first solve (n-1) equations for each dependent sensor. For example for the ith sensor for $j = 1, \cdots, n, i \neq j, k = 0,1$ we solve for w_{ijk} in $\begin{bmatrix} \underline{1} & \underline{x_j} \end{bmatrix} \begin{bmatrix} w_{ij0} \\ w_{ij1} \end{bmatrix} = \underline{x_i}$.

Let the estimate of sensor x_i by sensor x_j be $y_{ij}(t) = w_{ij0} + w_{ij1} x_j(t)$. We compute the estimate for sensor x_i at time t as $z_i(t) = median_{j=1,..,n, i\neq j}\, y_{ij}(t)$.

Note that when it is known that at most αn dependent sensors are faulty, alpha-trimmed mean can be used instead of the median. The alpha-trimmed mean discards the largest and smallest αn numbers in the computation of the mean. Alpha-trimmed mean is equivalent to the regular mean for $\alpha = 0$ and it is equivalent to the median for $\alpha = 0.5$.

Note also that if the estimation errors e_{ij} have different variances σ_{ij}^2, weighted trimmed mean with weights proportional to $1/\sigma_{ij}$ should be used.

3. EXPERIMENTAL RESULTS

Together with our new method, we experimented on the following methods of sensor estimation:

1. Mean of the original sensors x_j,
2. Median of the original sensors x_j,
3. Mean of the sensor estimates y_{ij},
4. Median of the sensor estimates y_{ij}.

Method 1. is the traditional simple redundancy method used in for example [1]. In order to eliminate the different dc values for each sensor [1] suggested subtracting the first value of the sensor. In order to get less noisy results, we subtract the mean of 100 random samples in training data from each sensor. We used this pre-processing for all the methods above.

In order to verify our results we used blade path temperature sensors from a power plant. These sensors are quite correlated with each other. There are n=36 sensors. It is known that two of the sensors have an actual drift at the end of the available data. We partitioned the available data into three portions in time: a) clean training data b) clean data not used for training c) faulty data. We tested the four different methods of sensor estimation mentioned above.

In order to test each method under different conditions, we inspected the residuals (actuals –estimates) for the faulty and non-faulty sensors. A good method should result in very small residual for a normal sensor (i.e. small spillover) and exactly the fault for the faulty sensor (i.e. good error recognition).

We examined the residuals under the following conditions:

a) We used all n=36 sensors.
b) We used only a subset n=6 of all available sensors.

We examined the models for the following types of faults:

i. The actual fault on the sensor test data. Two sensors drifted by about -20F.
ii. We introduced a large drift (from 0 to -500F) on one of the sensors. The artificial drift is added on the clean data between the training data (beginning, 0F) and the faulty test data (end, -500F).

Figures 2-4 show our results. As seen in figure 3, when there are many correlated sensors and the faults are small, all methods perform similarly well. The fault is caught on the faulty sensor and the spillover is small on the normal sensors. However, when the number of correlated sensors are small (see figure 2), the median of estimates performs better than both of the mean methods. The median of estimates is also better than the median of originals, as seen by the disturbances on the residuals of the good sensors. When the faults are large, as seen in figure 4 with the artificial fault residuals, the median of estimates outperforms the mean methods. This result is expected since the median is more robust to outliers/noise than the mean.

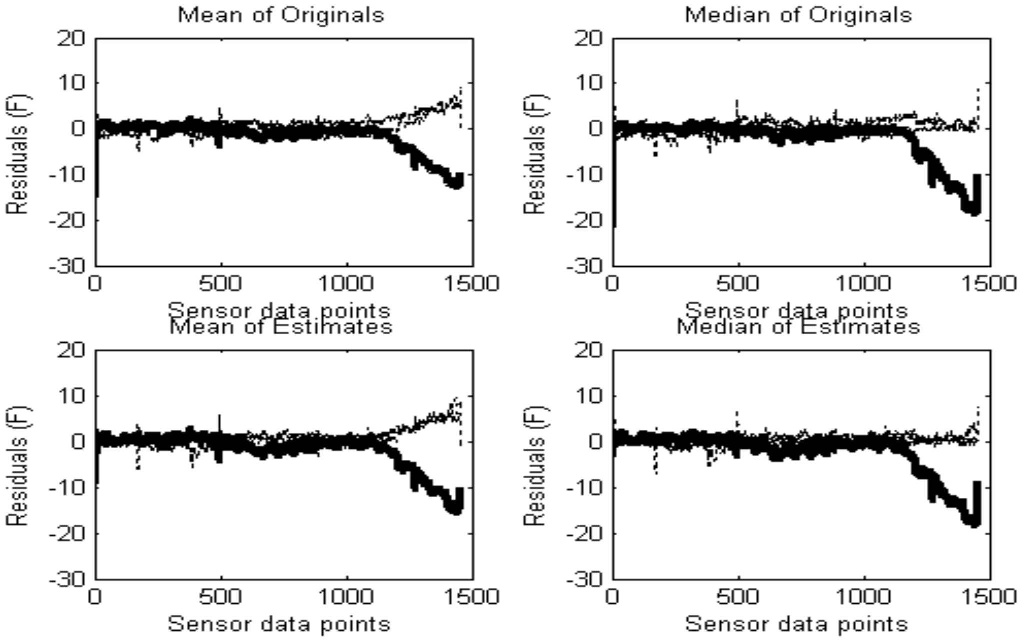

Figure 2. *The residual behavior of each 4 methods on the faulty (solid) and normal (dashed) sensors for the real fault. In this plot only n=6 dependent sensors are used. The fault is a drift of about -20F. The median of estimates is the best method since it does not show any spillover (increased residual) on the normal sensors.*

