Two-Tier Framework for Sensor Fault Characterization in Sensor Networks

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***Abstract*—For a sensor network to be reliable and useful, sensor data must sustain high Quality of Information (QoI). While QoI depends on many factors, the most crucial is the integrity of sensor data sources themselves. Sensor data quality may be compromised by causes such as noise, drifts, calibration, and faults. On-line detection and isolation of such misbehavior are crucial to assure high QoI for the end-user, and efficient management of network resources. We describe a two-tiered system for on-line detection of sensor faults. A local tier running at resource-constrained nodes uses an embedded model of the physical world with a hypothesis-testing detector to identify potential faults and notifies a global tier. In turn, the global tier uses these notifications for consistency checking among sensors and provides more robust estimates for events of interest, and also generates feedback to update the local models. We demonstrate the performance of our system by investigating its impact on the application QoI.**[1]

I. Introduction

A sensor network is deployed to aid decision making to estimate an *event of interest*. The *event of interest* is estimated or calculated by a fusion module that aggregates the information provided by various sensors within the network. The quality of information provided by the network depends not only on the fusion function, but also on knowing when a sensor is misbehaving. A sensor may misbehave due to an inherent failure or due to an inappropriate environmental condition [1], [2]. We describe a two-tiered system for on-line detection of sensor faults and hence positively impact the network QoI .

II. The Formulation

The proposed framework is illustrated in Figure 1. Sensor fault characterization is done at two tiers—a local tier and a global tier. The local FDIR exploits high frequency data available at the sensing node. As shown in Figure 1, the local FDIR uses a model that assumes that the sensor responds to changes in the measurand as a linear dynamical model within a small time window $0 \leq t \leq T$ which is smaller than the time constant of the "event" being tracked by the network. The dynamics of the transducer response model is determined by A, while ν indicates the noise introduced in the transducer. B is indicative of bias introduced in the sensor. C is the calibration or the gain factor, while ϵ signifies the noise introduced by the sensor electronics.

$p \iff \{A, B, C, Q, R\}$ defines the parameters for the local sensor model. Sensor behavior (normal and faulty) is described as labeled regions in this 5-dimension parameter space. Let $p_0 \iff \{A_0, B_0, 1, Q_0, R_0\}$ defines

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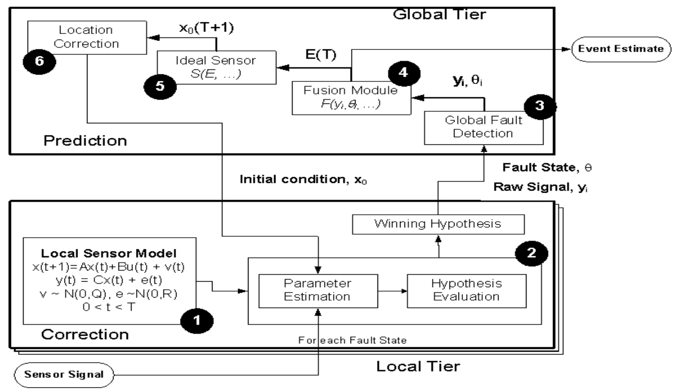

Fig. 1. The proposed two-tier framework for sensor fault detection

baseline values for a no-fault sensor. The sensor FDIR problem (block labeled 2 Figure 1) is a two-step process of parameter estimation and hypothesis evaluation.

State θ_0: Normal.	Estimate R.	$H_0 : R = R_0$
State θ_1: Noisy.	Estimate Q.	$H_0 : Q > q^u$
State θ_2: Frozen.	Estimate Q.	$H_0 : Q < q^l$
State θ_3: Saturation.	Estimate C.	$H_0 : \lvert C\rvert > c^l$
State θ_4: Bias.	Estimate B.	$H_0 : B > b^u, B < b^l$
State θ_*: Unknown.	None of the above	

Algorithmically, baseline values p_0 are established using no-fault data and the thresholds are expressed as a percent of this baseline value. At each time T interval, the ith sensor tier based on its measurements classifies the incoming signal into one of pre-enumerated fault states θ_k and this augmented information is sent to the global tier.

The global fault detection (labeled 3 in Figure 1) may further exploit the analytic and physical redundancy to augment the local fault detection algorithm. The global tier also includes a fusion module that estimates the event of interest E every T interval of time. It fuses $y_i(t)$ along with $\theta_{k,i}$ from all N sensors to calculate $\hat{E}$ which is the event of interest. We call this fault aware fusion $\mathcal{F}$. The estimated value $\hat{E}(T)$ is then fed to an ideal sensor model $\mathcal{S}$, which *predicts* what the sensor reading should be given the event. This is a no-fault ideal sensor prediction model. An optional module may correct this predicted value to account for sensor location. This value is provided as a feedback to the local tier as x_0 for the next round of FDIR calculation.

Continuous feedback from the global tier to the local tier formulates a predictor-corrector scheme wherein (1) a faulty sensor is progressively isolated (2) a fault-aware fusion progressively discounts information provided by a fault sensor; and (3) contributes positively towards network QoI.

