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OPTIMISATION OF THE VLSI ARCHITECTURE IN WIRELESS SENSOR NETWORK

Anil durgam[1] L.Rajeshwar Reddy[2]

[1]M.tech student, ECE , LIET Hyderabad, Andhra Pradesh, India Email: durgam.anil1@gmail.com
[2]Asst.Professor, ECE Dept., LIET Hyderabad, Andhra Pradesh, India Email: lotukal.rajesh@gmail.com

ABSTRACT

Optimisation of vlsi architecture in wireless sensor network (WSN) scheme for fusion centre to detect the faults of sensor nodes via efficient collaborative sensor fault detection (ECSFD), these scheme identifies the sensor node fault percentage and its efficiency of the particular sensor node. In real world most of the applications of WSN are based on ASIC and the standalone devices. So this optimized efficient collaborative wireless sensor fault detection scheme is less expensive area of the chip is very less and fast in performance.

***Index Terms* — Wireless sensor network, Collaborative sensor fault detection, Efficient collaborative sensor fault detection, Fusion centre, Fault detection.**

I. INTRODUCTION

Now a day's utilization of wireless sensor network is rapidly increasing. Day by day we were changing our network to fastest and wireless type. wireless sensor network giving new challenges to engineers and researchers .it is having wide varieties of applications like home appliances, weather detection and remote sensing applications, battle field surveillances ,agricultural technology and many more.

The wireless sensor network is having energy efficient and fault tolerance characteristics, these characteristics performs the scalability and fault tolerance [1][2]. These factors are vary much important in wireless sensor network. at fusion centre estimating the sensor faults and detecting the errors and making them availability. Then the performance will increase the entire network. The distributed estimation system has increased speedily in the recent years [3-5]. In the practical networks fault tolerance is a major concern. The sensor nodes works with battery power. Sensor nodes are deployed at randomly and they are not easy to replace. Sensor nodes are damaged due to weather conditions .for solving this problem we are proposing efficient collaborative sensor fault detection scheme by optimising the architecture in wireless sensor networks [6].

We have proposed collaborative fault detection (CSFD) scheme [6] to detect the faulty nodes within the network such that their quantized messages can be excluded from the parameter estimation process. CSFD takes the concept of collaborative signal processing to perform robust distributed estimation. Specifically, this work employs the homogeneity test [10] to implement CSFD scheme to detect the faulty nodes within the network such that their quantized messages can be excluded from the parameter estimation process.

As predicted, CSFD performs better than the conventional approach in estimating theta in terms of different sensor faulty types and faulty number In the detecting process, CSFD requires such extensive computations as logarithm and division though it achieves very good performance some VLSI circuits for transmitter, receiver, demodulator, sensor node, and specific detector in WSN have been presented Illustrates the basic structure of the distributed estimation network considered in the present study. The Bayesian formulation is considered here. Let $S=\{s_{1,},s_2....s_n\}$ be a finite set corresponding N to the sensor nodes observing sensor measurement sequences generated from a common status of phenomenon θ € Θ , the parameter under estimation. It is assumed that the distribution θ of is known and is denoted by p(θ).The observation sequences taken by sensor s_n are denoted by $\{x_n^t\}_{t=1}^{\infty}$, where n is the node index and t is the time index. Every sensor node quantizes its own observations x_n^t to output m_n^t and send it to the fusion center. The local messages m_n^t are mapped to a binary signal vector b_n^t =(b_{n1}^t .,m_{nG}^t)where $G=\log_n^M$ is the number of bits used to represent the local message and is the number of partition levels at the local sensors.

In the distributed estimation network shown in Fig. 1, two types of errors may affect the received quantized messages at the fusion center. The first error is caused by the faulty node. The considered WSN herein is very possible to contain faulty nodes because of random deployment in a harsh environment. The second error is the channel transmission error due to interference or noise. In this situation, the received m_n^t at the fusion center may not be equal $\hat{m}_n^t$ to and we denote $\Pr[\ddot{b}_{nj}^t \neq \hat{b}_{nj}^t]$ by for all t and n.

