Information Fusion 18 (2014) 175–186

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

A new multiple decisions fusion rule for targets detection in multiple sensors distributed detection systems with data fusion

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ARTICLE INFO

Article history:
Received 20 May 2012
Received in revised form 10 September 2013
Accepted 10 September 2013
Available online 23 September 2013

Keywords:
Data fusion
Target detection
Distributed detection systems
Binary detection systems
Decision fusion

ABSTRACT

Currently, multiple sensors distributed detection systems with data fusion are used extensively in both civilian and military applications. The optimality of most detection fusion rules implemented in these systems relies on the knowledge of probability distributions for all distributed sensors. The overall detection performance of the central processor is often worse than expected due to instabilities of the sensors probability density functions. This paper proposes a new multiple decisions fusion rule for targets detection in distributed multiple sensor systems with data fusion. Unlike the published studies, in which the overall decision is based on single binary decision from each individual sensor and requires the knowledge of the sensors probability distributions, the proposed fusion method derives the overall decision based on multiple decisions from each individual sensor assuming that the probability distributions are not known. Therefore, the proposed fusion rule is insensitive to instabilities of the sensors probability distributions. The proposed multiple decisions fusion rule is derived and its overall performance is evaluated. Comparisons with the performance of single sensor, optimum hard detection, optimum centralized detection, and a multiple thresholds decision fusion, are also provided. The results show that the proposed multiple decisions fusion rule has higher performance than the optimum hard detection and the multiple thresholds detection systems. Thus it reduces the loss in performance between the optimum centralized detection and the optimum hard detection systems. Extension of the proposed method to the case of target detection when some probability density functions are known and applications to binary communication systems are also addressed.

1. Introduction

Multiple sensors data fusion systems have wide varieties of civilian and military applications [1–6]. Detection of targets is one of its major applications [7–9]. In a target detection (or search) and tracking system, a sensor (such as radar, sonar, and infrared) detects targets in background noise by receiving noisy observations from targets within its research volume. The received observations are then processed to determine the presence or absence of targets (H_1 or H_0). When hypothesis H_0 is decided, targets should be searched for and when H_1 is decided, targets should be followed and tracked to determine its characteristics such as range and velocity. Targets detection and tracking are essential processing in surveillance systems. For example, in navigation and air traffic control systems, sonar and radar detection and tracking of targets are two major processing. In this paper, we focus on detection of targets using observations from distributed multiple sensors.

In distributed multiple sensor detection systems with data fusion, distributed multiple sensors monitor a certain volume and send their individual (hard) decisions to a central processor (fusion center), which fuses the sensors hard decisions into a single overall (global) decision. [10–12]. The distributed multiple sensors observe the same targets and send their individual hard decisions to the central processor. The central processor combines the individual sensors hard decisions and decides overall detections about the same targets. Such systems have better performances than single sensor systems in terms of reliability and immunity to interference, noise, and electronic attack [13–16].

The three techniques for combining information in distributed sensors detection systems are centralized detection, hard (binary) detection, and soft detection. In centralized detection technique, all sensors data are sent to a central processor where an overall decision is taken. Although this technique achieves the highest performance, it requires very large bandwidth in order to obtain real-time results. In fact, centralized detection is not implemented in practice due to cost, communication bandwidth, survivability, and reliability considerations [17,18]. In hard detection technique, some preliminary data processing is implemented at each individual sensor to derive sensors hard decisions. The local hard decisions are then transmitted to a central processor to obtain an overall decision [19,20]. The hard detection has some advantages

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http://dx.doi.org/10.1016/j.inffus.2013.09.002

over the centralized detection in terms of the required bandwidth, reliability, and complexity. In hard detection, the central processor processes only hard decisions received from the distributed multiple sensors. Thus there is a loss in performance in the hard detection technique compared to the centralized detection technique. In soft detection technique, each individual sensor derives a soft decision (a value between zero and 1) rather than a hard one. Soft detection measures the confidence in each sensor detections. In this case, each local sensor transmits several bits, instead of single-bit detections [21,22]. Soft detection is used to decrease the loss in performance between the hard detection and the centralized detection. Unfortunately, the calculation of the optimum combining rule in case of soft detection is very complicated and feasible solution is not possible [23,24]. Thus most publications focus on hard detections.

