DOPPLER RADAR DATA PROCESSING AND CLASSIFICATION

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ABSTRACT

DOPPLER RADAR DATA PROCESSING AND CLASSIFICATION

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In this thesis, improving the performance of the automatic recognition of the Doppler radar targets is studied. The radar used in this study is a ground-surveillance doppler radar. Target types are car, truck, bus, tank, helicopter, moving man and running man. The input of this thesis is the output of the real doppler radar signals which are normalized and preprocessed (TRP vectors: Target Recognition Pattern vectors) in the doctorate thesis by Erdogan (2002). TRP vectors are normalized and homogenized doppler radar target signals with respect to target speed, target aspect angle and target range. Some target classes have repetitions in time in their TRPs. By the use of these repetitions, improvement of the target type classification performance is studied. K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) algorithms are used for doppler radar target classification and the results are evaluated. Before classification PCA (Principal Component Analysis), LDA (Linear Discriminant

Analysis), NMF (Nonnegative Matrix Factorization) and ICA (Independent Component Analysis) are implemented and applied to normalized doppler radar signals for feature extraction and dimension reduction in an efficient way. These techniques transform the input vectors, which are the normalized doppler radar signals, to another space. The effects of the implementation of these feature extraction algoritms and the use of the repetitions in doppler radar target signals on the doppler radar target classification performance are studied.

Keywords: Doppler radars, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Non-negative Matrix Factorization (NMF), Independent Component Analysis (ICA), K-Nearest Neighbor (KNN), Support Vector Machine (SVM).

ÖZ

DOPPLER RADAR VERİ İŞLEME
VE SINIFLANDIRMA

Aygar, Alper
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Bu tezde, doppler radar hedeflerinin otomatik olarak tanınma performansının artırılması üzerine çalışmalar yapılmıştır. Gerçek Doppler radar sinyallerinin bir doktora tezi kapsamında Erdogan (2002) ön işleme ve normalizasyondan geçirilmesi sonucu elde edilen çıktılar bu tezin girdilerini (HTÖ vektörleri: Hedef Tanıma Örüntüsü vektörleri) oluşturmaktadır. HTÖ vektörleri hedeflere ait doppler ses sinyallerinin hedef hızı, hedefe bakış açısı, hedef menzili gibi etkilerden arındırılmaya çalışılmış ve homojenize edilmiş halleridir. Bazı hedef sınıflarının HTÖ vektörlerinde zamanda tekrarlamalar bulunmaktadır. Bu tekrarlamaların kullanımı ile hedef tipi tanıma performansının artırılması üzerine çalışılmıştır. KNN (K-Nearest Neighbor) ve SVM (Support Vector Machine) sınıflandırma yöntemleri doppler radar verileri hedef tanıma için kullanılmış ve sonuçlar incelenmiştir. Sınıflandırma öncesinde

Temel Bileşenler Analizi (TBA), Lineer Diskriminant Analizi (LDA), Bağımsız Bileşenler Analizi (BBA), Negatif Olmayan Matris Ayrıştırma (NOMA) yöntemleri kullanılmış, öz nitelik çıkarımı ve boyut düşürümü için normalize edilmiş doppler radarı sinyallerine uygulanmıştır. Bu yöntemler doppler radar sinyallerinin normalize edilmiş halleri olan girdi vektörlerini başka bir boyuta dönüştürmektedir. Tüm bu yöntemlerin ve hedef sinyallerindeki tekrarlamaların kullanımının sınıflandırma başarımı üzerine etkileri incelenmiştir. Bu çalışmada kullanılan radar doppler tabanlı bir kara gözetleme radarıdır. Hedef tipleri ise araba, kamyon, otobüs, tank, helikopter, yürüyen adam ve koşan adamdır.

Anahtar Kelimeler: Doppler radarları, Temel Bileşenler Analizi, Lineer Diskriminant Analizi, Negatif Olmayan Matris Ayrıştırma, Bağımsız Bileşenler Analizi, K-Nearest Neighbor (KNN), Support Vector Machine (SVM).

To my family

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TABLE OF CONTENTS

ABSTRACT iv
ÖZ vi
ACKNOWLEDGEMENTS ix
LIST OF TABLES xii
LIST OF FIGURES xv
LIST OF ABBREVIATIONS xvii
CHAPTER 1 INTRODUCTION 1
1.1 Statement of the Problem 8
1.2 Scope of the Thesis 9
1.3 Contribution of the Thesis 10
1.4 Organization of the Thesis 10
CHAPTER 2 BACKGROUND 11
2.1 Background on Doppler Radars 11
2.2 Background on Doppler Radar ATR Studies 13
2.3 Data Acquisition and Preprocessing 18
2.3.1 Data Acquisition 18
2.3.2 Preprocessing of Signals 18
2.4 Data Used in the Thesis 21
2.5 Background on Pattern Recognition 25
2.6 Performance Measures 25
2.7 Feature Extraction and Classification Methods 29
2.7.1 PCA 29
2.7.2 LDA 30
2.7.3 ICA 31
2.7.4 NMF 32
2.7.5 KNN 33

2.7.6 SVM 33
CHAPTER 3 THE PROPOSED ATR SYSTEM 35
3.1 The General Structure of the ATR System 35
3.2 N-bin Data Generation 36
3.3 Feature Extraction & Dimension Reduction 38
3.4 Classification 39
3.5 Hierarchical Classification 39
3.6 Clustering and Classification Performance Analysis 43
3.6.1 Clustering Quality Evaluation 43
3.6.2 Classification Performance Evaluation 44
CHAPTER 4 EXPERIMENTAL RESULTS 45
4.1 Clustering Quality Results 45
4.2 Classification Performance Results 56
4.3 Hierarchical Classification Performance Results 79
4.4 Confusion Matrices 96
4.5 Classification Performance Summary 99
CHAPTER 5 CONCLUSION 101
REFERENCES 103
APPENDIX A ASKARAD TECHNICAL SPECIFICATIONS 106

LIST OF TABLES

TABLES

Table 2.1 Structures for different target classes that generate doppler frequencies 12
Table 4.1 Clustering quality values of training samples for 2 principal components (For different number of time bins)........ 51
Table 4.2 Clustering quality values of test samples for 2 principal components 52
Table 4.3 Clustering quality values of training samples for 3 principal components 52
Table 4.4 Clustering quality values of test samples for 3 principal components 53
Table 4.5 Clustering quality values of training samples for 4 principal components 53
Table 4.6 Clustering quality values of test samples for 4 principal components 54
Table 4.7 Clustering quality values of training samples for 5 principal components 54
Table 4.8 Clustering quality values of test samples for 5 principal components 55
Table 4.9 Khat values for confusion matrices of PCA and KNN applied on test data for different number of time-bins and different number of principal components. 58
Table 4.10 Average recognition rates of PCA and KNN applied on test data for different number of time-bins and different number of principal components 59
Table 4.11 Khat values for confusion matrices of PCA and SVM applied on test data........ 60
Table 4.12 Average recognition rates of PCA and SVM applied on test data ... 61
Table 4.13 Khat values for PCA and KNN applied test data 63
Table 4.14 Khat values of LDA and KNN applied on test data 64