III. Application

TABLE I
APPLICATION SCENARIO PARAMETERS

Parameters	Application 1	Application 2
Source or Ground Truth:		
Signal, $E^*(T)$	50	$200 + 300 * (1 - e^{-T/3})$
Location	$(2, 2)$	$(0, 0)$
Time period	$0 \leq T \leq 50$	$0 \leq T \leq 8$
Attenuation, a_k	$1/(1 + d_k^2)$	$T_{diff} = (T_{hot} - T_{amb})$ $- \log(T_{diff})/(d_k^2 + e_k^2)$
Prop. Delay, τ_k	d_k/ν ($\nu = 344m/s$)	n/a
Sensor Network:		
Number	4	10
Location	$(1, 1), (5, 1), (5, 5)$ $(1, 5)$	$(-5, 27), (-10, 18)$ $(4, 22), (17, 14), (-24, -9)$ $(-27, 10), (-15, 13), (25, 9)$ $(-30, 0), (12, 21)$
Noise Var. σ_{s_k}	$1, \forall k$	$1, \forall k$
Fault Injection:		
Sensor	1	3
Type	Multiplicative bias	Additive bias
Signature	$0.5, T \geq 1$	$-4°C, 30 < T < 50$

A. Acoustic Event Detection

In this application, the affect of fault detection and event detection coupling is studied. The scenario parameters are listed in table I. Location of sensors, source and source signal are known while the time of event occurrence is unknown. In the specific studied scenario, we have assumed one of the worst cases where the closest sensor to the event has a multiplicative bias of less than one (0.5). A local tier running at nodes uses a Bayesian event detection hypothesis test along a local fault detector. At each T, local tier detect faults by checking the estimated parameters with their acceptable bounds, as figure 2 shows, for sensor 1, parameter B doesn't stay in the acceptable bound, which shows the presence of fault at it.

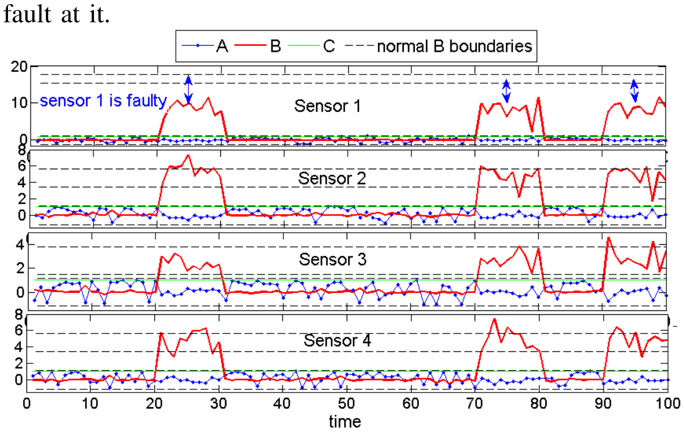

Fig. 2. Trace of Model Coefficients

After each T, global tier receives local detection decisions along with fault notification. Global tier cross validates the fault notifications and removes the faulty sensors from the process of event detection for that time frame. In global fusion of event detection different sensors have different weights, the closer sensors have higher weights in fusion. The global fault detector use the fault notifications and also distance information to make a more robust final decision on event detection. Final decision will be sent back to local tiers to provide the initial state for the local models. As figure 3 shows for the whole scenario period (100 time units), event occurs 3 times. Figure 3 shows our two-tiered architecture has efficiently improved the event detection at presence of fault and it showed that without that there is more chance to make wrong decisions.

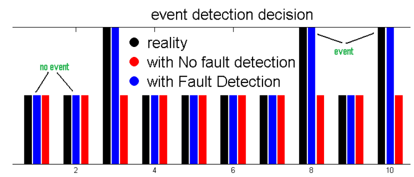

Fig. 3. comparing decisions for different cases

B. Hot spot Intensity Estimation

In this application, the affect of fault detection and event intensity estimation is studied. The scenario parameters are listed in table I. Location of sensors, source and source signal are known while the intensity of a hotspot is unknown.
Our task is to generates estimates for the hotspot intensity $\hat{E}$ using the sensor network, once every minute. The fault aware fusion function $\mathcal{F}$ is a 2D lookup table—which maps the hotspot temperature with the average value provided by all sensors in the network at time T. If the ith sensor was detected to be misbehaving, we did not use it in the average calculation. The ideal no-fault sensor model $\mathcal{S} = \mathcal{F}^{-1}$ and hence the same x_0 is fedback from the global tier to each local sensor FDIR model. The local FDIR model parameters are calculated using 10 samples within each 1 minute window. p_0 parameters are established using measurements within the first 7 minutes.

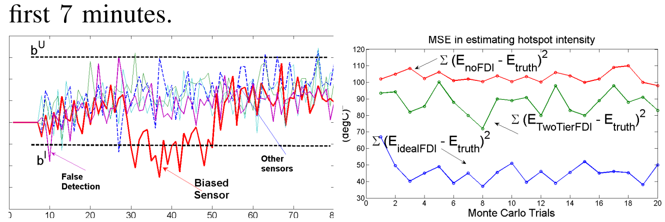

Fig. 4. (A): Trace of Model coefficient B (B): Ground truth estimation error with and without sensor FDIR

Figure 4(A) shows the trace of the model parameter B. It clearly shows that the 'sensor bias" fault hypothesis is established between $30 - 50$ minutes. Figure 4 that the 2-tier sensor FDIR framework consistently produces lesser estimation error and consequently higher network QoI.

IV. Conclusions

The work presented in this short short paper shows some initial results in using the 2-tier framework for detecting sensor faults within a sensor network application.

References

[1] B. A. and B. M., *Detection of Abrupt Changes in Signals and Dynamical Systems*. Springer Berlin / Heidelberg, 1984.
[2] W. Qin, S.J. Li, "Detection and identification of faulty sensors in dynamic processes with maximized sensitivity," in *AIChE Journal*, 2001.