There are two major criteria for optimum binary decentralized detection in distributed multiple sensor systems; Bays criterion and Neyman–Pearson criterion. In Bayes' criterion, two assumptions are made: (1) Each hypothesis has known probability, i.e. $pr(H_1)$ and $pr(H_0)$ are known, where $pr(H_1) + pr(H_0) = 1$, and (2) A cost function is defined for each detection case, i.e. C_{ij}, where C_{ij} is the corresponding cost when H_i is decided while the true decision is H_j, $i, j = 0, 1$. Bays' criterion determines the decision rule such that the average cost (risk) is minimum. The result of the Bayes rule is to compare the likelihood ratio with a threshold. The likelihood ratio is a ratio between the probability density functions under both hypotheses. The threshold is a function of the cost function C_{ij}, $\forall i, j = 0, 1$, and the probability of hypotheses ($pr(H_0)$ and $pr(H_1)$). Assignment of costs to different courses of action and knowledge of prior probabilities are required for the solution of Bayes criterion. The minimum error probability criterion is a special sense of Bays' criterion when the costs of errors are equal to 1 ($C_{01} = C_{10} = 1$), the cost of correct decisions are equal to 0($C_{00} = C_{11} = 0$), and the probability of the two hypotheses are assumed to be equal ($pr(H_0) = pr(H_1) = 0.5$). This is suitable for binary communication systems and it is equivalent to maximization of the a posteriori probabilities; thus it is also called the maximum a posteriori criterion. The minimax criterion is another special case of a Bayes rule with a least favorable prior. Minimax criterion considers ordering decision rules according to the worst that could happen, i.e. it constructs a decision rule that yields the best possible worst-case performance. This criterion is robust with respect to uncertainty in the a priori probabilities. It minimizes the maximum possible risk by the Bayes test.

An alternative to Bayes decision rule for binary hypothesis testing problem is the Neyman–Pearson criterion. This is often used for signal/target detection (our case). In Neyman–Pearson criterion, the probability of detection is optimized (maximized) for a given pre specified probability of false alarm. In contrast to the Bayes' criterion, Neyman–Pearson criterion does not need known probabilities of hypotheses and known cost functions. The Neyman–Pearson criterion for hard hypothesis detection problems can be used when different cases of error do not have same consequences or the hypotheses probabilities are not known.

In most approaches to binary hypothesis testing problems, the decision rules are optimized to minimize the total error probability. However, in some practical situations it is more useful to avoid one type of error than the other. For examples, some of these situations arise in case of fraud detection, machine monitoring, disease diagnosis, and target detection (which is our case). Thus we focus on the Neyman–Pearson criterion.

The optimum combining strategy, according to Neyman–Pearson criterion, is derived in [25] assuming that the conditional densities are completely known and each local sensor utilizes its own likelihood ratio to obtain its own hard decision. This is called optimum hard (binary) detection. The optimal combining rule that maximizes the overall probability of detection for a pre specified overall probability of false alarm, is derived in [26]. This solution assumes the case of independent hard decisions. The results showed that the optimal solution at the sensor levels is to implement the local likelihood ratios and the optimal solution at the central processor level is to implement the Neyman–Pearson strategy. Unfortunately, this method does not obtain the global optimal solution at both the sensors and the central processor levels. This is clearly addressed in [27,28].

The optimal hard detection, based on the Neyman–Pearson strategy, is presented in [29,30] when each sensor sends a hard quality bit in addition to its own binary decision. This method is called multiple thresholds approach since each individual sensor processes its own observations using three threshold levels (minimum, intermediate, maximum). In this case, a hard 1 quality bit is transmitted with the local sensor decision when the value of the sensor likelihood is either higher than the maximum threshold or less than the minimum threshold. This corresponds to a decision with a high confidence. Otherwise, a hard 0 quality bit is transmitted which corresponds to a decision with a low confidence. The multiple thresholds method achieves higher performance than the optimum hard detection at the expense of required additional information.

The concept of quasi-convexity is addressed in [31] where it is shown that the optimality in [26] yields the optimal solution at the central processor level but the optimum global solution (at both the central processor and the individual sensors levels) is not achieved. Since the global solution is computationally infeasible [31–35], most publications assume the optimal solution only at the central processor level, therefore significant performance degradation occurs. The global performance of n-sensor distributed detection systems, in the Neyman–Pearson sense, is analyzed in [36–39].

Some of recent significant contributions, addressing the topic of multiple sensors distributed detection systems, are presented in [23,30,40–43]. Two methods are proposed in [40] to estimate the probability density functions under hypothesis; a least squares method and a maximum likelihood method. The estimation of probability density functions is extended to the case of M-ary distributed detection systems. Simulation results in case of multiple hypothesis are also presented. A decentralized distributed detection system with multilevel fusion, based on simple majority-like fusion strategies, is proposed in [41]. In this case, the distributed sensors send their own local decisions to an intermediate central processor (access point) and then to a main central processor. A solution which minimizes the overall error probability and also minimizes the overall energy consumption is proposed in [42] in case of parallel and serial distributed detection systems. This problem is considered as a multiobjective optimization problem. Simulation results showed that the structure of the parallel fusion has lower overall probability of error and the structure of the serial fusion has lower overall energy consumption. An optimal fusion rule for the general structure of parallel distributed detection systems is developed in [43]. This solution depends on an iterative algorithm to simultaneously obtain the optimal combining strategy of the central processor and the optimal individual sensor strategies. An iterative algorithm for global optimization of distributed multiple sensors detection systems is proposed in [23]. This algorithm obtains, for a pre specified overall probability of false alarm, the optimum local sensor thresholds, the overall threshold of the central processor, as well as the central processor combining strategy, to maximize the overall probability of detection. The proposed algorithm performs efficient determination of the optimum global solution. The global solution is independent of the initial starting values. A soft detection approach, for distributed multiple sensor detection systems, based on Neyman–Pearson strategy, is pro-