COLLABORATIVE CLASSIFICATION APPLICATIONS IN SENSOR NETWORKS

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ABSTRACT

Distributed sensor networks are a significant technology nowadays. Inexpensive, smart devices with multiple sensors provide opportunities for instrumenting, monitoring and controlling targeting systems. Such sensor nodes have capability for acquiring and embedded-processing of variety of data forms. Collaborative signal processing and fusion algorithms are needed to aggregate the distributed data from among the nodes in the network, including possibly multiple modalities of data within a sensor node, to make decisions in a reliable and efficient manner. One of the important sensor network applications is target classification in battlefields. This paper presents improved moving vehicle target classification performance using data obtained from sensor networks with collaboration both across nodes and within a node in terms of multimodal fusion. Results show that a 50% relative improvement in classification error can be obtained using collaboration both in the case of single vehicle target and those involving multi-vehicle convoys.

1. INTRODUCTION

Distributed sensor networks are a significant technology nowadays. Inexpensive, smart devices with multiple sensors provide opportunities for instrumenting, monitoring and controlling targeting systems such as, for instance, the environment, buildings, and high-risk areas (e.g. battlefields)[3]. Such sensor nodes have capabilities for acquiring and embedded-processing of variety of data forms such as acoustic, seismic, and infrared signals. The challenge is how to gain the most meaningful information from the data collected by the distributed nodes in an efficient and robust manner. There are several challenges: limited observation window at a sensor, ambient noise and interference, processing limitations at the sensor in terms of power and memory, and sensor reliability issues. Therefore, collaborative signal processing and fusion algorithms are needed to aggregate the distributed data from among the nodes in the network, including possibly multiple modalities of data within a sensor node, to make decisions in a reliable and efficient manner. Even though problems in the fields of array signal processing and data fusion have been studied for a number of years, advances in sensor technologies, especially those aimed at military applications, have created new scenarios for applying signal processing ideas. One of the important sensor network applications is target classification in battlefields e.g. identifying types of moving vehicles in a field. Recently, this specific application has been discussed in the context of single sensor node processing [4] of single vehicle targets. This paper presents improved performance of classification algorithms applied over the sensor network with collaboration within a node, in terms of multimodal fusion, and across nodes in two different approaches i.e. data sharing and statistical confidence boost techniques. Proposed classification algorithms are also applied to the multiple targets scenarios i.e., target involving multiple vehicles in a convoy. The emphasis is on experiments using real seismic and acoustic data collected from the SITEX00 experiments performed as a part of the DARPA SensIT program [9].

2. COLLABORATIVE TARGET CLASSIFICATION

Target classification and tracking is one of the key battlefield tactical applications. The target of classification provides different types of data in terms of the physical signal generated by each type of target e.g., acoustic and seismic data. Moreover, moving targets cause the change of data in time domain which is differently detected by sensors located in different places. Gathering all obtainable data is certainly useful for classification algorithms in order to improve the performance robustness and this could be done by deploying different types of sensor installed in each sensor node distributed in the area of the moving target's path. To aggregate such, possibly, diverse types of data, collaboration techniques are required both within a sensor node and across nodes. The following are collaboration techniques are considered in this paper.

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2.1 Collaboration between heterogeneous sensors: Multimodal fusion

Since targets have different signatures corresponding to multiple modalities, e.g. acoustic and seismic, multimodal fusion aims to aggregate such data optimally to improve the overall classification performance. The rationale is that individual modalities provide complementary information especially in the presence of specific interference types. Combining both acoustic and seismic data by using higher dimensional feature vectors for tracking moving vehicles is considered in this paper.

2.2 Collaboration across nodes within the target Field of View: Data Sharing Technique

In sensor network applications, the data extracted from targets are collected by a number of sensor nodes. The correspondence of such data can be specified if sufficient information is provided, e.g. the locations of nodes. Given the limited sensing times at a given node, and possible interference effects, more reliable information on the feature of targets to be classified could be obtained by sharing data across nodes. Such information is hoped to provide a more efficient and accurate classifier. In this paper, we applied a simple data sharing technique. The idea is to compute the average of the feature vectors extracted from target data by different nodes and used as the modified input to the classifier.