Table 4.15 Average recognition rates of LDA and KNN applied on test data ... 65
Table 4.16 Khat values of LDA and SVM applied on test data ... 66
Table 4.17 Average recognition rates of LDA and SVM applied on test data ... 67
Table 4.18 Khat values of ICA and KNN applied on test data ... 69
Table 4.19 Average recognition rates of ICA and KNN applied on test data ... 70
Table 4.20 Khat values of ICA and SVM applied on test data ... 71
Table 4.21 Average recognition rates of ICA and SVM applied on test data ... 72
Table 4.22 Khat values of NMF and KNN applied on test data ... 74
Table 4.23 Average recognition rates of NMF and KNN applied on test data ... 75
Table 4.24 Khat values of NMF and SVM applied on test data ... 76
Table 4.25 Average recognition rates of NMF and SVM applied on test data ... 77
Table 4.26 Khat values of PCA and KNN applied on test data ... 80
Table 4.27 Average recognition rates of PCA and KNN applied on test data ... 81
Table 4.28 Khat values of PCA and SVM applied on test data ... 82
Table 4.29 Average recognition rates of PCA and SVM applied on test data ... 83
Table 4.30 Khat values of LDA and KNN applied on test data ... 84
Table 4.31 Average recognition rates of LDA and KNN applied on test data ... 85
Table 4.32 Khat values of LDA and SVM applied on test data ... 86
Table 4.33 Average recognition rates of LDA and SVM applied on test data ... 87
Table 4.34 Khat values of ICA and KNN applied on test data ... 88
Table 4.35 Average recognition rates of ICA and KNN applied on test data ... 89
Table 4.36 Khat values of ICA and SVM applied on test data ... 90
Table 4.37 Average recognition rates of ICA and SVM applied on test data ... 91
Table 4.38 Khat values of NMF and KNN applied on test data ... 92
Table 4.39 Average recognition rates of NMF and KNN applied on test data ... 93
Table 4.40 Khat values of NMF and SVM applied on test data ... 94
Table 4.41 Average recognition rates of NMF and SVM applied on test data ... 95
Table 4.42 Confusion matrix of LDA+SVM for 1 time-bin and 12 principal components ... 97

Table 4.43 Confusion matrix of LDA+SVM for 9 time-bin and 12 principal components 97
Table 4.44 Confusion matrix of ICA+SVM for 1 time-bin and 15 principal components 98
Table 4.45 Confusion matrix of ICA+SVM for 10 time-bins and 15 principal components 99
Table 4.46 Summary of classification performance tables 100

LIST OF FIGURES

FIGURES

Figure 1.1 10 seconds long Car record...2
Figure 1.2 Another Car record...2
Figure 1.3 Tank record 3
Figure 1.4 Helicopter record 3
Figure 1.5 Two STFT time frames for car 4
Figure 1.6 3-dimensional STFT of a car. 5
Figure 1.7 3-dimensional STFTs for time frames before amplitude normalization 6
Figure 1.8 3-dimensional STFTs for time frames after amplitude normalization 6
Figure 1.9 3-dimensional STFTs of time frames after frequency normalization 7
Figure 2.1 Doppler radar factors affecting the received signal...............13
Figure 2.2 3-dimensional STFT frames of Walking Man........................19
Figure 2.3 TRP vectors of training data for CAR class 21
Figure 2.4 TRP vectors of training data for TRUCK class......................22
Figure 2.5 TRP vectors of training data for BUS class...........................22
Figure 2.6 TRP vectors of training data for TANK class 23
Figure 2.7 TRP vectors of training data for HELICOPTER class 23
Figure 2.8 TRP vectors of training data for WALKING MAN class.........24
Figure 2.9 TRP vectors of training data for RUNNING MAN class 24
Figure 2.10 Separating hyperplane for 2 dimensions 34
Figure 3.1 Block scheme of the target recognition system proposed 35
Figure 3.2 Time-bin – Amplitude plot for Walking Man training data......36
Figure 3.3 Time-bin – Amplitude plot for Running Man training data.....37

Figure 3.4 Time-bin – Amplitude plot for Helicopter training data 37
Figure 3.5 Feature Extraction & Dimension Reduction of the target recognition system.......... 38
Figure 3.6 Classification stage of the pattern recognition system 39
Figure 3.7 Hierarchical grouping of data according to their similarities.. 40
Figure 3.8 Hierarchical target recognition system.......... 41
Figure 4.1 Target clusters of train data set for 1 bin data with PCA reduced components. 45
Figure 4.2 Target clusters of train data set for 5 bin data with PCA reduced components. 46
Figure 4.3 Target clusters of train data set for 10 bin data with PCA reduced components. 46
Figure 4.4 Target clusters of test data set for 1 bin data with PCA reduced components. 47
Figure 4.5 Target clusters of test data set for 5 bin data with PCA reduced components 47
Figure 4.6 Target clusters of test data set for 10 bin data with PCA reduced components. 48
Figure 4.7 Target clusters of PCA applied training data set for 1 bin data with respect to first and third principal components 49
Figure 4.8 Target clusters of PCA applied training data set for 1 bin data with respect to second and third principal components 49
Figure 4.9 Target clusters of PCA applied training data set for 10 bin data with respect to first and third principal components 50
Figure 4.10 Target clusters of PCA applied training data set for 10 bin data with respect to second and third principal components 50
Figure A.1 ASKARAD 106

LIST OF ABBREVIATIONS

ATR	Automatic Target Recognition
ASKARAD	Aselsan ASKARAD Ground Surveillance Radar
FFT	Fast Fourier Transform
ICA	Independent Component Analysis
LDA	Linear Discriminant Analysis
NMF	Non-Negative Matrix Factorization
PCA	Principal Components Analysis
RCS	Radar Cross Section
STFT	Short-Time Frequency Transform
SVM	Support Vector Machine
TCB	Target Characteristics Band
TFV	Target Feature Vector
TRP	Target Recognition Pattern

CHAPTER 1

INTRODUCTION

Radar (Radio Detection and Ranging) is a device that detects objects such as aircrafts, ships, vehicles and people. These objects reflect radio waves. Radar radiates radio waves to space and the signals reflected from objects are processed to detect the targets. Radars can operate at day and night, in different weather conditions such as rain, snow and fog. There are several types of radars used for different purposes (Stimson, 1998). Radars are used in military, air traffic controllers, highway safety, aircraft and ship safety (Skolnik, 2001).

Doppler Radars detect moving targets by using doppler principle. According to the doppler principle, due to the relative velocity of the target with respect to the radar, the motion of the target will create corresponding frequencies in the received signal (Richards, 2005). More detailed information about doppler radars is given in Section 2.1.

Since motion of a target is the triggering effect for the doppler radars, targets which show different motion characteristics can be classified according to the different doppler frequency information received from them. There are some studies in the literature on doppler radar target classification based on target motion characteristics. One of them is the doctorate thesis study by Erdogan (2002) in METU EEE Computer Vision and Intelligent Systems Research Laboratory.

In Erdogan (2002) ASELSAN ASKARAD Ground Surveillance Doppler Radar is used. In this radar, the received doppler signals are also used at the speakers and headphones of the radar operator, so radar operator can listen these signals to classify targets. Doppler audio signals received from car, truck, bus, tank, helicopter, walking man and moving man targets are gathered. Two audio signal records received from a car at different times are presented in Figure 1.1

and Figure 1.2 . X axis shows time and Y axis shows amplitude of the received signal.