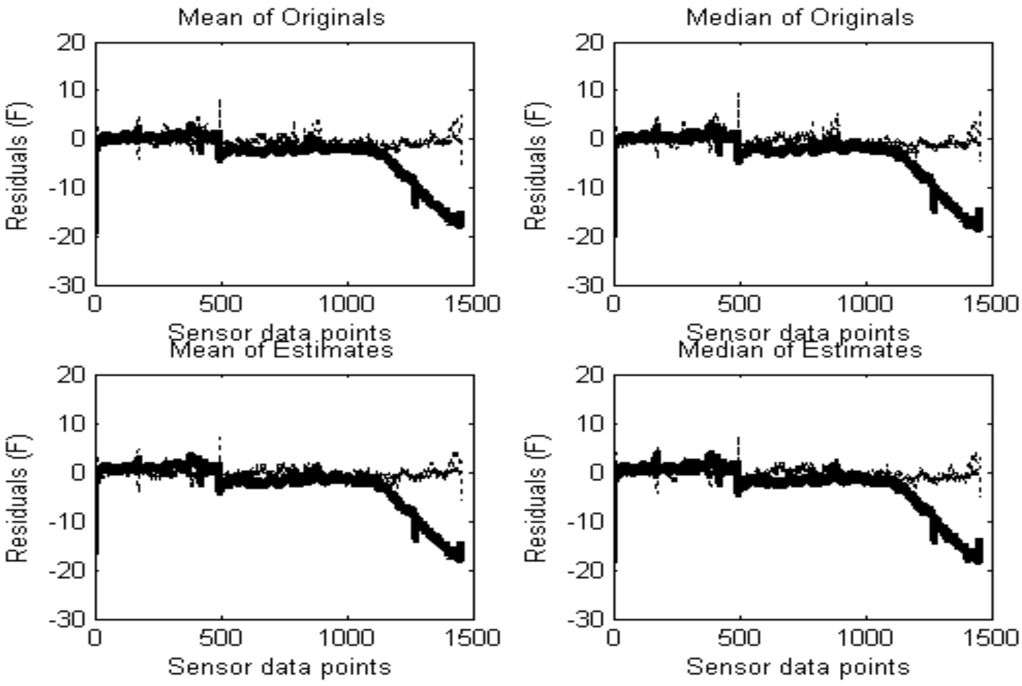

Figure 3. *The residual behavior of each 4 methods on the faulty (solid) and normal (dashed) sensors for the real fault. In this plot all n=36 dependent sensors are used. The fault is a drift of about -20F. All methods behave equally well when there are a lot of dependent sensors.*

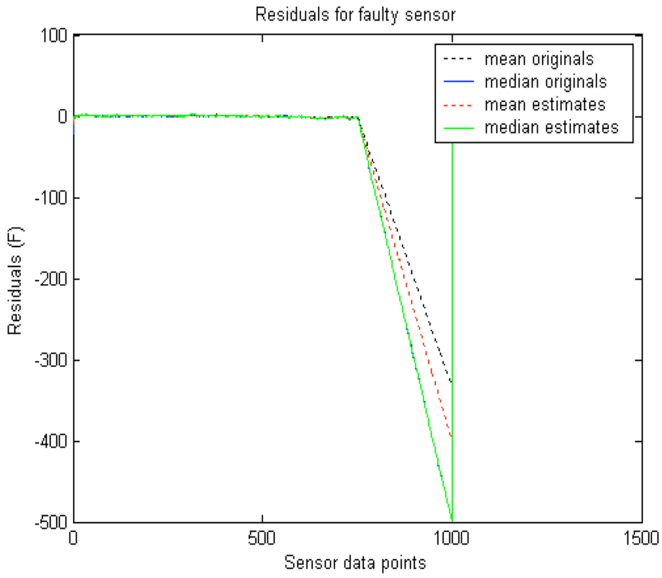

Figure 4. *The residuals for the faulty sensor when n=6 sensors are used and an artificial drift is applied on the clean data between the training data (beginning, 0F) and the faulty data (end, -500F). Mean of the originals is the worst method and the median methods are the best. The difference between methods is more prominent when the fault is large.*

4. CONCLUSIONS

We presented a new method to identify faults among a set of correlated sensors. The new method, first estimates each sensor in terms of other sensors one by one. The median of these estimates is used as the estimate for the sensor. This method outperforms the traditional mean of the original sensors estimate both in terms of error recognition on a faulty sensor and spillover on the non-faulty sensors. The method is especially good when

- the number of correlated sensors is small or
- the amount of fault is large or
- the fault is on a large proportion of sensors.

Due to the breakpoint of the median [7] this method can find out the faulty sensor as long as less than half of the total number of sensors are faulty.

The method can be used in cases where the estimates for a sensor are nonlinear. When the estimates are noisy, the method could be modified so that instead of the median a weighted average around the median (weighted trimmed mean) is taken to be the estimate.

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