Collaborative Multi-Modality Target Classification in Distributed Sensor Networks*

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Abstract – *A new computing paradigm which utilizes mobile agents to carry out collaborative target classification in distributed sensor networks is presented in this paper. Instead of each sensor sending local classification results to a processing center where the fusion process is taken place, a mobile agent is dispatched from the processing center and the fusion process is executed at each sensor node. The advantage of using mobile agent is that it achieves progressive accuracy and is task-adaptive. To improve the accuracy of classification, we implement Behavior Knowledge Space method for multi-modality fusion. We also modified the classical k-nearest-neighbor method to be adaptive to collaborative classification in a distributed network of sensor nodes. Experimental results based on a field demo are presented at the end of the paper.*

Keywords: target classification, sensor fusion, multi-modality fusion, mobile agent, distributed sensor network.

1 Introduction

In recent years, distributed sensor networks (DSNs) have spurred great research interest due to the relatively low cost of sensors, the availability of high speed communication networks, and the increased computational capability [1]. DSNs can be deployed in a wide variety of military and civilian applications, where multi-target detection, classification, and tracking are typical ones.

The use of DSNs has many advantages over single sensor deployment structure, which can be addressed from four fundamental aspect: the redundancy, complementarity, timeliness and cost of the information [2].

Redundancy: When each sensor in a sensor network captures the same features of an environment with different fidelity, they can provide redundant information of the environment. The fusion among multiple sensor information will reduce the overall uncertainty of the system and thus improve the accuracy. Furthermore, the use of DSNs can also avoid systems being vulnerable to a single component failure [3].

Complementarity: Complementary sensor networks may give a representation of data over a large area, or provide several aspects of the same phenomenon that can be used together for studying one event which is otherwise impossible to perceive using individual sensor [2, 3]. If the measured features are considered as dimensions of a feature space, then the sensor network provides complementary information when each sensor is only able to provide a subset of the features, i.e., sensors do not depend on each other directly.

Timeliness: By fusing the information from multiple sensors, it is possible to achieve higher processing speed. This is due to either the actual speed of operation of each sensor or the processing parallelism of the fusion algorithm [2].

Cost: The advance in sensor technology and MEMS fabrication allows better, cheaper, and smaller sensors to be used and has caused the use of large amount of sensors in a DSN economically feasible.

Even though the deployment of DSNs has many advantages over traditional single sensor architecture, there are several technical challenges that must be overcome before DSNs can be used for today's increasingly complex information gathering tasks [4]. These tasks are usually time-critical, cover a large geographical area, and require reliable delivery of accurate information for their completion. Another important aspect is the issue of energy consumption since the energy reserved at each sensor is limited and each operation of

*This research was supported in part by DARPA under grant N66001-001-8946

sensors consumes certain amount of energy. Furthermore, sensors in DSNs typically communicate through wireless network where the communication bandwidth is much lower than for wired communication while data volumes being transferred are much larger than single sensor deployment. Unreliable network connection and data faulty are also more possible since the environment is more unreliable. All of these issues bring new challenges to the design of DSNs.

In classical DSNs, it is assumed that all the local sensors communicate their data to a central processor that performs data processing tasks, called the **processing element**. This kind of structure is referred to as the client/server model that supports many distributed systems, such as remote procedure calling, common object request broker architecture [4]. However, the client/server model has several drawbacks that has limited its usage, including the heavy network traffic, the strong dependence on a healthy network connection, and its inflexibility in dealing with the environmental change [4].

In our previous paper [4], we proposed an improved DSN architecture using mobile agent which is referred to as mobile-agent-based DSN (MADSN). MADSN adopts a new computation paradigm that data stay at the local site, while the processing task (code) is moved to the data sites. By transmitting the computation engine instead of data, MADSN offers several important benefits, including reduced network bandwidth, better network scalability, extendibility, and stability.

In this paper, we develop a mobile-agent-based sensor fusion algorithm for collaborative target classification. Sec. 2 introduces the target classification algorithm used in each local node. Sec. 3 presents the algorithm design of multi-modality fusion between acoustic and seismic channels and its implementation by mobile agent among distributed sensor nodes. Sec. 4 provides the experimental results based on data collected in a field demo.

2 Target classification algorithm

Target detection, classification, and tracking are all typical applications of DSNs. Our discussion in this section concentrates on ground vehicle classification which uses unattended ground sensors at the local site. Both the acoustic and seismic signals are commonly used in battlefield surveillance due to their simplicity and the easy deployment of microphones and geophones. On the other hand, they are also strongly nonstationary because of the interference by many factors such as the speed of the target, noise from various moving parts and frictions, and environmental effects [5]. Therefore, it is crucial to extract representative and robust features in order to classify targets correctly.

