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Dynamic Target Classification in Wireless Sensor Networks

Ying Sun

University of Tennessee - Knoxville

To the Graduate Council:

I am submitting herewith a thesis written by Ying Sun entitled "Dynamic Target Classification in Wireless Sensor Networks." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Computer Engineering.

Hairong Qi, Major Professor

We have read this thesis and recommend its acceptance:

Itamar Elhanany, Cheng Wang

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Dynamic Target Classification in Wireless Sensor Networks

A Thesis
Presented for the
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Abstract

Information exploitation schemes with high-accuracy and low computational cost play an important role in Wireless Sensor Networks (WSNs). This thesis studies the problem of target classification in WSNs. Specifically, due to the resource constraints and dynamic nature of WSNs, we focus on the design of the energy-efficient solution with high accuracy for target classification in WSNs.

Feature extraction and classification are two intertwined components in pattern recognition. Our hypothesis is that for each type of target, there exists an optimal set of features in conjunction with a specific classifier, which can yield the best performance in terms of classification accuracy using least amount of computation, measured by the number of features used. Our objective is to find such an optimal combination of features and classifiers. Our study is in the context of applications deployed in a wireless sensor network (WSN) environment, composed of large number of small-size sensors with their own processing, sensing and networking capabilities powered by onboard battery supply. Due to the extremely limited resources on each sensor platform, the decision making is prune to fault, making sensor fusion a necessity.

We present a concept, referred to as *dynamic* target classification in WSNs. The main idea is to dynamically select the optimal combination of features and classifiers based on the "probability" that the target to be classified might belong to a certain

category. We use two data sets to validate our hypothesis and derive the optimal combination sets by minimizing a cost function.

We apply the proposed algorithm to a scenario of collaborative target classification among a group of sensors which are selected using information based sensor selection rule in WSNs. Experimental results show that our approach can significantly reduce the computational time while at the same time, achieve better classification accuracy without using any fusion algorithm, compared with traditional classification approaches, making it a viable solution in practice.

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Chapter 1

Introduction

1.1 Wireless Sensor Networks

1.1.1 Introduction

Since the first decade of the 21^{st} century, the Wireless Sensor Network (WSN) has been a very active research field. Due to the small size of sensors and the untethered communication ability, it becomes a very promising area. It can be envisioned that wireless sensor networks will play a key role to the real ubiquitous computing. Sensor networks will eventually permeate the physical world and provide grounding for the Internet [45].

The WSN is composed of spatially distributed autonomous sensor nodes which are responsible for sensing, data processing and communication. From the functionality point of view, the goal of wireless sensor network is to make decision or gain knowledge based on the data it has sensed. Unlike the traditional computer networks, sensor networks are designed to detect events and monitor environments, collect and fuse the data, report events or information to interested users [19]. Owing to the characteristics such as self-organizing, fast deploying, changing topology, short-range broadcasting and multihop routing, collaborative information processing, localization and tracking capabilities, WSNs have captured more attention of researchers and will create a digital skin that senses a wide variety of phenomena of interest in all kinds of fields of applications [46]. MIT's Technology Review magazine called sensor networks as "One of the ten technologies that will change the world" [4].

The features of the WSN determine its uniqueness which makes it different from current information services provided by the Internet from the following aspects.

1. The WSN is $data - centric$ [46], which means that the network collects, routes or accesses data based on the external information such as physical location, environment temperature, humidity, etc. This makes a vivid contrast with the internet that is an $address - centric$ network, which exchanges information via logical properties of ends related to the network structure.

2. Unlike the Internet where a large amount of information is worldwide oriented and it might be worthless for most of users and easy to be stale, sensor networks can sense the properties of the environments, detect the physical phenomena, and provide the precisely localized information in time or space to a couple of interested users.

3. WSNs bridge the discrepancy between the Internet and the physical space. The sensor internet will extend human's vision from the virtual world into the physical world and integrate them into a global information space through sensor nodes and actuator technologies [46].

4. The most fascinating features that WSNs have are self-configuration and self-adaptability. In many application scenarios such as battlefield surveillance, medical monitoring, WSNs need to change topology due to the uncertain environment or link/node failure. Thus, network sensors require to relocate and

organize themselves to best obtain and deliver the information. On the contrary, the traditional networks always have a fixed structure once the users' demands are settled.

5. The dynamic nature combined with power restriction determines the WSN's distinctive protocol stack that is different from standard TCP/IP protocol stack in many aspects. First, data-centric property requires network to address sensors using their physical properties such as location instead of IP address. Second, discovery protocols is in great need for sensor networks because it is an effective way for sensors to construct the local structure in order to implement self-deployment according to the environmental change. Third, cross-layer protocols need to be designed in order to get highly reliable communication with minimal energy expenditure. Fourth, stack structure difference, as shown in Figure 1.1 [6], which requires new protocols to balance the power usage, movement detection, and task scheduling. Fifth, existing protocols in TCP/IP stack are lack of energy-efficient solutions which are the necessity in the WSN protocol design. Finally, mobility and dynamics in WSNs exclude all the existing edge-network gateway protocols for internetworking IP and sensor networks [46].

6. Compared with the Internet nodes, the nodes composed of WSNs have limited energy capacity, a small amount of memory and restricted computational capability. They also have limited communication bandwidth and finite longevity.

1.1.2 WSN's applications

Over the past years, with the fast development in MEMS and wireless communications, low-cost sensing ability and computing devices, a large-scale, low power, inexpensive sensor network starts to be deployed in many applications. This kind of

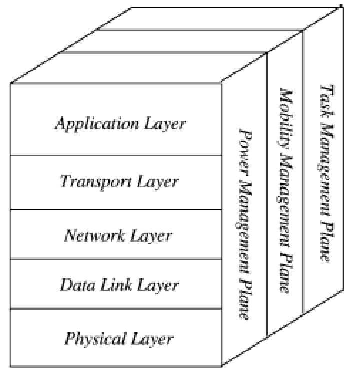

Figure 1.1: The sensor network protocol stack [7].

sensor deployment not only extends the spatial coverage and achieves higher resolution, but also increases the fault tolerance and robustness of the system [3]. WSNs may consist of many different types of sensors such as acoustic, seismic, magnetic, infrared, and radar. The various sensing modalities are able to monitor a wide variety of ambient conditions that include the following [17]: temperature, humidity, vehicular movement, lightening condition pressure, soil makeup, noise levels, the presence or absence of certain kinds of objects, mechanical stress levels on attached objects, and the current characteristics such as speed, direction, and size of an object.

The concept of micro-sensing and wireless connection of these nodes promise many new application areas [7]. We categorize the applications into military, environment, and other commercial areas.

Military Applications: Wireless sensor networks can be an integral part of military command, control, communications, computers, intelligence, surveillance, reconnaissance and tracking systems. The rapid deployment, self organization and fault tolerance characteristics of sensor networks make them a very promising sensing technique for military applications. Since sensor networks are based on the dense deployment of disposable and low cost sensor nodes, destruction of some nodes by hostile actions does not affect a military operation as much as the destruction of a traditional sensor. Some of the military applications are monitoring friendly forces, equipment and ammunition; battlefield surveillance; reconnaissance of opposing forces and terrain; targeting; battle damage assessment; and nuclear, biological and chemical attack detection and reconnaissance [39].

Environmental Applications: Some environmental applications of sensor networks include tracking the movements of species, i.e., habitat monitoring; monitoring environmental conditions that affect crops and livestock; irrigation; macro instruments for large-scale Earth monitoring and planetary exploration; and chemical/biological detection [21, 10, 39, 34, 31, 20, 9].

Commercial Applications: The sensor networks are also applied in many commercial supplications. Some of them are building virtual keyboards; managing inventory control; monitoring product quality; constructing smart office spaces; and environmental control in office buildings [21, 39, 31, 9].

1.2 Motivations

Although wireless sensor networks have the superiority of low cost sensor device, onboard sensing, and wireless communication, the number of potential applications of wireless sensor networks is huge, the biggest impediment to widespread deployment and adoption of sensor networks comes from the following core challenging issues [37].

First, scalability. With the rapid development of low cost, small size intelligent sensors and the increased demand on the applications, dense deployment of sensor networks become a reality. In order to obtain the compelling vision and accurate information, a number of hurdles about the scalability stringent to be surmounted such as the methodologies for scaling up sensors to get adequate but minimized coverage of the interested region, the algorithms of scaling down the energy consumption to eke out the longevity of the network with current battery technology.

