SERIAL DISTRIBUTED DETECTION STRATEGIES FOR WIRELESS SENSOR NETWORKS

by

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FOR WIRELESS SENSOR NETWORKS

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ABSTRACT

SERIAL DISTRIBUTED DETECTION STRATEGIES FOR WIRELESS SENSOR NETWORKS

The interest in wireless sensor networks (WSNs) has been significantly increased over the past years due to their promising future in wide range of application areas like health, military and home. Various technical issues of WSNs have been investigated recently such as topology management, efficient routing protocols and collaborative signal processing. This thesis considers serial distributed detection in WSNs. Unlike traditional distributed detection algorithms where error-free transmissions of local decisions to the fusion center are assumed, lossless communication is not applicable in WSNs since wireless transmission channels are subjected to fading and interference. Suggested distributed detection algorithms in WSNs should deal with the channel uncertainty due to fading and noisy effects of non-ideal channel under low power transmission.

In this thesis, we first propose suboptimal fusion rules to the optimal fusion rule for serial distributed detection. In particular, we derive the low and high SNR approximations of the optimal rule in order to relieve some requirements of the optimal fusion rule. Then, we investigate effects of node failure to the serial distributed detection performance and we suggest more robust decision fusion rules under node failure. Lastly, we analyze effects of decision feedback at serial network topology. In order to improve serial distributed detection performance we propose feedback strategies and derive appropriate decision fusion rules for suggested strategies.

ÖZET

TELSİZ DUYARGA AĞLARDA DAĞITIK SERİ SEZİMLEME STRATEJİLERİ

Sağlık, askeri ve ev gibi çok değişik uygulama alanlarında gelecek vaadeden telsiz duyarga ağlarına ilgi son yıllarda önemli ölçüde arttı. Telsiz duyarga ağlarında topoloji yönetimi, etkili yol saptama protokolleri, ortak sinyal işleme ve buna benzer çeşitli teknik sorunlar incelenmeye başlandı. Bu tezde, telsiz duyarga ağlarda dağıtık seri sezimleme algoritmaları incelenecektir. Geleneksel duyarga ağlarında lokal duyarga kararlarının hatasız olarak tümleştirme merkezine iletildiği farzedilmektedir. Geleneksel duyarga ağlarının aksine, kablosuz iletim kanalı sönümlemeye ve girişime maruz kaldığı için telsiz duyarga ağlarda kayıpsız haberleşme öngörülemez. Telsiz duyarga ağları için önerilen dağıtık sezimleme algoritmalarında, düşük güç iletiminde kanalın sönümleme ve gürültü etkilerini de hesaba katmalıdır.

Bu tezde, ilk olarak dağıtık seri sezimleme için en iyi kaynaşım kuralına alt kaynaşım kuralları önerilmektedir. Daha da özel olarak, en iyi kaynaşım kuralının gereksinimlerini azaltmak için düşük ve yüksek işaret-gürültü oranlarında (SNR) en iyi kaynaşım kuralına yaklaşımlar elde ettik. Daha sonra, duyargaların kullanım dışı olduğu durumlarda dağıtık seri sezimleme performansının nasıl etkilendiğini inceledik ve duyargaların kullanım dışı olduğu durumlarda daha gürbüz çalışan karar kaynaşım kuralları önerdik. Son olarak, karar geribeslemelerinin dağıtık seri sezimlemeyi nasıl etkilediğini inceledik. Dağıtık seri sezimleme başarımını arttırmak için geribesleme yöntemleri önerdik ve bu yöntemlere uygun karar kaynaşım kuralları türettik.

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Dedicated to my family…

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1. INTRODUCTION

The interest in wireless sensor networks (WSNs) has been significantly increased over the past years due to their promising future in wide range of application areas like health, military and home. Various technical issues of WSNs have been investigated recently such as topology management, efficient routing protocols and collaborative signal processing. In this thesis, we consider serial distributed detection in WSNs. Distributed detection in traditional sensor applications like sonar and radar networks had gained a great research interest in the 90s. In traditional sensor applications, error free transmission of local sensor decisions to the fusion center assumption is made. Error free transmission can be realized with transmitting decisions at high power, using powerful error correction coding and very complex signal processing algorithms which consume considerable power of each node. However, power consumption is one of the primary challenges in WSNs. For that reason, assumption of error free transmission is not applicable in WSNs. Non ideal transmissions in WSNs require considering the distributed detection process together with transmission process. Suggested distributed detection algorithms in WSNs should deal with the channel uncertainty due to fading and noisy effects of non-ideal channel under low power transmission. There are different topologies for distributed detection applications like parallel, serial and tree configurations. In this thesis, we consider serial network topology. Importance of serial network topology comes from that, in large scale WSNs, it enables multi hop transmission which is more energy efficient compared to single hop transmission as in the case of parallel network topology. In literature, optimum decision fusion rule for serial distributed detection in WNS was analyzed. However, as for as our knowledge, there is no more detailed study about serial distributed detection in WSN. In this thesis, we aim to extend studies about serial distributed detection in WSNs.

1.1. Thesis Contributions

This thesis has 3 main contributions: suboptimal fusion rules have derived for serial distributed detection to relieve some requirements of optimal fusion rule and decrease computational complexity, more robust decision fusion rules have proposed under node failure case and decision feedback strategies for serial distributed detection have suggested which improve detection performance considerably.

In more detail, firstly we propose suboptimal fusion rules for serial distributed detection in WSNs. Optimal decision fusion rule for serial distributed detection requires performance indices of previous sensor node and the channel state information (CSI). We propose the low and high SNR approximation to the optimal decision fusion rule which relieve some requirements of the optimal decision fusion rule and decrease computational complexity. We observe that simplified decision fusion rules approach to the performance of the optimal fusion rule at high and low channel SNR respectively.

We investigate methods of handling node failure in serial distributed detection. Firstly, we propose the optimal decision fusion rule in case of node failure for existent serial network topology. Then we suggest using more than one previous sensor node decisions and we derive new decision fusion rule for this strategy. Lastly, we combine these two propositions and derive new decision fusion rule which is more complex compared to previous decision fusion rules but which also gives best detection performance in case of node failure.

We also investigate effects of decision feedback to the performance of serial distributed detection. We propose three decision feedback strategies and derive decision fusion rules for these strategies. We observe that, we can increase detection performance of serial distributed detection considerably with decision feedback.

1.2. Thesis Organization

This thesis organized as follows:

In chapter 2, we start by giving a brief introduction to WSNs together with stressing main requirements and challenges of it. After that, we explain difference between distributed detection and centralized detection. At the end of chapter 2, we specifically talk about key aspects of distributed detection in WSNs.

In chapter 3, we firstly give the system model of serial network topology and we give the optimal decision fusion rule for serial distributed detection. Then, we propose simplified decision fusion rules to the optimal decision fusion rule under low and high channel SNR values. We simulate proposed simplifications and compare performance with the optimal decision fusion rule.

In chapter 4, firstly, we investigate reasons of node failure in WSNs and explain how failed nodes can decrease the performance of serial distributed detection. Subsequently, we propose three new decision fusion rules in order to overcome negative affects of node failure to the performance serial distributed detection.

In chapter 5, we present decision feedback strategies for serial distributed detection in WSNs. We investigate effects of decision feedback to the performance of serial distributed detection. Then, we propose three new feedback strategies and derive appropriate decision fusion rules.

And finally, in chapter 6 we conclude our studies and give possible directions for future works.

2. BACKGROUND

2.1. Wireless Sensor Networks

The interest in automatic sensing technologies has been significantly increased over the past years both in academic and industrial research because of their promising future. In fact, the idea of intelligent objects which react and adapt to the environment is not a new subject to research world. However, recent advances in wireless communication and electronics have stimulated development of new low-cost, low-power, multifunctional sensor nodes that are small in size and has communication components which leads the idea of sensor networking [1]. Wireless networking capability of new sensor nodes have gained much more interest compared to classical sensor applications. Although large macro sensors are more sensitive, they are much more expensive compared to new developing sensor nodes. Beside that, tiny sensor nodes can easily be deployed in application area and wireless sensor networks (WSNs) have fault tolerant characteristic. On the contrary, when one macro sensor is broken entire system can fail.

Depending on the requirements of application, size of sensor nodes can vary from the size of a shoebox to the size of grain of dust [2]. Various sizes of sensor nodes that are produced until now is shown in Figure 2.1 where each of them are compared with a coin to visualize their size. Although coin size sensor nodes are currently present in commercial industry, costs of these little sensor nodes make it hard to enable them in wide range of applications. With development in micro-electronics, size of sensor nodes will continue to decrease and their prices will reduce which will facilitate spreading of current applications.

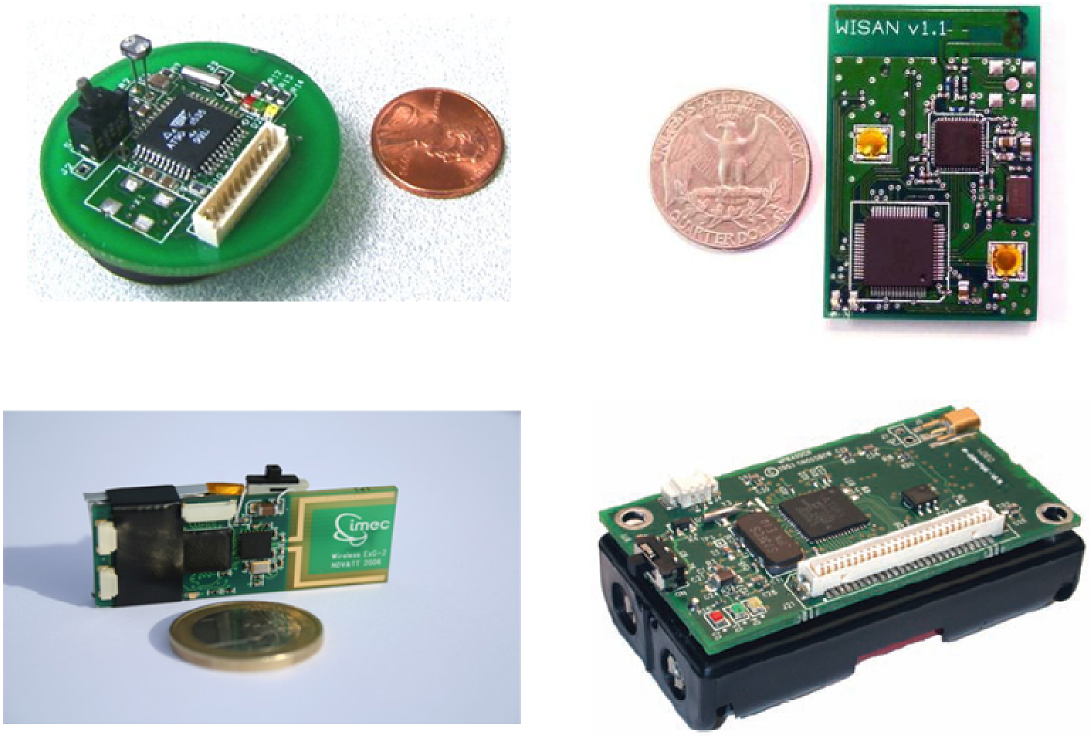

Figure 2.1 Various sizes of sensor nodes depicted in [4]-[7]

Sensor nodes are composed of four main components: sensor device, signal processing unit, communication module and power component [3]. Depending on the requirements of application new module can be added to nodes which increase both size and cost of each node. Main components of a sensor node are depicted in Figure 2.2. Main data flow between each component is illustrated with arrows. Advances in micro electronics technology made available small size and relatively cheap sensors that can collect data of various physical phenomenon like temperature, humidity, pressure, acoustic, photo, moisture and smoke. A sensor node can contain more than one of these sensors together in its hardware which increase usage area of the node. However, it should be kept in mind that adding lots of sensors to a node increase the size of the node and the cost of production.

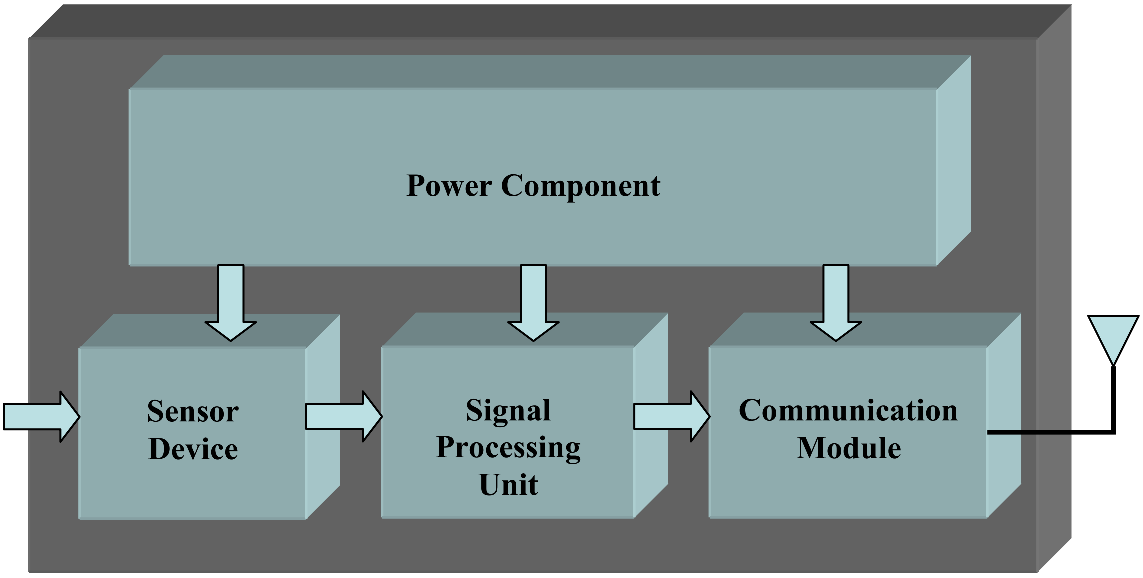

Figure 2.2 Main components of a sensor node

Large numbers of densely deployed sensor nodes in an application region constitute a wireless sensor network which is depicted in Figure 2.3. All sensor nodes in the region collect data about required application and forward their data to a special node referred as the base station or the sink. The base station sends all received and preprocessed data to the user side of application which can be seen as a gateway between wireless sensor networks and application manager side. WSNs have great deal of advantages compared to classical sensor applications due to characteristics of system as investigated in [1]. The positions of these sensor nodes need not to be predetermined in application area which enables random deployment of nodes in unreachable environment. However, this random deployment feature requires self organizing capability of network. Wireless sensor networks are also fault-tolerant since large numbers of sensor nodes are densely deployed and broken sensor nodes do not affect general system performance. The signal processing component of sensor nodes enable processing capability the observed data from the environment and transmit preprocessed data to the required destination which decrease the data traffic on the network. Explained features of WSNs until now ensure a great deal of applications which are described in the remaining of this section.

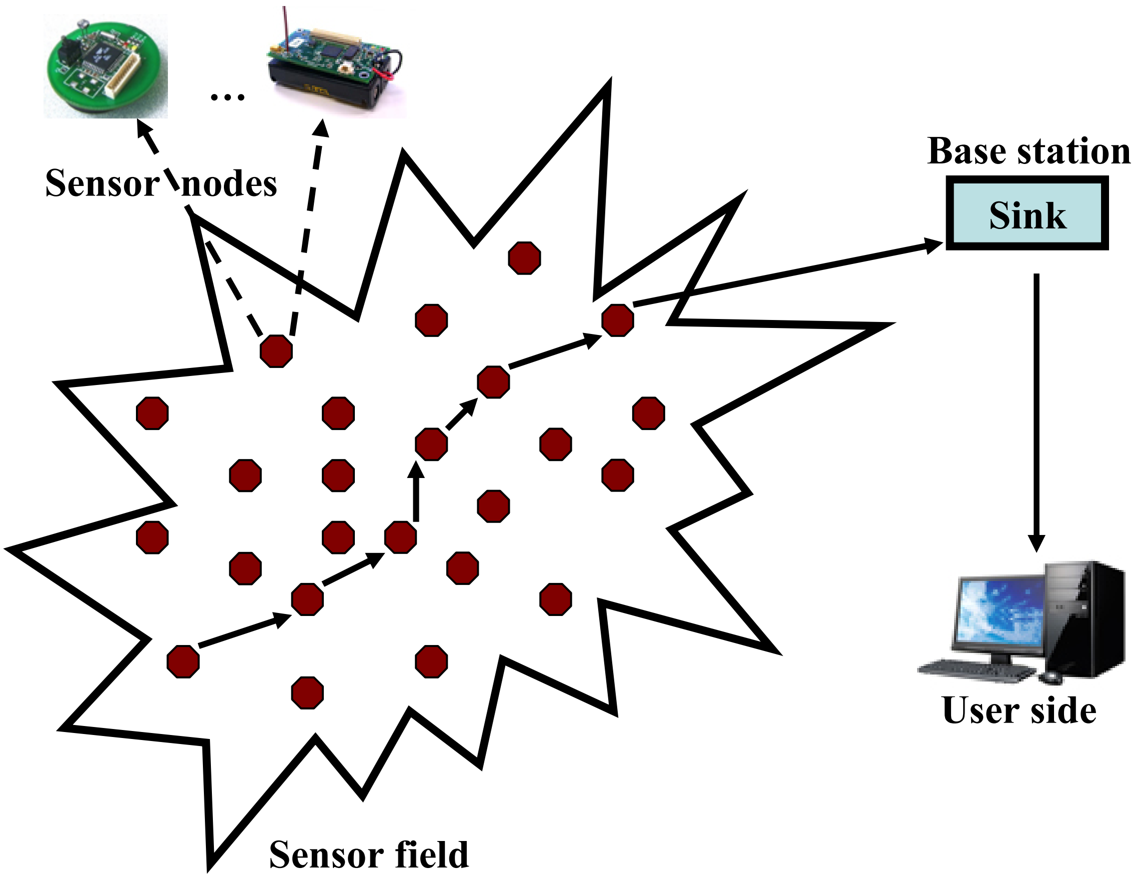

Figure 2.3 Wireless sensor network architecture

Although wireless sensor networks promise unlimited applications, it still has many challenges to be resolved. One of the main challenges is the requirement of long-lived operation for great deal of applications [8]. In unreachable territory, once nodes are randomly deployed, it is not feasible to recharge or change batteries of sensor nodes. For that reason, while realizing wireless sensor network applications limited capacity of batteries should always be considered as one of the most important issues. Energy efficiency of all operations in sensor nodes has been a goal of most studies about hardware and software design as stated in [8]. In [9], a few more research challenges are stated beside energy constrain like security and privacy issues, lack of programming abstraction and real-time requirements of applications. Current security algorithms are not easily applicable for wireless sensor networks applications since these applications have different requirements than traditional network applications. In [9], it is proposed that one of the key issues for development of wireless sensor network applications is programming abstraction for software developers. Lack of this abstraction forces software developers to deal more with low level details which slows down their speed. Real time requirement is also a very important issue that should be dealt properly for some applications like security monitoring or monitoring of forest fires, etc.

