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A new adaptive decentralized soft decision combining rule for distributed sensor systems with data fusion

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ABSTRACT

A new adaptive decentralized soft decision combining rule for multiple-sensor distributed detection systems with data fusion is proposed. Unlike previously published rules, the proposed combining rule fuses soft decisions of sensors rather than hard decisions of sensors and does not require the knowledge of the false alarm and detection probabilities of the distributed sensors. Such a fusion rule is adaptive, insensitive to the instabilities of the sensor thresholds, and has the advantage of soft decision fusion. The proposed combination rule is derived: (1) for the case where the fusion center estimates the error probabilities of the sensors and (2) for the case where the fusion center does not estimate the error probabilities of the sensors. The performance of the proposed approach is evaluated, and illustrative examples are presented in the cases of Gaussian and Rayleigh distributed observations. Comparisons with the optimum centralized fusion, the optimum soft decision fusion, a soft decision fusion approach based on fusing confidence levels, and the optimum decentralized hard decision fusion are also presented. The results indicate that the proposed approach significantly outperforms the optimum decentralized hard decision fusion, is better than the approach based on fusing confidence levels, and has a performance similar to that of the optimum soft decision fusion.

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1. Introduction

Multiple-sensor data fusion systems have attracted the attention of many researchers, due to the increasing demand in the deployment of multiple sensors for military and civilian purposes [3,4,5–7,13,24,27,31,41,51,55,66]. These multiple-sensor systems have the advantages of greater performance, reliability, and survivability than single-sensor systems. One of the main aspects of the data fusion of multiple sensors is the detection using distributed multiple sensor systems [38,51,64,67]. Multiple-sensor systems have many applications, such as intrusion detection [20,46,64], multi-access channels [37,65], diversity communication systems [11,15,24], fault detection [35,47,69], surveillance using distributed radar networks [21,32], wireless sensor networks [28,30,40,43,54,63], data mining [45,49], biomedical applications [19], image detection [17], target tracking [6,7], mobile service robots [14], world wide web [2,22,48,53], and fire detection [42]. We have focused on target detection [8–10].

In distributed detection systems, there are multiple sensors that observe multiple targets and send local information about a hypothesis to a combining center. The combining (data fusion) center is responsible for combining the information collected by each of the individual sensors to determine a global hard decision (0 (target is absent) or 1 (target is present)) about the same hypothesis. Such systems are expected to exhibit improved performance and be more reliable and immune

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to noise interference [9,10]. There are three methods for combining the information from the sensors in multiple-sensor distributed detection systems: centralized fusion, decentralized hard decision fusion, and decentralized soft decision fusion [1,8,59]. In centralized fusion, all the sensor observations are transmitted directly, without any signal processing, to the combining center to determine the final global decision. This fusion method achieves the optimum performance at the expense of the need for a high communication bandwidth and large memory. Due to these limitations, the centralized fusion method is not convenient for real-time processing and is never implemented in practice [8,16,23,26,57,61,62,68]. In the decentralized hard decision fusion method, the distributed sensors are allowed to determine local hard decisions, and then these local decisions are sent to the combining center to determine the final global decision [24,58,59,61,68]. This fusion method has the advantages of a low communication bandwidth requirement and low cost. However, the combining center has only partial hard information, as communicated by the sensors [9,18,61]. The result is a loss of performance compared to that of the centralized fusion method. In the decentralized soft decision fusion method, each distributed sensor determines a soft decision (a value between 0 and 1) rather than a hard decision (0 or 1). This method is used to reduce the performance loss between the decentralized hard decision fusion method and the centralized fusion method.