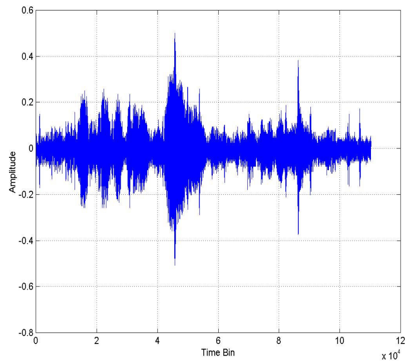

Figure 1.1 10 seconds long Car record

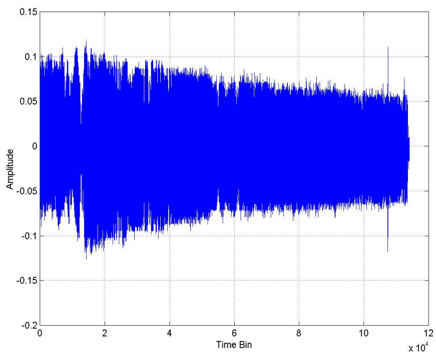

Figure 1.2 Another Car record

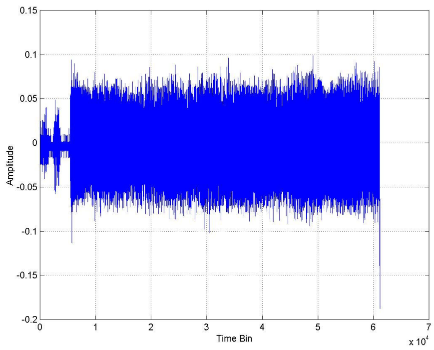

Figure 1.3 Tank record

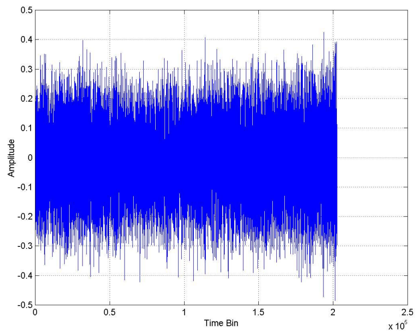

Figure 1.4 Helicopter record

Observing Figures 1.1 to 1.4, intiutively we can say that classifying the targets using only time domain data is not feasible since even for the same target type (in this case car) different signal envelopes are obtained and for different target types (in this case tank and helicopter) similar signal envelopes are obtained. So it is not possible get discriminative information only using time domain anaysis. For a doppler radar, target aspect angle and target speed factors affect the frequency information of received doppler signal. The target aspect angle is the angle between the direction of motion of the target and line of sight of the radar. Since target aspect angle and speed factors change in time, frequency information of the received doppler signal will change in time. So frequency information must be analyzed in time, so a Time-Frequency transform will be convenient for this purpose. STFT (Short Time Fourier Transform) is used for time-frequency analysis because it is implementable for radar systems. Time domain data is sampled at 11025 Hz. As the STFT parameters, FFT (Fast Fourier Transform) frame size is 512, FFT window type is Kaiser and FFT Overlap Ratio is %50. As an example, two STFT time frames for car target is given in Figure 1.5.

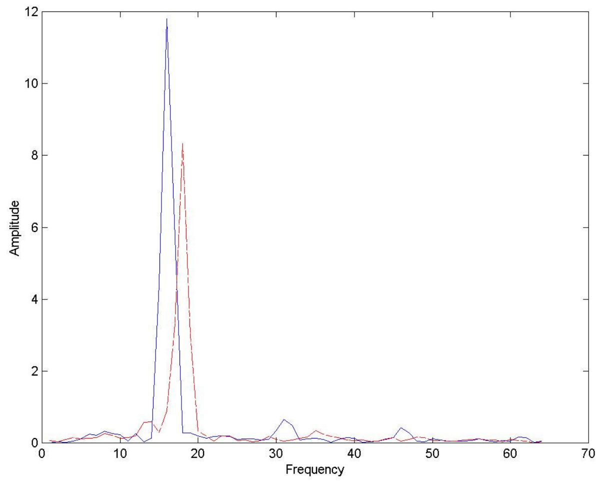

Figure 1.5 Two STFT time frames for car

By concetanating the STFT time frames shown in Figure 1.5, 3-dimensional STFT plots for targets are obtained. These plots show the change of the STFT doppler spectrums with respect to time frames. The car target, whose STFT time frames are presented in Figure 1.6, made a motion between 80^0 and 60^0 aspect angles and also the car speed is increased during the motion. As it can be seen from Figure 1.6, there is a peak with a significant amplitude in the doppler spectrum of each time frame. The location and amplitude of this peak changes from frame to frame. The peak frequency location changes due to the changing radial speed and aspect angle of the target.

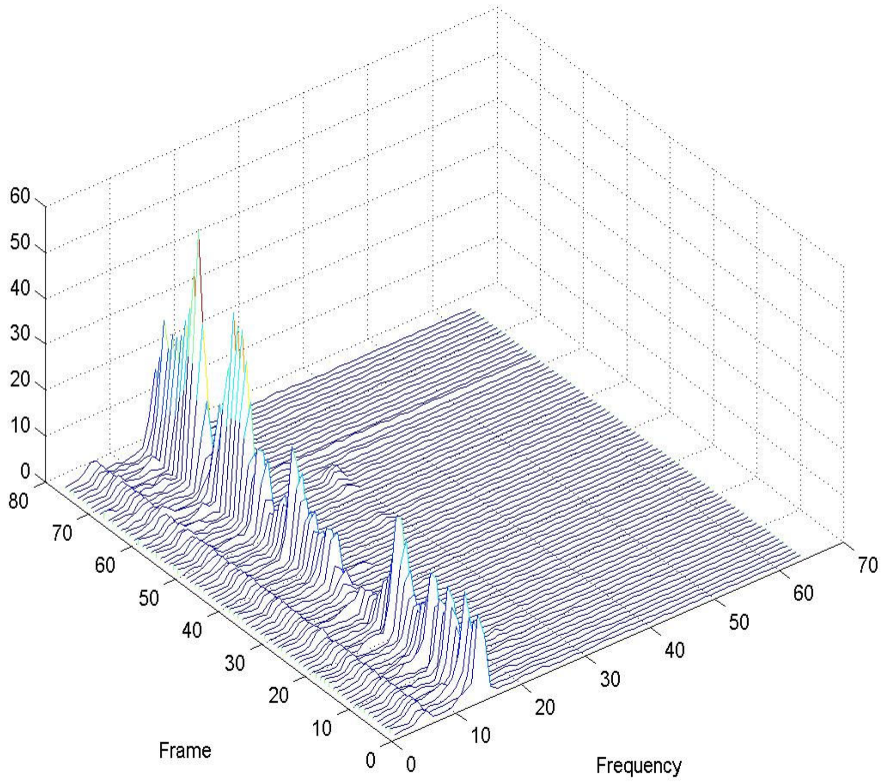

Figure 1.6 3-dimensional STFT of a car.

The amplitude of the doppler spectrums change in time frames due to the target range factor so doppler spectrum for each time frame must be normalized in amplitude. For this purpose, amplitudes of frequency components of each time frame are divided by the energy of that time frame. Amplitude normalization step is explained in detail in Section 2.3. In Figure 1.7 the doppler spectrums for time frames before amplitude normalization are shown. In Figure 1.8 the doppler spectrums of time frames after amplitude normalization are shown.

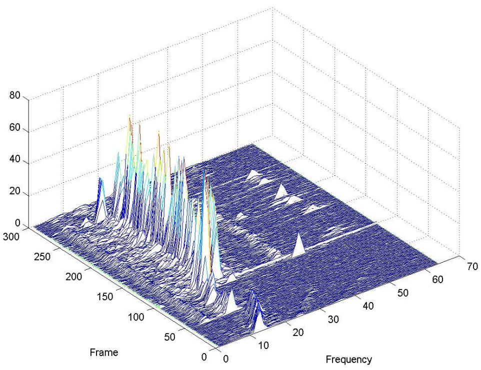

Figure 1.7 3-dimensional STFTs for time frames before amplitude normalization

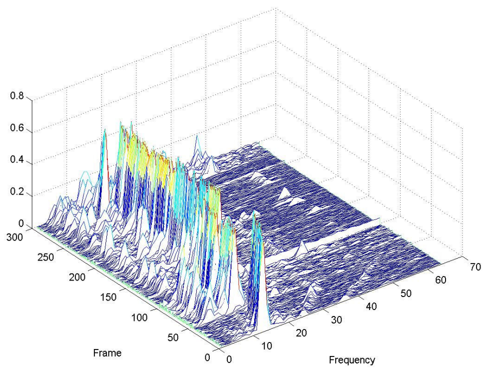

Figure 1.8 3-dimensional STFTs for time frames after amplitude normalization

After frame amplitude normalization, frequency information of doppler spectrums must be normalized since target radial speed and aspect angle factors changes the frequency information of doppler spectrums. The frame frequency normalization step is explained in section 2.3. After frequency normalization of time frames, the STFTs become in the form presented in Figure 1.9.

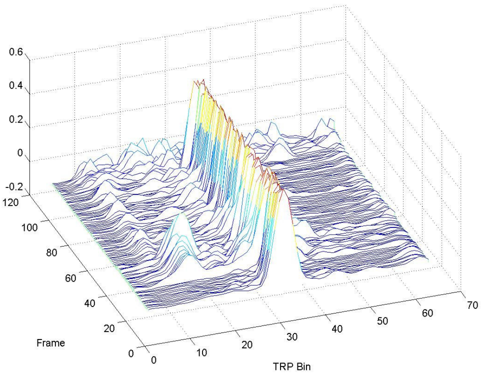

Figure 1.9 3-dimensional STFTs of time frames after frequency normalization

Amplitude and frequency normalized doppler spectrums of time frames are called TRP (Target Recognition Pattern) vectors. TRP vectors form the preprocessed doppler radar signals that can be used for classification.