Capability of wireless sensor network which combines sensing, processing and communication in their hardware, ensure a wide range of applications. In [10], the author classified applications into three main categories: environmental data collection, security monitoring and sensor node tracking. Majority of wireless sensor network applications can be categorized under these three main classes. Environmental data collection applications requires collecting data from special area at regular intervals, analyzing the data and finally reaching a conclusion about long term trends in that specified area. These kinds of applications require long system lifetime, precise synchronization, low data rates and relatively static topologies [10]. The aim of the second kind of applications is detecting an anomaly in the area and warning the system before the damage happened. Rather than collecting data at regular intervals, each node regularly checks out the environment and only transmits data when there is a security violation. The primary system requirement is immediate and reliable communication [10]. The last category of applications is tracking an object through a region that is monitored by sensor nodes. The object can be tagged which facilitates tracking or it can be untagged like unwanted object in the specified area. These applications can be realized in great range of areas like health, military, commercial and environmental issues due to characteristics of wireless sensor networks like rapid deployment, self organization and fault tolerance [1].

Many aspects of wireless sensor networks including specified challenges have being investigated both in academy and industry. In this thesis, we examine distributed detection task at wireless sensor networks for serial network topology. In the next section, we investigate distributed detection in classical sensor applications and then we specify the special cases that should be taken account in wireless sensor network applications.

2.2. Distributed Detection in Classical Sensor Applications

In distributed detection, all local sensors that are spread over the region carry out some processing for their observation data and then transmit their condensed information to a special node, known as the fusion center, where combination of these local information is performed according to some predetermined fusion rules. On the contrary, in centralized detection, local sensors do not change their observations and they forward exactly the same observation data to the central processing unit.

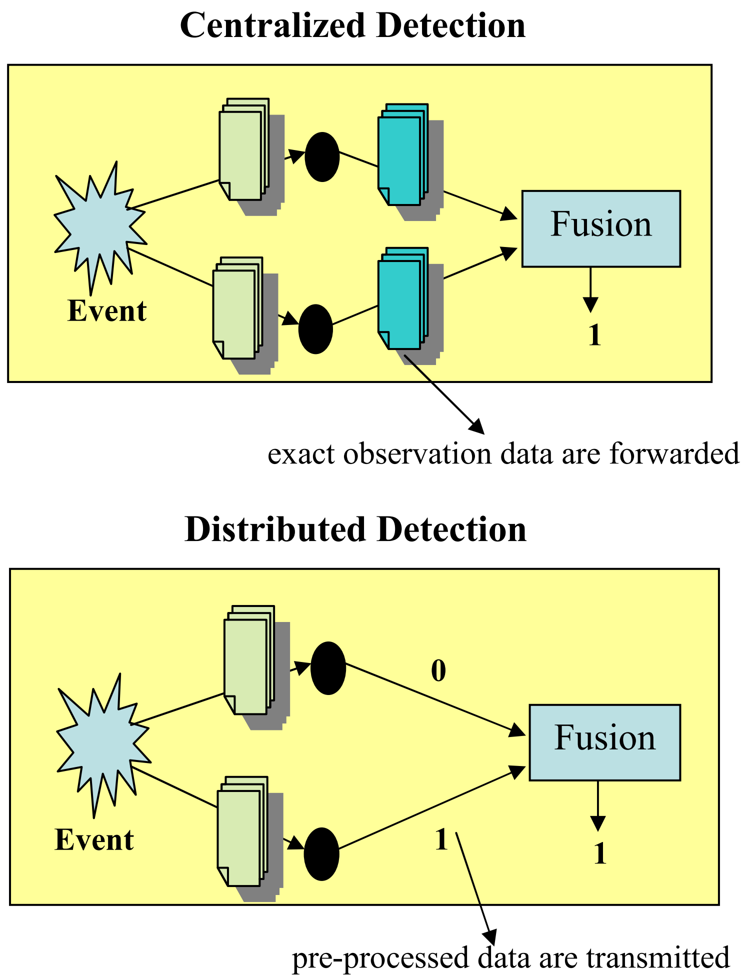

Figure 2.4 Centralized and distributed detection

There is in illustration of difference between distributed detection and centralized detection for binary hypotheses testing, the absence or presence of target, in Figure 2.4. In distributed detection, all local sensors give a decision, 1 or 0 depending on their own observation and transmit their decisions to the fusion center. On the contrary, in centralized detection local sensors are simply data collectors which do not perform any data processing on their observation. Performing some preprocessing on the collected data and transmitting that condensed information to the fusion center reduces communication bandwidth which is an advantage of distributed detection over centralized detection [11]. On the contrary, since fusion center has only partial information about observed data of local sensors, there is a performance loss in distributed detection. This performance loss can be minimized with proper processing of observed data at local sensors and fusion center [12].

Distributed detection in classical sensor applications, where assumption of error free transmissions of local sensor decisions to the fusion center is made, had gained a great research interest in the 90s. Decision rules for local sensors and fusion center under conditional independence assumption of observations were derived in [11], [13] and [14] for both Bayesian and Neyman-Pearson framework and their optimality are proved. Correlated (dependent) observation case which is more intractable compared to conditional independent case was investigated in [15]-[17]. Decision fusion under some communication constraint where optimal bit selection for decision or number of optimal sensor selection for given conditions were considered in [18]-[21]. Distributed detection under non-ideal channel and networking delay consideration was examined by Thomopoulos and Zhang in [22]. In [23], Duman and Salehi looked into transmissions of local sensor decisions to the fusion center over multi-access channel and effect of this multi access channel usage to distributed detection performance. Decision fusion rule under global decision feedback of the fusion center to the all local sensors case and performance improvement under this condition were studied in [24]-[26]. Optimizing local sensors thresholds with person by person optimization (PBPO) under Bayesian approach was suggested in [27]. In the next section, we investigate distributed detection in WSNs where assumption of error free transmission is invalid.

2.3. Distributed Detection in WSNs

Error-free transmissions of decisions can be assumed in traditional sensor applications. However, lossless communication is not applicable in WSNs since power consumption is one of the primary challenges. Error free transmission can be realized with transmitting decisions with high power, using powerful error correction coding and very complex signal processing algorithms which consume undesired energy of nodes [28]. Since additional energy consumption is not wanted in wireless sensor network applications, we have to use low transmission power without using any complex error correction coding. In classical distributed detection applications, there is only the source uncertainty due to noise. Beside the source uncertainty, the distributed detection algorithms in WSNs should also have to deal with the channel uncertainty due to fading and noisy effects of non-ideal channel under low power transmission [29]. These uncertainties of WSNs for distributed detection are depicted in Figure 2.5.

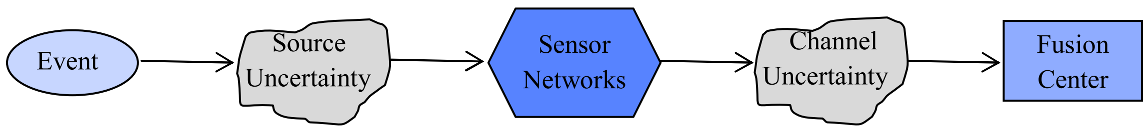

Figure 2.5 Uncertainties in wireless sensor networks

Including channel non-idealities to the decision fusion rule in WSNs have started to being investigated since the beginning of 2000s. In [28], [30] , the authors incorporated the effects of channel non-ideality to the decision process in the fusion center for parallel network structure and they suggested some approximation to the optimal fusion rule which reduce the requirements of the fusion rule. Optimality of decisions rule for serial and parallel network structures were proved in [31], [32] and they derived analytical expressions of false alarm and detection probabilities for fusion nodes. Multi-bit local decisions case was also studied in these proposals. Forwarding local decisions to the fusion center over multi-hop transmission were investigated in [33], [34]. Local optimal decision rules for parallel network structure were studied in [35]. In [36], [37], for large number of sensor nodes more practical decision fusion rule was suggested which simply uses total number of detections received from local sensors. A security mechanism for distributed detection in WSNs was proposed in [38].

3. DISTRIBUTED BINARY DETECTION FOR SERIAL TOPOLOGY

In this chapter, we investigate problem of binary serial distributed detection in WSNs under fading and noisy effects of non-ideal transmission channel. In large scale wireless sensor networks, serial network topology enables multi hop transmission which is more energy efficient compared to single hop transmission as in the case of parallel network topology. Serial network topology can also be used in a part of clustered sensor networks where local sensor nodes need multi hop transmission to reach cluster head node. In the first section, we give the system model of serial network structure in WSNs and state the optimal decision fusion rule under serial network structure which was analyzed in [31]. In the second section, we propose two approximations to the optimal decision fusion rule of serial network topology in the high and low channel SNR values, parallel to the suboptimum fusion rules for parallel distributed detection as proposed in [30].

3.1. Serial Distributed Detection

3.1.1. System Model

In serial network structure, sensor nodes (*SN*) are connected in a way that at each stage sensor node transmits its decision to the next stage over non-ideal channel as shown in Figure 3.1 We assume that sensor nodes in each stage are separated equally.

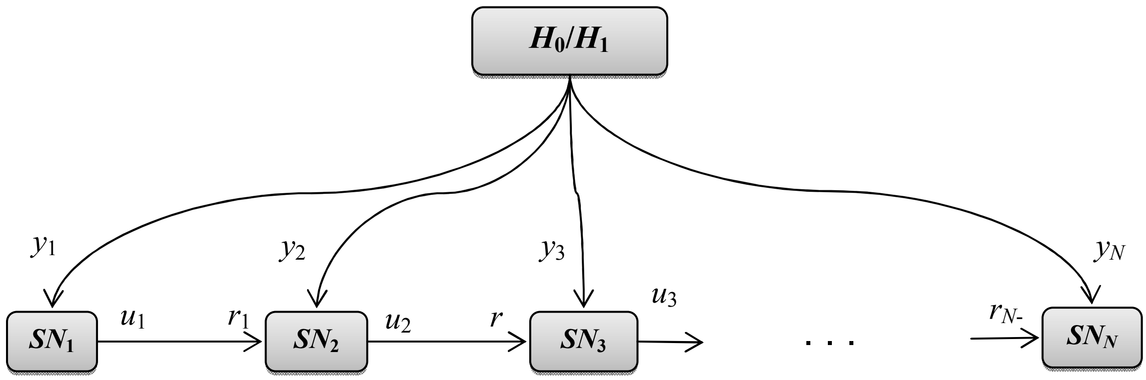

Figure 3.1 Serial fusion network structure in WSNs

We consider detection of a binary event: target-present under the hypothesis H_1 or target-absent under hypothesis H_0. All sensors acquire observations to detect a DC level signal in real additive white Gaussian noise (AWGN) as follows

$$y_j = \begin{cases} m + v_j & , H_1 \\ v_j & , H_0 \end{cases} \tag{2.1}$$

where y_j is observation of *j*th sensor about event, *m* is the DC level signal which is assumed to be one when target is present and zero when target is absent. v_j is observation noise which is assumed to be real AWGN with zero mean and variance of one denoted by $N(0,1)$.

Binary decision at *j*th stage, $u_j \in \{0,1\}$, is based on own observation, y_j, and received signal, r_{j-1}, over which decision of SN_{j-1} is propagated. Assuming coherent detection, received signal model for SN_j in serial network structure is given as

$$r_{j-1} = \sqrt{\rho} g_{j-1} s_{j-1} + n_{j-1} \tag{2.2}$$

where g_{j-1} is the real valued Rayleigh fading channel coefficient between node SN_{j-1} and SN_j, ρ is transmit power gain which is assumed to be same for all nodes, s_{j-1} is binary phase-shift keying (BPSK) modulated decision of SN_{j-1} which can be either 1 when $u_j = 1$ or -1 when $u_j = 0$ and lastly n_{j-1} is receiver electronics noise at each sensor which is assumed to be real AWGN with zero mean and variance of one at SN_j. We assumed phase coherent reception in the receiver node that is why real valued fading envelope and real valued AWGN information are enough for our system model. After SN_j produces a single-bit decision, one level quantization about phenomenon, it forwards its current decision to next stage, SN_{j+1}, over fading and noisy channel. Global decision of system is assumed to be made at last *SN* in the network which will be referred as the global fusion center.

3.1.2. The Optimal Decision Fusion Rule

In previous subsection, it is explained that decision at a stage is based on both current observation of a node and received signal corresponding to the previous node decision. On the Neyman-Pearson (N-P) decision lemma [39], the goal is to maximize detection probability of a sensor, $P_{D,j} = \Pr\left(u_j = 1 \mid H_1\right)$ for given false alarm probability, $P_{F,j} = \Pr\left(u_j = 1 \mid H_0\right)$. Under N-P lemma for binary detection problem, it is shown in [31] that if y_j and r_{j-1} at each stage are conditionally independent for each hypothesis, the optimal decision fusion rule at *j*th stage is appropriate likelihood ratio (LR), given in the following equation

$$\begin{aligned}\Gamma(y_j, r_{j-1}) &= \frac{p\left(y_j, r_{j-1} \mid H_1\right)}{p\left(y_j, r_{j-1} \mid H_0\right)} \\ &= \underbrace{\frac{p\left(y_j \mid H_1\right)}{p\left(y_j \mid H_0\right)}}_{\Lambda(y_j)} \underbrace{\frac{p\left(r_{j-1} \mid H_1\right)}{p\left(r_{j-1} \mid H_0\right)}}_{\Upsilon(r_{j-1})}\end{aligned} \tag{2.3}$$

where $\Gamma(y_j, r_{j-1})$ denotes decision fusion rule based on y_j and r_{j-1}. It is assumed that channel state information (CSI), g_{j-1}, is known to each *SN*. $\Lambda(y_j)$ is the own observation component and $\Upsilon(r_{j-1})$ is the received signal component of decision fusion rule. Since we try to detect a DC level signal, *m*, under real AWGN with zero mean and variance of one at SN_j, explicit form of $\Lambda(y_j)$ becomes as follows.

$$\Lambda(y_j) = \frac{p\left(y_j \mid H_1\right)}{p\left(y_j \mid H_0\right)} = \frac{\frac{1}{\sqrt{2\pi}} e^{\frac{-\left(y_j - m\right)^2}{2}}}{\frac{1}{\sqrt{2\pi}} e^{\frac{-y_j^{\,2}}{2}}} \tag{2.4}$$

Received signal component, $\Upsilon(r_{j-1})$, depends on previous node decision. We can obtain LR of received signal component by summing it over possible values of previous sensor decision under real AWGN with zero mean and variance of one as follows

$$\begin{aligned} \Upsilon(r_{j-1}) &= \frac{p\left(r_{j-1} \mid H_1\right)}{p\left(r_{j-1} \mid H_0\right)} = \frac{\sum_{u_{j-1}} p\left(r_{j-1}, u_{j-1} \mid H_1\right)}{\sum_{u_{j-1}} p\left(r_{j-1}, u_{j-1} \mid H_0\right)} \\ &= \frac{P_{D,j-1} e^{-\frac{\left(r_j - \sqrt{\rho} g_{j-1}\right)^2}{2}} + \left(1 - P_{D,j-1}\right) e^{-\frac{\left(r_j + \sqrt{\rho} g_{j-1}\right)^2}{2}}}{P_{F,j-1} e^{-\frac{\left(r_j - \sqrt{\rho} g_{j-1}\right)^2}{2}} + \left(1 - P_{F,j-1}\right) e^{-\frac{\left(r_j + \sqrt{\rho} g_{j-1}\right)^2}{2}}} \end{aligned} \tag{2.5}$$

Then, LR test (LRT) at the *j*th stage is given by

$$\Gamma(y_j, r_{j-1}) = \Lambda(y_j)\Upsilon(r_{j-1}) \underset{H_1}{\overset{H_0}{\lessgtr}} t_j \tag{2.6}$$

where t_j denotes a threshold value to be determined for jth stage. After LR is calculated according to equations given in (2.4) and (2.5) it is compared with a predetermined threshold value. If LR metric is bigger then predetermined threshold value, existing hypothesis will be decided as H_1 and vice verse if LR metric is smaller than threshold value. In the logarithmic domain, log-likelihood ratio test (LLRT) becomes

$$\Gamma^*(y_j, r_{j-1}) = \Lambda^*(y_j) + \Upsilon^*(r_{j-1}) \underset{H_1}{\overset{H_0}{\lessgtr}} t_j^* \tag{2.7}$$

where $\Gamma^*(y_j, r_{j-1}) = \log\Gamma(y_j, r_{j-1})$, $\Lambda^*(y_j) = \log\Lambda(y_j)$, $\Upsilon^*(r_{j-1}) = \log\Upsilon(r_{j-1})$ and $t_j^* = \log t_j$. It is clear that for the first stage we have $\Upsilon^*(r_{j-1}) = 0$, since first sensor node makes decision using just its own observation.

3.2. Suboptimal Fusion Rules for Serial Distributed Detection

The optimal fusion rule given in equation (2.3), requires complete knowledge of fading channel coefficient, g_{j-1}, and performance indices, $P_{D,j-1}$ and $P_{F,j-1}$, of previous sensor node. In this section, we investigate suboptimal fusion rules which relieve requirements of optimal fusion rule and decrease computational complexity of optimal fusion rule. In [30], the high signal-to-noise ratio (SNR) approximation and low SNR approximation are proposed as suboptimum fusion rules for parallel distributed detection in WSNs. They showed that for the high SNR approximation channel gains are not required for fusion, although it still needs performance indices, detection probability and false alarm probability, of local sensors. On the contrary, in low SNR approximation knowledge of channel gains are required while performance knowledge of local sensor is not needed. In literature, suboptimum fusion rules for serial distributed detection in WSNs have not been studied, as far as our knowledge. In the following subsections, we derive suboptimum fusion rules for serial network structure. Following the same strategy as in [30], we propose two suboptimum fusion rules: the high SNR approximation and low SNR approximation of optimum fusion rule given in equation

(2.3). Own observation component of optimum fusion rule does not change in these suboptimum fusion rules since we approximate received signal component of optimum fusion rule.

3.2.1. The High SNR Approximation

The optimum fusion rule given in equation (2.3) jointly considers the previous sensor output and fading channel effect. For the high SNR approximation of parallel distributed detection, it is suggested to separate this joint process into two stages in [30]. In the first stage, received signal is used to infer about decision of previous stage and then at the second stage, optimum fusion rule is applied to decision estimate of previous sensor node. We follow the same procedure to derive the high SNR approximation for serial distributed detection.