Second, dynamics. Since WSNs are connected with the physical world which fills with uncertainty, asynchrony, and unpredictability, they will experience extreme dynamics [13]. Environmental variations such as temperature, humidity, node failure can induce dramatic changes in network performance or structures. In addition, sensors will change in their energy availability, sensing reachability, position or task objectives. Therefore, the WSN must be self-adaptive and self-configuring in order to perform task effectively and autonomously during its lifetime in the dynamic, heterogeneous environment.

Third, accuracy. The objective of sensor networks is to detect environment, sense and process the data in order to make an accurate decision. However, it adopts untethered communication, which makes information and decision unreliable. To meet this challenge, algorithms need to be improved through collaborative detection and estimation.

Fourth, energy balance is a great concern in WSNs. To achieve a long-lived network, energy load must be evenly distributed among all sensor nodes so that the energy at a single sensor node or a small set of sensor nodes will not be drained out quickly [42].

Finally, resource constraints. The superiority of sensor networks at the same time balances with a unique set of resource constraints such as limited energy, communication bandwidth and memory. Energy management is pivotal since battery-driven sensors directly influence the overall performance and longevity of the networks. Meanwhile, energy saving requires least information redundancy, which will lead to low fault tolerance. Furthermore, moldy memory and communication bandwidth will degrade network's accuracy which favors redundancy and collaborative processing.

1.3 Related work

In this section, we review the recent progress on target detection, localization, and classification.

Recent target localization algorithms in WSNs address the problems in various ways. On group focuses on the localization in an unsecured environment. The other group proposed the solution for the environment with incomplete information. One research direction is on building the real testbed for localization, the other direction is on statistical learning theory for localization.

In "A Kernel-Based Learning Approach to Ad Hoc Sensor Network Localization" [33], X. Nguyen et al. introduce a pattern recognition based localization method using kernel methods from statistical learning theory. This is based on the fact that the kernel function can be defined in terms of the matrix of signal strengths received by the sensors. Therefore a simple and effective localization algorithm can be derived in the natural coordinate system provided by the physical devices. The algorithm is particularly applied for networks with densely distributed sensors. They evaluate their algorithm on both simulation and physical sensor networks.

L. Lazos and R. Poovendran address the problem known as the secure localization problem in their article "SeRLoc: Robust Localization for Wireless Sensor Networks" [27]. This issue enables nodes of wireless sensor networks to determine their location in an untrusted environment. They present the SEcure Range-independent LOCalizaion scheme (SeRLoc) [26] based on beacon information gathered by the locators even when attack presents. They also describe well known security threats such as the wormhole attack [44, 35], the Sybil attack [23, 24] and evaluate the probability of success for each type of attack using spatial statistics theory. The simulation results demonstrate the accuracy of SeRLoc over other existing range-independent localization schemes.

J. A. Costa et al. [15] introduce a distributed weighted-multidimensional scaling (dwMDS) algorithm which is suitable for nodes localization in WSNs. DwMDS algorithm incorporates network communication constraints in its design and this algorithm is nonparametric: it cannot be influenced by any special channel or range measurement models. This makes dwMDS suitable for a wide range of distance measurements such as RSS, TOA. Through simulation, the algorithm shows excellent bias and variance performance than CRB [32].

In the article, titled "Semidefinite programming based algorithms for sensor network localization" [11], Biswas et al. developed an SDP relaxation based method to solve the localization problem through inaccurate and incomplete information. In order to yield a semidefinite program and solve it more efficiently, the authors relaxed the nonconvex constraints in their formulation. They also extended the SDP method to an iterative way and compare the results with different iteration numbers. Their SDP relaxation and the overall distance geometry model can be applied to any other problem with mutual distance and angle information between two points.

In the paper, titled "Coherent Acoustic Array Processing and Localization on Wireless Sensor Networks" [25], Chen et al. implement a Linux-based wireless networked acoustic sensor array testbed successfully using COTS products [41]. They consider the coherent acoustic sensor array processing and localization problem in distributed wireless sensor networks. Then they review localization algorithms based on time-delay followed by least-squares estimations and the maximum-likelihood method and built the testbed using iPAQs. The experiments show their localization and time synchronization algorithms can yield good results.

In recent years, continuous efforts have been made in the target tracking research field. For example, Brooks et al. [38] present collaborative signal processing (CSP) framework for target classification and tracking in sensor networks. The framework uses location-aware data routing which restricts the range of CSP to relevant subset of nodes conserving network resources. They use the simple Euclidean metric to compute the difference of the last target track estimate projected to the time of current detection. If a track is continued, the manager node defines a new cell. The tracking process repeats at this point. They outline a CSP approach to target classification based on node measurements within a cell. They discuss that Gaussian classifiers also apply to arbitrary classifiers.

Several research groups work on target detection and classification in WSNs. In this research field, due to the resource constraints that WSNs inherently has, the design of feature extraction and classification algorithm with high accuracy at low computational cost becomes the most challenging problem. Therefore, the research mainly focuses on these two aspects: feature extraction and classification.

In "Vehicle classification in distributed sensor networks" [16], Duarte et al. compiled SITEX02 [16] data set, extracted spectral feature vectors, and baseline classification results using the maximum likelihood classifier. They detailed the data collection procedure, the feature extraction and pre-processing steps, and baseline classifier development. Their contribution benefits a lot to the subsequent researchers whose focus is on target classification area.

Qi's group [1] developed several techniques on collaborative target classification. For collaborative target classification, they developed a general purpose multi-modality, multi sensor fusion hierarchy for information integration using a mobile-agent-based framework in sensor networks [36]. They also developed several algorithms on single target, multi-target, and unknown target identification [1].

1.4 Contribution of the thesis

This thesis discusses the benefit of dynamic target classification in wireless sensor networks. More specifically, the following contributions are made:

1. Dynamic target classification algorithm is proposed in the context of wireless sensor networks based on the hypothesis that for each type of target, there exists an optimal set of features combining with a specific classifier, which can yield the best performance in terms of classification accuracy using least amount of features.

2. In order to find the optimal combination of features and classifiers, we set up a cost function, and the solution is obtained by minimizing this cost function.

3. In the thesis, we describe an application scenario in order to illustrate how dynamic classification algorithm works. Furthermore, we reconstruct the scenario using the real data collected at the SensIT situational experiments carried out at the Marine Corps Air Ground Combat Center in Twenty-nine Palms, CA.

4. Information-based sensor selection rule is introduced in this thesis.

1.5 Outline of the thesis

The outline of the thesis is as follows:

In chapter 1, we review the wireless sensor network including the introduction of WSNs and their applications. We also address the motivation of this thesis and related works that have been done in target detection, localization, and classification. At the end of the chapter, we give the synopsis of the thesis.

In chapter 2, we review the basic knowledge on signal processing, several techniques such as sampling the signal, time, frequency, and time-frequency domain signal analysis will be discussed in this chapter.

In chapter 3, we propose the dynamic target classification mechanism based on our hypothesis that for each type of target, there exists an optimal set of features in conjunction with a specific classifier, which can yield the best performance in terms of classification accuracy using least amount of computation, measured by the number of features.

In chapter 4, we use a target classification scenario to illustrate how the dynamic classification algorithm works. In addition, the information-based sensor selection rule is explained and applied to the scenario in order to assist the dynamic classification scheme to achieve the better performance.

In chapter 5, two experiments are performed and the results are analyzed. Experimental results generated from the target classification scenario show the hypothesis' validity, and demonstrate the proposed approach is an energy-efficient algorithm with the accuracy as high as 95.57% without applying any fusion algorithms.

In chapter 6, we made a conclusion that dynamic classification approach can significantly reduce the computational time and at the same time, achieve better classification accuracy, compared with traditional classification approaches. The proposed algorithm can also be extended to other application fields of pattern recognition.

Chapter 2

Signal Processing

2.1 Overview

Time-frequency signal analysis and processing concerns the analysis and processing of signals with time-varying frequency content. Such signals are best represented by a time-frequency distribution. which is intended to show how the energy of the signal is distributed over the two-dimensional time-frequency space. Processing of the signal may then exploit the features produced by the concentration of signal energy in two dimensions (time *and* frequency) instead of only one (time *or* frequency).