In this thesis improving the performance of the doppler radar automatic target classification system given in Erdogan (2002) is studied. The target types are car, truck, bus, tank, helicopter, walking man and running man.

The main doppler radar target concept used in this thesis is *Target Recognition Pattern.* Other useful doppler radar target concepts related to this thesis are *Target Doppler Signal* and *Target Doppler Spectrum*.

Target Doppler Signal is the doppler signal received from the target.

Target Doppler Spectrum is the frequency spectrum of the *Target Doppler Signal.*

Target Recognition Patterns are the normalized *Target Doppler Spectrums* in Erdogan (2002) with respect to amplitude and frequency variations which are triggered by target characteristics such as target range, target aspect angle, target radial speed.

This thesis uses *Target Recognition Patterns* as input. *Target Recognition Patterns* used in this thesis are the normalized *Target Doppler*

Spectrums of *Target Doppler Signals* obtained by the ASELSAN ASKARAD Ground Surveillance Doppler Radar. (Appendix A)

1.1 Statement of the Problem

In some doppler radar systems, received doppler signals can also be listened at the headphones of the radar operator as audio signal. Radar operators can listen these signals to classifiy targets. However this task requires an extra radar operator to perform only this job. Making the target classification in an automatic manner could yield better classification performance and less operator workload for such systems. The doctorate thesis Erdogan (2002) was such a study to make the target the classification system of such a system (ASKARAD) automatic.

The main goal of this thesis is to improve the classification performance of the automatic target recognition system which was proposed during the doctorate thesis study Erdogan (2002). In Erdogan (2002), even though a classification based on neural networks was considered, the main challange of the thesis was the preprocessing stage. We will use the preprocessing stage of Erdogan (2002) and construct a target classification system that feeds multiple time frames to classify the targets and increase the classification performance. Time frames in Erdogan (2002) will be called as time bins in this thesis.

The goals of this thesis are:

- Constructing an automatic target recognition system that uses various feature extraction and classification methods.
- To present the input data (Target Recognition Patterns) by considering multiple time bins to the automatic target recognition system in order to improve the classification performance of the system.
- Comparing the methods that are used for feature extraction and classification according to the classification performance values of them.

- To test the performance of a classification scheme which uses multiple classifiers organized hierarchically (Hierarchical Classification)
- To study target classification performance metrics such as clustering quality, khat values and average recognition rate to use on the ATR system classification results.
- To inspect the best ATR system parameters (feature extraction method, classification method, data handling method and other system parameters) to classifiy car, truck, bus, tank, helicopter, walking man and running man targets with a high classification performance value.

1.2 Scope of the Thesis

Some ATR system concepts are not in the scope of this thesis. These are listed below:

- Data Acquisition stage of the ATR system is not implemented. This thesis uses the acquired data of Erdogan (2002). There is no target detection implementation, the target was detected by the operator. Also target detection was done for single target conditions. The operations done for data acquisition are explained in Chapter 2.
- Preprocessing stage of the ATR system is not implemented but the one developed in Erdogan (2002) is used. The operations done for the preprocessing is described briefly in Chapter 2.

The concepts that are in the scope of this thesis are listed below:

- Feature Extraction and Classification stages of the ATR system are implemented.
- In the Feature Extraction stage of the ATR system, PCA, LDA, ICA and NMF methods are implemented.
- In the Classification stage of the ATR system, KNN and SVM classifiers are implemented.

- A Hierarchical Classification approach is also examined.
- Clustering Quality and Classification performance metrics are searched and used.
- The TRP vectors obtained by considering multiple time bins are also examined.

1.3 Contribution of the Thesis

In the traditional doppler ATR systems, the variations of the preprocessed Target Doppler Spectrums in time are not evaluated (See Chapter 2 Background - Literature Survey part). This study examines the performance of various feature extraction and classification methods and evaluates the effects of using time variations of preprocessed Target Doppler Spectrums on the classification performance.

1.4 Organization of the Thesis

The thesis is organized as follows:

Chapter 2 gives background on doppler radars, studies about doppler radar ATR systems, a brief explanation about the prepocessing stage in Erdogan (2002), pattern recognition, clustering quality measures, classification performance metrics, feature extraction methods used in the thesis, classification methods used in the thesis.

Chapter 3 explains the ATR system used in the thesis.

Chapter 4 gives the experimental results of the ATR system explained in Chapter 3.

Chapter 5 gives conclusions and possible feature works.

CHAPTER 2

BACKGROUND

2.1 Background on Doppler Radars

Doppler Radars use the doppler effect to detect moving targets and calculate the velocities of the targets. According to the doppler effect the relative velocity of the target will create corresponding frequencies at the signal received from the target (Richards, 2005). Doppler radars utilize these frequencies to detect the target and find the characteristics of the target. This is due to the common physical phenomenon that the phase of the reflected signal for a stationary object is constant whereas for a moving object it is changing. The change in the phase (doppler frequency shift) is proportional to the radial speed of the target. The doppler frequency shift f_d is given by the derivation:

$$f_d = (2 * f_t * v_r) / c \qquad (2.1)$$

where

f_d : *Doppler frequency shift*

f_t : *Frequency transmitted*

v_r : *Radial speed of the target*

c : *Speed of the light*

For approaching targets the doppler frequency shift will be added up to the transmitted frequency and for diverging targets the doppler frequency shift will be subtracted from the transmitted frequency. If the target has moving parts, each distinct moving part of the target will create a different doppler frequency on the received signal due to the different speeds of the different moving parts of the target. This can be utilized to classify targets since different target types show different motion characteristics.

In Table 2.1 physical structures for different target classes that will generate doppler frequencies is presented.

Table 2.1 Structures for different target classes that generate doppler frequencies

TARGET CLASS	STRUCTURE
Car	Body and Wheels
Truck	Body and Wheels
Bus	Body and Wheels
Tank	Body, Wheels and Track
Helicopter	Body, Main and Back Propellers
Walking Man	Body, Legs and Arms
Running Man	Body, Legs and Arms

The most important factors that affect the received signal for a doppler radar are target range, target aspect angle and target radial speed factors. These factors were defined before. In Figure 2.1 we present these factors visually (Erdogan, 2002).

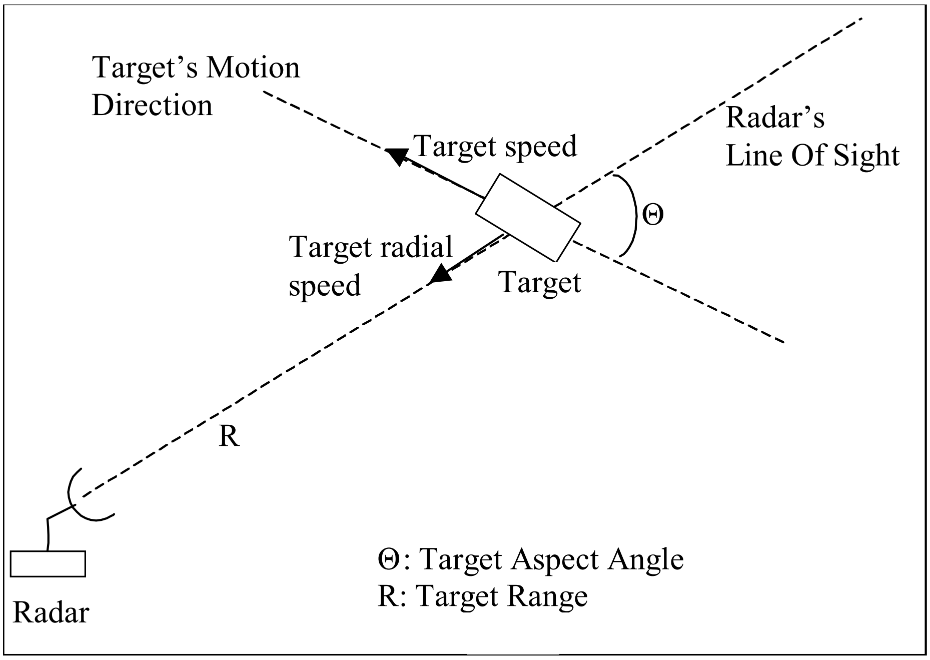

Figure 2.1 Doppler radar factors affecting the received signal

Target range affects the amplitude of the received signal, whereas target aspect angle and target radial speed factors affect the frequency information of the received signal.