In the first stage, we find maximum likelihood (ML) estimate of previous decision as

$$\hat{u}_{j-1} = sign\left(r_{j-1}\right) \tag{2.8}$$

where *sign* is the signum function and defined as follows

$$sign(x) = \begin{cases} 1 & ,x \geq 0 \\ -1 & ,x < 0 \end{cases} \tag{2.9}$$

According to that, decision estimate takes two possible values, either 1 or -1. Using the decision estimate of previous sensor, received signal component of optimum fusion rule, given in equation (2.5), can be rewritten as

$$\begin{aligned} \Upsilon(r_{j-1}) = \mathrm{I}(r_{j-1}) & \frac{P_{D,j-1} + \left(1 - P_{D,j-1}\right) e^{-2\sqrt{\rho} r_{j-1} g_{j-1}}}{P_{F,j-1} + \left(1 - P_{F,j-1}\right) e^{-2\sqrt{\rho} r_{j-1} g_{j-1}}} + \\ \left(1 - \mathrm{I}(r_{j-1})\right) & \frac{P_{D,j-1} e^{2\sqrt{\rho} r_{j-1} g_{j-1}} + 1 - P_{D,j-1}}{P_{F,j-1} e^{2\sqrt{\rho} r_{j-1} g_{j-1}} + 1 - P_{F,j-1}} \end{aligned} \tag{2.10}$$

where $\mathrm{I}(r_{j-1})$ is an indicator function and it is used to separate received signal component into two parts according to decision estimate. The indicator function is defined as

$$\mathrm{I}(r_{j-1}) = \begin{cases} 1 & ,\hat{u}_{j-1} = 1 \\ 0 & ,\hat{u}_{j-1} = -1 \end{cases} \tag{2.11}$$

If decision estimate, $\hat{u}_{j-1}$ equals to 1, the indicator function becomes 1 which states that only the first part of the fusion rule in equation (2.10) is used where second part equals to zero. On the contrary, if decision estimate, $\hat{u}_{j-1}$ equals to -1, the indicator function becomes 0 and as a result of that the second part of fusion rule turns out to be effective while first part equals to zero.

For the high SNR approximation, we fix noise power to a certain level and increase signal power. We assume that transmit power gain at each node goes to infinity, $\rho \to \infty$, at high SNR. As $\rho \to \infty$, $e^{-2\sqrt{\rho} r_{j-1} g_{j-1}} \to 0$ in the first part of the fusion rule given in (2.10) since r_{j-1} is assumed to be positive. With the same reasoning, we can show that $e^{2\sqrt{\rho} r_{j-1} g_{j-1}} \to 0$ in the second part of the fusion rule since r_{j-1} assumed to be negative. Using these approximations we can rewrite equation (2.10) as

$$\lim_{\rho \to \infty} \Upsilon(r_{j-1}) = \mathrm{I}(r_{j-1}) \frac{P_{D,j-1}}{P_{F,j-1}} + \left(1 - \mathrm{I}(r_{j-1})\right) \frac{1 - P_{D,j-1}}{1 - P_{F,j-1}} = \Upsilon_{high-SNR}(r_{j-1}) \tag{2.12}$$

and when we take logarithm of both sides we obtain log version of the high SNR approximation as

$$\lim_{\rho \to \infty} \log\left(\Upsilon(r_{j-1})\right) = \log\left(\mathrm{I}(r_{j-1}) \frac{P_{D,j-1}}{P_{F,j-1}} + \left(1 - \mathrm{I}(r_{j-1})\right) \frac{1 - P_{D,j-1}}{1 - P_{F,j-1}} \right) = \Upsilon^{*}_{high-SNR}(r_{j-1}) \tag{2.13}$$

Received signal component of optimal fusion rule given in equation (2.5) requires both fading channel coefficient and performance indices of previous sensor node. In the high SNR approximation of optimal fusion rule, expressed in equation (2.13), there is no need to channel gain knowledge anymore, but performance indices $P_{D,j-1}$ and $P_{F,j-1}$ are still required. We relieve channel gain knowledge requirement of the optimum fusion rule with the high SNR approximation. Beside that, the high SNR approximation is less complicated in terms of computational complexity compared to the optimum fusion rule where we have to deal with exponentials.

3.2.2. The Low SNR Approximation

In order to obtain the low SNR approximation of the optimum fusion rule we express optimum fusion rule, given in equation (2.5), as

$$\Upsilon(r_{j-1}) = \frac{P_{D,j-1} + \left(1 - P_{D,j-1}\right) e^{-2\sqrt{\rho} r_{j-1} g_{j-1}}}{P_{F,j-1} + \left(1 - P_{F,j-1}\right) e^{-2\sqrt{\rho} r_{j-1} g_{j-1}}} \tag{2.14}$$

By using first order Taylor polynomial approximation, $e^{-2\sqrt{\rho} r_{j-1} g_{j-1}}$ terms in equation (2.14) is simplified to $1 - 2\sqrt{\rho} r_{j-1} g_{j-1}$. We obtain approximate LR of equation (2.14) as

$$\begin{aligned}\lim_{\rho \to 0} \Upsilon(r_{j-1}) &= \frac{P_{D,j-1} + \left(1 - P_{D,j-1}\right)\left(1 - 2\sqrt{\rho} r_{j-1} g_{j-1}\right)}{P_{F,j-1} + \left(1 - P_{F,j-1}\right)\left(1 - 2\sqrt{\rho} r_{j-1} g_{j-1}\right)} \\ &= \frac{1 - \left(1 - P_{D,j-1}\right)\left(2\sqrt{\rho} r_{j-1} g_{j-1}\right)}{1 - \left(1 - P_{F,j-1}\right)\left(2\sqrt{\rho} r_{j-1} g_{j-1}\right)}\end{aligned} \tag{2.15}$$

We assume that transmit power gain at each node goes to zero, $\rho \to 0$, at low SNR. The logarithmic version of equation (2.15) can be expressed as

$$\lim_{\rho \to 0} \log \Upsilon(r_{j-1}) = \log\left(1-\left(1-P_{D,j-1}\right)\left(2\sqrt{\rho}r_{j-1}g_{j-1}\right)\right) - \log\left(1-\left(1-P_{F,j-1}\right)\left(2\sqrt{\rho}r_{j-1}g_{j-1}\right)\right) \tag{2.16}$$

We can use the fact that $\log(1+x)$ can be simplified as $x+o(x)$ for x close to zero where $o(x)$ denotes a term with $\lim_{x\to 0} = o(x)/x = 0$. Applying this property to equation (2.16), we obtain following equation

$$\lim_{\rho \to 0} \log \Upsilon(r_{j-1}) = -\left(1-P_{D,j-1}\right)\left(2\sqrt{\rho}r_{j-1}g_{j-1}\right) + \left(1-P_{F,j-1}\right)\left(2\sqrt{\rho}r_{j-1}g_{j-1}\right) \tag{2.17}$$

This which can be simplified to get low SNR approximation of equation (2.5) as

$$\lim_{\rho \to 0} \log \Upsilon(r_{j-1}) = \left(P_{D,j-1} - P_{F,j-1}\right) 2\sqrt{\rho}r_{j-1}g_{j-1} = \Upsilon^{*}_{low-SNR}(r_{j-1}) \tag{2.18}$$

It is important to state that, we cannot continue to simplify this equation by scaling it with $P_{D,j-1} - P_{F,j-1}$ and $2\sqrt{\rho}$ as suggested in [30]. That is because, in complete fusion rule there is also log version of own observation component as summation term which does not allow omitting performance indices, $P_{D,j-1}$ and $P_{F,j-1}$, of previous sensor nodes. Hence, the low SNR approximation of optimal fusion rule still requires both of channel gain knowledge and performance indices of previous sensors. However, in terms of computational complexity, the low SNR approximation of fusion rule is simpler compared to the optimum fusion rule since we do not have to deal with exponentials.

3.3. Simulation Results

In this section, we give simulation results of new derived suboptimum fusion rules in previous sections and compare detection performance of them with performance of the optimum decision fusion rule. We made all our simulations in MATLAB environment. In these simulations, a DC level signal is tried to be detected by all sensor nodes under real AWGN as expressed in equation (2.1). The DC-level signal, *m,* in equation (2.1) is supposed to be one. Real AWGN is assumed to be independent and identically distributed (i.i.d.) for all sensor nodes with zero mean and variance of one denoted by $N(0,1)$. Each sensor nodes modulate its decision with BPSK and forward modulated decision to the next stage. Sensor node at next stage receive transmitted signal of previous sensor node which is degraded by noise and fading. Real AWGN with zero mean and variance of one is assumed for receiver electronics noise. We fixed receiver electronics noise power and vary transmit power of each sensor node in order to obtain different SNR values for transmission channel. We assume a Rayleigh fading channel with unit power, $E\left[\left|g_j\right|^2\right]=1$. The gain of the fading channel is considered as a constant during the transmission of decision. We define SNR as transmit signal power over noise power as follows

$$SNR = \frac{P_{signal}}{P_{noise}} = \frac{E\left[\left|\sqrt{\rho}g_{j-1}\right|^2\right]}{\sigma^2} \tag{2.19}$$

where σ is the standard deviation and σ^2 is the variance of real AWGN. Since we assume real AWGN with variance of one and fading channel with unit power, SNR simply reduces to the transmit power gain as

$$SNR = \rho \tag{2.20}$$

Logarithmic decibel scale version of SNR is as follows

$$SNR(dB) = 10\log_{10}\rho \tag{2.21}$$

In our simulations we try to maximize detection probability, $P_{D,N,}$ of the global fusion center for given false alarm probability, $P_{F,N}$ for the global fusion center under N-P decision criteria. Optimum threshold values, t_j , j=1,2,..,N for all sensors, provide maximum detection performance for given false alarm probability. However, determining optimum threshold values for all sensors requires multidimensional search for all possible combination of threshold values as stated in [14]. Due to that computational burden, we assume that threshold values of all sensors to be identical, $t_j = t$, within each simulation separately as in [31].

In Figure 3.2 we compare detection performance of optimum threshold values and identical threshold values for given false alarm probabilities with N=2. In order to produce an accurate error rate, we should obtain at least 100 errors. Error type in our simulations is false alarm rate which can be defined as making decision of 1 under hypothesis H_0. In our graphs, false alarm probability ranges from 10^{-4} to 10^{0}. Therefore, in order to accumulate approximately 100 false alarm error, at least 10^6 simulation runs are required under hypothesis H_0. As a consequence, our simulation outcomes are obtained as a result of $2*10^6$ Monte-Carlo simulations runs under both hypotheses H_0 and hypothesis H_1. Limiting number of sensor nodes with 2 simplify our multidimensional search for finding optimum threshold values. We observe that there is a slight difference between detection performance of optimum threshold values and identical threshold values. For some range of false alarm probabilities, optimum threshold values and identical threshold values give almost the same detection performance. For that reason, it is reasonable to select threshold values to be identical. By selecting identical threshold values for all sensor nodes, we decrease computational complexity of determining threshold values and beside that we do not observe significant performance loss.

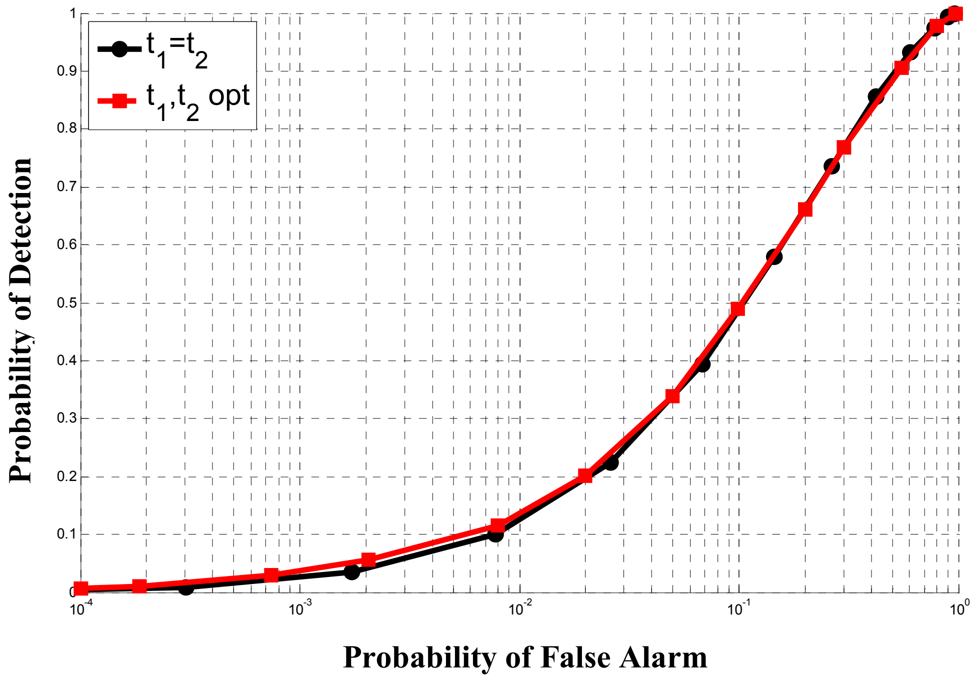

Figure 3.2 Performance comparison of optimum threshold values vs. identical threshold values when N=2

Figure 3.3 and Figure 3.4 gives detection probability of system (the global fusion sensor) as a function of channel SNR for number of sensors 4 and 8 respectively. We fixed false alarm probability of the global fusion center to 0.1. As seen from the graph, the optimal LRT outperforms suboptimal fusion rules for all SNR values. Suboptimum fusion rules that are derived in previous sections approach to the optimum fusion rule for high and low SNR respectively. System performance of the low SNR approximation requires a detailed explanation since increasing channel SNR constantly; do not increase detection performance regularly. At low SNR values, received signal component of the low SNR approximation given in equation (2.18), approaches to zero since $\rho \to 0$. For this reason, own observation part becomes dominant for low SNR values and system performance is detection performance of one node system which makes decision depending on its observation. On the contrary, for high SNR, received signal component dominates own observation part in all stages except the first stage which just use its own observation for decision as stated previously. Hence, detection performance of system again is very close to performance of first node at high SNR values. At moderate SNR values, both own observation and received signal components contribute similarly to the decision fusion rule. Hence, system performance of the low SNR approximation fusion rule for moderate range of SNR values is better compared to high and low SNR values.

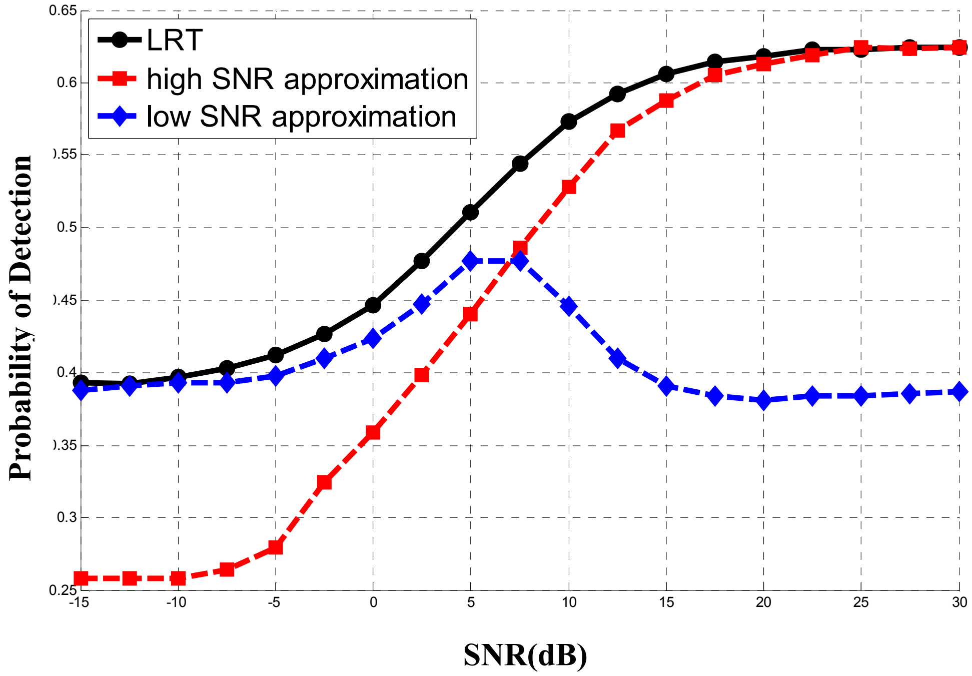

Figure 3.3 Probability of Detection as function of SNR for $P_{F,8}$=0.1, N=4

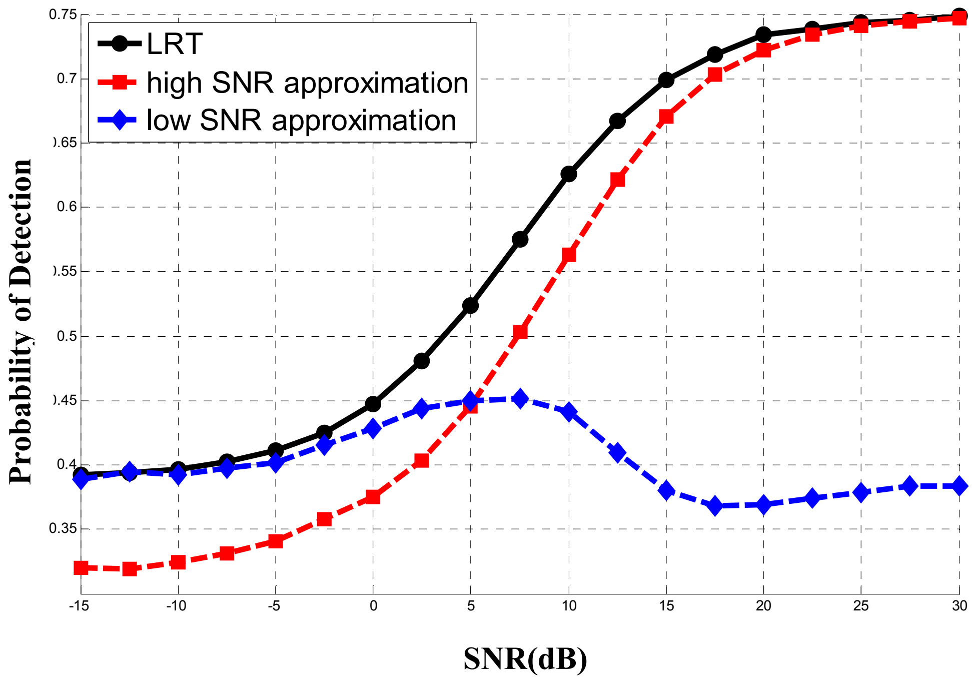

Figure 3.4 Probability of Detection as function of SNR for $P_{F,8}$=0.1, N=8

In Figure 3.5, we obtain the receiver operating characteristics (ROC) curves for optimum and suboptimum fusion rules under SNR=10dB for N=8. We observe that, LRT gives best performance over all false alarm probabilities as expected. We made our simulations in fairly high SNR values in which large SNR approximation fusion rule gives better performance result compared to low SNR approximation.