2.1 Feature extraction and classification

Feature extraction is the process to obtain signal characteristics from the time series data. It can be considered as a data compression process which removes irrelative information and preserve relevant one from the raw data [6]. Feature extraction plays an important role in target classification problem since the performance of the classifier largely depends on the quality of the feature vectors. In order to conquer the nonstationarity of both the acoustic and seismic signals, we derive features from the original time series data in both the frequency and time-frequency domains [6]. The block diagram of the feature extraction procedure is shown in Figure 1.

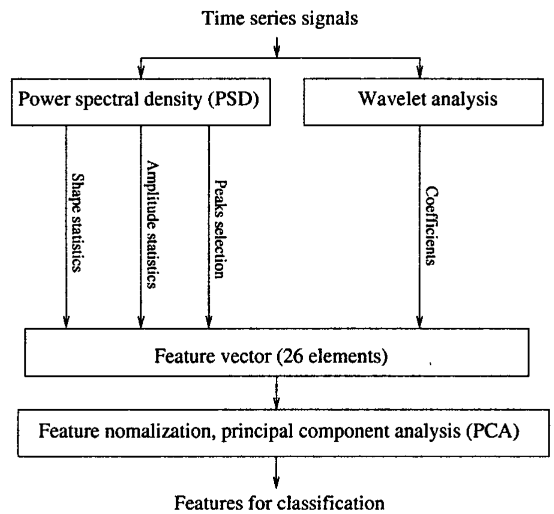


Figure 1: Block diagram of the feature extraction procedure.

The feature vectors include 26 elements that are derived from the power spectral density (PSD) and the wavelet coefficients of the time series data. PSD describes the energy distribution of the signal in the frequency domain. We derive 4 elements of the feature vector by calculating the high-order shape statistics and another 4 elements by calculating the amplitude statistics of the PSD. These features provide statistical measurements of local spectral energy content over the signal bands. Shape statistics is defined as:

$$\text{Mean:} \quad \mu_{shape} = \frac{1}{S}\sum_{i=1}^{N} iC(i)$$

$$\text{Stan. dev.:} \quad \theta_{shape} = \sqrt{\frac{1}{S}\sum_{i=1}^{N}(i-\mu_{shape})^2 C(i)}$$

$$\text{Skewness:} \quad \gamma_{shape} = \frac{1}{S}\sum_{i=1}^{N}(\frac{i-\mu_{shape}}{\theta_{shape}})^3 C(i)$$

$$\text{Kurtosis:} \quad \beta_{shape} = \frac{1}{S}\sum_{i=1}^{N}(\frac{i-\mu_{shape}}{\theta_{shape}})^4 C(i) \quad (1)$$

where $S = \sum_{i=1}^{N} C(i)$, $C(i)$ is the PSD magnitude for the ith frequency bin, and N is the number of the frequency bins.

Amplitude statistics is defined as:

$$\text{Amplitude:} \quad \mu_{amp} = \frac{1}{N}\sum_{i=1}^{N} C(i)$$

$$\text{Stan. dev.:} \quad \sigma_{amp} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(C(i)-\mu_{amp})^2}$$

$$\text{Skewness:} \quad \gamma_{amp} = \frac{1}{N}\sum_{i=1}^{N}(\frac{C(i)-\mu_{amp}}{\sigma_{amp}})^3$$

$$\text{Kurtosis:} \quad \beta_{amp} = \frac{1}{N}\sum_{i=1}^{N}(\frac{C(i)-\mu_{amp}}{\sigma_{amp}})^4 \quad (2)$$

The peak locations of the PSD represent dominant frequencies of the time series signal. They indicate the frequencies of the vibration of vehicles, and are suitable features for representing and classifying different targets. In our approach, we choose the frequency locations of the 3 highest peaks and their corresponding magnitudes as 6 elements of the feature vector.

The other 12 elements of the feature vector are derived from the wavelet coefficients of the time series signal. Wavelet transform is a solid time-frequency domain signal analysis method which is designed to analyze non-stationary signals. After the wavelet transformation using Daubchies wavelets as the mother wavelet, we can get totally four levels of wavelet coefficients. The elements of the feature vector include the average, the standard derivation and the energy of these four levels of wavelet coefficients.