Consider the case where the fusion center estimates θ at some arbitrary time T . Note that in performing this estimation process, all the messages received from the local nodes up to time T, i.e, $\hat{\boldsymbol{m}}_{\boldsymbol{n}}^{\boldsymbol{t}} = \{\{\hat{m}_n^t\}_{t=1}^T, \ldots, \{\hat{m}_N^t\}_{t=1}^T\}$, are available at the fusion center. If sensor faults exist within the network, the estimated value of θ is liable to deviate significantly from the true value. To solve the problem, CSFD adopts the concept of collaborative signal processing to identify the faulty nodes$\{S_n\}= F_T$ where F_T is the set of faulty nodes at

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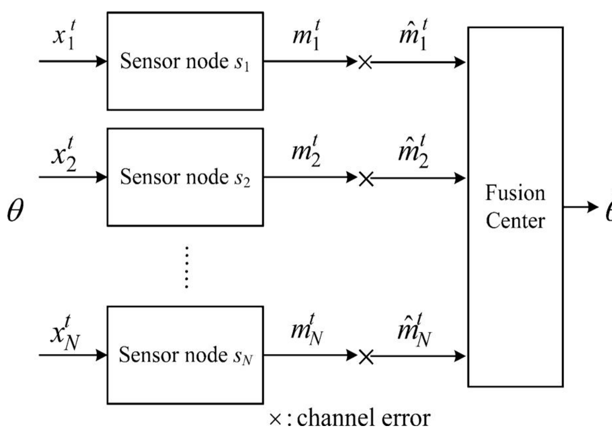
time. Then, the fusion center can eliminates the local message associated with these nodes $\{S_n\}$ € F_T and makes the final estimate $\theta^{\wedge n}$ at time T , based only on the censored messages, $\{\{\hat{m}_n^t\}_{t=1}^T\}_{n\in S\backslash F_T}$, where n €$\{S_n\}/F_T$ denotes $n \in S$ and $n \notin F_T$.



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ig 1. System model for distributed estimation fusion scheme

In CSFD, the following sensor fault models are considered in order to include different misbehaviour. Given M partition levels $\{q_k = 1,....,M\}$ for the quantizer $p_{i|\theta} = \Pr[\hat{m}_n^t = q_i|\theta]$, then we denote when node S_n operates in a fault-free manner. In one fault model, the output of local quantizes is independent of the parameter θ. For example, a stuck-at fault may occur in which the output of the affected node is frozen at a fixed quantization level. Alternately, a random fault may arise in which the distribution of the output of a faulty node is different from the normal situation and equals a particular value regardless of the true parameter. By contrast, some nodes may exhibit a θ dependent error in which a sensor offset bias transforms the sensor measurement uniformly to a certain value and therefore alters the value of $\Pr[m_n^t | \theta]$.

The process of CSFD can be divided into three stages. The first stage is to measure the faulty weights of all nodes. Then, the faulty nodes are determined. The final distributed estimate is generated in the last stage. The detail of each stage is described as follows.

2. Measuring Faulty Weight*:*

This stage consists of two steps and its aim is to decide the faulty weight of each node. The faulty weight is used to measure the deviation of a node. In first step, we compute the number of Q_n received from sensor S_n and denote it as O_{ni}.

$$o_{ni} = \sum_{t=1}^{T} 1\{\hat{m}_n^t = q_i\},$$

Where is the indicator function. As mentioned in [17], the Kullback–Leibler (K-L) distance between distributions can be used to measure sensor-fault aviation. In CSFD, we use K-L distance to estimate the faulty weights of all sensors. According to the local decisions $\{\{\hat{m}_n^t\}_{t=1}^T\}_{n\in S}$, the K-L distance for node is employed to measure the distribution distance from average sensor weight $(1/N)\sum_{n=1}^N \hat{m}_n^t$ to faulty sensor weight , and is defined as

$$ED_n(\hat{v}_i||\hat{r}_{ni}) = \sum_{i=1}^{M} \hat{v}_i \log\frac{\hat{r}_{ni}}{\hat{v}_i},$$

Where

$$\hat{r}_{ni} = \frac{o_{ni}}{T}$$ And $$\hat{v}_i = \frac{\sum_{n=1}^N o_{ni}}{NT}.$$