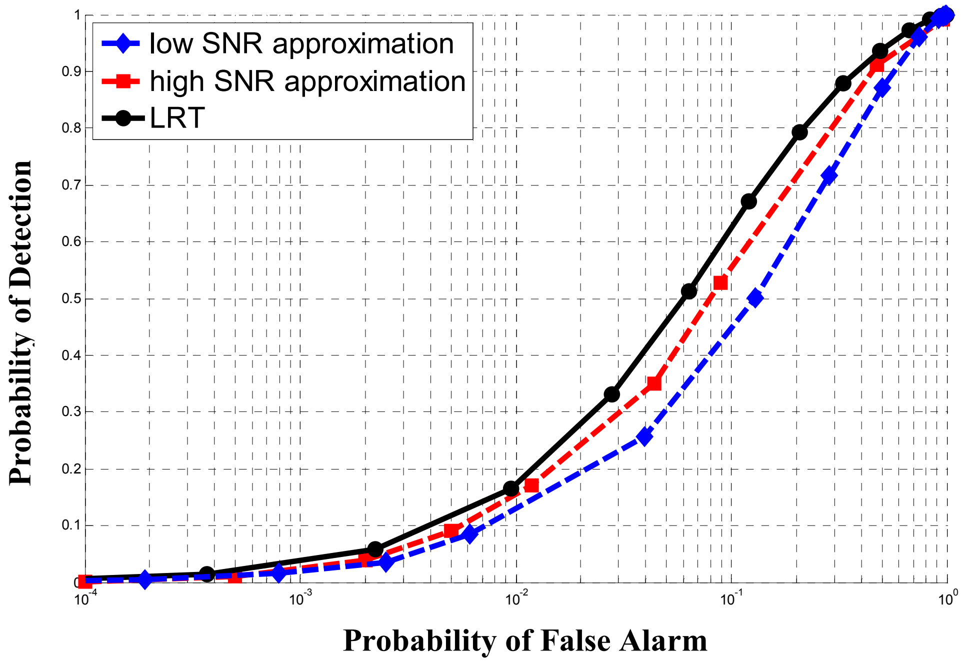

Figure 3.5 ROC Curves for SNR = 10dB, N=8

4. NODE FAILURE HANDLING IN SERIAL DISTRIBUTED DETECTION

One of the main advantages of WSNs over traditional sensor applications is fault tolerant characteristic. However, sensor nodes in WSNs are vulnerable to failure for variety of reasons. Hence, fault-tolerant algorithm design is very crucial to provide robustness to system against failures. Effects of node failure to the distributed detection performance in WSNs have not been investigated yet in the literature, as far as we know. All suggested distributed detection algorithms since now, assume that sensor nodes are completely functional. However, it is obvious that node failure influence the performance of distributed detection of the system. In this chapter, we study how node failure affects serial distributed detection performance of serial network and we propose new decision fusion algorithms which are more robust to node failure than existing decision fusion rules.

4.1. Node Failure in WSNs

There are varieties of reasons that sensor nodes can fail and can not participate to distributed detection algorithms. Firstly, as stated in chapter 1 sensor nodes have limited power source and in most applications it is not feasible to provide additional power source after sensor nodes are deployed in application region. After limited lifetime of sensor nodes come to an end due to power insufficiency, sensor nodes fail to contribute distributed detection algorithms. In order to use limited power efficiently, sensor nodes do not listen their environment continuously as mentioned in [8]. Sensor nodes go to passive mode periodically in which sensors do not take any measurements from environment. At the end of that passive made, nodes wake up and sample their sensors to detect any anomaly. While sensor nodes can completely operate on their active states, they have no contribution to the distributed detection at their passive states in which sensor nodes may be supposed to be failed. Additional reasons are mentioned in [41], when sensor nodes could fail. Sensor nodes can also fail due to hardware corruption. In addition, environmental conditions like electromagnetic noise and physical destructions can cause nodes to temporarily fail to participate in current networks activities.

It is obvious that node failure decreases distributed detection performance of the serial network topology. We suggest novel ways to decrease node failure effects to the distributed detection performance. In the first option, we model node failure probability with a Markov model and suggest a new decision fusion rule which includes node failure probability at each stage. In the existent serial distributed detection where each node uses just 1-previous node information besides its own observation and fuse them to make decision. As a second option to overcome node failure problem, we suggest to exploit broadcast nature of wireless channel and use n-previous node decisions during the fusion. We developed a new decision fusion rule which can combine n-previous information coming from previous sensor nodes and current observation at each stage. For the third way to overcome effects of node failure, we can combine first two options and extend that to a new decision fusion rule which uses n-previous information of nodes together with own observation and considers node failure probability.

4.2. Optimal Fusion Rule Under Node Failure

The node failure model that we use is illustrated in Figure 4.1 which was presented in [40]. In that figure, “0” represents “off” state and “1” represents “on” state of sensor nodes. Stationary probability of a node being in the “off” state is given by $P_{off} = \lambda / (\lambda + \mu)$ where λ and μ are transition probabilities between “on” and “off” states, and vice versa. In the off state, sensor nodes could not able to make any decision because of the failure and sensor nodes could not contribute distributed detection algorithm of network. That is to say, sensor nodes could not be able to benefit from previous sensor node decisions in the fusion process if previous sensor node fails.

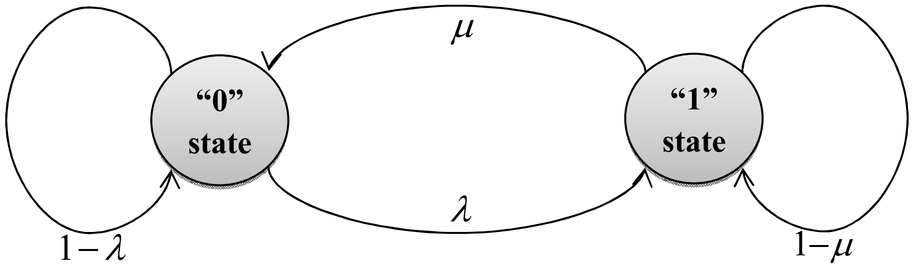

Figure 4.1 A markov chain model for transition between "on" and "off" states presented in [40]

Fusion rule in equation (2.3) assumes that all sensor nodes operate perfectly. For that reason, a new fusion rule which include node failure probability can compensate decrease of detection performance when nodes are failed. Normally, in the "on" state, sensor node makes a decision of either "1" or "0". In the case of failure, sensor node could not able to make any decision which will be denoted by "x". Hence, there are 3 possible decision results of previous sensor node for subsequent sensor node: "1", "0" and "x". Own observation component of the optimal fusion rule given in (2.4) is not affected by node failure. However, we have to change received signal component of optimal fusion rule presented in equation (2.5) in order to include failure probability of previous sensor which does not provide any decision in case of failure. We can derive received signal part of new fusion rule for *j*th sensor node by summing received signal over both three possible decision of previous sensor node and state of previous sensor node.

$$\Upsilon_1(r_{j-1}) = \frac{\sum\limits_{q_{j-1}}\sum\limits_{u_{j-1}} p\left(r_{j-1}, u_{j-1}, q_{j-1} \mid H_1\right)}{\sum\limits_{q_{j-1}}\sum\limits_{u_{j-1}} p\left(r_{j-1}, u_{j-1}, q_{j-1} \mid H_0\right)}$$

$$= \frac{\sum\limits_{q_{j-1}}\sum\limits_{u_{j-1}} \Pr\left(q_{j-1} \mid H_1\right)\Pr\left(u_{j-1} \mid q_{j-1}, H_1\right) p\left(r_{j-1} \mid u_{j-1}, q_{j-1}, H_1\right)}{\sum\limits_{q_{j-1}}\sum\limits_{u_{j-1}} \Pr\left(q_{j-1} \mid H_0\right)\Pr\left(u_{j-1} \mid q_{j-1}, H_0\right) p\left(r_{j-1} \mid u_{j-1}, q_{j-1}, H_0\right)} \tag{3.1}$$

where q_{j-1} denote state of previous sensor node, which can be either "0", when a node fails, or "1", when node operates perfectly. Decision of previous sensor node is represented by u_{j-1} which can take values of "1", "0" and "x". Explicit form of equation (3.1) can be expressed as,

$$\Upsilon_1(r_{j-1}) = \frac{\begin{array}{l} \Pr\left(q_{j-1}=1\right)\Pr\left(u_{j-1}=1 \mid q_{j-1}=1,H_1\right)p\left(r_{j-1} \mid u_{j-1}=1,q_{j-1}=1,H_1\right)+ \\ \Pr\left(q_{j-1}=1\right)\Pr\left(u_{j-1}=0 \mid q_{j-1}=1,H_1\right)p\left(r_{j-1} \mid u_{j-1}=0,q_{j-1}=1,H_1\right)+ \\ \Pr\left(q_{j-1}=1\right)\overbrace{\Pr\left(u_{j-1}=x \mid q_{j-1}=1,H_1\right)}^{1}p\left(r_{j-1} \mid u_{j-1}=x,q_{j-1}=1,H_1\right)+ \\ \Pr\left(q_{j-1}=0\right)\overbrace{\Pr\left(u_{j-1}=1 \mid q_{j-1}=0,H_1\right)}^{2}p\left(r_{j-1} \mid u_{j-1}=1,q_{j-1}=0,H_1\right)+ \\ \Pr\left(q_{j-1}=0\right)\overbrace{\Pr\left(u_{j-1}=0 \mid q_{j-1}=0,H_1\right)}^{3}p\left(r_{j-1} \mid u_{j-1}=0,q_{j-1}=0,H_1\right)+ \\ \Pr\left(q_{j-1}=0\right)\Pr\left(u_{j-1}=x \mid q_{j-1}=0,H_1\right)p\left(r_{j-1} \mid u_{j-1}=x,q_{j-1}=0,H_1\right) \end{array}}{\begin{array}{l} \Pr\left(q_{j-1}=1\right)\Pr\left(u_{j-1}=1 \mid q_{j-1}=1,H_0\right)p\left(r_{j-1} \mid u_{j-1}=1,q_{j-1}=1,H_0\right)+ \\ \Pr\left(q_{j-1}=1\right)\Pr\left(u_{j-1}=0 \mid q_{j-1}=1,H_0\right)p\left(r_{j-1} \mid u_{j-1}=0,q_{j-1}=1,H_0\right)+ \\ \Pr\left(q_{j-1}=1\right)\overbrace{\Pr\left(u_{j-1}=x \mid q_{j-1}=1,H_0\right)}^{4}p\left(r_{j-1} \mid u_{j-1}=x,q_{j-1}=1,H_0\right)+ \\ \Pr\left(q_{j-1}=0\right)\overbrace{\Pr\left(u_{j-1}=1 \mid q_{j-1}=0,H_0\right)}^{5}p\left(r_{j-1} \mid u_{j-1}=1,q_{j-1}=0,H_0\right)+ \\ \Pr\left(q_{j-1}=0\right)\overbrace{\Pr\left(u_{j-1}=0 \mid q_{j-1}=0,H_0\right)}^{6}p\left(r_{j-1} \mid u_{j-1}=0,q_{j-1}=0,H_0\right)+ \\ \Pr\left(q_{j-1}=0\right)\Pr\left(u_{j-1}=x \mid q_{j-1}=0,H_0\right)p\left(r_{j-1} \mid u_{j-1}=x,q_{j-1}=0,H_0\right) \end{array}} \tag{3.2}$$

where probabilities that are stressed with numbers can be eliminated since they are not possible to happen. For example, a node makes a decision of either "1" or "0" when it operates perfectly. Hence, probability of a node to give decision of "x" when it operates perfectly, $\Pr\left(u_{j-1}=x \mid q_{j-1}=1,H_1\right)$, is zero. $\Pr\left(q_{j-1}=0\right)$ is the probability of being a node in off state and $\Pr\left(q_{j-1}=1\right)$ is the probability of being a node in "on" state. After eliminating unrealistic probabilities and denoting failure probability of a node with P_{off} and "on" state of a node with P_{on}, we can obtain simplified version of equation (3.2) as

$$\Upsilon_1(r_{j-1}) = \frac{P_{on,j-1}P_{D,j-1}e^{-\frac{\left(r_j-\sqrt{\rho}g_{j-1}\right)^2}{2}} + P_{on,j-1}\left(1-P_{D,j-1}\right)e^{-\frac{\left(r_j+\sqrt{\rho}g_{j-1}\right)^2}{2}} + P_{off,j-1}e^{-\frac{\left(r_j\right)^2}{2}}}{P_{on,j-1}P_{F,j-1}e^{-\frac{\left(r_j-\sqrt{\rho}g_{j-1}\right)^2}{2}} + P_{on,j-1}\left(1-P_{F,j-1}\right)e^{-\frac{\left(r_j+\sqrt{\rho}g_{j-1}\right)^2}{2}} + P_{off,j-1}e^{-\frac{\left(r_j\right)^2}{2}}} \tag{3.3}$$

Received signal component of fusion rule given equation (3.3) is the optimal decision rule for received signal in case of failure probability. Together with own observation component we can express optimal decision fusion rule under node failure as

$$\Gamma_1(y_j, r_{j-1}) = \Lambda(y_j)\Upsilon_1(r_{j-1}) \underset{H_1}{\overset{H_0}{\lessgtr}} t_j \tag{3.4}$$

4.3. Decision Fusion Rule Using *n*-Previous Decisions

One of the main features of WSNs is that they are densely deployed inside the application region as explained in section 2.1. Because of that dense deployment characteristic of WSNs and broadcast nature of wireless transmission channel, sensor nodes can use more than one sensor decisions in the fusion process. In this section, we extend received signal component of decision fusion rule given in (2.3) which uses just 1-previous node decision information in the fusion process. Assuming that 2-previous sensor node decisions are used in the decision procedure, we can update received signal model for *j*th node given in equation (2.2) as follows

$$w_{j-1} = \alpha\sqrt{\rho}g_{j-1,j}s_{j-1} + \alpha^2\sqrt{\rho}g_{j-2,j}s_{j-2} + n_{j-1} \tag{3.5}$$

where second part of the equation is the additional information coming from second previous sensor node, α is the signal attenuation factor (path-loss coefficient) between subsequent sensor nodes due to distance which is an addition to the received signal model given in equation (2.2). In our system model which is explained in subsection 3.1.1, we suppose that sensor nodes are separated equally. For that reason, path loss coefficient between two subsequent sensor nodes can be expressed with α^2 as in second part of equation (3.5). We slightly change our notation for fading channel coefficient as we can see in Figure 4.2. Channel gain between nodes SN_j and SN_{j-2} can be denoted as $g_{j-2,j}$.

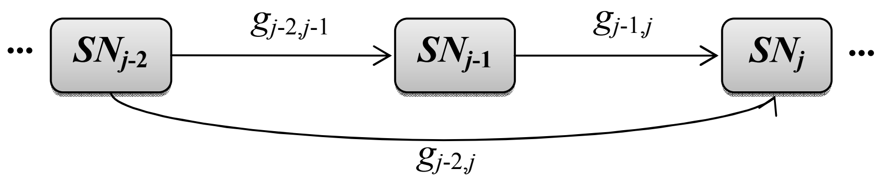

Figure 4.2 Received signal model for *j*th sensor node

If we generalize 2-previous sensor information to *n*-previous sensor information, we can update received signal model at *j*th node as

$$w_{j-1} = \sum_{k=1}^{n}\left(\alpha^k \sqrt{\rho} g_{j-k,j} s_{j-k}\right) + n_{j-1} \tag{3.6}$$

However, we use 2-previous sensor information in our analytic derivations and simulations since information signal coming from more previous sensor nodes degrade badly due to path-loss effect. Additionally, using more than two previous sensor information increases computational complexity of new decision fusion rule and analytical derivations become intractable.

With new proposed signal model, the decision at the jth stage is based on the observation, y_j, and received signal w_{j-1}. It is assumed that the observations and the received signals at the sensors are statistically independent conditioned on the hypothesis. Using LR at each stage, we can express new suggested fusion rule as

$$\begin{aligned}\Gamma_2(y_j, w_{j-1}) &= \frac{p\left(y_j, w_{j-1} \mid H_1\right)}{p\left(y_j, w_{j-1} \mid H_0\right)} \\ &= \frac{p\left(y_j \mid H_1\right)}{p\left(y_j \mid H_0\right)} \frac{p\left(w_{j-1} \mid H_1\right)}{p\left(w_{j-1} \mid H_0\right)}\end{aligned} \tag{3.7}$$

We define two component of the fusion rule as described in subsection 3.1.1. Let $\Lambda(y_j) = p\left(y_j \mid H_1\right) / p\left(y_j \mid H_0\right)$ and $\Upsilon_2(w_{j-1}) = p\left(w_{j-1} \mid H_1\right) / p\left(w_{j-1} \mid H_0\right)$. Own observation component, $\Lambda(y_j)$, is the same with equation (2.4). Therefore, we focus on received signal component, $\Upsilon_2(w_{j-1})$. We can express implicit form of $\Upsilon_2(w_{j-1})$ as

$$\begin{aligned}\Upsilon_2(w_{j-1}) &= \frac{\sum\limits_{\substack{u_{j-1} \\ u_{j-2}}} p\left(w_{j-1}, u_{j-1}, u_{j-2} \mid H_1\right)}{\sum\limits_{\substack{u_{j-1} \\ u_{j-2}}} p\left(w_{j-1}, u_{j-1}, u_{j-2} \mid H_0\right)} \\ &= \frac{\sum\limits_{\substack{u_{j-1} \\ u_{j-2}}} \Pr\left(u_{j-1}, u_{j-2} \mid H_1\right) p\left(w_{j-1} \mid u_{j-1}, u_{j-2}, H_1\right)}{\sum\limits_{\substack{u_{j-1} \\ u_{j-2}}} \Pr\left(u_{j-1}, u_{j-2} \mid H_0\right) p\left(w_{j-1} \mid u_{j-1}, u_{j-2}, H_1\right)}\end{aligned} \tag{3.8}$$

In the sake of simplicity, we define joint probability of two previous decisions as follows

$$P_{j-1,j-2}^{u_{j-1}u_{j-2}} = \Pr\left(u_{j-1}, u_{j-2} \mid H_1\right)$$

$$Q_{j-1,j-2}^{u_{j-1}u_{j-2}} = \Pr\left(u_{j-1}, u_{j-2} \mid H_0\right) \tag{3.9}$$

Then we can express explicit form of $\Upsilon_2(w_{j-1})$ as follows

$$\Upsilon_2(w_{j-1}) = \frac{\begin{aligned} &P_{j-1,j-2}^{00} e^{-\frac{\left(w_{j-1}+\alpha\sqrt{\rho}g_{j-1,j}+\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}} + P_{j-1,j-2}^{01} e^{-\frac{\left(w_{j-1}+\alpha\sqrt{\rho}g_{j-1,j}-\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}} + \\ &P_{j-1,j-2}^{10} e^{-\frac{\left(w_{j-1}-\alpha\sqrt{\rho}g_{j-1,j}+\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}} + P_{j-1,j-2}^{11} e^{-\frac{\left(w_{j-1}-\alpha\sqrt{\rho}g_{j-1,j}-\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}} \end{aligned}}{\begin{aligned} &Q_{j-1,j-2}^{00} e^{-\frac{\left(w_{j-1}+\alpha\sqrt{\rho}g_{j-1,j}+\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}} + Q_{j-1,j-2}^{01} e^{-\frac{\left(w_{j-1}+\alpha\sqrt{\rho}g_{j-1,j}-\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}} + \\ &Q_{j-1,j-2}^{10} e^{-\frac{\left(w_{j-1}-\alpha\sqrt{\rho}g_{j-1,j}+\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}} + Q_{j-1,j-2}^{11} e^{-\frac{\left(w_{j-1}-\alpha\sqrt{\rho}g_{j-1,j}-\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}} \end{aligned}} \tag{3.10}$$

Using 2 previous decision in the fusion process as in equation (3.10), increases computational complexity compared to1 previous decision fusion rule. As a trade off, since we increase diversity about event, we obtain better detection performance. More importantly, if one of the previous nodes fails, decision of the other sensor node can still be used in decision process which is not possible if just 1 previous decision was used in the decision process. There is no additional power cost except calculation of new decision fusion rule since additional transmission is not required. In order to obtain 2 previous decisions, we exploit broadcast nature of wireless transmission channel. With same reasoning, we do not increase traffic overhead of the system.