2.2 Classifier design

After feature extraction, an important step is to choose the classifier which will be used to categorize the target into specified classes based on the properties of both the specific problem and the derived feature vector. In this project, k-Nearest-Neighbor (kNN) algorithm is chosen as the classifier. The basic idea for kNN is to look into a neighborhood of the test data for k samples. If within that neighborhood, more samples lie in class i than any other classes, we assign the unknown test as belonging to class i.

3 Fusion methods

As larger amount of sensors are deployed to form distributed sensor arrays, it is important to develop a robust and fault tolerant data fusion technique in order to handle uncertainty of sensor outputs. There are totally three levels of data fusion in our approach for target classification: 1) Temporal fusion of classification results from 1-second data samples over a detection event; 2) multi-modality fusion of the classification results from the acoustic and seismic signals; 3) distributed sensor fusion. The hierarchical structure of these three levels of data fusion is shown in Figure 2.

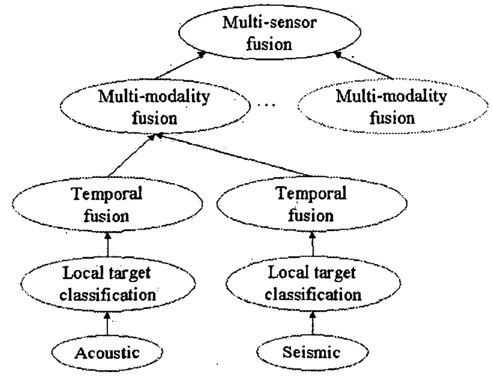


Figure 2: The hierarchical structure of three levels of data fusion.

3.1 Temporal fusion

In the terminology of target detection and classification, the duration of time that the sensors can detect a target passing by is called an event. In this sense, the objective of temporal fusion is to fuse all the 1-second local classification results that are corresponding to one event in order to give the event classification result. Since the signals detected at different time can be considered as independent, majority voting is used to do the fusion.

3.2 Multi-modality fusion between the acoustic and seismic channels

Since both the acoustic and seismic signals captured at each sensor node give the information of the whole scenario of the targets, the classifiers using either the acoustic or seismic signal can be considered as being trained over the whole feature space, and are thereby

s_1, s_2	Numbers from each class	Cell label
1, 1	10/3/3	1
1, 2	3/0/6	3
1, 3	5/4/5	1, 3
2, 1	0/0/0	0
2, 2	1/16/6	2
2, 3	4/4/4	1, 2, 3
3, 1	7/2/4	1
3, 2	0/2/5	3
3, 3	0/0/6	3

Table 1: A possible BKS look-up table.

considered as competitive rather than complementary, which is a typical case of classifier fusion technique. The classifiers can also be considered as independent without loss of generality since the signals are captured through independent devices. In this sense, we can implement some simple classifier fusion algorithm to perform the multi-modality fusion on each sensor node in order to improve the overall accuracy. We choose to use the Behavior-Knowledge Space (BKS) method [7] as a 2-class fusion algorithm that combines the classification results from the acoustic and seismic signals.

Suppose $s_1, \ldots, s_L$ are the crisp class labels assigned to x by classifiers $D_1, \ldots, D_L$ respectively. Then every possible combination of class labels is an index to a cell in a look-up table with each entry one of the following: a **single class label** which is the one that is most ofter encountered among all the training samples belonging to this cell; **no label** which means there are no training samples give the respective combination of class labels; or a set of **tied class labels** which is the case that more than one class have the same highest number of training samples in this cell. A 2-classifier fusion example using BKS algorithm is shown as follow.

Example: Let the number of classes $c = 3$, the number of classifiers $L = 2$, and the number of testing samples $N = 100$. A possible BKS look-up table is displayed in Table 1 [7].

3.3 Distributed sensor fusion

After carrying out both the temporal fusion and multi-modality fusion at the local site, it is very important to fuse the results from different sensor nodes in order to handle uncertainty and faulty sensor readout. This section first reviews the original multi-resolution integration (MRI) algorithm proposed for DSNs. A modified MRI algorithm is then described in order to take advantage of the mobile agent to implement MRI distributively and to achieve better network scalability and fault tolerance.

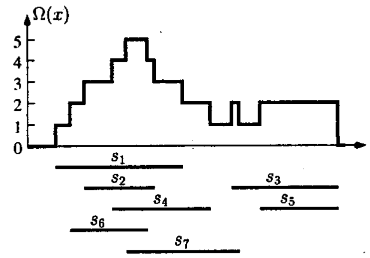


Figure 3: The overlap function for a set of 7 sensors.