2.3 Collaboration between nodes not within the same Field of View: Confidence Boost Technique

The more challenging issue of collaboration between nodes that are spatially isolated with respect to target observation can be posed as a model (or data) adaptation problem to boost the confidence on some prior hypothesis. If one assumes that the target being observed is the same at neighboring nodes and the goal is to verify this hypothesis, it can be posed as a detection problem. The problem is to iteratively improve the detection likelihood. The more general case where independent classification is required at each node can benefit from inter-sensor collaboration through a Bayesian formulation [7]. The computation of posterior probabilities $P(\omega_i \mid \mathbf{x})$ lies at the heart of Bayesian classification. Bayes formula allows us to compute these probabilities $P(\omega_i)$ and the class-conditional densities $P(\mathbf{x} \mid \omega_i)$. The best approach is to compute $P(\omega_i \mid \mathbf{x})$ using all of the information at our disposal. Part of this information might be prior knowledge, such as the prior hypothesis from the previous "neighboring" sensor. If we let D denote the training samples, then we can emphasize the role of the samples by saying that our goal is to compute the posterior probabilities $P(\omega_i \mid \mathbf{x}, D)$. Given the sample D, Bayes formula then becomes

$$P(\omega_i \mid \mathbf{x}, D) = \frac{p(\mathbf{x} \mid \omega_i, D) P(\omega_i \mid D)}{\sum_{j=1}^{c} p(\mathbf{x} \mid \omega_j, D) P(\omega_j \mid D)}$$

Assuming the prior probabilities are independent of the training samples D, $P(\omega_i) = P(\omega_i \mid \mathbf{x}, D)$ and we can approximate $P(\omega_i)$ from the likelihood value or confidence score obtained from the classifier operated in the previous sensor.

3. EXPERIMENTAL RESULTS

Three types of military vehicles -- AAV, DW and LAV -- were the targets to be classified. Our experiments initially focused on single target classification and explored the classification performance with and without collaboration and then extended the application to the multi target classification to investigate the robustness of such classification algorithms in more complex scenarios. Classification involving multiple targets (vehicles in convoy) poses several challenges: number of targets is unknown, diverse target types could be involved and inter-target interference could be expected to severely degrade target classification performance.

3.1 Single Target Classification

The relevant events from the SensIT experiment were selected to collect the time-series data needed for the experiments, for e.g., a single vehicle moving from one node to another. The feature vectors were computed from the normalized energy of 16 frequency bands of the seismic and acoustic signal spectra for 0.5-second data frames which are extracted from a 10-second interval while the target is closest to a given sensor node. In total, the numbers of acoustic and seismic feature vector sets extracted from various events in the experiment for AAV, DW and LAV were 360, 360 and 480, respectively. Two basic classifiers; k-Nearest and Maximum Likelihood, were exploited in the experiment. Classification performance was evaluated by randomly selecting 200 feature vectors from each vehicle type as a training set to train the classifier. The rest of the feature vectors belong to a testing set used to estimate the probability of misclassification. The results are presented in the comparison between performance of the classifiers with and without collaboration.

Figure 1 illustrates the classification performance improvement by collaboration across nodes within the target Field of View: Data Sharing Technique. The classifiers operated on up to five frames of testing data obtained while the vehicle was moving from the first node to the second node obtained about every twenty seconds. The analysis frame rate was determined empirically in the preliminary experiments so as to minimize the amount of processing at the nodes. To share the data, at each analysis point, features were extracted from the data collected from both nodes. All elements of each feature vector were simply combined by computing the average. Assuming the features have a normal density distribution, averaging decreases the variance of the features and likely to provide better classification results with same feature dimensions. The dotted lines represent the classifiers' performance without collaboration. The solid lines represent the classifiers' performance with collaboration. Obviously collaboration over two nodes provides better classification performance especially with limited data. Such improvements in classification under limited data, afforded by collaboration, are desirable for situations requiring rapid decisions.

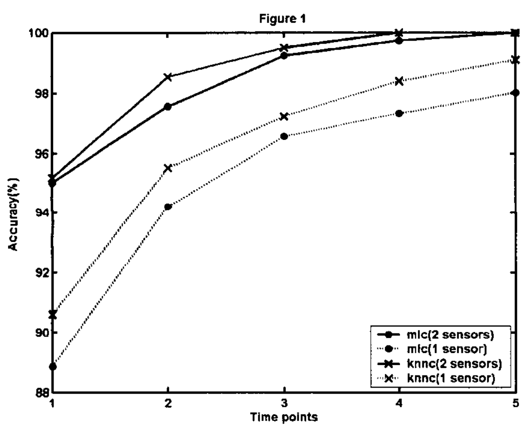

Figure1: Classification performance for inter-node collaboration between two sensors (solid lines) for 2 different classifier types; Maximum Likelihood (mlc) and k-Nearest (knnc) plotted against duration of sampling.