The following sections present the key concepts needed to formulate time-frequency methods. They also explain why time-frequency methods are referred for a wide range of applications in which the signals have time-varying characteristics or multiple components.

2.2 Time-Frequency Concepts

The two classical representations of a signal are the time-domain representation $s(t)$ and the frequency-domain representation $S(f)$. In both forms, the variables t and f

are treated as mutually exclusive: to obtain a representation in terms of one variable, the other variable is "integrated out". Consequently, each classical representation of the signal is **non-localized** with respect to the excluded variable; that is, the frequency representation is essentially averaged over the values of the time representation at *all* times, and the time representation is essentially averaged over the values of the frequency representation at *all* frequencies. In the time-frequency distribution, denoted by $\rho(t, f)$, the variables t and f are *not* mutually exclusive, but are present together. The time-frequency distribution representation is **localized** in t and f.

2.2.1 Time-Domain Representation

Any signal can be described naturally as a function of time, which we may write $s(t)$. This representation leads immediately to the instantaneous power, given by $|s(t)|^2$, which shows how the energy of the signal is distributed over time; the total signal energy is

$$E = \int_{-\infty}^{\infty} |s(t)|^2 \mathrm{d}t \tag{2.1}$$

But the time-domain description has limitations, as may be seen by applying it to a **musical performance** example [12]: A musical performance can be represented as an air pressure curve a t a particular pint in space. Each such curve is a time-varying pressure, and may e converted by a microphone and amplifier into an electrical signal of the form $s_1(t)$. Indeed, music is routinely recorded and broadcast in this way. However, the function $s_1(t)$ is nothing like the form in which a composer would write music, or the form in which most musicians would prefer to read music for the purpose of performance. Neither is it of much use to a recording engineer who wants to remove noise and distortion form an old "vintage" recording. Musical waveforms are so complex that a graph of $s(t)$ vs. t would be almost useless to musicians and engineers alike.

This example show that the time-domain representation tends to obscure information about frequency, because it assumes that the two variables t and f are mutually exclusive.

2.2.2 Frequency-Domain Representation

Any practical signal $s(t)$ can be represented in the frequency domain by its Fourier transform $S(f)$, given by

$$S(f) = F_{t \to f} s(t) \triangleq \int_{-\infty}^{\infty} s(t) e^{-j2\pi f t} \mathrm{d}t \tag{2.2}$$

For convenience, the relation between $s(t)$ and $S(f)$ may be written "$s(t) \leftrightarrow S(f)$". The Fourier transform (FT) is in general complex; its magnitude is called the **magnitude spectrum** and its phase is called the **phase spectrum**. The square of the magnitude spectrum is the **energy spectrum** and shows how the energy of the signal is distributed over the frequency domain; the total energy of the signal is

$$E = \int_{-\infty}^{\infty} S(f)^2 \mathrm{d}f = \int_{-\infty}^{\infty} S(f) S^*(f) \mathrm{d}f \tag{2.3}$$

where the superscripted asterisk (*) denotes the complex conjugate. Although the representation S(f) is a function of frequency only–time having been "integrated out"– the FT is a complete representation of the signal because the signal can be recovered form the FT by taking the inverse Fourier transform (IFT):

$$s(t) = F^{-1}_{t \leftarrow f} S(f) = \int_{-\infty}^{\infty} S(f) e^{j2\pi f t} \mathrm{d}f. \tag{2.4}$$

But the "completeness" of the FT representation does not make it convenient for all purposes, as may be seen by considering the same example.

The musical performance has a magnitude spectrum which tells us what frequencies are present, but not when they are present; the latter information is again encoded in the phase. The magnitude spectrum may exhibit as many as 120 peaks corresponding to the notes of the chromatic scale in the audible frequency range, and the relative heights of those peaks may tell us something about the tonality of the music (or whether it is tonal at all), but the timing of the notes will not be represented in the magnitude spectrum and will not be obvious from the phase spectrum.

The examples show that the frequency-domain representation "hides" the information about timing, as $S(f)$ does not mention the variable t.

2.2.3 Joint Time-Frequency Representation

As the conventional representations in the time domain or frequency domain are inadequate in the situations described above, an obvious solution is to seek a representation of the signal as a *two-variable* function or distribution whose domain is the two-dimensional (t, f) space. Its constant-t cross-section should show the frequency or frequencies present at time t, and its constant-f cross-section should show the time or times at which frequency f is present. Such a representation is called a **time-frequency representation** (TFR) or **time-frequency distribution** (TFD).

Non-stationary signals for which a TFD representation may be useful occur not only in broadcasting, seismic exploration and audio, from which our examples are taken, but also in numerous other engineering and interdisciplinary fields such as telecommunications, radar, sonar, vibration analysis, speech processing and medical diagnosis. **Time-frequency signal processing** (TFSP) is the processing of signals by means of TFDs.

2.3 Signal Analysis Techniques

2.3.1 Fast Fourier Transform

The fast Fourier transform (FFT) is a discrete Fourier transform algorithm. Although the DFT is the most straightforward mathematical procedure for determining the frequency content of a time-domain sequence, it's terribly inefficient. As the number of points in the DFT is increased to hundreds, or thousands, the amount of necessary number crunching becomes excessive. In 1965 a paper was published by Cooley and Tukey describing a very efficient algorithm to implement the DFT [22]. The algorithm is now known as fast Fourier transform (FFT).

FFT reduces the number of computations needed for N points from N^2 to $N/2 \lg N$ (lg is the base-2 logarithm). To appreciate the FFT's efficiency, let's consider the number of complex multiplications necessary for our old friend, the expression for an N-point DFT:

$$X(m) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi nm/N} \tag{2.5}$$

where $X(m)$ is the mth DFT output component, m is the index of the DFT output in the frequency domain, $x(n)$ is the sequence of input samples, n is the time-domain index of the input samples, $j = \sqrt{-1}$ and N is the number of samples of the input sequence and the number of frequency points in the DFT output.

For an 8-point DFT, Eq. 2.5 tells us that we'd have to perform N^2 or 64 complex multiplications. For an N-point FFT, the number of complex multiplications is approximately:

$$\frac{N}{2} \log N \tag{2.6}$$

Figure 2.1 compares the number of complex multiplications required by DFTs and radix-2 FFTs as a function of the number of input data points N. When $N = 512$,

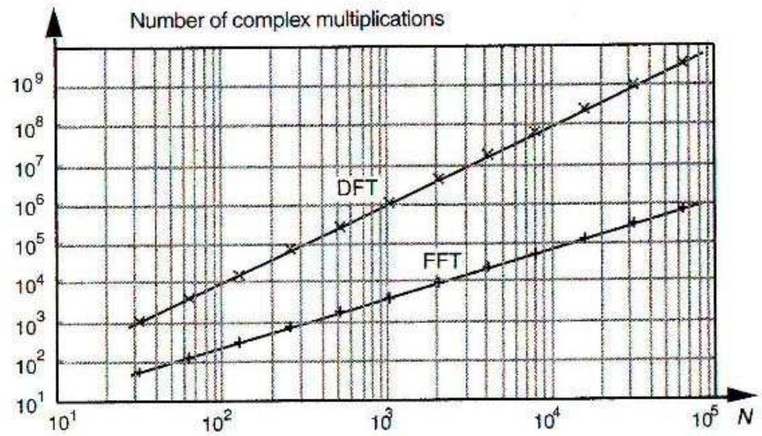

Figure 2.1: Number of complex multiplications in the DFT and the radix-2 FFT as a function of N [28].

for example, the DFT requires 200 times more complex multiplications than those needed by the FFT.

FFT algorithms generally fall into two classes: decimation in time, and decimation in frequency. The radix-2 algorithms are the simplest FFT algorithms. The decimation-in-time (DIT) radix-2 FFT recursively partitions a DFT into two half-length DFTs of the even-indexed and odd-indexed time samples. The outputs of these shorter FFTs are reused to compute many outputs, thus greatly reducing the total computational cost. The equation is shown as follows:

$$X(m) = \sum_{n=0}^{(N/2)-1} x(2n)W_{N/2}^{nm} + W_N^m \sum_{n=0}^{(N/2)-1} x(2n+1)W_{N/2}^{nm} \tag{2.7}$$

and

$$X(m+N/2) = \sum_{n=0}^{(N/2)-1} x(2n)W_{N/2}^{nm} - W_N^m \sum_{n=0}^{(N/2)-1} x(2n+1)W_{N/2}^{nm} \tag{2.8}$$

where we define $W_N = e^{-j2\pi/N}$ to represent the complex phase angle factor that is constant with N, all the rest parameters are the same as in Eq. 2.5. Figure 2.2 shows Radix-2 Decimation-in-Time FFT algorithm for a length-8 signal.