Which sensor nodes are faulty, based on the faulty weights computed in the previous stage. First, all sensor nodes are sorted in descending order based on their magnitude $\{ED_n\}_{n=1}^N$ of to get the faulty-weight-oriented sequence $F = \{s_{(1)}, s_{(2)} \dots, s_{(N)}\}$. After F is determined, we can obtain the candidate set of faulty sensors, denoted as $F_{(z)} = \{s_{(1)}, s_{(2)} \dots, s_{(z)}\}$ where is z the possible number of faulty nodes, $F_{(0)}$ and let represent the empty set. ϕ. In order to determine the value of, the following homogeneity testing problem can be formulated to test for the existence of a set of sensor nodes F_T at time T.

$$H_0 : \Pr[\hat{m}_n^t = q_i|\theta] = p_{i|\theta} \quad \text{for all} s_n \in S\backslash F_T;$$
$$H_1 : \text{otherwise}.$$

Then, the following statistics are utilized for homogeneity testing to determine whether or not a candidate set F_T is F_T:

$$H(S\backslash\tilde{F}_T) = \sum_{n=1}^{N} 1\{s_n \in S\backslash\tilde{F}_T\} \sum_{i=1}^{M} \frac{(o_{ni} - e_i)^2}{e_i},$$

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Where

$$e_i = \frac{\sum_{n=1}^{N} 1\{s_n \in S\backslash\tilde{F}_T\} o_{ni}}{N - |\tilde{F}_T|}.$$

Utilizing the statistic $H(S\backslash F_T)$, the binary hypothesis testing problem given in (4) can be set as follows:

$$H_0 : H(S\backslash\tilde{F}_T) < \chi^2_{1-\alpha,(N-|\tilde{F}_T|-1)(M-1)};$$
$$H_1 : H(S\backslash\tilde{F}_T) > \chi^2_{1-\alpha,(N-|\tilde{F}_T|-1)(M-1)};$$

Where $\chi^2_{1-\alpha,(N-|\tilde{F}_T|-1)(M-1)}$ is a threshold indicating the critical value of the chi-square distribution with $(N-F_T-1)(M-1)$degrees of freedom at a significance level α.

3.EFFICIENT CSFD:

CSFD performs better than the conventional approach with regard to fault tolerance. However, there are three difficulties to be overcome for implementing CSFD with a VLSI circuit. The first one is that it requires some extensive and complex computations, such as logarithm and division in the detecting process (see [2][6]. The second difficulty is that the integration required for the estimate of θ_n in [7] is quite complex. The last difficulty is that the calculation of numerical integration needs many bits. In order to overcome these difficulties, we modify CSFD and propose an efficient collaborative sensor fault detection (ECSFD) scheme in this paper. ECSFD is simple and requires lower computational complexity, thus lower hardware cost and power consumption can be achieved. Furthermore, ECSFD achieves almost the same performance as CSFD.

3.1Simplify the Integration

However, minimum MSE in (7) needs integral operation which is difficult for hardware implementation. Therefore, the numerical integration is used in the stage of making distributed estimation (7) can be written in the following form:

$$\begin{aligned}\hat{\theta}^{(T)}_{\mathrm{MSE}} &= \mathrm{E}\left[\theta | m_n^t \in S\backslash F_T\right] \\ &= \int \theta P\left(\theta \,|\, m_n^t \in S\backslash F_T\right) d\theta \\ &= \frac{\int_{\theta=-\infty}^{\infty} P(m_n^t \in S\backslash F_T|\theta)P(\theta)\theta d\theta}{\int_{\theta=-\infty}^{\infty} P(m_n^t \in S\backslash F_T|\theta)P(\theta)d\theta};\end{aligned}$$

Where (13)

$$P\left(m_n^t \in S\backslash F_T|\theta\right) = \prod_{m_n^t \in S\backslash F_T} f(m_n^t = q_i|\theta).$$

In the issue of wireless communication, the additional noise model can be reasonable assumed as a Gaussian function $(0, \sigma_w^2)$. Therefore, $f(m_n^t = q_i|\theta)$ can be given as

$$f\left(m_n^t = q_i|\theta\right) = \int_{x_n^t \in L_i} \frac{1}{\sqrt{2\pi\sigma_w^2}} e^{\frac{-(x_n^t-\theta)^2}{2\sigma_w^2}} dx_n^t,$$