Next the usefulness of combining the acoustic and seismic information sources is explored. Figure 2 illustrates the performance of the Maximum Likelihood classifier using the two modalities of data: Multimodal Fusion. With the same experiment setup as in the previous section, the additional factors are feature types. By using higher dimensional feature vectors for the two modalities; seismic and acoustic, the classification performance is significantly improved compared to just using either seismic or acoustic data.

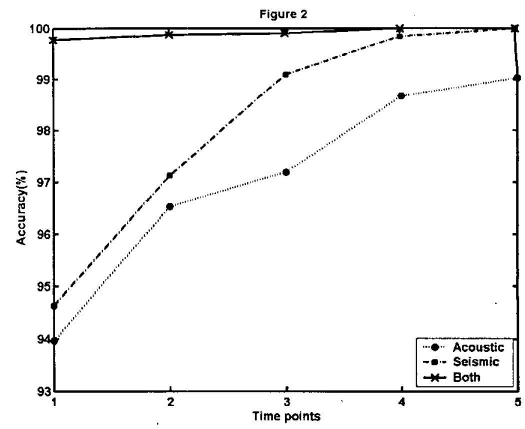

Figure 2: Classification performance with intra-node collaboration between acoustic and seismic sensors plotted against duration of sampling.

Classifiers	Accuracy (%)
Within the first node	80.6
Within the second node	81.5
Data Sharing Technique	90.3
Confidence Boost Technique	88.9

Table1: Classification performance with different approaches of collaboration: Sharing Feature and Confidence Boost Method compared with individual classifier operated in each single node.

Two nodes are assumed to be isolated with respect to target observation in the experiment to study the confidence boost technique for collaborative classification. The information during the movement of vehicles from the first node to the second is also assumed to be unknown. Therefore, the collaborative classifier can be operated only when vehicles reach the second node. In this method we assume that the classification hypothesis from the first node is also transmitted to the second node. The collaborative classifier earns the confidence boost by mapping the likelihood value of each vehicle type computed from the classifier operated in the first node to constitute the prior probabilities for the classifier in the second node.

Table 1 illustrates the performance of the collaborative classifier with confidence boost technique, compared to the classifier without collaboration, operated individually within each node. The performance is obviously improved by collaborative classification (relative improvement is around 50%). We also present the data sharing technique performance in the same table. Note that the data sharing technique performs somewhat better than confidence boost method. However, the disadvantage is that to communicate features between nodes (by sending the feature which is usually in large dimension across nodes) requires a larger bandwidth communication channel and consumes more energy than sending only the classification results or likelihood values.

3.2 Multiple targets classification

In likely scenarios in a battlefield, the target to be classified is sometimes a convoy of vehicles. In the SensIT experiment, multiple targets were set up to be a column of vehicles moving past the sensor field. Three scenarios chosen from the experiment were considered in this paper: a convoy of 2 AAVs, a convoy of 7 LAVs, and multiple vehicle convoy containing 2 LAVs, DW, and 2 AAVs respectively.

Figure 3 illustrates the acoustic and seismic data collected from a convoy of 7 LAVs and the multiple vehicles convoy. Due to the interference between vehicles, degradation of classification performance is expected. The acoustic data seems to have more impact than seismic data. The approach to mitigate the interference is to operate the classifier while each vehicle is closest to the sensor. Considering the seismic data shown in the figure, we are able to point out the interval that the energy of the signal reaches the local maximum, i.e. each vehicle in the convoy is closest to the sensor node. This is also the advantage of combining the information from different data types in the multimodal fusion point of view.

We exploited the classifier trained in the single target classification experiment. The sharing data collaboration technique was embedded in such classifier. However, due to the effect of interference between targets, the eligible sharing data for multiple target scenarios is likely to be the data collected when each target is closest to the node. Therefore, unlike the single target classification scenarios, we could not operate classifiers up to five frames of testing data obtained while the vehicle was moving from the first node to the second node. The sharing data process can be applied only when the vehicle reaches the second node.