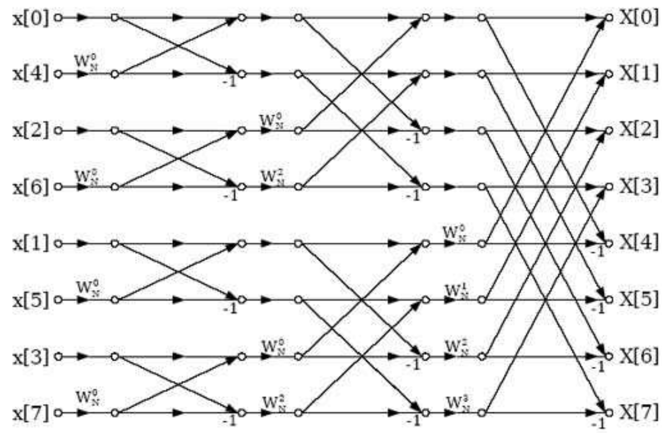

Figure 2.2: Radix-2 Decimation-in-Time FFT algorithm for a length-8 signal [2].

2.3.2 Wavelet Transform

The Fourier transform is a tool widely used for many scientific purposes, but it is well suited only to the study of stationary signals where all frequencies have an infinite coherence time. The Fourier analysis brings only global information which is not sufficient to detect compact patterns. Morlet introduced the Wavelet Transform in order to have a coherence time proportional to the period [30].

The wavelet transform presents a time-frequency representation of the signal. It replaces the Fourier transform's sinusoidal waves by a family generated by translations and dilations of a window called a wavelet. It takes two arguments: time and scale. It is defined by:

$$\int \psi(t)\mathrm{d}t = 0, \psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{2.9}$$

where a is the scaling factor and b is the translation factor. The translation and scaling of the mother function will generate a family of functions. a changes the scale of the wavelet and b controls the translation of the wavelet.

2.3.3 Spectrogram Analysis

Spectrogram analysis is based a quadratic time-frequency transform on the short-time (windowed) Fourier transform (STFT) [8]. Let $x(t) \in L^2(\mathbb{R})$ and let $w(t)$ be a window function. The spectrogram with respect to $w(t)$, written $X_{S,w}(\mu, \omega)$, is:

$$X_{S,w}(\mu, \omega) = |X(\mu, \omega)|^2 = \left| \int_{-\infty}^{\infty} x(t)w(t-\mu)e^{-j\omega t}\mathrm{d}t \right|^2 \tag{2.10}$$

where $X_{S,w}(\mu, \omega)$, is the STFT of $x(t)$ with respect to $w(t)$.

Thus, the spectrogram of $x(t)$ is the squared magnitude of the STFT of $x(t)$ with respect to $w(t)$. The spectrogram is thus a natural generalization of the windowed Fourier methods we have been comfortable in using. However, despite the more intuitive feel, spectrograms are far from being the most popular quadratic time-frequency transforms. For one thing, $X_{S,w}$ relies on a window function. But it also has some other undesirable traits that have motivated signal theorists to search out other transform techniques. Among these better transforms is the classic transform of Wigner and Ville.

Chapter 3

Dynamic Target Classification

Generalization comes at the cost of redundancy. In the context of target classification, same feature set has been used for the classification of different types of targets in the training set even though certain feature(s) might perform significantly better for certain target. Generalization is not an issue in resource-abundant environments, however, it becomes a big concern in resource-constraint environments where redundancy should be eliminated. Wireless sensor networks (WSNs) provide a typical example of the latter.

WSNs have unique superiority in monitoring the physical world via a network of low-cost wireless sensor nodes equipped with sensing, processing, and networking capabilities. The sensor nodes are powered by an on-board battery, thus *energy* becomes the major constraint of individual sensor node since battery replacement is not an option once the sensor is deployed. Computation is one of the operations that would consume energy. The longer the computation, the more energy consumed. Target detection and classification is an important pattern recognition application in WSNs. Due to the resource constraints that WSNs inherently present, the design of an energy-efficient classification algorithm with high accuracy becomes a highly challenging problem.

Signal processing algorithms such as frequency or time-frequency analysis are the most commonly used feature extraction techniques for target classification. However, traditional signal analysis techniques often prove too complex for energy-and-cost-effective WSN nodes[18]. For example, in [16] and [41], they perform classification based on 50 and 26 features respectively. This large size of feature space incurs high computational cost, which is a big hurdle when applying the algorithm to sensor networks in realistic environments.

In this section, we propose dynamic target classification algorithm. In this approach, each sensor performs classification by dynamically changing the feature set and the classifier according to the "probability" that the potential target might be of certain class. Although the algorithm follows the traditional signal processing techniques, in the feature extraction phase, it only uses the most compact set of features for certain target. Thus the average dimension of the problem would be dramatically reduced, resulting in low computational complexity. In addition, We study if the above hypothesis holds. We also design a cost function to determine the optimal combination of features and classifiers selection.

In the following paragraphs, we abbreviate the term "optimal combination of features and classifiers" as "optimal combination set". We use two data sets to generate the optimal combination set for each type of target.

3.1 Feature extraction

3.1.1 The normal curve analysis

The normal curve has long been important in statistics[29]. It has been described as a mathematical model defined by a particular equation that depends on two specific numbers: the mean and the standard deviation, signifying that many normal distributions exist and each has different mean or standard deviation[5]. These two statistics are then used to calculate the other two statistics: skewness and kurtosis. These four elements, the **mean**, the **standard deviation**, the **skewness**, and the **kotosis**, are called **the first four moments of a normal distribution**.

Both the amplitude statistics and the shape statistics belong to normal curve analysis. These two methods remove the influence of distribution variability. Therefore, we use these two analysis to extract features. Eq. 3.1 and Eq. 3.2 show the calculation of these two statistical analysis.

$$\begin{gathered}
\mu_{amp} = \tfrac{1}{N}\textstyle\sum_{j=1}^{N} r_j \\
\sigma_{amp} = \sqrt{\tfrac{1}{N}\textstyle\sum_{j=1}^{N}(r_j - \mu_{amp})^2} \\
\gamma_{amp} = \tfrac{1}{N}\textstyle\sum_{j=1}^{N}(\tfrac{r_j-\mu_{amp}}{\sigma_{amp}})^3 \\
\beta_{amp} = \tfrac{1}{N}\textstyle\sum_{j=1}^{N}(\tfrac{r_j-\mu_{amp}}{\sigma_{amp}})^4
\end{gathered} \tag{3.1}$$

$$\begin{gathered}
\mu_{shape} = \tfrac{1}{S}\textstyle\sum_{j=1}^{N} j r_j \\
\sigma_{shape} = \sqrt{\tfrac{1}{S}\textstyle\sum_{j=1}^{N}(j - \mu_{shape})^2 r_j} \\
\gamma_{shape} = \tfrac{1}{S}\textstyle\sum_{j=1}^{N}(\tfrac{j-\mu_{shape}}{\sigma_{shape}})^3 r_j \\
\beta_{shape} = \tfrac{1}{S}\textstyle\sum_{j=1}^{N}(\tfrac{j-\mu_{shape}}{\sigma_{shape}})^4 r_j
\end{gathered} \tag{3.2}$$

where $S = \sum_{j=1}^{N} r_j$, r_j is the summation of features over the whole range of feature space, r_j is the feature value for a specific sample j, and N is the total number of sampled used in the feature vector.

3.1.2 Feature extraction process

In the sensor network, each sensor node collects time series signals from the environment. In order to obtain the signal characteristics, we apply fast Fourier transform (FFT), wavelet transform (WT), and spectrogram analysis on the sampled data set. We apply shape statistics (with four features) and amplitude statistics (another four features [40]) to derive the global features in FFT. The frequencies corresponding to the peaks in the FFT indicate the dominant frequencies of the vehicle's vibrations. Therefore, we extract frequency locations of the three largest peaks and the corresponding magnitudes as another 6 features in FFT. Since FFT does not contain time-domain information which is crucial for non-stationary signal analysis, we apply wavelet transform on the data set. We use the average, the standard deviation, and the energy of the four levels of wavelet coefficients as the 12 feature vectors from WT. In the spectrogram analysis, we extract locations of three largest peaks and their magnitudes as the rest 6 feature vectors. After these analysis the dimension of the feature space becomes 32. Figure 3.1 summarizes the feature extraction process.