3.3.1 Original MRI algorithm

The original MRI algorithm was proposed by Prasad, Iyengar and Rao in 1994 [8]. The basic idea consists of constructing a simple overlap function from the outputs of the sensors in a cluster and resolving this function at various successively finer scales of resolution to isolate the region over which the correct sensor lie [4, 5]. Each sensor in a cluster measures the same parameters. It is possible that some of them are faulty. Hence it is desirable to make use of this redundancy of the readings in the cluster to obtain a correct estimate of the parameters being observed.

Let sensors $S_1, \ldots, S_N$ feed into a fusion processor P. Let the abstract interval estimate of S_j be I_j ($1 \leq j \leq N$) which is a bounded and connected subset of the real number $[a_j, b_j]$. The characteristic function χ_j of the jth sensor S_j is defined as:

$$\chi_j(x) = \begin{cases} 1 & x \text{ is in } [a_j, b_j] \\ 0 & x \text{ is not in } [a_j, b_j] \end{cases} \tag{3}$$

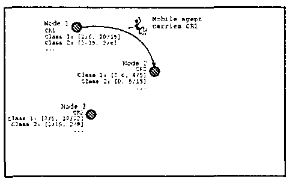
The overlap function of N sensors is defined as $\Omega(x) = \sum_{j=1}^{N} \chi_j(x)$. Figure 3 illustrates the overlap function for a set of 7 sensors.

Multi-resolution analysis provides a hierarchical framework for interpreting the overlap function. Given a sequence of increasing resolutions, at each resolution, MRI picks the crest which is a region in the overlap function with the highest peak and the widest spread, and resolve only the crest in the next finer resolution level.

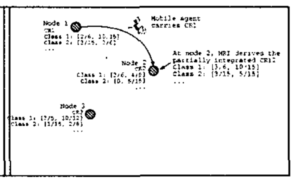
3.3.2 Mobile-agent-based collaborative sensor fusion

In a distributed sensor network, since each sensor transfers its readout to a central processing center where the fusion task is performed, with the increasing amount of sensors, the network traffic increases dramatically. In order to handle this problem, mobile-agent-based fusion paradigm is used.

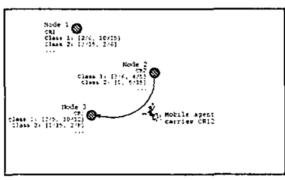
In an MADSN, the mobile agents migrate among the sensor network and collect readouts. Each mobile agent carries a partially integrated overlap function which is accumulated into a final version at the processing element after all the mobile agents return. Since the carriage of partially integrated overlap function in its finest resolution counteracts the advantages of the mobile agent, the original MRI algorithm is modified so that MRI is applied before accumulating the overlap function. We use a 1-D array, ω_x, to serve as an appropriate data structure to represent the partially integrated overlap function at a specific resolution requirement. The coarser the resolution, the smaller the data buffer. The implementation of the mobile-agent-based fusion with 3 sensors is illustrated in Figure 4.



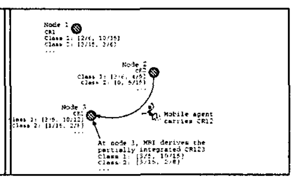
(a) Stage 1.



(b) Stage 2.



(c) Stage 3.



(d) Stage 4.

Figure 4: Mobile-agent-based multiple sensor fusion.

Suppose there are totally 3 sensor nodes and the mobile agent starts from node 1, carrying the overlap function of classification generated by node 1 to node 2 (Figure 4 (a)). With a combination of overlap functions $CR1$ and $CR2$, at node 2, the mobile agent can generate a partially integrated confidence range ($CR12$) as shown in Figure 4 (b). From node 2, the mobile agent continues its itinerary to node 3, carrying the partially integrated result (Figure 4 (c)). At node 3, using a combination of the partially integrated result ($CR12$) and the local overlap function of node 3 ($CR3$), another partially integrated result ($CR123$) can be derived (Figure 4 (d)). If $CR123$ achieves the required accuracy, then the classification task can be terminated. Otherwise, the mobile agent needs to continue its migration. The advantage of using mobile-agent-based paradigm is that it provides *progressive accuracy*. When the accuracy requirement has been reached, the mobile agent can return to the processing center immediately without finishing the scheduled route.