4.4. Combined Fusion Rule

As a next option, we can combine previously derived fusion rules in a way that fusion rule contains both 2-previous sensor information and node failure probability. Combined decision fusion rule is more complicated compared to previously suggested decision fusion rules. However, we see in simulation section that, combined decision fusion rule gives best detection probability in case of node failures. We express implicit form of received signal component of combined decision fusion as

$$\Upsilon_3(w_{j-1}) = \frac{\sum\limits_{\substack{q_{j-1}\\q_{j-2}}} \sum\limits_{\substack{u_{j-1}\\u_{j-2}}} p\left(w_{j-1}, u_{j-1}, u_{j-2}, q_{j-1}, q_{j-2} \mid H_1\right)}{\sum\limits_{\substack{q_{j-1}\\q_{j-2}}} \sum\limits_{\substack{u_{j-1}\\u_{j-2}}} p\left(w_{j-1}, u_{j-1}, u_{j-2}, q_{j-1}, q_{j-2} \mid H_0\right)}$$

$$= \frac{\sum\limits_{\substack{q_{j-1}\\q_{j-2}}} \sum\limits_{\substack{u_{j-1}\\u_{j-2}}} \Pr\left(q_{j-1}, q_{j-2} \mid H_1\right) \Pr\left(u_{j-1}, u_{j-2} \mid q_{j-1}, q_{j-2}, H_1\right) p\left(w_{j-1} \mid u_{j-1}, u_{j-2}, q_{j-1}, q_{j-2}, H_1\right)}{\sum\limits_{\substack{q_{j-1}\\q_{j-2}}} \sum\limits_{\substack{u_{j-1}\\u_{j-2}}} \Pr\left(q_{j-1}, q_{j-2} \mid H_1\right) \Pr\left(u_{j-1}, u_{j-2} \mid q_{j-1}, q_{j-2}, H_0\right) p\left(w_{j-1} \mid u_{j-1}, u_{j-2}, q_{j-1}, q_{j-2}, H_0\right)} \tag{3.11}$$

In sake of simplicity, we do not provide explicit form of received signal component here. However, explicit form can easily be derived in similar ways as explained previous sections (see Appendix A).

4.5. Simulation Results

In this section, we give simulation results of new derived fusion rules which are more robust under node failure cases. We compare detection performance of new fusion rules with existing fusion rules under ROC curves. We made all our simulations in MATLAB environment. Our simulation details are almost the same with section 3.3. Additionally, we added path loss component to our received signal as given in equation (3.5). In our simulations, we assumed 1dB loss at signal power between subsequent sensor nodes due to distance. We also assigned failure probability, P_{off}, to each node which means a node can fail with probability P_{off} at each Monte-Carlo runs.

In Figure 4.3 and Figure 4.4, simulation results for failure probability included fusion rule are provided for number of sensors 4 and 8 respectively. In our simulations, we set failure probability for all sensors to be 0.25 and compare detection performance of new decision fusion rule with different number of sensor nodes. Performance of the fusion rule which does not include failure probability in the decision process, given in equation (2.3), degrades considerably in case of P_{off}=0.25 in both cases. In the moderate range of false alarm probability in Figure 4.4, nearly 20% degradation can be observed. Failure probability included fusion rule, derived in section 4.2, performs better than old fusion rule. For specific false alarm probabilities, new derived optimal fusion rule, given in equation (3.4), can increase system performance up to 10%.

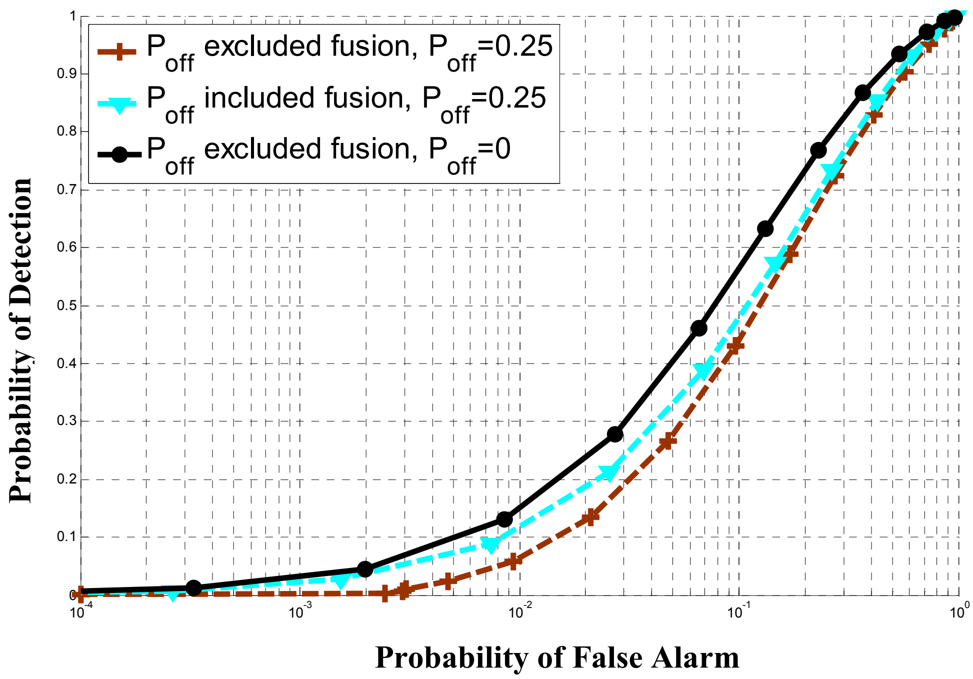

Figure 4.3 Simulations of probability of failure included fusion rule, SNR=10dB, N=4

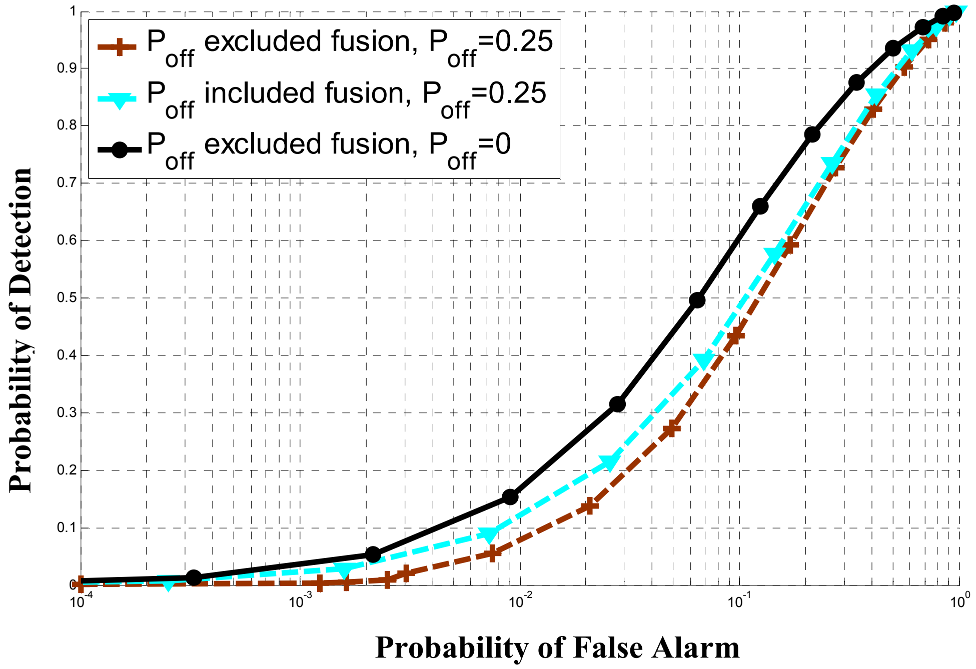

Figure 4.4 Simulations of probability of failure included fusion rule, SNR=10dB, N=8

In Figure 4.5 and Figure 4.6, simulation results of 2-previous decision fusion rule is shown which is derived in section 4.3 for number of sensors 4 and 8 respectively. The joint probability of decisions, $P_{j-1,j-2}^{u_{j-1}u_{j-2}}$ and $Q_{j-1,j-2}^{u_{j-1}u_{j-2}}$ given in equation (3.9), are calculated according to our simulation results. As can be observed from the graphs, when nodes are always in active state, in case when $P_{off}=0$, 2-previous decision fusion rule performs better than 1-previous decision fusion, given in equation (2.3). The important thing here is that, when nodes fail with a probability, in our example we set $P_{off}=0.25$, 2-previous decision fusion rule gives about 12% better result for specific false alarm probabilities. We can also state that, when we increase number of nodes from 4 to 8, improvement in 2-previous decision fusion rule becomes more apparent in the provided graphs.

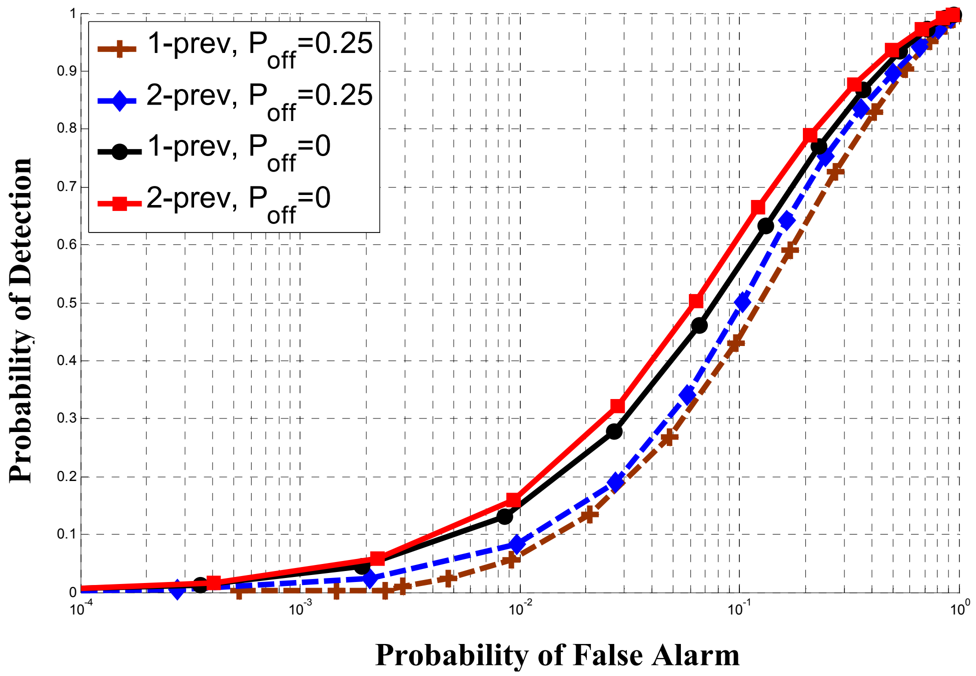

Figure 4.5 Simulations of 2-prevous decision fusion rule, SNR=10dB, *N*=4

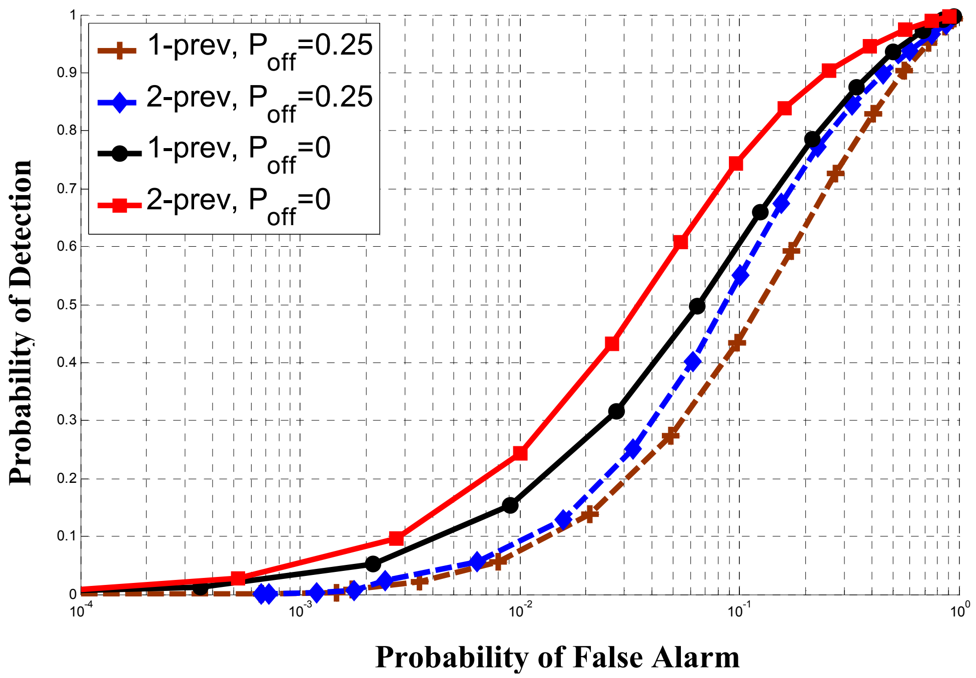

Figure 4.6 Simulations of 2-prevous decision fusion rule, SNR=10dB, *N*=8

Probability of failure included decision fusion rule and the fusion rule that uses 2 previous decision perform better than the fusion rule given in given in equation (2.3). As the third approach, we can combine effects of both failure probability inclusion and using more previous sensor decision in the fusion rule. Using that idea, we derived new decision fusion rule in section 4.4. The combined fusion rule is more complex in terms of computational complexity. However, the combined fusion rule gives better result than previously suggested decision fusion rules as we can see, in Figure 4.7 and in Figure 4.8. We observe that performance of the combined fusion rule under $P_{off} = 0.25$, is very close to performance of the optimal decision fusion rule under $P_{off} = 0$.

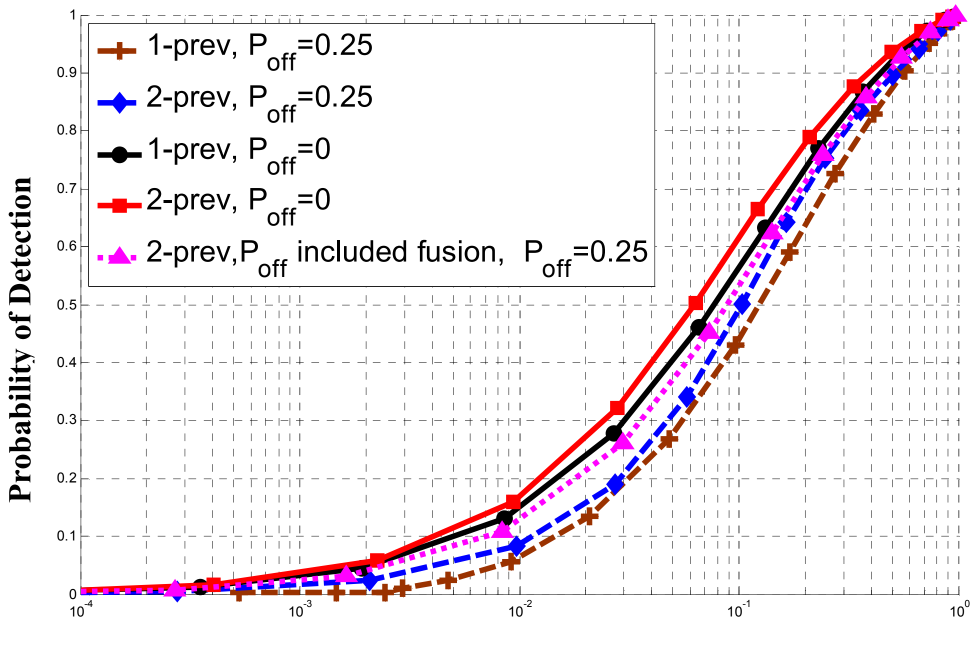

Figure 4.7 Simulations of combined fusion rule, SNR=10dB, *N*=4

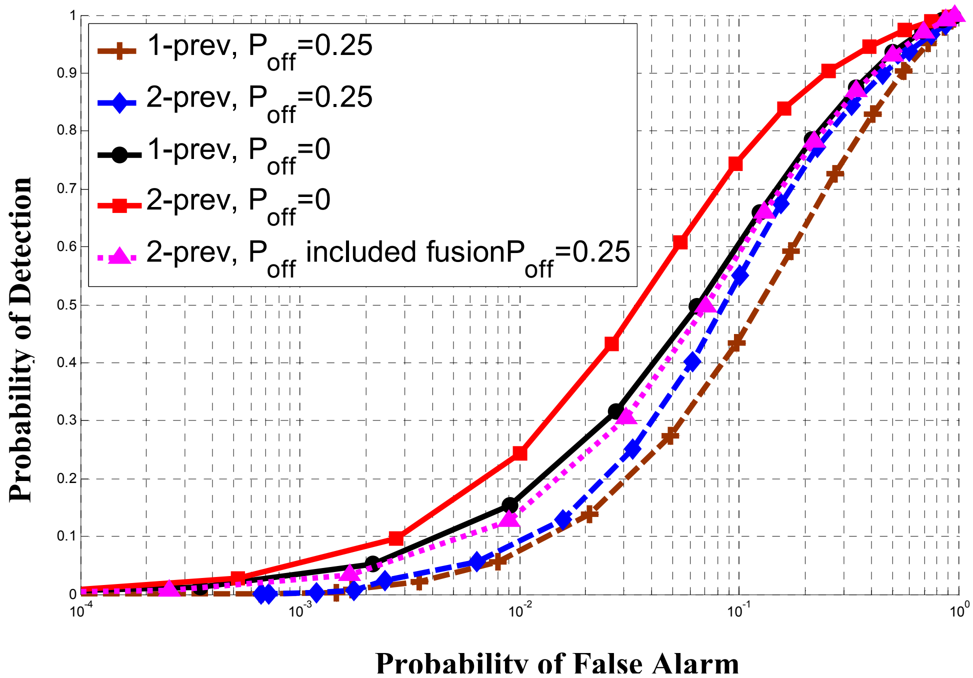

Figure 4.8 Simulations of combined fusion rule, SNR=10dB, N=8

In previous simulations, we have obtained ROC curves of suggested decision fusion rules for a fixed SNR value. In Figure 4.9, we obtain the detection probabilities of the proposed fusion rules as a function of different SNR values. We set false alarm probability of the global fusion center to be 0.1 and failure probability of all nodes to 0.25. We observe from figure that combined the decision fusion rule gives best detection performance in whole SNR range in case of node failure. For high SNR values we can obtain about 12% performance increase compared to 1-prev decision rule which is optimal when nodes do not fail but performance degradetion occurs when nodes fail.