3.2 Classification

We use two types of supervised classification algorithms, one is the simple nonparametric approach–k-Nearest Neighbor estimation (kNN), which assigns the unknown sample to the class i if more samples belong to class i within the k nearest neighbors of the unknown. The other is a parametric technique–Maximum Posterior Probability

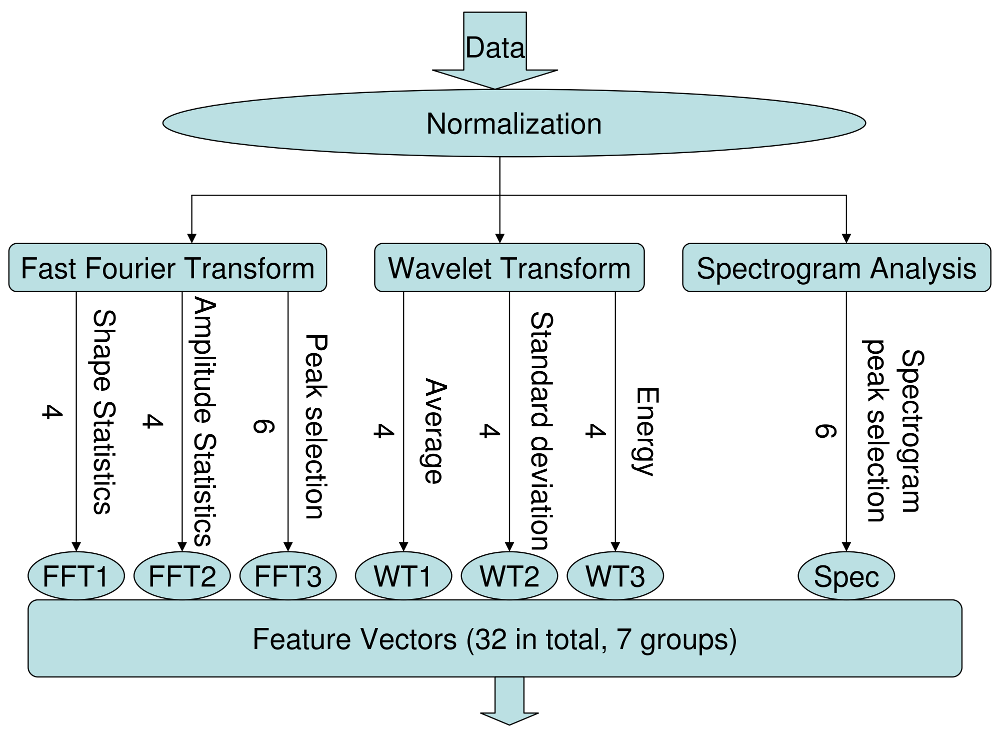

Figure 3.1: Block diagram of the feature extraction procedure.

(MPP), which assumes both the training and the test set are Gaussian distributed and assigns the unknown to the class that has the largest posterior probability than the others.

3.3 Optimal combination of features and classifiers

As we mentioned before, the dynamic classification is based on the hypothesis, in which each specific target corresponds to an optimal combination of features and classifiers that can yield the best classification performance using as small number of features as possible.

The key issue of dynamic classification lies in the optimal combination set selection. Hence, our task is to set up a rule to find this optimal set for each target. Note that the dimension of the feature space is $N = 2^M - 1$ corresponding to all possibilities for the presence or absence of each feature except for the all-absence case, where M is the number of feature vectors. For the sake of simplicity, we grouped the feature vectors into 7 subcategories: in FFT, 4 shape statistics, 4 amplitude statistics, and 6 peaks are abbreviated to *FFT1*, *FFT2*, and *FFT3*, respectively; in wavelet transform, *WT1*, *WT2*, *WT3* indicate 4 average vectors, 4 standard deviations vectors, and 4 energy vectors respectively; *Spec* denotes 6 peaks in spectrogram analysis (Refer to Fig. 3.1). Consequently, the dimension of the feature space is reduced from 4.295×10^9 to 127.

When we select the optimal combination set for each type of target, our major concern is on two parameters: accuracy and computational cost. Therefore, we construct the cost function F as:

$$F_{min}(x, y) = \frac{f_1(x, y)}{f_2(x, y)} \tag{3.3}$$

Type	Method	Optimal set	Threshold	Accuracy	Time	Cost
AAV	MPP	FFT1	0.8	0.8204	1.1367	1.3856
DW	MPP	WT2, WT3	0.7	0.7463	0.7850	1.0518
HMMWV	MPP	WT3	0.7	0.7325	0.6288	0.8584

Table 3.1: Optimal combination set results validated on SITEX00 and SITEX02 data sets.

where f_1 denotes the computation time function and f_2 is the accuracy function. x is a binary string denoting the feature combination. It has the form of $x = (FFT1, FFT2, FFT3, WT1, WT2, WT3, Spec)$, with each parameter being either 1 or 0, with the value of 0 indicating the absence of the feature set or 1 the presence of the feature set. For example, x =(0 0 1 0 1 0 0) indicates we only select FFT3 and WT2 feature vectors for classification. y denotes the classifier with the value of 1 for kNN and 0 for MPP. We apply exhaustive search on the entire combination space to generate the accuracy and the computation time. The combination corresponding to the minimum cost is our solution. However, the minimum cost corresponding to the poor accuracy is not desirable, therefore, we set a threshold for the accuracy for each target type based on the validation results.

Chapter 4

A Target Classification Scenario

4.1 Scenario description

To illustrate how dynamic classification strategy works, we consider a task of vehicles running through the sensing field. We assume at each run only one target will present in the field. We reconstruct the site and test dynamic classification algorithm based on SITEX series data sets which we used to generate the optimal combination set. The network map accords with Figure 4.1 which depicts the entire sensor field in SITEX02 experiment. The emphasis of the paper is on dynamic target classification, hence, we only focus on the dynamic classification phase, skipping the detection phase and sensor selection details. The following lists the steps that dynamic classification follows:

1. A target enters the sensor network.

2. The first node (denoted as A) is activated to sense the event and performs local classification using the full set of features.

3. Node A selects the next best sensor which is node B and hands off the classification result to node B.

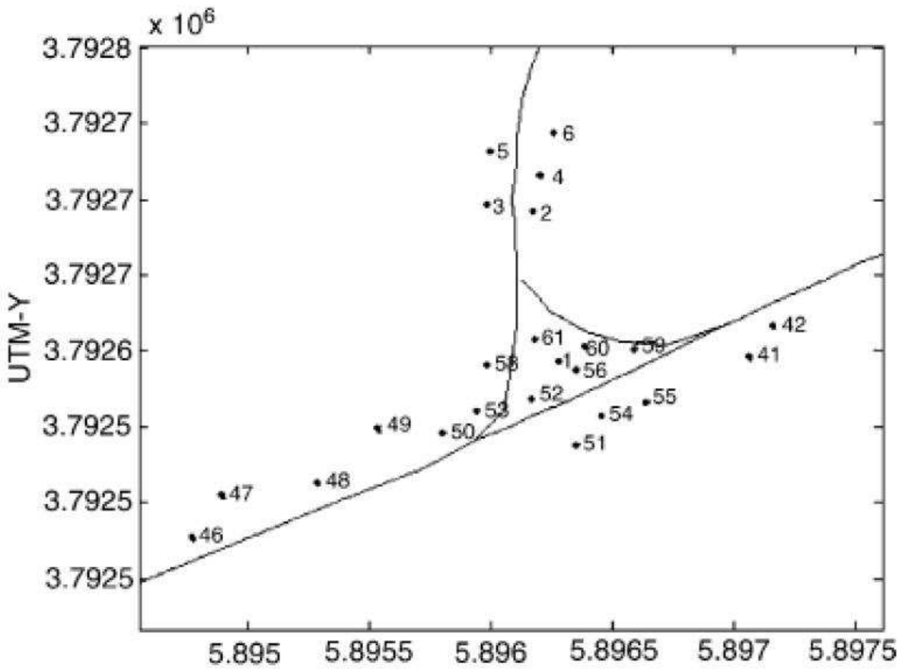

Figure 4.1: Sensor field layout [16].