Where denotes the quantized range of .Let $f_i^\theta = f(m_n^t = q_i|\theta)$ and denote the number of received from in the fusion centre. Then $\hat{\theta}^{(T)}_{\mathrm{MSE}}$ can be calculated by the following equation:

$$\hat{\theta}^{(T)}_{\mathrm{MSE}} = \frac{\int_{-\infty}^{\infty} \Pi_{i=1}^{M} \left(f_i^\theta\right)^{Q_i} P(\theta)\theta}{\int_{-\infty}^{\infty} \Pi_{i=1}^{M} (f_i^\theta)^{Q_i} P(\theta)}.$$

(15) Using the numerical integration $\hat{\theta}^{(T)}_{\mathrm{MSE}}$, can be approximated by integrating from to with an interval(16)

$$\hat{\theta}^{(T)}_{\mathrm{MSE}} = \frac{\sum_{\theta=-a}^{b} \Pi_{i=1}^{M} \left(f_i^\theta\right)^{Q_i} P(\theta)\theta}{\sum_{\theta=-a}^{b} \Pi_{i=1}^{M} \left(f_i^\theta\right)^{Q_i} P(\theta)}.$$

In addition, the value of , and are decided according to the prior distribution of θ.

3.2Transform the Numerical Integration:

However, the bit width required for the numerical representations of the numerator and the denominator in (16) are quite large when is large enough. With the aid of logarithm property, we transform and to and $\sum_{\theta=-a}^{b} \Pi_{i=1}^{M} (f_i^\theta)^{Q_i} P(\theta)\theta$, which need smaller bit

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width, respectively. Hence, $\sum_{\theta=-a}^{b} \Pi_{i=1}^{M} (f_i^\theta)^{Q_i} P(\theta)$ to $\log \sum_{\theta=-a}^{b} \Pi_{i=1}^{M} (f_i^\theta)^{Q}$ can be rewritten as

$$\hat{\theta}_{\mathrm{MSE}}^{(T)} = \frac{\sum_{\theta=-a}^{b} 2^{\sum_{i=1}^{M} \left(Q_i \times \log_2 f_i^\theta\right) + \log_2 P(\theta) + \log_2 \theta}}{\sum_{\theta=-a}^{b} 2^{\sum_{i=1}^{M} \left(Q_i \times \log_2 f_i^\theta\right) + \log_2 P(\theta)}} = \frac{2^{D_1} + 2^{D_2} + \cdots + 2^{D_i}}{2^{G_1} + 2^{G_2} + \cdots + 2^{G_i}}.$$

Then, all the items of the numerators and denominators are sorted to find the one with the maximum exponent denoted as 2^{Max}. According to the found value, all the other items which satisfy Max – D_i<10 or Max-G_i<10or are selected to calculate the value of approximated $\hat{\theta}_{\mathrm{MSE}}^{(T)}$. The selected items are times larger than the ignored ones.) With the aid of the logarithm and the sorting process, the can be calculated efficiently.

4. CHIP ARCHITECTURE FOR ECSFD:

Observing the required operations in ECSFD, we develop a low-cost VLSI architecture for ECSFD where and is set as 8 and 3, respectively, in the current implementation. This setting, as mentioned in [6], is suitable for general applications in WSN. Furthermore, the word length of signals is decided based on the following two considerations:

a) The performance of ECSFD circuit must be comparable to that of CSFD.
b) The hardware cost of ECSFD circuit must be minimized.