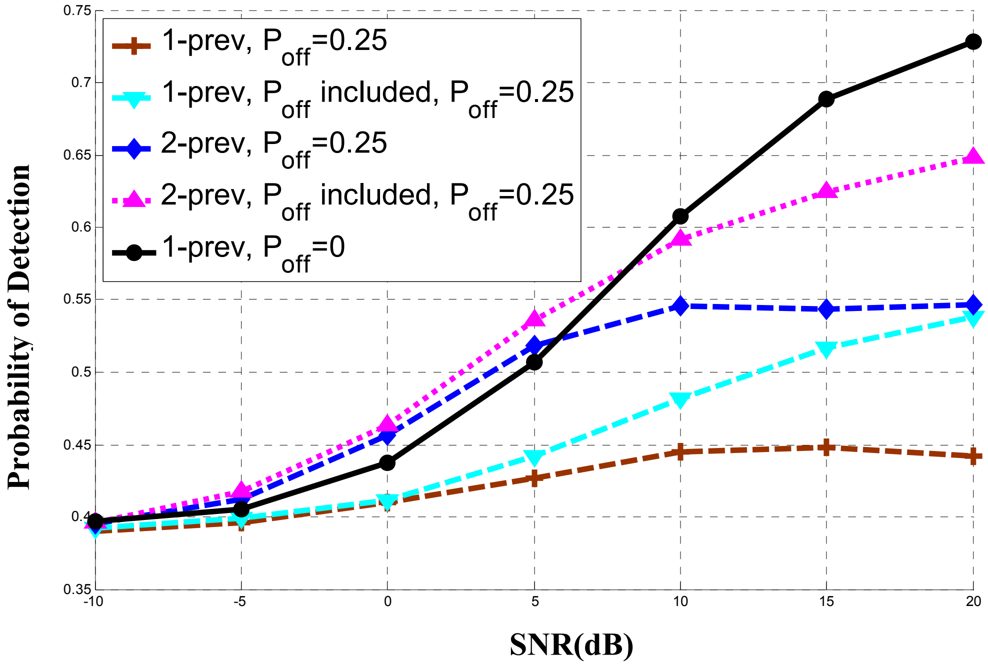

Figure 4.9 Probability of detection under various channel SNR for $P_{F,8}$=0.1, N=8

5. FEEDBACK STRATEGIES IN SERIAL DISTRIBUTED DETECTION

In this chapter, we investigate effect of decision feedback on distributed detection performance of the system. In literature, several feedback mechanisms for distributed detection are proposed in [24]-[26] for classical sensor applications where error free transmission of local decisions to the global fusion center is assumed. However, effect of decision feedback to distributed detection performance in WSNs has not been investigated yet according to our knowledge. In WSNs, we cannot assume error free transmission of local decisions to the global fusion center for variety of reasons as explained in chapter 1. Specifically, we propose feedback strategies for serial distributed detection in WSNs. We analyze effects of decision feedback at serial network topology and investigate how detection performance of system changes with suggested feedback strategies.

5.1. Decision Feedback in Classical Sensor Applications

In literature, there are several approaches about integration of feedback mechanism into distributed detection system in classical applications where error free transmissions of local decisions are assumed. In most research, the network structure is usually assumed to be parallel topology as illustrated in Figure 5.1. In the absence of any feedback mechanism as depicted in Figure 5.1, all local sensors have observations, $y_1, y_2, ..., y_k$, under H_0 or H_1. Each local sensor gives a local decision, u_k, about the phenomenon using just their own observations. Receiving these decisions without any error, fusion center gives the global decision, u_0, about the event using all local decision.

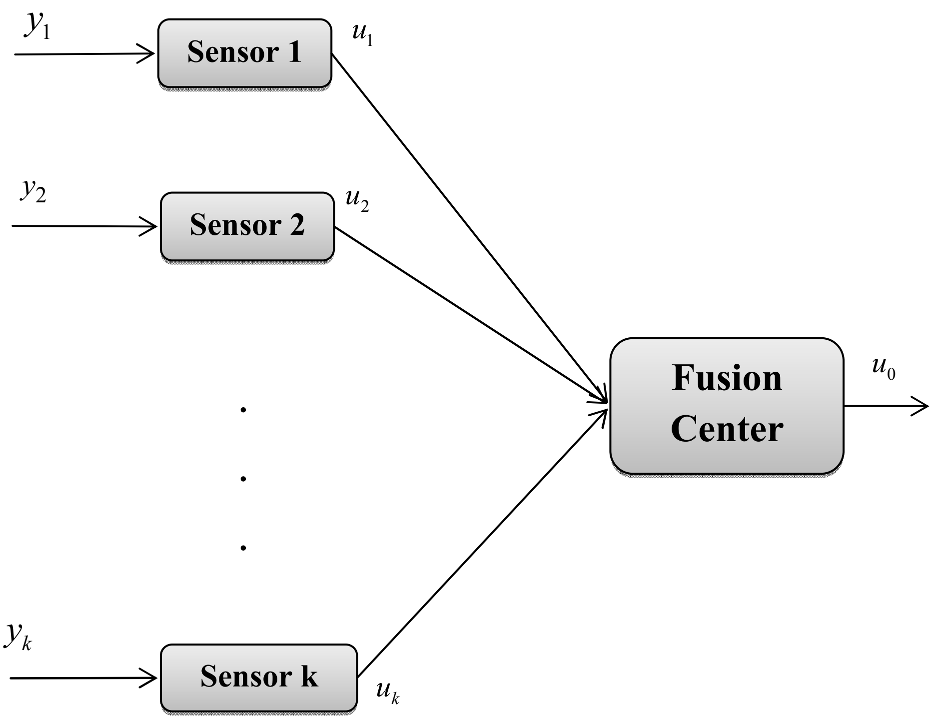

Figure 5.1 Parallel fusion network structure

In [13], Varshney suggests a feedback mechanism, shown in Figure 5.2, where fusion center sends its global decision at time step, *t*-1, u_0^{t-1}, to all local sensors. At time step *t*, the *k*th local sensor makes the local decision, u_k^t, based on previous global local decision, u_0^{t-1}, the current observation of its own, y_k^t, and the previous observations, $y_k^{t-1}, y_k^{t-2}, ..., y_k^1$. Fusion center gives global decision, u_0^t, after receiving these entire local decisions at time step *t*, and feedback this information to all local sensors. Global center gives decision according to Bayesian detection criteria which tries to minimize Bayes risk function. In [24]-[25], the same feedback mechanism as in Figure 5.2 is used, where Neyman-Pearson (N-P) decision criteria is utilized at fusion center that differs from [13]. Another difference of these studies is that, local sensors do not use their previous observations but use just their current observations. Reference [25] additionally suggests new feedback mechanism policy where local sensors use their own decision in subsequent time step which can be seen as feedback of local decisions to local sensors. Feedback of local decisions also investigated in [26], where they use Bayesian detection criteria at fusion center.

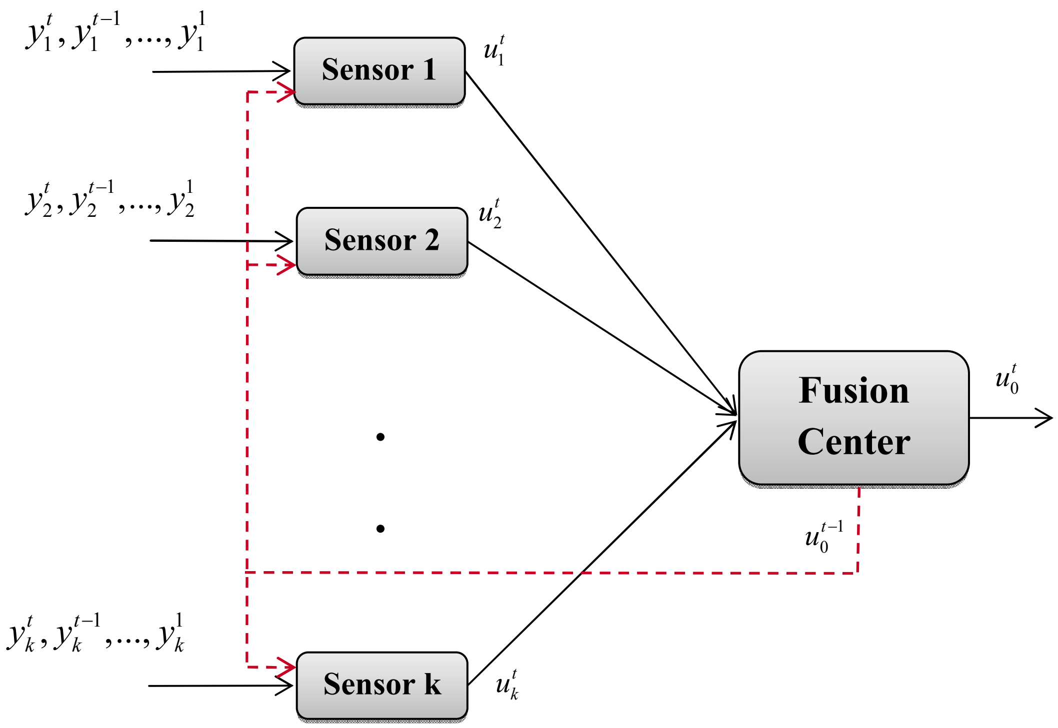

Figure 5.2 Parallel fusion network structure with decision feedback

Distributed detection with decision feedback in WSNs, as far as we know, has never investigated in literature yet. In remaining of this chapter, we investigate effects of decision feedback to serial distributed detection in WSNs.

5.2. Decision Feedback at Serial Topology in WSNs

We want to investigate how decision feedback could affect overall system performance of serial distributed detection in wireless sensor networks. In serial topology, last sensor is assumed to be the fusion center which gives global decision about the phenomenon. Feedback of the global decision to all local sensors, all previous nodes of fusion center, appears to be unpractical in serial topology. Due to path-loss effect, far distant local nodes to the fusion center hardly receive feedback information of global decision. Additionally, feedback signal is also be corrupted by fading and noise. For that reason, rather than using feedback of global decision to all local nodes, feedback between consecutive sensor nodes seems to be more practical. We mainly offer three different feedback strategies for serial network topology. We derive new decision fusion rule for each strategy and then investigate whether feedback improve system performance or not.

5.2.1. Subsequent Sensor Decision Feedback Using The Same Observation

In the first feedback scheme, we use decision of subsequent sensor node as feedback to update decision for the same observation. Initially, without any feedback information jth sensor gives decision based on its own observation and received signal of previous sensor. While j+1th sensor forward its decision to next stage, jth sensor also hears that decision due to wireless channel feature. Hence, this information can be used as feedback of next sensor node. With that feedback information jth sensor can update its decision based on the same observation using the updated received signal of j-1th sensor node and feedback information of j+1th sensor node. Illustration of this mechanism is given in Figure 5.3. Superscripts over variable represent the time order for the same observation. For example, u_j^1 is the first decision of jth sensor without subsequent feedback and u_j^2 is the second decision updated with subsequent feedback. As a result, each node uses decision of subsequent node as feedback information and updates decision for the same observation.

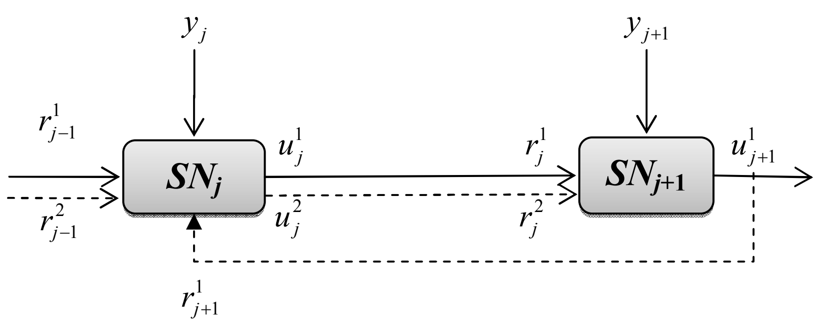

Figure 5.3 Subsequent sensor decision feedback using the same observation

Since nodes transmit their decisions more than once, depending on number of feedback information used, we should keep total power of the system fixed, in order to compare performance of feedback with normal case. If we use feedback information one time, we have to half transmit power of each node, in order to keep total power consumption of system unchanged. Received signal model at *j*th sensor node for suggested feedback strategy can be updated as

$$w_{j-1} = \sqrt{\rho} g_{j-1} s_{j-1}^{2} + \sqrt{\rho} g_{j} s_{j+1}^{1} + n_{j-1} \tag{4.1}$$

where s_{j+1}^{1} is decision of subsequent sensor node that is used as feedback information and s_{j-1}^{2} is decision of previous sensor node which is updated with feedback of *j*th node. With this new signal model, the decision at the *j*th stage is based on the observation, y_j, and received signal w_{j-1} which is combination of previous and subsequent sensor decisions. It is assumed that the observations and the received signal at the sensors are statistically independent conditioned on the hypothesis. Using likelihood ratio test at each stage, we can derive received signal component of new fusion rule with feedback as follows

$$\begin{aligned}\Upsilon_1(w_{j-1}) &= \frac{\sum\limits_{\substack{u_{j-1}^{2}\\ u_{j+1}^{1}}} p\left(w_{j-1}, u_{j-1}^{2}, u_{j+1}^{1} \mid H_1\right)}{\sum\limits_{\substack{u_{j-1}^{2}\\ u_{j+1}^{1}}} p\left(w_{j-1}, u_{j-1}^{2}, u_{j+1}^{1} \mid H_0\right)} \\ &= \frac{\sum\limits_{\substack{u_{j-1}^{2}\\ u_{j+1}^{1}}} \Pr\left(u_{j-1}^{2}, u_{j+1}^{1} \mid H_1\right) p\left(w_{j-1} \mid u_{j-1}^{2}, u_{j+1}^{1}, H_1\right)}{\sum\limits_{\substack{u_{j-1}^{2}\\ u_{j+1}^{1}}} \Pr\left(u_{j-1}^{2}, u_{j+1}^{1} \mid H_0\right) p\left(w_{j-1} \mid u_{j-1}^{2}, u_{j+1}^{1}, H_1\right)}\end{aligned} \tag{4.2}$$

In the sake of simplicity, joint probability of j-1th and j+1th sensor node decisions can be defined as follows,

$$P_{j-1,j+1}^{u_{j-1}^{2}u_{j+1}^{1}} = \Pr\left(u_{j-1}^{2}, u_{j+1}^{1} \mid H_1\right)$$
$$Q_{j-1,j+1}^{u_{j-1}^{2}u_{j+1}^{1}} = \Pr\left(u_{j-1}^{2}, u_{j+1}^{1} \mid H_0\right) \tag{4.3}$$

Then we can express open form of $\Upsilon_1(w_{j-1})$ as follows,

$$\Upsilon_1(w_{j-1}) = \frac{\begin{array}{l} P_{j-1,j+1}^{00} e^{-\frac{\left(w_{j-1}+\sqrt{\rho}g_{j-1}+\sqrt{\rho}g_j+n_{j-1}\right)^2}{2}} + P_{j-1,j+1}^{01} e^{-\frac{\left(w_{j-1}+\sqrt{\rho}g_{j-1}-\sqrt{\rho}g_j+n_{j-1}\right)^2}{2}} + \\ P_{j-1,j+1}^{10} e^{-\frac{\left(w_{j-1}-\sqrt{\rho}g_{j-1}+\sqrt{\rho}g_j+n_{j-1}\right)^2}{2}} + P_{j-1,j+1}^{11} e^{-\frac{\left(w_{j-1}-\sqrt{\rho}g_{j-1}-\sqrt{\rho}g_j+n_{j-1}\right)^2}{2}} \end{array}}{\begin{array}{l} Q_{j-1,j+1}^{00} e^{-\frac{\left(w_{j-1}+\sqrt{\rho}g_{j-1}+\sqrt{\rho}g_j+n_{j-1}\right)^2}{2}} + Q_{j-1,j+1}^{01} e^{-\frac{\left(w_{j-1}+\sqrt{\rho}g_{j-1}-\sqrt{\rho}g_j+n_{j-1}\right)^2}{2}} + \\ Q_{j-1,j+1}^{10} e^{-\frac{\left(w_{j-1}-\sqrt{\rho}g_{j-1}+\sqrt{\rho}g_j+n_{j-1}\right)^2}{2}} + Q_{j-1,j+1}^{11} e^{-\frac{\left(w_{j-1}-\sqrt{\rho}g_{j-1}-\sqrt{\rho}g_j+n_{j-1}\right)^2}{2}} \end{array}} \tag{4.4}$$

Using subsequent sensor decision as a feedback to update current decision does not increase total power consumption of the system, since we decrease transmit power by every decision feedback and keep total power of the system fixed. However, using this strategy increase traffic overhead of the system. In order to obtain subsequent decision, we do not require additional transmission since we exploit broadcast nature of wireless channel. However, after each sensor node update their current decision by using decision feedback, additional transmissions are required in order to forward updated decision to the next stage. Computational complexity of decision fusion rule is similar to 2 previous decision rule that is derived in section 4.3.

5.2.2. Subsequent Sensor Decision Feedback Using Subsequent Observation

In that feedback scheme, we do not want to half the transmit power of each sensor node since decreasing transmit power can degrade performance of feedback system. Performance of previously suggested decision feedback strategy does not depend on correlation between consecutive phenomenons. However, in a realistic scenario it is obvious that there are consecutive observations under the same phenomenon. In Figure 5.4, there are 8 sensor nodes in serial network structure deployed in application region. When target is present, consecutive observations of all sensors are under H_1 phenomenon, as it is seen in Figure 5.4 where multiple paths of target are shown. If there is no target, it is clear that consecutive observations are under H_0 phenomenon.