4. Node B looks up the optimal combination set table which is stored in each node and selects the one according to the predicted target type it has received from node A to make a new decision.

5. If the decisions made by both node A and B agree with each other, then go to step 3, till the target is out of the region.

6. Otherwise, node B uses the entire feature set and performs the classification process again, then go to step 3.

From the above steps, we notice that the previous sensor's decision is very important since it will affect all the rest decision making. Therefore in the following section, we employ the information-based sensor selection rule to the scenario to assist dynamic target classification algorithm to yield the best performance.

4.2 Information-based sensor selection

In sensor selection, we try to incorporate those sensors which can provide the most useful information. The criterion is based on the information gain of individual sensor contributions. The goal of selection is to maximize this information gain [14].

We assume there are N sensors labeled from 1 to N and the corresponding measurements of the sensors are $\{\theta_i\}_{i=1}^{N}$. Denote the state of a target we wish to estimate is x, in the scenario, it is the position of the target. The belief is defined as a representation of the current a posteriori distribution of x given measurements θ_1,...,θ_N:

$$p(x|\theta_1, ..., \theta_N)$$

Let $U \subset \{1, ..., N\}$ denote the set of sensors which have been incorporated into the belief. Our task is to choose a sensor which has not been incorporated into the belief yet, but provides the most information. Incorporating a measurement θ_j, where $j \notin U$ with the current belief state which yields the new belief state:

$$p(x|\{\theta_i\}_{i\in U} \cup \{\theta_j\})$$

Furthermore, define the information gain function based on the Mahalanobis Distance (MD) of the sensors as:

$$MD(x_j) = (x_j - \mu)^T \Sigma^{-1} (x_j - \mu) \tag{4.1}$$

The MD measures the distance to the center of the error ellipsoid, normalized by the covariance matrix Σ. Smaller distance means more reduction in the uncertainty of the current belief [14]. So we choose the smallest MD which we believe will provide the most uncertainty reduction. Therefore, our information gain function should be:

$$IG_j = -MD(x_j) \tag{4.2}$$

Thus, the selection of sensor $\hat{j} \in A = \{1, ..., N\} - U$ can be expressed as:

$$\hat{j} = \arg_{j\in A} \max IG_j \tag{4.3}$$

which equals to:

$$\hat{j} = \arg_{j\in A} \max(-(x_j - \mu)^T \Sigma^{-1} (x_j - \mu)) \tag{4.4}$$

where the mean and the covariance of the belief state are calculated by

$$\mu = \int xp(x|\theta)\mathrm{d}x \tag{4.5}$$

$$\Sigma = \int (x-\mu)(x-\mu)^T p(x|\theta)\mathrm{d}x \tag{4.6}$$

The above selection rule is a generic approach and especially for densely deployed sensor networks. Since our scenario belongs to the small and relative sparse network, we simplified the information gain in the experiments as:

$$IG_j = \frac{a_j}{(ED_j)^\gamma} + ce_j \tag{4.7}$$

where a is the amplitude of the signal detected from the target, γ is a known attenuation coefficient, c is a constant factor to scale the remaining energy e of sensor j. ED is the Euclidean Distance between the sensor j and the mean:

$$ED(x_j) = (x_j - \hat{x})^T(x_j - \hat{x})) \tag{4.8}$$

Where $j \in A$ and $\hat{x}$ is the state mean of sensors in the neighborhood.

Thus the selection rule is simplified as:

$$\hat{j} = \max_{j \in A}\left(\frac{a_j}{(ED_j)^\gamma} + ce_j\right) \tag{4.9}$$

Chapter 5

Performance Evaluation

5.1 Experiment description

Following chapter 4's procedures, we carried out the experiments on SITEX02's data set using seismic signals captured by the geophone on each local WINS NG 2.0 sensor node. The seismic time series are sampled at 5 KHz (4960.32 Hz to be exact) and are down-sampled to 512 Hz in our experiments. The training set is a 540 by 513 matrix and the test set is 180 by 513 matrix with each row a sample and each column a feature, the last column is the true label of the target. Each sample is a 1-second segment extracted from the event signal. The training set are composed of 180 samples from each target.

The experiments are composed of two parts: one is for hypothesis validation (refer to Chapter 3), the other is for dynamic classification. After feature extraction, we perform 4-cross validation on the data set to get the validation results for the hypothesis. Then we simulate the site and position the nodes according to Figure 4.1. A subset of sensors is chosen using information-based sensor selection rule for each target in dynamic classification case, as shown in Figure 5.1- 5.3.

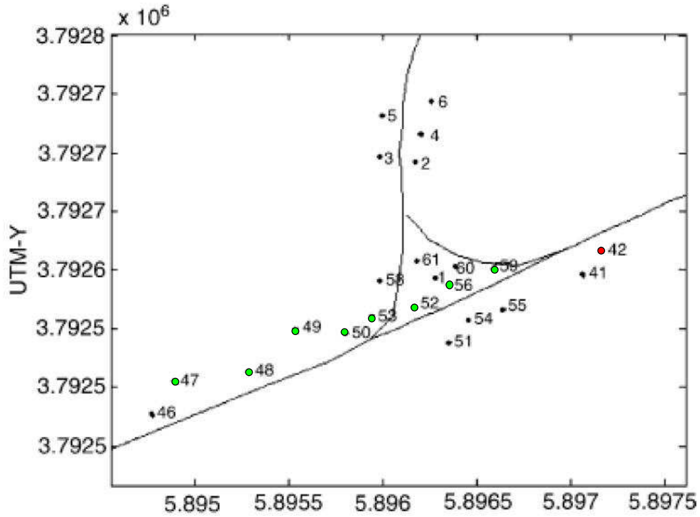

Figure 5.1: The selected nodes in AAV run. Red node indicates the first activated sensor, green ones indicate the rest selected sensor using simplified information-based sensor selection rule.

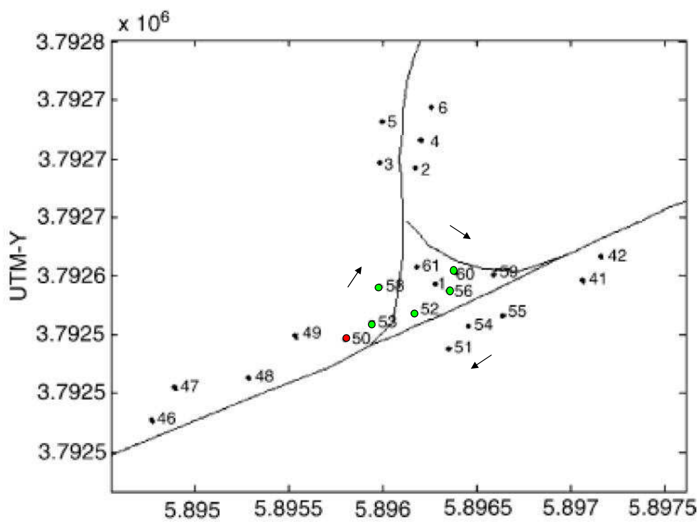

Figure 5.2: The selected nodes in DW run. Red node indicates the first activated sensor, green ones indicate the rest selected sensor using simplified information-based sensor selection rule.

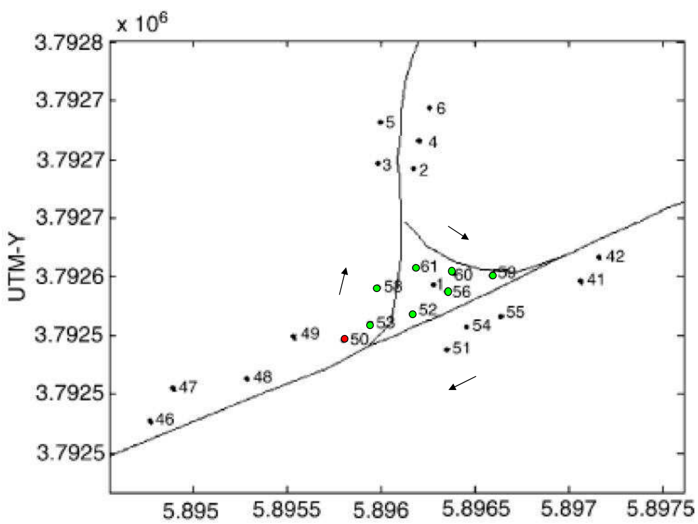

Figure 5.3: The selected nodes in HMMWV run. Red node indicates the first activated sensor, green ones indicate the rest selected sensor using simplified information-based sensor selection rule.