2.2 Background on Doppler Radar ATR Studies

There are several studies performed on doppler radar automatic target recognition. This section gives information about them.

In Castalez (1988), they classified 4 artillery munition classes with the use of their doppler time signatures which were obtained by Hughes AN/TPQ-37 radar. Back-Propagation Neural Network was used for classification and its input was 15 doppler frequency bin amplitudes returned from the target and time information which is fed to the 16. input. The 16-16-16 Back-Propagation was trained with 32 samples for each target class and tested with 256 samples for each class. Training samples were fed to the network for several thousand cycles. The classification performance obtained was %92. They also used a 16-32-32 network but same level of performance was obtained. In their experiments they observed that three layer networks are sufficient and networks with more layers can degrade the classification performance.

In Bullard (1991), classification of rotary wing aircraft was performed based on the doppler signatures of the target. It was a study directed by MICOM (U.S. Army Missile Command) / Georgia Tech measurements in 1989-90. Target signatures of a Sikorsky S-55 helicopter were gathered with a high-pulse repetition frequency X-band coherent radar. Helicopter's main rotor blades, tail rotor blades and hub regions creates distinct doppler signatures such that it would be possible to identify helicopter characteristics such as rotor configuration, blade count and rotor parity. This study did not implement an automatic target classification system but it rather proposed methods to extract information about rotary wing aircraft.

In Madrid (1992), an automatic target recognition system was designed to classify four target types (airplanes and ground vehicles, helicopters, groups of small moving targets (e.g, persons) and clutter). Doppler signatures were used to implement the classification. The target classes were chosen in such a detail to obtain an adequate classification performance. These target classes have different spectral shape characteristics. Airplanes and ground vehicles do not have any vibrating or rotating parts, they only have a large rigid body so their signatures will include a large peak. Due to the main and tail rotor blades of the helicopter, it will have flat wide sidebands around the sharp peak. In a group of persons there will be members with different speeds. By considering the spectrum of this class as the sums of individual member spectrums, there can be more than one peak in the spectrum of this class. Since clutter has zero velocity, its spectrum will consist of a peak at zero doppler.

At the signal processing stage each frame was transformed by Discrete Fourier Transform. In the feature extraction step, four measurements including shift of the spectral maximum and bandwidths at three different levels were taken for each frame. The classifier is fed with 12 parameters which consist of the features of three frames. The classifier was a 2 hidden layered Multilayer Perceptron Neural Network with first and second hidden layers consist of 36 and 12 nodes respectively. For each target class, 200 samples were used at the test phase of the experiment. Also some extra controls were performed under certain conditions to prevent some kinds of errors. If aircrafts or group of persons had a mean doppler shift of zero, such detections were labeled again as clutter. RCS (Radar Cross Section) was utilized in some conditions such as the classification of an accelerating plane as group of persons. After the feature extraction and classification steps, for Aircraft/Vehicle and Helicopter target classes %100 classification performance were obtained while obtaining %97 and % 98 classification performances for Persons and Clutter target classes respectively. % 2 of Persons classified as Aircraft/Vehicle and %1 classified as Clutter. % 2 of Clutter classified as Persons.

In Jianjun (1996), they performed aircraft target classification using by using engine modulation on radar signatures obtained from the target. Radar signatures were taken with an air defense surveillance radar. Target class set consists of five aircrafts. Optical fourier transform was used for the extraction of modulation signatures.

The classifier was a semi-connected backpropagation neural network with one hidden layer. Numbers of training samples used for each target class were 43, 45, 41, 39 and 60 respectively. Since there were not enough samples for training samples, the leave-one-out technique is used for test. The classification performances for five target classes were % 99.87, %98.67, %99.33, %97.87 and % 98.27 respectively.

In Chen (2000), usefulness of micro-doppler signatures which are induced by the rotating and vibrating parts of the target for target detection, classification and recognition was considered. The modulations due to vibrations are at low frequencies with respect to the body doppler frequency while modulations due to rotations are at high frequencies with respect to the body doppler frequency. In this study Time-Frequency Domain Signatures of the targets such as stationary reflector, vibrating reflector, rotating blades and walking-man with swinging arms were investigated and it was observed that these targets have distinct time-frequency domain signatures which can be used for target classification.

In Yoon (2000), they used time-frequency analysis to determine the number of helicopter blades unambiguously. The main rotor rotation frequency then can be estimated after the number of blades is determined and all of these results can be used to determine the type of the helicopter. In the STFT of the helicopter echoes there are N sinusoids corresponding corresponding to the N rotor blades. They obtained satisfactory experiment results with a model helicopter with changeable rotor blades.

In Stove (2002), they used the target data of the MSTAR (Man Portable Surveillance and Tracking Radar) which is in use in U.K. and some other armed forces since 1989. This radar has audio which can be used by the radar operator to classify targets. The main aim of this study was to implement and test an automatic target classifier which can be used to provide classification service to the radar operator so that the workload of the radar operator can be reduced. The target classes of interest were wheeled vehicles, tracked vehicles and personnel. The sequences of audio samples were transformed by Fourier Transform. The classifier used was Fisher Linear Discriminator whose inputs were normalized spectrums. For a better performance, discrimination was implemented in two stages. Personnel and vehicle classes were discriminated first then wheeled vehicle and tracking vehicle classes were discriminated. %10 of the overall data is used for testing. As the result of the experiment average correct classification rates were % 86, % 83 and %83 for personnel, wheeled vehicles and tracked vehicles respectively. The biggest confusion rate was between wheeled vehicle and tracked vehicle classes. % 13 of the tracked vehicles classified as wheeled and % 14 of wheeled vehicles classified as tracked.

In McConaghy (2003), they implemented an automatic target recognition system that uses RBFNNs (Radial Basis Function Neural Networks) to classify real life audio signals collected by a ground surveillance radar mounted on a tank. With the implementation of such a system the number of personnels on the tank will be reduced since this job is done by the personnel by listening to the audio signals of the targets. In the neural network different signal classification methods were used. First method was to use a linear autoregressive model to extract the linear features of the audio data and second method was to use non-linear predictors to model the audio data and then classify the signals according to prediction errors. Target data was collected by AN/PPS-15 ground surveillance radar and the target types of concern were men-marching, walking-man, airplanes, trucks, tanks, crawling-man, birds and boats etc. By using a linear adaptive algorithm for the training of the network, The RBF network can be made implementable for real-time applications. % 75 of the overall data used for training and %25 used for test. Classification Performance was %86 and % 65 for training and test data by using AR (Autoregessive) feature extraction. Classification performance was %63 and %51 for training and test data by using linear predictors. They also experimented classification with human classification with a team of 40 humans and the classification performance was %27.

In Lei (2005), they used Gabor filtering method to extract micro-doppler signatures in the time-frequency domain. Dimension of the extracted features was reduced by PCA. Bayes linear, k-nearest neighbor and SVM classifiers were used and their classification performances were compared. This study used Gabor function since it is a good tool for extracting localized features in both spatial and frequency domain. Recognition rates were, between %44 and %92 for SVM, between %42 and %84 for KNN, between %38 and %78 for bayes linear classifier. Recognition rates were low when the number of features was below 500.

In Bilik (2005), they implemented an ATR system based on the Greedy learning of GMM (Gaussian Mixture Model). The aim was to classify doppler audio. Target class types were walking person(s), wheeled and tracked vehicles, animal and clutter. Target class probability density functions were modeled by GMMs. ML (Maximum Likelihood) and majority voting are used for classification. Greedy-GMM based classification technique is implemented using the linear predictive coding (LPC) and cepstrum coefficient feature sets, extracted from the data. A classification rate of % 88 obtained with ML classifier and %96 obtained with majority voting classifier.

2.3 Data Acquisition and Preprocessing

In this section data acquisition and preprocessing done in Erdogan (2002) for ASKARAD target signals are explained. The outputs of the prepocessing stage are TRP vectors which are also input to our target recognition system.