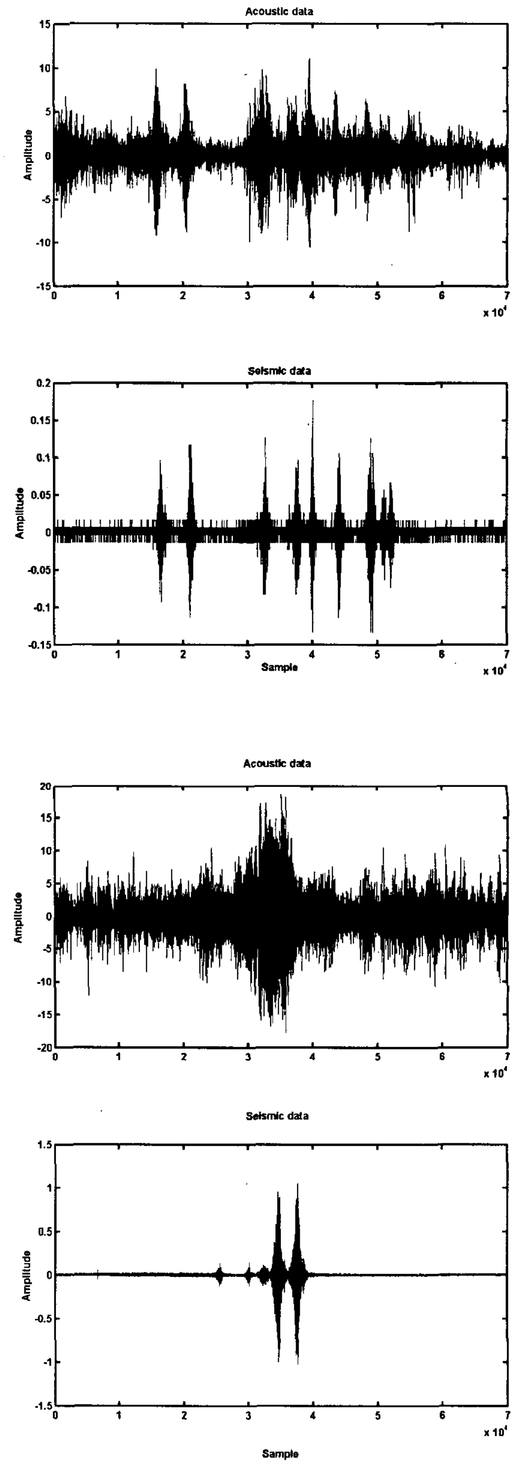

Figure 3: Acoustic and Seismic data in time domain collected from a convoy of 7 LAVs (2 upper graphs) and multiple vehicles convoy: a column of 2LAVs, DW, and 2AAVs (2 lower graphs).

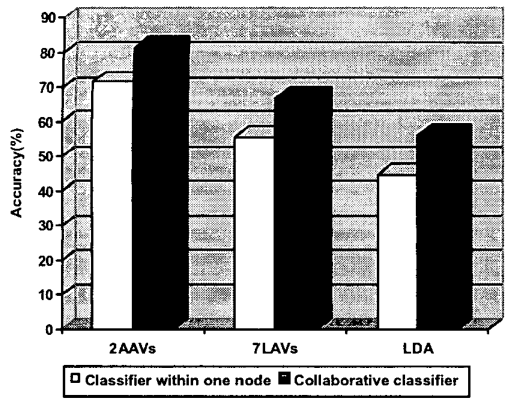

Figure 4: Multiple target classification performance with collaboration between two nodes compared with classifier without collaboration (2 AAVs, 7LAVs and LDA represent a convoy of 2 AAVs, a convoy of 7 LAVs, and a convoy containing 2 LAVs, DW, and 2 AAVs respectively).

In figure 4, the classifier performance is illustrated by the overall percentage of correct classification obtained from three scenarios. In this figure 4, "2AAVs", "7LAVs" and "LDA" represent a convoy of 2 AAVs, a convoy of 7 LAVs, and a multiple vehicle convoy containing 2 LAVs, a DW, and 2 AAVs respectively. The gray and white bars represent the performance of classifier operated in the second node with and without sharing the data transmitted from the first node, respectively. Obviously, the performance is degraded when the convoy contains a larger number of vehicles or vehicles of various types. Collaboration between two nodes still provides significant improvement for the classification performance.

4. SUMMARY AND ONGOING WORK

This paper focused on target classification applications related to distributed sensor networks. Such applications, especially in the military, desire faster and more reliable classification with limited data and processing. We showed preliminary results where single target classification can be improved by collaboration between sensor nodes under limited data using Multimodal Fusion, Data Sharing, and Confidence Boost techniques. The proposed collaborative classifiers were also applied to a challenging application under interference: classification when multiple targets are simultaneously present in the sensors' field of view.

The future work will focus on applying Hidden Markov Model to attack problems of multiple targets classification in the sense of dealing with non-stationary signal. Such a framework provides an efficient way of implementing collaboration through model adaptation. Furthermore, source separation approach will be exploited to reduce the inter-target interference in order to improve the classification performance.

5. REFERENCES

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