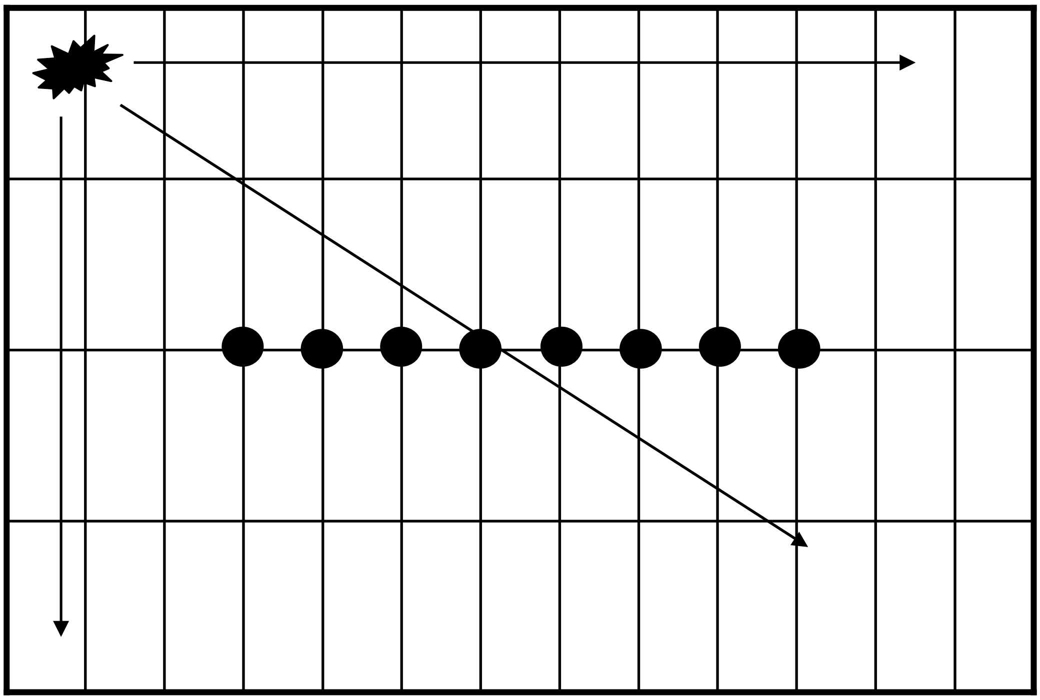

Figure 5.4 Scenario for correlation between consecutive phenomenons

We can update our feedback scheme using correlation between consecutive observations. Rather than using feedback information of subsequent sensor to update current decision for the same observation, we can use feedback information at subsequent observation period since there are multiple observations under same phenomenon. Suggested feedback strategy is illustrated in Figure 5.5. Superscripts of each variable represent time step for observation periods. All solid lines represent events in observation period t-1. Decisions given in period t-1 are used as feedback information by previous sensors in subsequent observation period, t, which is represented by dashed lines in Figure 5.5

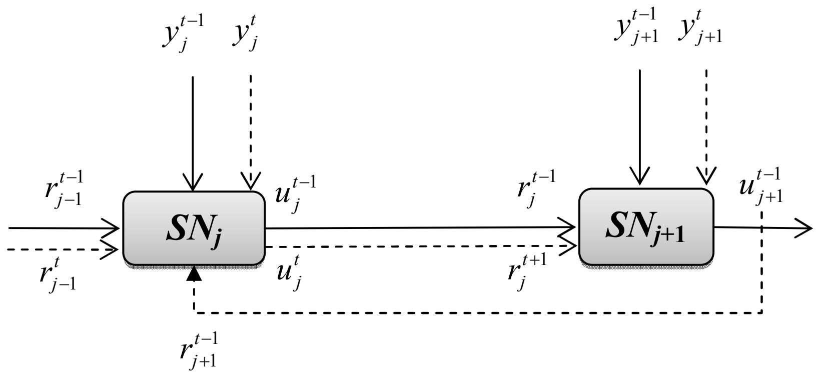

Figure 5.5 Subsequent sensor decision feedback using subsequent observation

Because of the fact that feedback information is used with new observations, there is no need to half the transmit power of sensor nodes as the first suggested feedback strategy. We can change received signal model at jth sensor node for observation period, t, as follows

$$w_{j-1}^t = \sqrt{\rho} g_{j-1} s_{j-1}^t + \sqrt{\rho} g_j s_{j+1}^{t-1} + n_{j-1} \tag{4.5}$$

where w_{j-1}^t is received signal at jth node at observation period, t, s_{j-1}^t decision of previous sensor node at observation period, t, s_{j+1}^{t-1} is decision of subsequent sensor node from previous observation period, t-1, which is used as feedback information in observation period t. Using likelihood ratio test at each stage, we can derive received signal component of new fusion rule with feedback as follows

$$\Upsilon_2(w_{j-1}^t) = \frac{\sum\limits_{\substack{u_{j-1}^t \\ u_{j+1}^{t-1}}} p\left(w_{j-1}^t, u_{j-1}^t, u_{j+1}^{t-1} \mid H_1\right)}{\sum\limits_{\substack{u_{j-1}^t \\ u_{j+1}^{t-1}}} p\left(w_{j-1}^t, u_{j-1}^t, u_{j+1}^{t-1} \mid H_0\right)}$$

$$= \frac{\sum\limits_{\substack{u_{j-1}^t \\ u_{j+1}^{t-1}}} \Pr\left(u_{j-1}^t, u_{j+1}^{t-1} \mid H_1\right) p\left(w_{j-1}^t \mid u_{j-1}^t, u_{j+1}^{t-1}, H_1\right)}{\sum\limits_{\substack{u_{j-1}^t \\ u_{j+1}^{t-1}}} \Pr\left(u_{j-1}^t, u_{j+1}^{t-1} \mid H_0\right) p\left(w_{j-1}^t \mid u_{j-1}^t, u_{j+1}^{t-1}, H_1\right)} \tag{4.6}$$

If define joint probability of decision as described in equation (4.3), we can express explicit form of received signal component of fusion rule as

$$\Upsilon_2(w_{j-1}^t) = \frac{\begin{array}{l} P_{j-1,j+1}^{00} e^{-\frac{\left(w_{j-1}^t + \sqrt{\rho} g_{j-1} + \sqrt{\rho} g_j + n_{j-1}\right)^2}{2}} + P_{j-1,j+1}^{01} e^{-\frac{\left(w_{j-1}^t + \sqrt{\rho} g_{j-1} - \sqrt{\rho} g_j + n_{j-1}\right)^2}{2}} + \\ P_{j-1,j+1}^{10} e^{-\frac{\left(w_{j-1}^t - \sqrt{\rho} g_{j-1} + \sqrt{\rho} g_j + n_{j-1}\right)^2}{2}} + P_{j-1,j+1}^{11} e^{-\frac{\left(w_{j-1}^t - \sqrt{\rho} g_{j-1} - \sqrt{\rho} g_j + n_{j-1}\right)^2}{2}} \end{array}}{\begin{array}{l} Q_{j-1,j+1}^{00} e^{-\frac{\left(w_{j-1}^t + \sqrt{\rho} g_{j-1} + \sqrt{\rho} g_j + n_{j-1}\right)^2}{2}} + Q_{j-1,j+1}^{01} e^{-\frac{\left(w_{j-1}^t + \sqrt{\rho} g_{j-1} - \sqrt{\rho} g_j + n_{j-1}\right)^2}{2}} + \\ Q_{j-1,j+1}^{10} e^{-\frac{\left(w_{j-1} - \sqrt{\rho} g_{j-1} + \sqrt{\rho} g_j + n_{j-1}\right)^2}{2}} + Q_{j-1,j+1}^{11} e^{-\frac{\left(w_{j-1} - \sqrt{\rho} g_{j-1} - \sqrt{\rho} g_j + n_{j-1}\right)^2}{2}} \end{array}} \tag{4.7}$$

Correlation between consecutive phenomenon lead to the idea of using subsequent sensor decision as a feedback in the next observation period. Since we use decision feedback in the next observation period with new observation, we do not have to update our current decision as in the case of previous strategy. For that reason, no additional transmission is required after using decision feedback which means traffic overhead of the system is the same.

5.2.3. Self Decision Feedback Using Subsequent Observation

The scenario that is suggested in previous section enabled all sensor nodes to transmit their decisions at full power. However, feedback information from subsequent sensor node is still exposed to effects of non-ideal channel. Assuming the same realistic scenario of previous subsection, it is possible to overcome effects of non-ideal channel to decision feedback by allowing all sensor nodes to keep their current decisions for subsequent observation period and use it as feedback information from previous observation period. Keeping own decision for next observation period can be considered as self-feedback of sensors. Since in assumed scenario, there is a correlation between consecutive phenomenons, self-feedback information is expected to increase performance of distributed detection system. Self-feedback strategy is illustrated in Figure 5.6 where solid lines represent events in observation period t-1 and dashed lines represent events in observation period t. Self-feedback information from time step t-1 is used at subsequent observation period t.

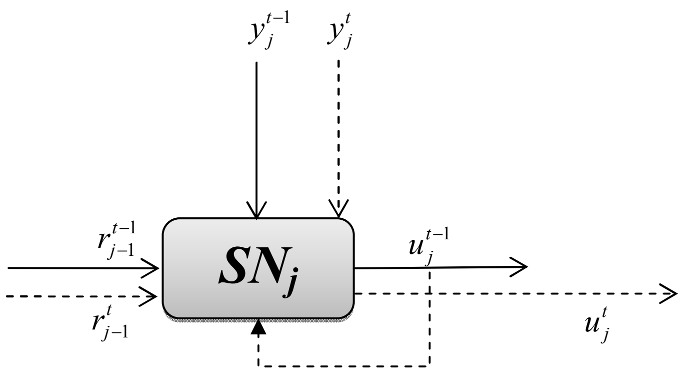

Figure 5.6 Self decision feedback using subsequent observation

Received signal model at jth node for suggested feedback strategy can be expressed as

$$w_{j-1}^t = \sqrt{\rho} g_{j-1} s_{j-1}^t + \sqrt{\rho} s_j^{t-1} + n_{j-1} \tag{4.8}$$

where we omitted the fading coefficient at the second part of the signal since that is self decision, s_j^{t-1}, which is saved from previous observation period. Received signal component of decision fusion rule is very similar to equation given in (4.7). and can be expressed as

$$\Upsilon_3(w_{j-1}^t)=\frac{\begin{array}{l}P_{j-1,j}^{00}e^{-\frac{\left(w_{j-1}^t+\sqrt{\rho}g_{j-1}+\sqrt{\rho}+n_{j-1}\right)^2}{2}}+P_{j-1,j}^{01}e^{-\frac{\left(w_{j-1}^t+\sqrt{\rho}g_{j-1}-\sqrt{\rho}+n_{j-1}\right)^2}{2}}+\\ P_{j-1,j}^{10}e^{-\frac{\left(w_{j-1}^t-\sqrt{\rho}g_{j-1}+\sqrt{\rho}+n_{j-1}\right)^2}{2}}+P_{j-1,j}^{11}e^{-\frac{\left(w_{j-1}^t-\sqrt{\rho}g_{j-1}-\sqrt{\rho}+n_{j-1}\right)^2}{2}}\end{array}}{\begin{array}{l}Q_{j-1,j}^{00}e^{-\frac{\left(w_{j-1}^t+\sqrt{\rho}g_{j-1}+\sqrt{\rho}+n_{j-1}\right)^2}{2}}+Q_{j-1,j}^{01}e^{-\frac{\left(w_{j-1}^t+\sqrt{\rho}g_{j-1}-\sqrt{\rho}+n_{j-1}\right)^2}{2}}+\\ Q_{j-1,j}^{10}e^{-\frac{\left(w_{j-1}-\sqrt{\rho}g_{j-1}+\sqrt{\rho}+n_{j-1}\right)^2}{2}}+Q_{j-1,j}^{11}e^{-\frac{\left(w_{j-1}-\sqrt{\rho}g_{j-1}-\sqrt{\rho}+n_{j-1}\right)^2}{2}}\end{array}} \tag{4.9}$$

5.3. Simulation Results

In this section, we give simulation results of new derived fusion rules for suggested decision feedback strategies. Our simulation environment is the same with simulation environment explained in section 3.3.

In Figure 5.7, the simulation results of first derived fusion rule for subsequent sensor decision feedback using the same observation is illustrated. We see that, detection performance of feedback scheme is worse compared to no feedback case. Although decisions of each local node get better, decrease of transmit power in each stage prevent increasing of performance at fusion center. That is because, at low transmit power transmitted signal is exposed to more errors in non-ideal channel due to fading and noise. Increasing number of decision feedback do not enhance detection performance since we reduce transmit power of each node for every decision feedback in order to keep total power of system fixed.

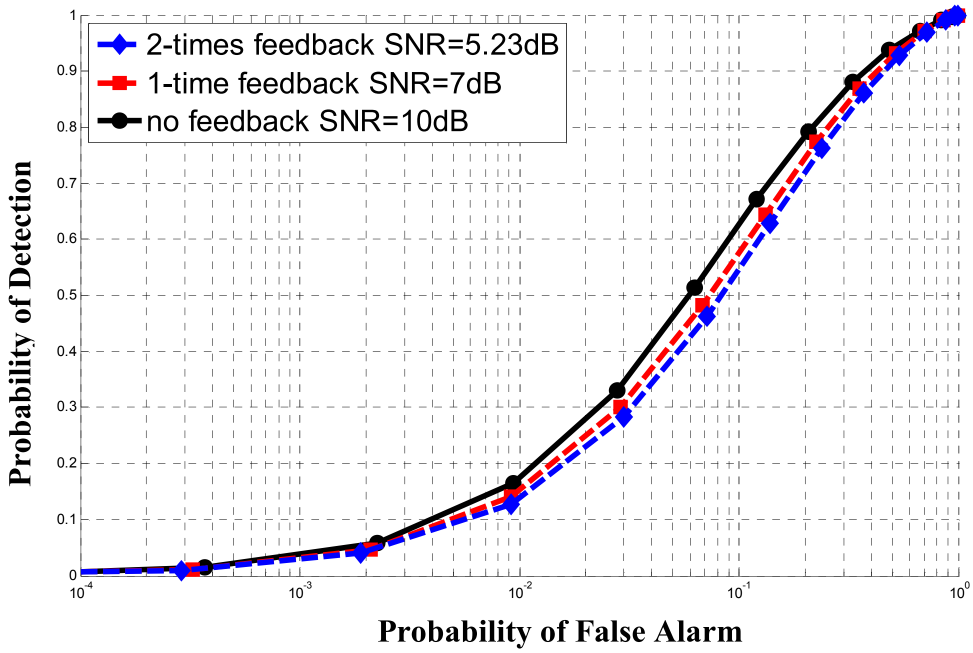

Figure 5.7 Subsequent sensor decision feedback using the same observation

In order not to decrease transmit power of each node; we have suggested a realistic scenario for rest of feedback schemes in section 5.2.2. We assume that, there are consecutive same observations under the same phenomenon. In that way, feedback information can be used at subsequent observation period which enable us to keep transmit power of each sensor the same. Depending on number of consecutive correlated phenomenon, performance of each fusion rule changes. The problem with that scenario is that, when successive observations occur under different phenomenon, feedback scheme can give wrong information about current phenomenon. In order to prevent negative effects of that case in feedback mechanism, we suggest comparing two metrics at each stage, with feedback and no-feedback, and using the one which is larger as follows

$$fusion = \begin{cases} \Gamma(y_j, r_{j-1}) & ,\Gamma(y_j, r_{j-1}) > \Gamma_2(y_j, w_{j-1}^t) \\ \Gamma_2(y_j, w_{j-1}^t) & ,otherwise \end{cases} \qquad (4.10)$$

where $\Gamma(y_j, r_{j-1})$ is decision fusion rule given in equation (2.3) and $\Gamma_2(y_j, w_{j-1}^t)$ is the new derived fusion rule in section 5.2.2 for subsequent sensor decision feedback using subsequent observation. We also compare metrics for self decision feedback using subsequent observation explained in section 5.2.3 as

$$fusion = \begin{cases} \Gamma(y_j, r_{j-1}) & ,\Gamma(y_j, r_{j-1}) > \Gamma_3(y_j, w_{j-1}^t) \\ \Gamma_3(y_j, w_{j-1}^t) & ,otherwise \end{cases} \tag{4.11}$$

Using this comparison method, we can obtain a detection performance for decision feedback at least as good as no-feedback case.

Simulation results for last two suggested feedback strategies are provided for different number of sensor nodes, 4 and 8 respectively, in Figure 5.8, Figure 5.9, Figure 5.10 and Figure 5.11. In these figures, R represents number of consecutive correlated phenomenon. As can be observed from figures, detection performance of suggested feedback scheme improves as number of correlated phenomenon increases. For R=6, there are considerable performance improvement for both feedback strategies. In Figure 5.11, for R=6, suggested decision feedback gives about 40% better performance result for $P_{F,8}$=0.06. Comparison of these two feedback strategies is shown in Figure 5.12. Self decision feedback strategy performs better since decision is not corrupted by fading and noise.