2.3.1 Data Acquisition

Doppler Signal is obtained from a range. This received signal is processed in the radar receiver in order to make it suitable for the target detection. In ASKARAD, doppler signal can also be listened by the radar operator as an audio signal. The audio signal is recorded as an analog signal, digitized at 11025 Hz and saved as 8 bit mono wav file. Information such as target range and azimuth can not be obtained from this signal.

2.3.2 Preprocessing of Signals

For a doppler radar there are several factors affecting the received target doppler signal. Most important of them are target range, target aspect angle and target radial speed. Target range is the distance between the target and the radar. Target aspect angle is the angle between the direction of the motion of the target and line of sight of the radar. Target Radial Speed is the target speed component along the line of sight of the radar. Target range affects the amplitude information of the received doppler signal, target speed and target aspect angle factors affect the frequency information of the received doppler signal. Since target speed and aspect angle can change in time, frequency analysis must be done in time.

Each audio signal received at a time-bin is transformed into frequency domain by using STFT (Short Time Fourier Transform). This transformed signal can be called as STFT frame. In Figure 2.2 STFT frames for a walking man target are presented.

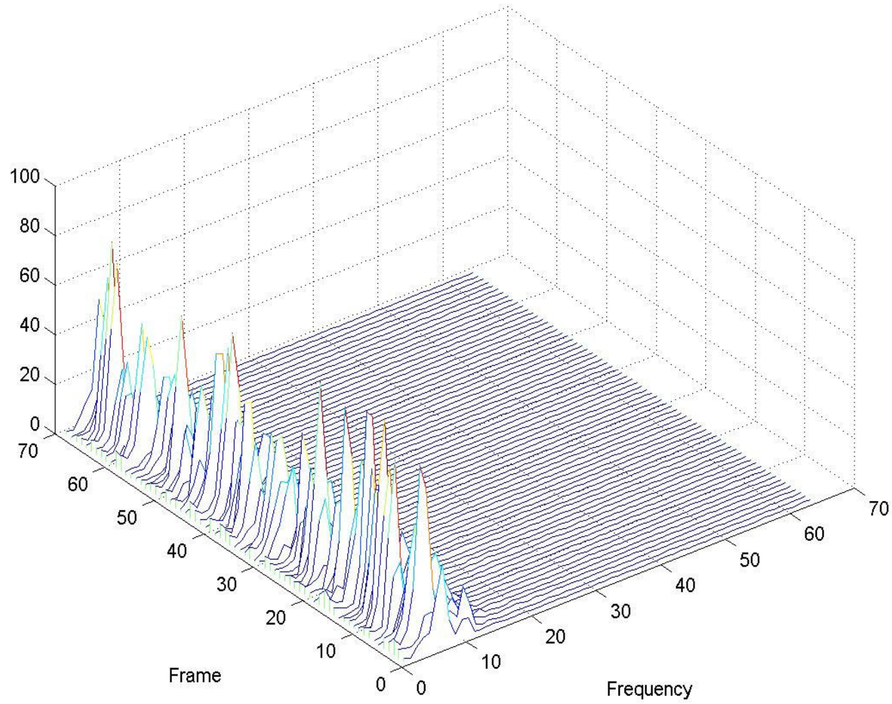

Figure 2.2 3-dimensional STFT frames of Walking Man

As mentioned previously the input to the ATR system designed in the thesis are the TRP vectors. In the following paragraphs, the preprocessing steps applied in order to obtain TRP vectors are explained.

Amplitude Normalization is done for each STFT frame by dividing amplitudes of the frequency components for an STFT frame by the frame energy.

After frame amplitude normalization step, frequency normalization is performed. The aim of this step is to find the TCB (Target Characteristics Band) for each STFT frame. Target Characteristics Band can be defined as the part of the STFT spectrum where the target characteristics reside. TCB can be expressed by mean frequency and TCB width.

The mean frequency of a STFT frame is:

$$\textit{Mean Frequency} = ((\textit{Frame Amplitudes Vector})^3 * \textit{Frame Bin Vector}) / (\sum \textit{Frame Bin Vector}) \quad (2.2)$$

where

$$\textit{Frame Bin Vector} = [1, 2,.., \textit{Frame Length}]$$

The average of the mean frequencies of the STFT frames is defined as the mean frequency of STFT frames. Mean frequency averaging is done on a specified number of consecutive frames. TCB is located at the mean frequency and its width is set equal to the twice of the mean frequency.

As the last step in the prepocessing stage, TCB frame is transformed into fixed length TRP vector. TRP vectors form the basis for feature extraction since target doppler signal is amplitude and frequency normalized and characteristic part of the frequency spectrum is extracted regardless of the actual frequency components. The dimension of TRP vector is chosen as 63.

2.4 Data Used in the Thesis

This thesis uses the Target Recognition Patterns (preprocessed Target Doppler Spectrums of ASELSAN ASKARAD Ground Surveillance Doppler Radar Target Signals). Half of TRP vectors are used for training and half of them used for testing. The Data Acquisition and Preprocessing done in is explanied in section 2.3.

TRP vectors used for training are presented in Figures 2.3 to 2.9. The data dimension of each time bin is 63.