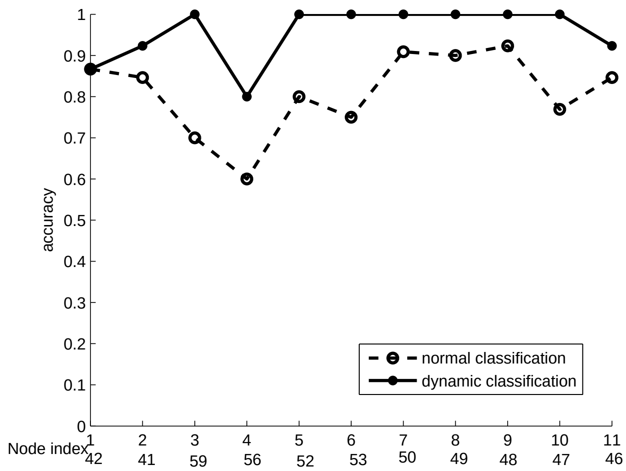

Figure 5.4: Accuracy comparison between normal and dynamic classification for AAV. Solid line: dynamic classification; Dash line: normal classification. X-axis: selected nodes Index, Y-axis: accuracy

5.2 Accuracy and response time comparison

In our experiments, the target types include AAV, DW, and HMMWV. The accuracy comparison of using normal classification and dynamic classification is evaluated in Figure 5.4, Figure 5.5, and Figure 5.6. The response time comparison of using normal classification and dynamic classification is evaluated in Figure 5.7, Figure 5.8, and Figure 5.9. In each figure, the solid line indicates the results from dynamic classification and the dash line indicates the results from normal classification. X-axis denotes the index of the selected nodes for each type of target. As we observed from these two figures, at each node, the accuracy is improved and the response time is decreased using dynamic classification algorithm.

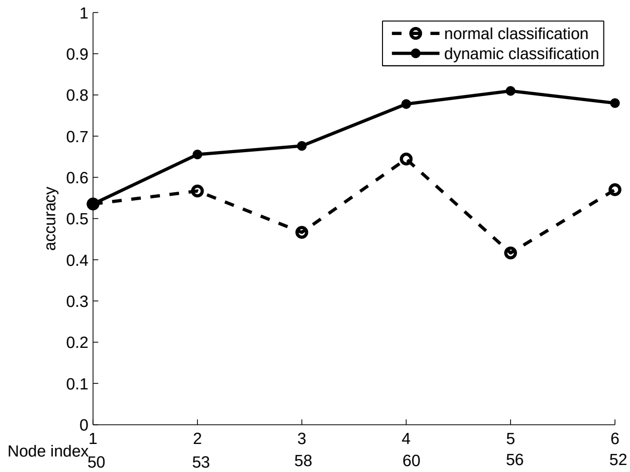

Figure 5.5: Accuracy comparison between normal and dynamic classification for DW. Solid line: dynamic classification; Dash line: normal classification. X-axis: selected nodes Index, Y-axis: accuracy

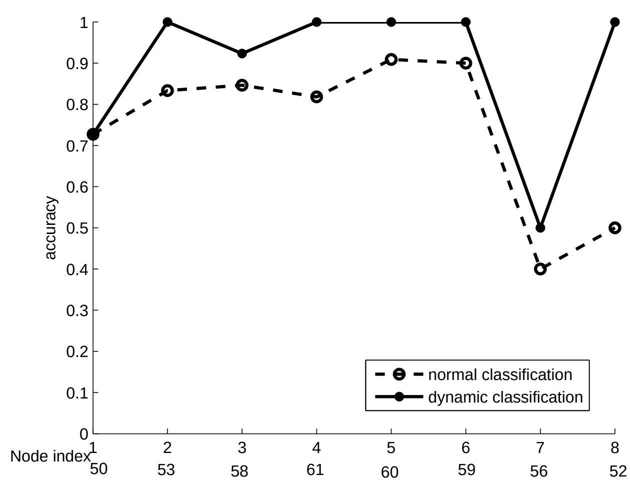

Figure 5.6: Accuracy comparison between normal and dynamic classification for HMMWV. Solid line: dynamic classification; Dash line: normal classification. X-axis: selected nodes Index, Y-axis: accuracy

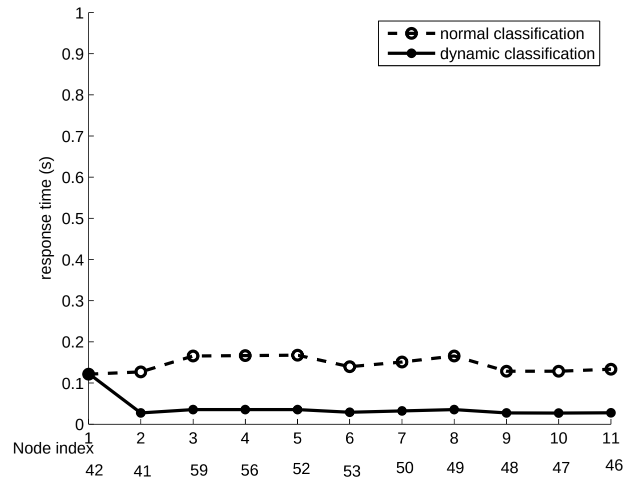

Figure 5.7: Response time comparison between normal and dynamic classification for AAV. Solid line: dynamic classification; Dash line: normal classification. X-axis: selected nodes Index, Y-axis: response time

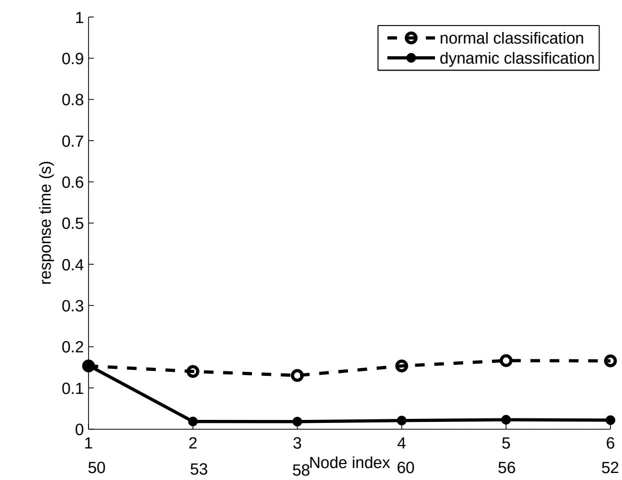

Figure 5.8: Response time comparison between normal and dynamic classification for DW. Solid line: dynamic classification; Dash line: normal classification. X-axis: selected nodes Index, Y-axis: response time

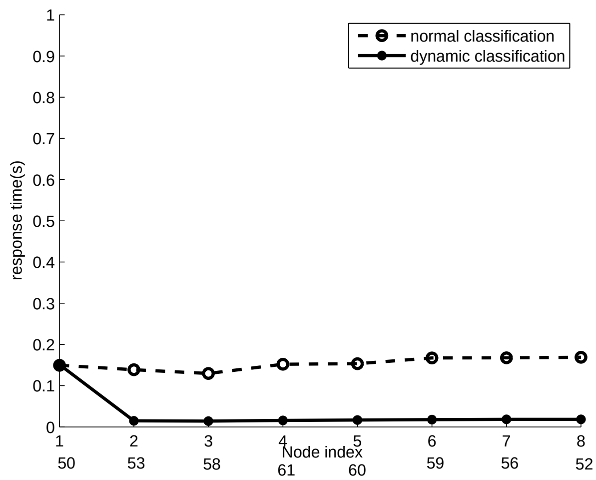

Figure 5.9: Response time comparison between normal and dynamic classification for HMMWV. Solid line: dynamic classification; Dash line: normal classification. X-axis: selected nodes Index, Y-axis: response time

The following lists the numerical data that generated from the dynamic classification experiment. Table 5.1 shows the numerical results of normal classification and dynamic classification in terms of response time and accuracy for AAV. Table 5.2 shows the numerical analysis of normal classification and dynamic classification in terms of response time and accuracy for DW. Table 5.3 shows the experimental results of normal classification and dynamic classification in terms of response time and accuracy for HMMWV. From these tables we can clearly see that no matter what kind of military vehicle presents in the experiment, dynamic classification performs better than normal classification in terms of both accuracy and response time.