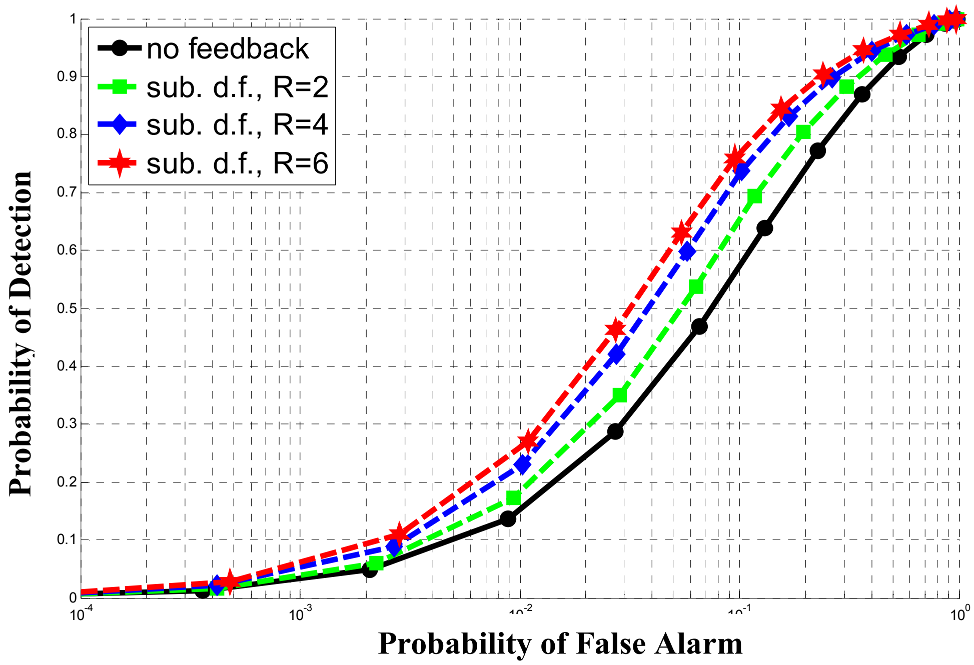

Figure 5.8 Subsequent sensor decision feedback using subsequent observation SNR=10dB, N=4

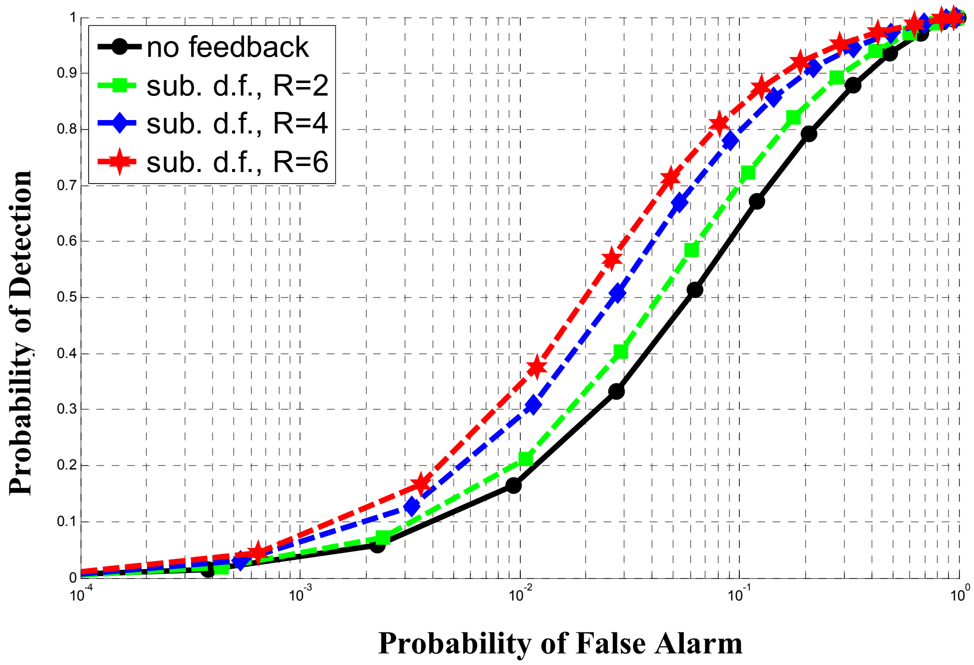

Figure 5.9 Subsequent sensor decision feedback using subsequent observation SNR=10dB, N=8

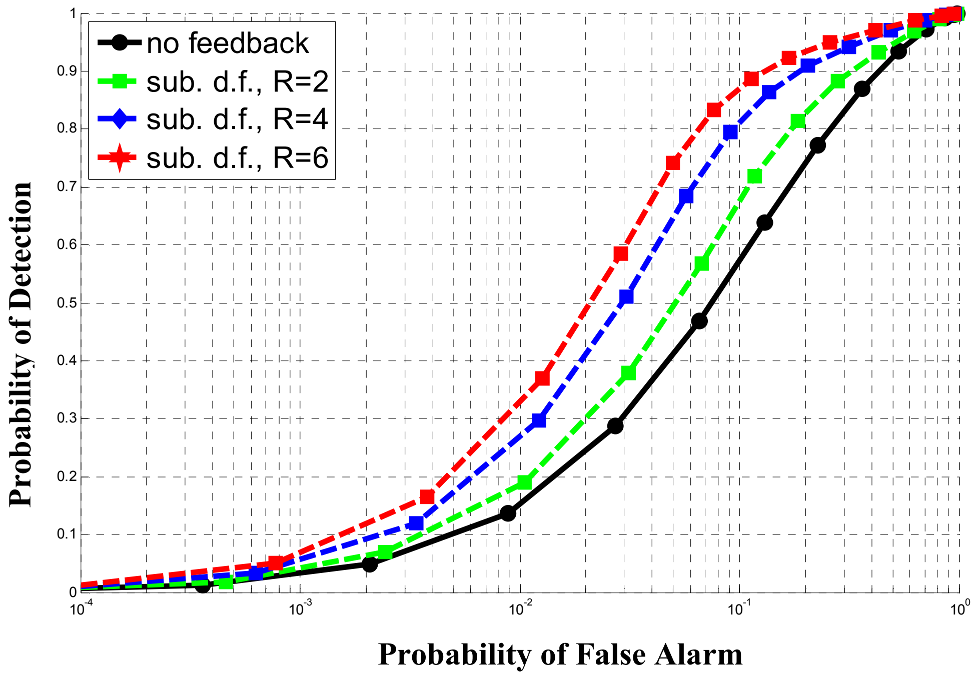

Figure 5.10 Self decision feedback using subsequent observation, SNR=10dB, N=4

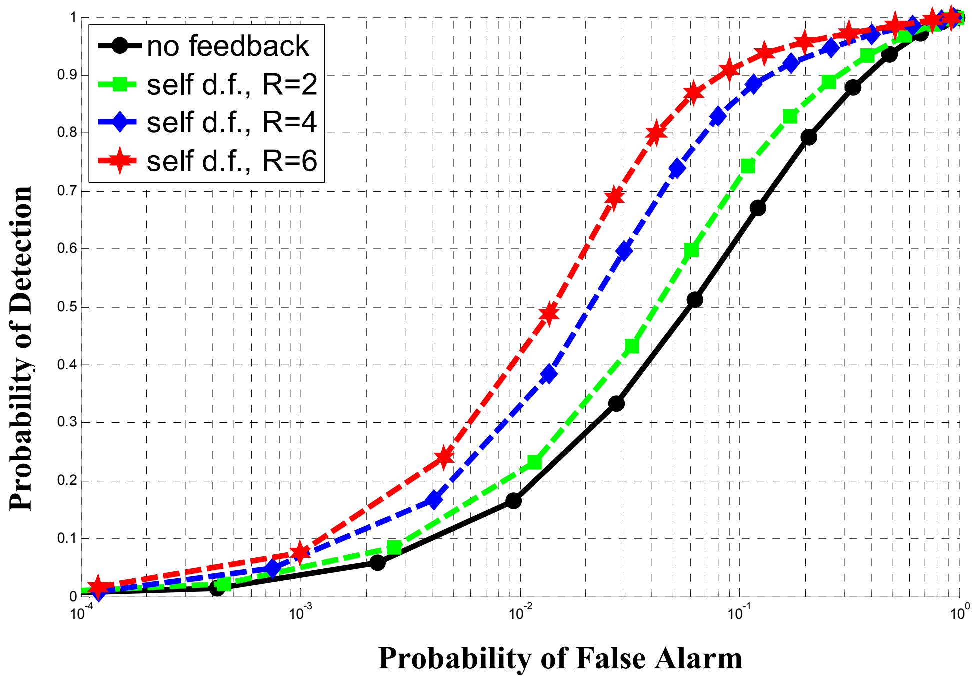

Figure 5.11 Self decision feedback using subsequent observation, SNR=10dB, N=8

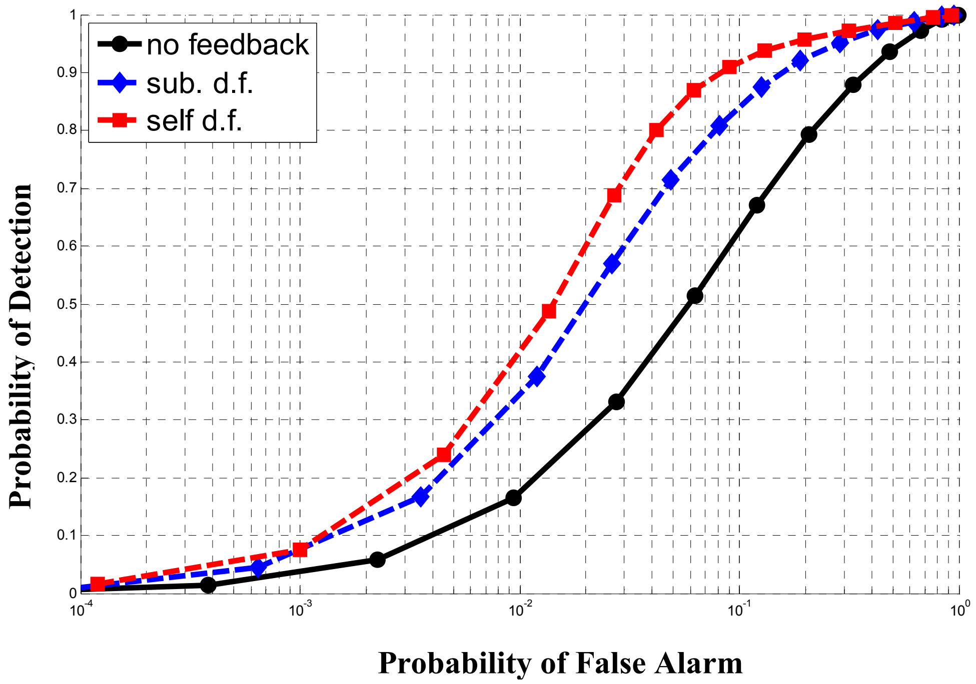

Figure 5.12 Performance comparison of subsequent and self decision feedback

R=4, SNR= 10dB, N=8

It is clear that when we increase number of sensor nodes, performance improvement with decision feedback becomes clearer. Lastly, we give simulation results for various SNR values with N=8 in Figure 5.13 for subsequent decision feedback and self decision feedback. We fixed the global false alarm probability to 0.1 and number of correlated phenomenon to 4. We observe that, for low channel SNR values detection performances of feedback strategies are approaches to non-feedback case. That is because decision feedback and previous decision are corrupted under bad channel conditions and have no contributions to decision fusion rules. In the moderate range and high SNR values, both decision feedback strategies outperform no feedback case. When we compare detection performance of subsequent decision feedback and self decision feedback, we see for all SNR values self decision feedback give better result. Especially for moderate range of SNR values, self decision feedback gives up to 20% better result than subsequent decision feedback.

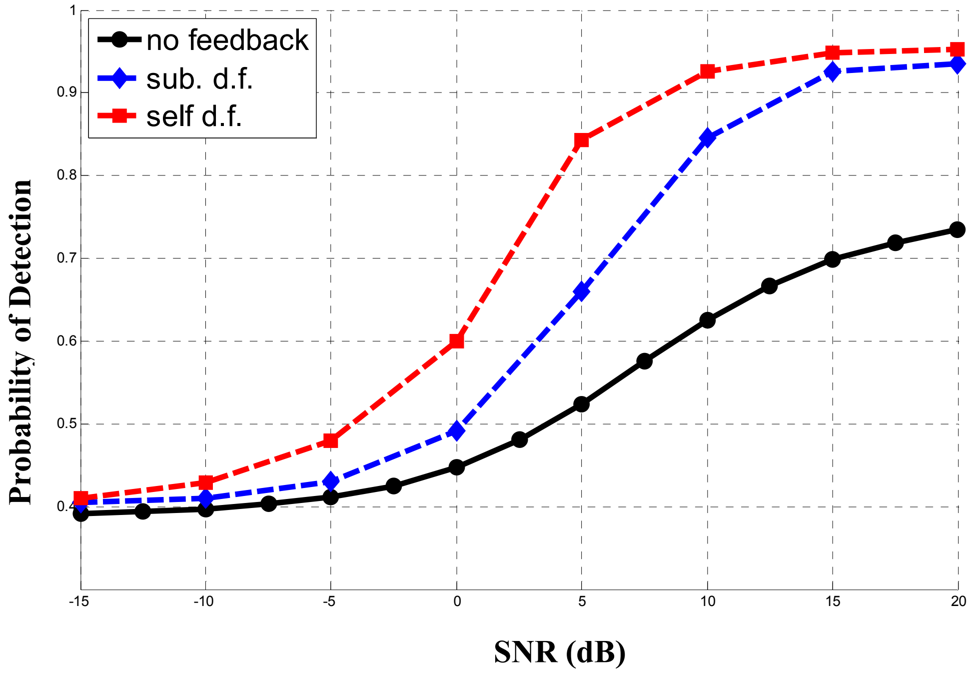

Figure 5.13 Probability of detection under various channel SNR for $P_{F,8}$=0.1, R=4

6. CONCLUSIONS AND FUTURE WORK

In this thesis, several aspects of serial distributed detection in WSNs are investigated. In literature, optimum decision fusion rule for serial distributed detection in WNS was analyzed. However, as for as our knowledge, there is no more detailed study about serial distributed detection in WSN where assumption of error free transmission is not valid as in the case of traditional sensor applications. In large scale wireless sensor networks, serial network topology enables multi hop transmission which is more energy efficient compared to single hop transmission as in the case of parallel network topology. For that reason, in this thesis, we have analyzed serial distributed detection in more various ways. This thesis has 3 main contributions: suboptimal fusion rules have derived for serial distributed detection to relieve some requirements of optimal fusion rule and decrease computational complexity, more robust decision fusion rules have proposed under node failure case and decision feedback strategies for serial distributed detection have suggested which improve detection performance considerably.

In chapter 1, we give the optimal decision fusion for serial distributed detection. The optimal decision rule requires both fading channel coefficient and performance indices of previous sensor node. We have proposed suboptimal decision fusion rules: the high SNR approximation and low SNR approximation. Suboptimal fusion rules relieve some requirement of the optimal decision fusion rule and decrease computational complexity. At high and low channel SNR values, suboptimal fusion rules approaches to the performance of optimal decision fusion rule.

In WSNs sensor nodes are vulnerable to failure for variety of reasons such as limited power source, hardware failure and environmental conditions. We have investigated how node failure can affect the performance of serial distributed detection. We have proposed new decision fusion rules in order to overcome negative effect of node failure to the detection performance.

Lastly, in order to improve serial distributed detection performance we have suggested several feedback strategies. We have also derived new decision fusion rules for suggested feedback mechanisms. We have obtained that some suggested feedback strategies increase distributed detection performance considerably.

As some suggestions for future work, we have obtained a quite good performance improvement for decision feedback strategies proposed in chapter 5. Performance improvement of decision feedback strategies could also be valid under node failure case which should be investigated. In our complete study, every sensor node makes a single-bit decision, one level quantization about phenomenon, about binary event. Multi-bit decision, multi level quantization, can increase distributed detection performance of serial topology. In chapter 4 and 5, the joint probability of decisions is calculated according to simulations results. In order to calculate joint probabilities analytically we should derive distribution of received signal model which is given in equation (3.5).

APPENDIX A

Explicit form of equation (3.11) is as follows

$$\sum_{\substack{q_{j-1} \\ q_{j-2}}} \sum_{\substack{u_{j-1} \\ u_{j-2}}} p\left(w_{j-1}, u_{j-1}, u_{j-2}, q_{j-1}, q_{j-2} \mid H_1\right) =$$

$$P_{on,j-1} P_{on,j-2} P_{j-1,j-2}^{11} e^{-\frac{\left(w_{j-1} - \alpha\sqrt{\rho} g_{j-1,j} - \alpha^2 \sqrt{\rho} g_{j-2,j}\right)^2}{2}} +$$

$$P_{on,j-1} P_{on,j-2} P_{j-1,j-2}^{10} e^{-\frac{\left(w_{j-1} - \alpha\sqrt{\rho} g_{j-1,j} + \alpha^2 \sqrt{\rho} g_{j-2,j}\right)^2}{2}} +$$

$$P_{on,j-1} P_{on,j-2} P_{j-1,j-2}^{01} e^{-\frac{\left(w_{j-1} + \alpha\sqrt{\rho} g_{j-1,j} - \alpha^2 \sqrt{\rho} g_{j-2,j}\right)^2}{2}} +$$

$$P_{on,j-1} P_{on,j-2} P_{j-1,j-2}^{00} e^{-\frac{\left(w_{j-1} + \alpha\sqrt{\rho} g_{j-1,j} + \alpha^2 \sqrt{\rho} g_{j-2,j}\right)^2}{2}} +$$

$$P_{on,j-1} P_{off,j-2} P_{j-1,j-2}^{1x} e^{-\frac{\left(w_{j-1} - \alpha\sqrt{\rho} g_{j-1,j}\right)^2}{2}} +$$

$$P_{on,j-1} P_{off,j-2} P_{j-1,j-2}^{0x} e^{-\frac{\left(w_{j-1} + \alpha\sqrt{\rho} g_{j-1,j}\right)^2}{2}} +$$

$$P_{off,j-1} P_{on,j-2} P_{j-1,j-2}^{x1} e^{-\frac{\left(w_{j-1} - \alpha^2 \sqrt{\rho} g_{j-2,j}\right)^2}{2}} +$$

$$P_{off,j-1} P_{on,j-2} P_{j-1,j-2}^{x0} e^{-\frac{\left(w_{j-1} + \alpha^2 \sqrt{\rho} g_{j-2,j}\right)^2}{2}} +$$

$$P_{off,j-1} P_{off,j-2} P_{j-1,j-2}^{xx} e^{-\frac{\left(w_{j-1}\right)^2}{2}}$$

$$\sum_{\substack{q_{j-1}\\ q_{j-2}}}\sum_{\substack{u_{j-1}\\ u_{j-2}}} p\left(w_{j-1},u_{j-1},u_{j-2},q_{j-1},q_{j-2}\mid H_0\right)=$$

$$P_{on,j-1}P_{on,j-2}Q_{j-1,j-2}^{11}e^{-\frac{\left(w_{j-1}-\alpha\sqrt{\rho}g_{j-1,j}-\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}}+$$

$$P_{on,j-1}P_{on,j-2}Q_{j-1,j-2}^{10}e^{-\frac{\left(w_{j-1}-\alpha\sqrt{\rho}g_{j-1,j}+\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}}+$$

$$P_{on,j-1}P_{on,j-2}Q_{j-1,j-2}^{01}e^{-\frac{\left(w_{j-1}+\alpha\sqrt{\rho}g_{j-1,j}-\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}}+$$

$$P_{on,j-1}P_{on,j-2}Q_{j-1,j-2}^{00}e^{-\frac{\left(w_{j-1}+\alpha\sqrt{\rho}g_{j-1,j}+\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}}+$$

$$P_{on,j-1}P_{off,j-2}Q_{j-1,j-2}^{1x}e^{-\frac{\left(w_{j-1}-\alpha\sqrt{\rho}g_{j-1,j}\right)^2}{2}}+$$

$$P_{on,j-1}P_{off,j-2}Q_{j-1,j-2}^{0x}e^{-\frac{\left(w_{j-1}+\alpha\sqrt{\rho}g_{j-1,j}\right)^2}{2}}+$$

$$P_{off,j-1}P_{on,j-2}Q_{j-1,j-2}^{x1}e^{-\frac{\left(w_{j-1}-\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}}+$$

$$P_{off,j-1}P_{on,j-2}Q_{j-1,j-2}^{x0}e^{-\frac{\left(w_{j-1}+\alpha^2\sqrt{\rho}g_{j-2,j}\right)^2}{2}}+$$

$$P_{off,j-1}P_{off,j-2}Q_{j-1,j-2}^{xx}e^{-\frac{\left(w_{j-1}\right)^2}{2}}$$

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