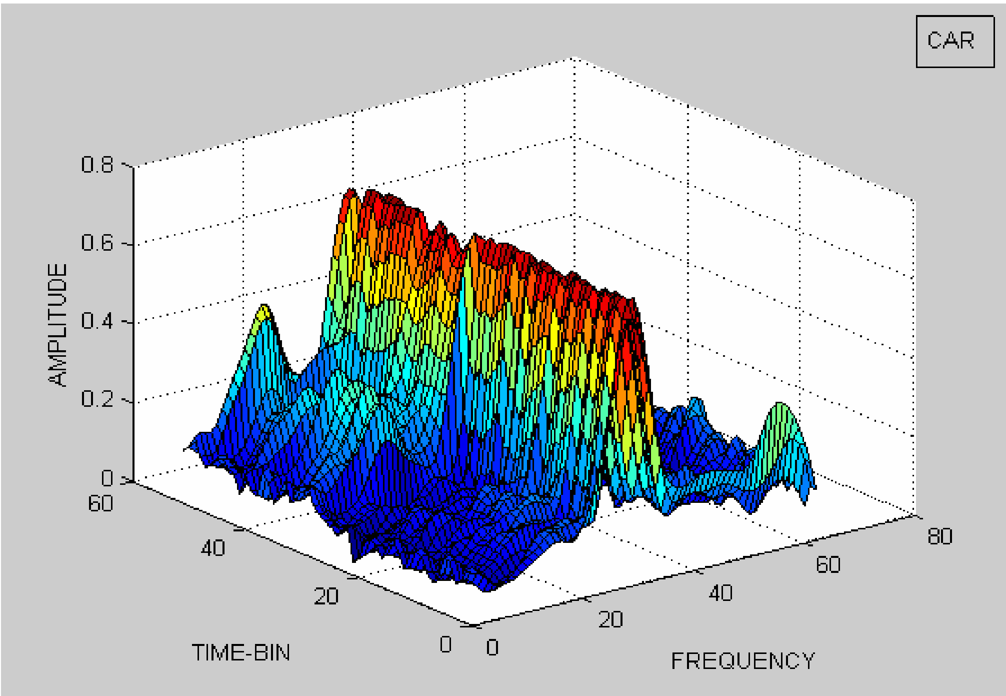

Figure 2.3 TRP vectors of training data for CAR class

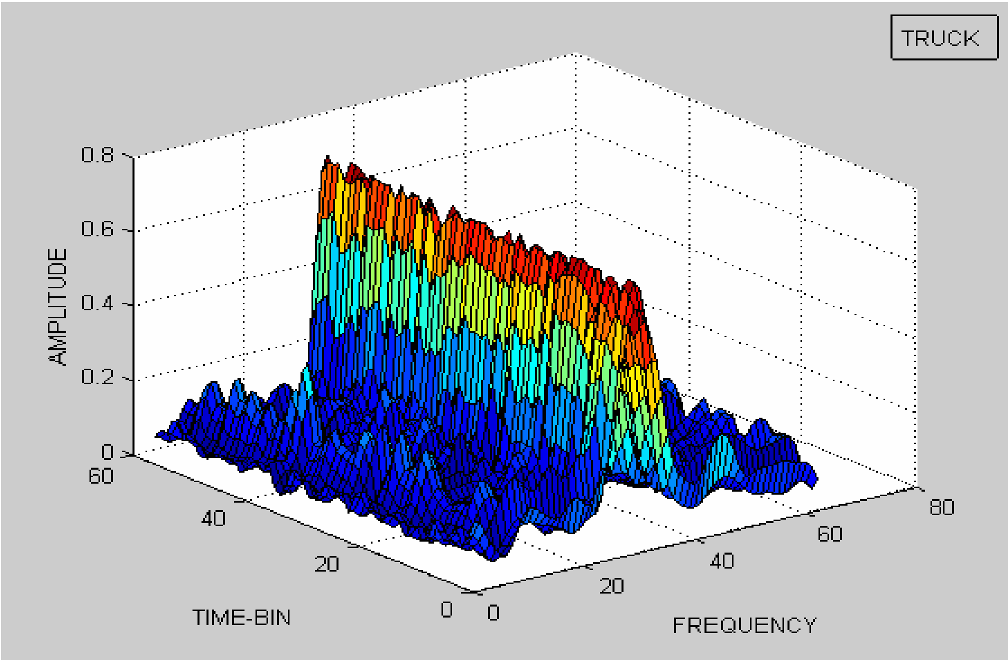

Figure 2.4 TRP vectors of training data for TRUCK class.