Selected Node		**Normal**		**Dynamic**	
	ID	**Time**	**Accuracy**	**Time**	**Accuracy**
First	42	0.1215	0.8667	0.1233	0.8667
Rest	41	0.1270	0.8462	0.0273	0.9231
	59	0.1656	0.7000	0.0354	1.0000
	56	0.1667	0.6000	0.0354	0.8000
	52	0.1677	0.8000	0.0354	1.0000
	53	0.1397	0.7500	0.0291	1.0000
	50	0.1510	0.9091	0.0322	1.0000
	49	0.1656	0.9000	0.0354	1.0000
	48	0.1286	0.9231	0.0273	1.0000
	47	0.1286	0.7692	0.0272	1.0000
	46	0.1334	0.8462	0.0276	0.9231
	Average	0.1450	0.8100	0.0396	0.9557

Table 5.1: Comparison of normal classification and dynamic classification in terms of response time and accuracy for AAV.

Selected Node		Normal		Dynamic	
	ID	**Time**	**Accuracy**	**Time**	**Accuracy**
first	50	0.0269	0.5354	0.0258	0.5354
Rest	53	0.0260	0.5667	0.0035	0.6556
	58	0.0261	0.4667	0.0038	0.6762
	60	0.0274	0.6444	0.0084	0.7778
	56	0.0263	0.4167	0.0044	0.8095
	52	0.0298	0.5700	0.0042	0.7800
	Average	0.0298	0.5333	0.0083	0.7057

Table 5.2: Comparison of normal classification and dynamic classification in terms of response time and accuracy for DW.

Selected Node		Normal		Dynamic	
	ID	**Time**	**Accuracy**	**Time**	**Accuracy**
first	50	0.0248	0.7273	0.0264	0.7273
Rest	53	0.0258	0.8333	0.0029	1.0000
	58	0.0266	0.8462	0.0028	0.9231
	61	0.0324	0.8182	0.0031	1.0000
	60	0.0441	0.9091	0.0051	1.0000
	59	0.0249	0.9000	0.0029	1.0000
	56	0.0255	0.4000	0.0029	0.5000
	52	0.0257	0.5000	0.0030	1.0000
	Average	0.0287	0.7418	0.0061	0.8938

Table 5.3: Comparison of normal classification and dynamic classification in terms of response time and accuracy for HMMWV.

5.3 One run comparison

Figure 5.10 and Figure 5.11 shows the accuracy and the response time of one-run comparison for each type of target, respectively. The statistical results show that using dynamic classification, the average accuracy for AAV is 95.57% compared with 81% using normal classification; for DW is 70.57% compared with 53.33% using normal classification; for HMMWV is 89.38% compared with 74.18% using normal classification. The total response time is reduced to less than 30% of the one in normal case.

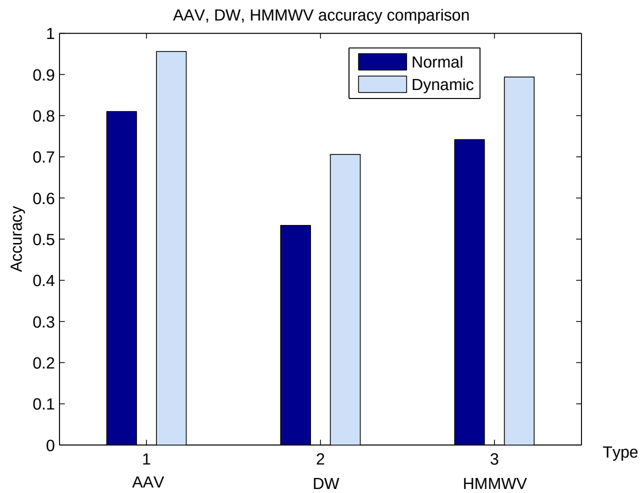

Figure 5.10: Normal and dynamic target classification average accuracy comparison for AAV, DW, HMMWV. X-axis denotes the type of the target, Y-axis indicates the accuracy.

In the experiments, we use the computation time to represent the response time. For the energy consumption, we can roughly computed by[43]:

$$E_{consumed} = T_{exec} \times P_{average} \tag{5.1}$$

For WINS NG 2.0 sensor node, the power dissipation for the processor at active status is 360mW. Therefore, we can calculate the total energy saved in dynamic classification for each target: for AAV, it is 417.528 mJ; for DW, it is 234.54 mJ; for HMMWV, it is 346.104 mJ.

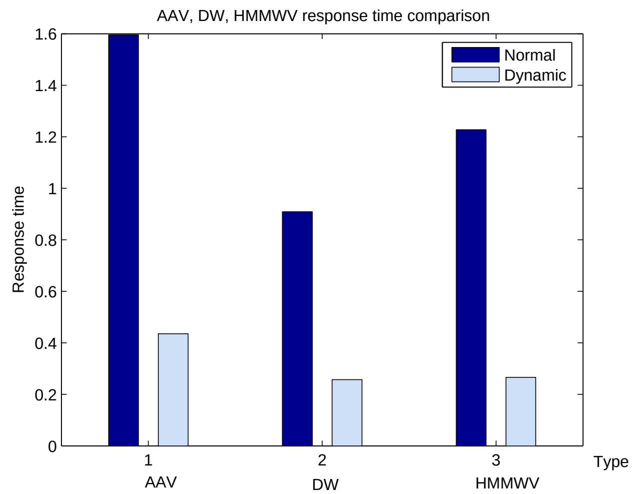

Figure 5.11: Normal and dynamic target classification total response time comparison for AAV, DW, HMMWV. X-axis denotes the type of the target, Y-axis indicates the response time in second.

Chapter 6

Conclusions and future work

6.1 Conclusions

In this paper, we presented dynamic target classification in an energy constrained network and applied it to a target classification scenario. The experimental results showed that using dynamic classification approach, the accuracy can reach as high as 95.57% at a very low computational cost. The idea of the proposed algorithm can also be extended to other applications, making it a practical solution.

In the context of WSNs, unlike other dimension reduction techniques which are applied to the feature space after deriving all features from the raw time series signals, such as principal component analysis (PCA), dynamic classification reduce the computational complexity right at the feature derivation stage. In our experiments, the dimension can be directly reduced from 32 to 4 or 8 by applying the proposed algorithm and at the same time, the accuracy even much better than before. If PCA is applied to the experiment, actually the computational cost will be increased and the accuracy will remain the same level.

6.2 Future work

1. In feature extraction phase, If we keep the original 32 features in the feature space, then the optimization problem becomes NP-hard since the total combination of features is 4.295×10^9. We can try to apply genetic algorithm to find the global minimum approximation. If this works, it is possible that the accuracy will be further improved and the computational cost will be further reduced as well.

2. Compare the results of using sensor selection rule with the one without using sensor selection rule to show the importance of sensor selection rule in dynamic classification.

3. In dynamic target classification experiment, which data have been transmitted during the whole precess.

4. By involving information-based sensor selection rule, more energy will be consumed, find the balance between the performance improvement and the energy consumption.

"A journey of a thousand miles begins with a single step."
—Confucius

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Vita

Ying Sun was born in Huadian, Jilin, P. R. China. After graduating in 1997 from Huadian Fourth High School, she attended Changchun University of Technology in Changchun, where she received a Bachelor of Engineering degree in 2001 from the school of Computer Science and Engineering. She worked at Changchun Hongda Information Technology Co., Ltd. as a software development engineer between 2001 and 2002. From 2002 to 2004, she worked at Jilin University Information Technology Co., Ltd. as a project software manager. In the fall of 2006, Ying enrolled into the doctoral program at the University of Tennessee at knoxville in the department of Electrical and Computer Engineering. At the same time, she joined the Advanced Imaging and Collaborative Information Processing group as a graduate teaching assistant and research assistant where she will complete her Master degree in the summer of 2008. She has been working on collaborative information processing and a 2-year project sponsored by South East Regional Research Initiative (SERRI), titled "A Data-Sharing Middleware for Information Dissemination among Heterogeneous Sources". Her major research areas are collaborative information processing, wireless sensor networks, pattern recognition, and image processing.