4 Experiments and results

In order to test the performance of the target classification and fusion schemes described above, we use the data set provided by DARPA SensIT (Sensor Information Technology) program in a field demo (SITEX02) held at 29 Palms, California in November, 2001. The node positions in the distributed sensor network is shown in Figure 5. A subset of sensors are chosen. A training set and a test set are generated by dividing the whole data set into three partitions, two are used as the training set and the other one is the test set.

Following the procedures discussed in Sections 2 and 3, firstly, features are extracted from the signals captured by the microphone and geophone on each local sensor. Local target classification is then performed. There are three levels of fusion in our scheme: temporal fusion, multi-modality fusion, and distributed sensor fusion.

In our experiment, signals from one event are generated by one class of target, including AAV, Dragon Wagon (DW) and HMMWV. Each event is divided into about 10 1-second segments. The performance evaluation for the three types of targets are shown in Figure 6. In each figure, the solid line indicates the classification accuracy using the acoustic signal and the dash line indicates the result using the seismic signal. The first data point along the x-axis is the average classification accuracy using 1-second segments. The second point indicates the accuracy after performing temporal fusion over one event using majority voting. The third point shows the accuracy by performing multi-modality fusion to combine the acoustic and seismic classification results using BKS. The last point is the accuracy using mobile-agent-based multi-sensor fusion in a cluster of 3 sensors.

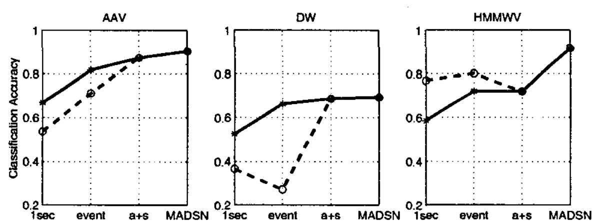
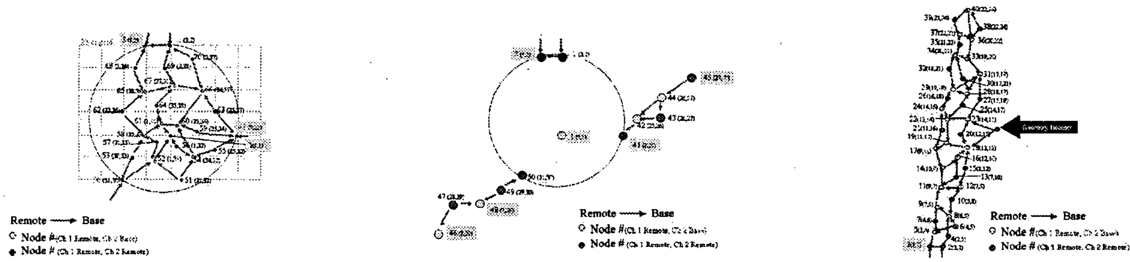


Figure 6: Performance evaluation of different classification schemes for AAV, DW, and HMMWV. Solid line: acoustic signal; Dash line: seismic signal; 1sec: averaged accuracy over one event using 1-second segments; event: temporal fusion result within one event; a+s: multi-modality fusion result; MADSN: multi-sensor fusion result using mobile agent.

From Figure 6, we observe that, in general, the tem-



(a) Center (b) East-West (c) North-south

Figure 5: Node positions of SITEX02 field demo.

poral fusion results are better than the 1-second classification results, the multi-modality fusion results are better than the event fusion results, and the multi-sensor fusion results are better than the multi-modality fusion results. That is, the hierarchical fusion scheme improves the classification accuracy steadily. Even though sometimes either the acoustic signals or the seismic signals can perform better than another, the multi-modality fusion results are mostly better than using either signal. In another word, acoustic classification and seismic classification results can compensate each other. For all the three targets, the multi-sensor fusion accuracy are always the highest.

5 Conclusion

In this paper, we present a hierarchical fusion scheme for collaborative target classification in a distributed sensor network. The scheme includes three levels of fusion: temporal fusion based on 1-second segments within the same event using majority voting, multi-modality fusion using BKS with results from both the acoustic and seismic signal classification, multi-sensor fusion using mobile agents with the modified kNN algorithm. The experimental results show a steady increase in the classification accuracy across the three levels. The multi-sensor fusion accuracy is always the highest which shows the importance of the use of distributed sensor networks. Mobile-agent-based computation presents a new paradigm to support fusion in DSNs.

Acknowledgement

The authors would like to thank Professor Yu Hen Hu and his students at University of Wisconsin-Madison for the tremendous amount of time they spent in generating the cross-validation data set based on the SITEX02 field demo. Without their data set, our research approach would have been difficult to validate.

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