After careful analysis and software simulation, we have chosen the 11-bit widths for representing different signals in the ECSFD circuit to meet the precision requirement and maintain the acceptable performance. The VLSI architecture of ECSFD consists of a logarithm unit, antilogarithm unit, sort unit, register file, 11x11multiplier unit, comparator unit, and adder/subtracter unit connected to a shared bus. A top-level FSM coordinates the operations among these functional units.
ECSFD, the faulty weights of sensors are represented as and is 3 in the current implementation, so we need to find the three biggest values from these eight

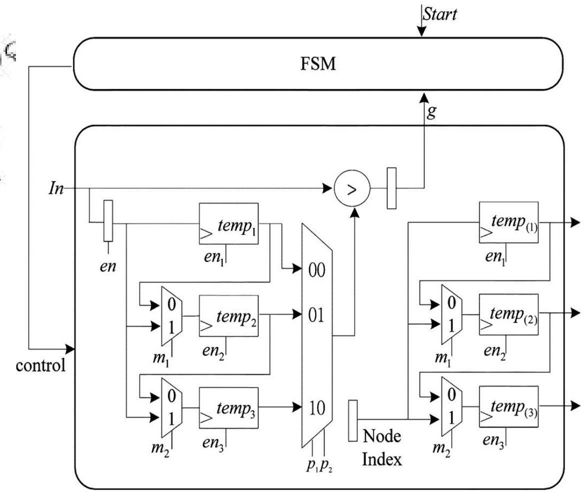

Fig 2. The structure of the sort module

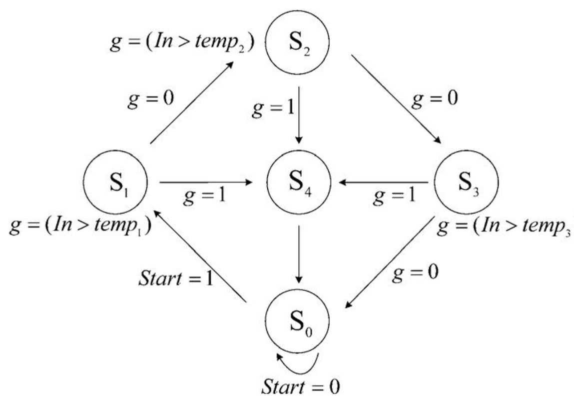

Fig 3. The state diagram of the sort module

numbers and identify their node indexes for the following usage. The order of the other five smaller values is not important. Since , and are calculated and generated sequentially in the previous stage, we design a special purpose insertion sorting circuit which maintains both the three bigger values and their indexes through the whole sorting procedure. Fig 3.7 shows the structure of controller and data path in sort module. Moreover, the state diagram of sort module. The calculated data are inputted to the sort module one by one in turn. The start signal will initialize the three registers with a small number and enable the sorting procedure. The current input is compared with the values in one by one from to, and the control signal will be set as 1 if the input is larger than. As soon as, the replacing procedure at is performed to save the current input to a proper register. Thus, the input value can be inserted to an appropriate position and is satisfied. The

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sort module spends 1 to 3 clock cycles to find the appropriate position or inserting the input, and the replacing operation needs another 1 clock cycle. The corresponding sensor numbers are recorded in the three registers and will be finally outputted

RESULTS:

after the synthesis and simulation result is shown in below of the wireless sensor network.

Device Utilization Summary (estimated values)			
Logic Utilization	Used	Available	Utilization
Number of Slices	59	4656	1%
Number of Slice Flip Flops	55	9312	0%
Number of 4 input LUTs	135	9312	1%
Number of bonded IOBs	35	232	15%
Number of GCLKs	1	24	[illegible]

CONCLUSION:

The results obtained on testing the hardware are satisfactory and the design is ready to be scaled for a full fledged Wireless Sensor Network. The objective of power reduction in the nodes has been realized. With the use of more sophisticated fabrication of the hardware this design is ideal to be used for implementation of various commercial and industrial applications. With regard to WSNs we may conclude that they have the potential to transform communications. Integrating WSNs with existing services is also a possibility which promises to usher in a revolution in communication technology. Unlike other networks, WSNs are designed for specific applications. Applications include, but are not limited to, environmental monitoring, surveillance systems, military target tracking and context aware homes. In the future, WSNs are expected to become integral parts of our lives through various such applications. Each application differs in features and requirements. To support this diversity of applications, the development of new communication protocols, algorithms, designs, and services are needed.

Using CSFD and ECSFD error detecting techniques in WSNs we will get the faulty nodes in the data matching. by detecting data match process we will get the desired output, when out data is matched with the input data.

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