There are previous significant contributions in the case of the decentralized hard decision fusion method and the decentralized soft decision fusion method. The optimum fusion rule, under the assumptions that the a priori probabilities are known and that each sensor uses the likelihood ratio test to arrive at its own local decision, is presented in [47,59,61]. The optimum fusion rule for unknown a-priori probabilities, in terms of the Neyman–Pearson test at the local sensors as well as at the fusion center, is derived in [58,59]. According to the Neyman–Pearson strategy, the global detection probability is maximized for a desired global false alarm probability. In [18,59,61], the globally optimal solution to the combining strategy is shown to be the solution that maximizes the global detection probability for a fixed global false alarm probability, when the distributed sensors transmit independent binary decisions to the fusion center, consists of performing likelihood ratio tests at all the sensors and a Neyman–Pearson test at the fusion center. Bayesian model-based multiple-sensor distributed detection systems for fusing the detection probabilities obtained from a distributed detection system have been presented in [33]. In this model, each local sensor generates a probability that represents its confidence on the signal present hypothesis. The fusion center combines all the reported probabilities and determines a global decision. This model, which is equivalent to soft decision fusion, requires known and stationary probability density functions.

The optimum decentralized soft decision fusion approach according to the maximum distance criterion, in the case of independent sensors and a fusion center, is derived in [34]. This work considered the optimum soft decision fusion in the general case of n sensors and provided the optimum sub-partitioning of the local decision spaces. In this case, each local decision space is partitioned into m exclusive regions instead of two exclusive regions. With more than two partitions, each local sensor is able to convey more information. As shown in [34], the optimum sub-partitioning of the local decision spaces is equivalent to partitioning of the false alarm and the detection probabilities. The details of the derivations of the expressions for optimum subpartitioning can be found in [34]. A target detection example and a comparison with the optimum centralized fusion, in the case of Rayleigh distributed observations, is presented in [34]. The extension of this method to the case of over three thresholds is very complicated and requires analytic expressions for the functional relationships between the detection probabilities, the false alarm probabilities, and their derivatives.

A soft decision fusion approach based on fusing the sensor confidence levels is proposed in [8]. In this case, each local sensor provides the fusion center with a soft decision rather than a hard decision. Each soft decision represents the confidence of a local sensor in its own decision. This representation is accomplished by smoothing the local sensor decisions using soft membership functions according to the difference between the likelihood ratios of the sensors and the thresholds of the sensors. The local-sensor soft decisions are then quantized and fused in the data fusion center. In this way, this soft decision fusion rule combines the reliability terms weighted by the corresponding confidence levels to generate a final global decision. The reliability terms depend on the false alarm and the detection probabilities of the local sensors. The reader is referred to [8] for expressions of the soft decision fusion rule, the terminals of the quantization intervals, and the representative levels. The performance of this soft decision fusion approach is evaluated and compared to the optimum centralized fusion method and the optimum decentralized hard decision fusion method in the cases of Gaussian and Rayleigh distributed observations. The soft decision fusion method depends on the known and stationary false alarm and detection probabilities. A soft decision fusion approach based on fuzzy detectors is presented in [36]. This soft approach is an extension of the classical hard decision fusion approach, in which the crisp binary threshold, which quantizes the received observations, is replaced with a fuzzy threshold. The fuzzy threshold is designed to overcome the reduction in performance due to the hard decision quantization while retaining some of its features. This improvement is accomplished in [36] by smoothing the sensor decisions using fuzzy thresholds. The performance of this approach is evaluated according to the Neyman–Pearson criterion and compared to the optimum decentralized hard decision fusion approach in the case of Gaussian distributed observations. Extension of this method to the cases of a large number of sensors and targets is impractical for real-time processing.

The optimal decision fusion in the Neyman–Pearson sense is derived in [58] and reconsidered in [8] when the local sensors transmit one binary quality information bit in addition to the individual binary sensor decisions. This method uses three different thresholds at each local sensor. A binary 1 quality bit indicates "confidence", whereas a binary 0 quality bit indicates "no confidence". A binary 1 quality bit is sent along with the individual sensor decision when the sensor likelihood ratio is either greater than the upper threshold or less than the lower threshold. Otherwise, a binary 0 quality bit is sent.

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