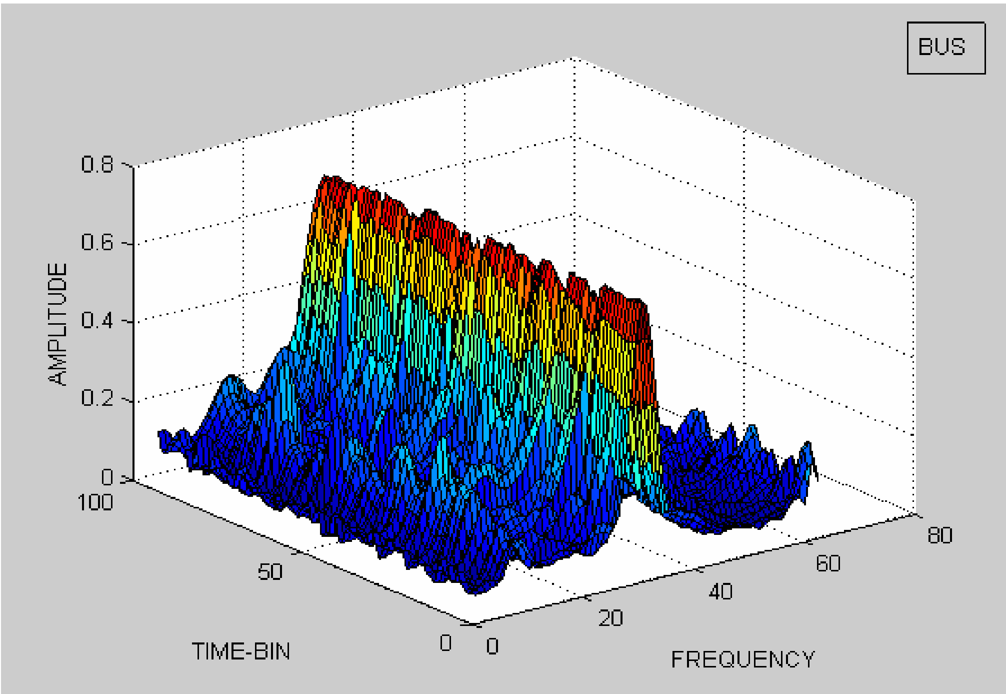

Figure 2.5 TRP vectors of training data for BUS class

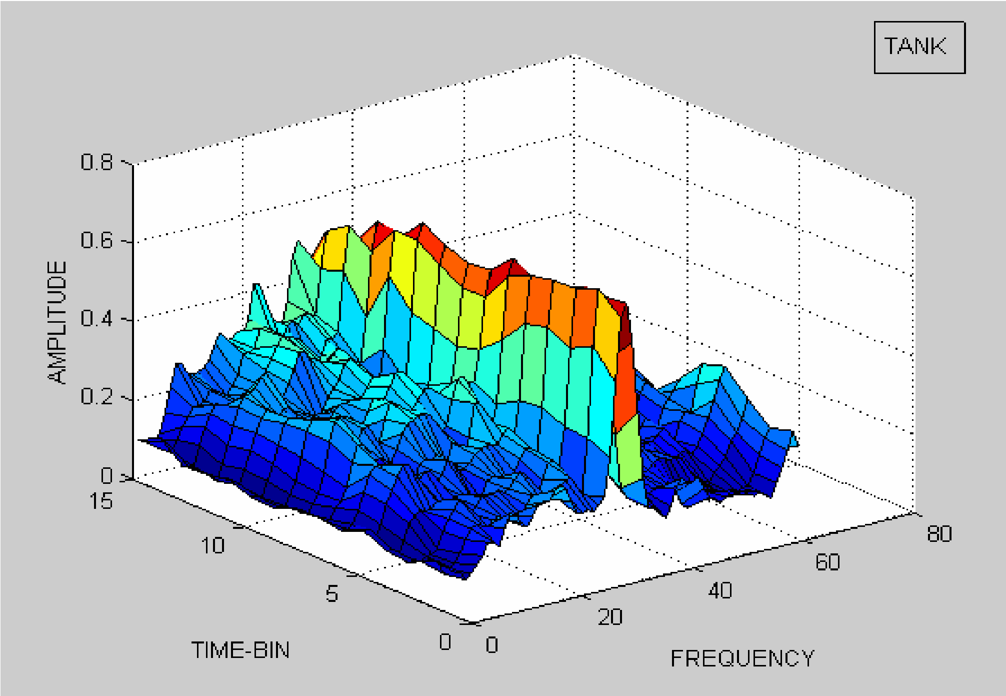

Figure 2.6 TRP vectors of training data for TANK class

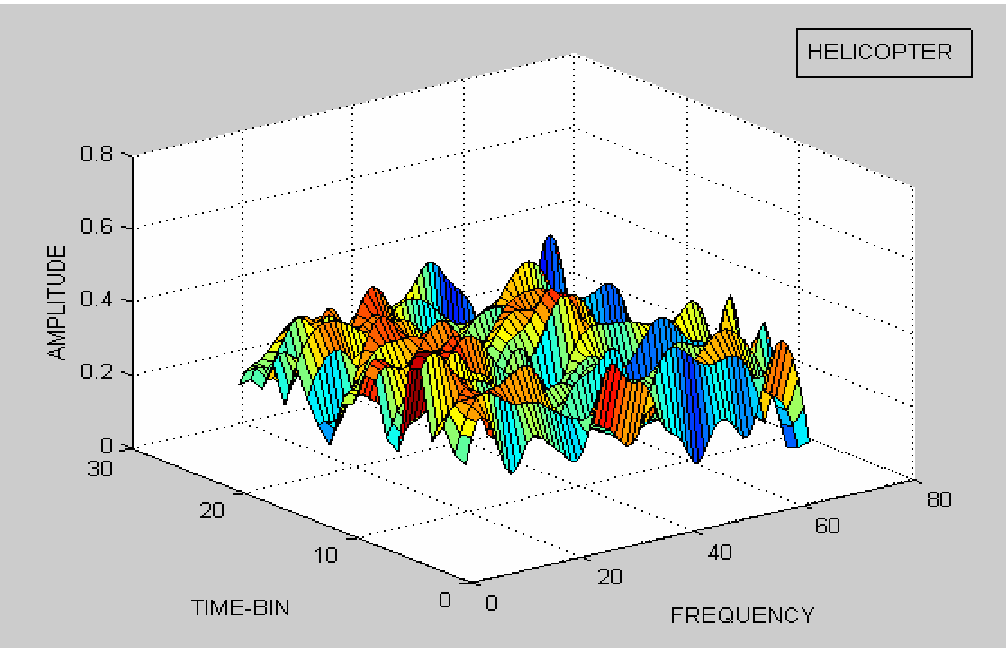

Figure 2.7 TRP vectors of training data for HELICOPTER class

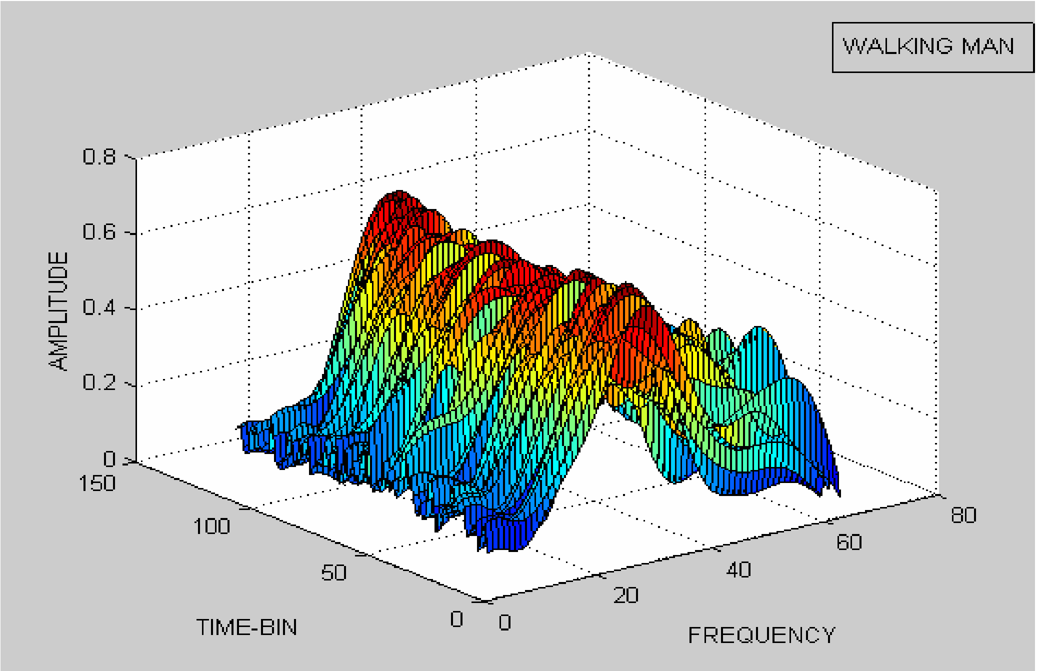

Figure 2.8 TRP vectors of training data for WALKING MAN class.

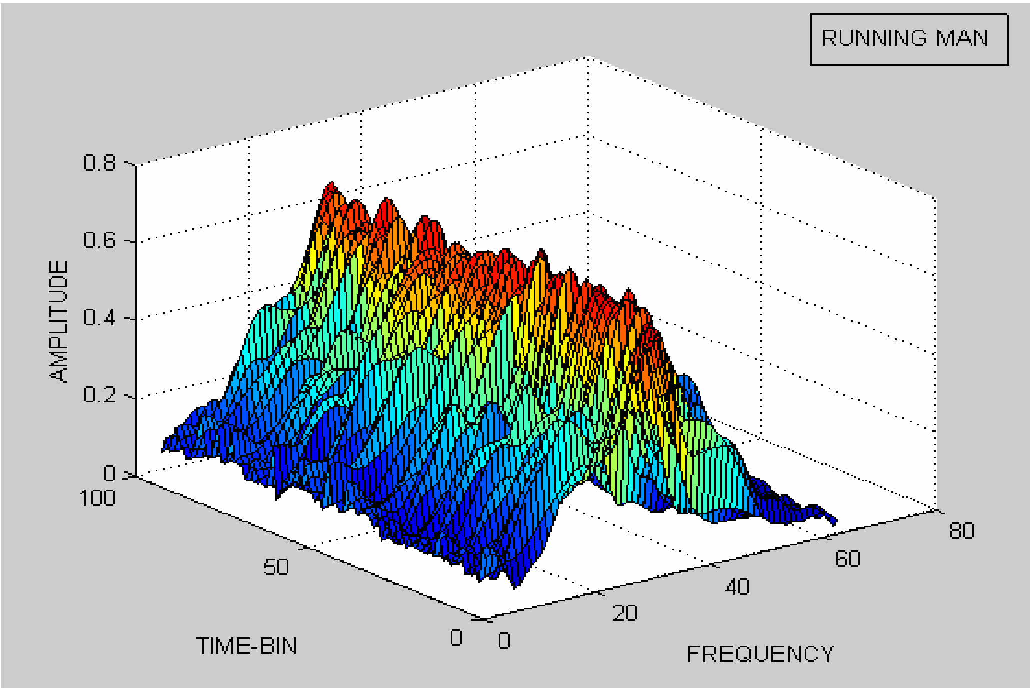

Figure 2.9 TRP vectors of training data for RUNNING MAN class

A total of 884 TRP vectors are used in this thesis. The number of TRP vectors for car, truck, bus, tank, helicopter, walking man and moving man classes are 104, 114, 188, 30, 42, 218 and 188 respectively. Half of the TRP vectors are used for training and half of them are used for test.

2.5 Background on Pattern Recognition

Pattern recognition aims to assign a measurement, object or data to one of the classes defined. Mainly a pattern recognition system consists of three stages which are data gathering, feature extraction and classification. Data gathering part or the sensor part gathers the raw data or takes the measurements that will be the input to the feature extraction part. Depending on the type of gathered data, there can be need of preprocessing for the data. This can be due to the noise or some other factors that are special to the data. The aim of the feature extraction part is to extract characteristic and relevant information (also can be called as features) from the raw data. Extracted features are input to the classification stage. The classification stage assigns the data or object to one of the defined classes based on the extracted features. The classification can be either supervised or unsupervised. In supervised classification there is a training data set which consists of classified data and the test data is classified according to this training data. In unsupervised classification, there is no priori information; classification is done based on the statistical information of the data.

2.6 Performance Measures

One of the main areas of interest in Pattern Recognition systems is to represent the performance of the feature extraction step mathematically in order to evaluate the feature extraction method performance separately from the classifier. To perform this, Clustering Quality Measures can be used. A clustering quality measure can be defined as a function whose input is a sample set and partition of the samples to the clusters and whose output is a number that represents the quality of clustering.

One of the CQMs (Clustering Quality Measures) is given in Schweitzer (1999). This measure is defined as the ratio of S_w (Within Class Scatter Matrix) to S_b (Between Class Scatter Matrix).

$$CQM = S_w / S_b \tag{2.3}$$

The S_b (Between Class Scatter Matrix) and S_w (Within Class Scatter Matrix) are defined as

$$S_b = \sum_j (m_j)(\mu_j - \mu)(\mu_j - \mu)^T \qquad j = 1..k \tag{2.4}$$

$$S_w = \sum_j \sum_i (x_i - \mu_j)(x_i - \mu_j)^T \qquad i = 1..G_j \tag{2.5}$$

The definition of mean of all samples is given below.

$$\mu = (\sum_j (m_j \, \mu_j)) / m \qquad j = 1..k \tag{2.6}$$

where

k : *Number of clusters.*

$G_1..G_k$: *Partition of the patterns into k clusters.*

m_j : *Number of samples in cluster j.*

x_i : *Samples in cluster j.*

$\mu_1.. \mu_k$: *Means of the clusters.*

μ : *Mean of all samples.*

m : *Number of all samples.*

A smaller value of the clustering quality measure S_w / S_b indicates a better clustering quality value since a smaller value of S_w and a larger value of S_b denotes a good clustering. Samples in a single cluster must be closer to each other and clusters must be far from each other for a good clustering.

Other clustering quality measure is given in Zardoshti (1993). This clustering quality measure is defined as cluster-to-cluster similarity. The cluster-to-cluster similarity value between two clusters is the ration of the difference of dispersions of clusters to the distance between the cluster means and its formula is given below.

$$R_{ij} = (S_i - S_j) / D_{ij} \tag{2.7}$$

Dispersion of cluster i (S_i) is defined as

$$S_i = \left(\left(\textstyle\sum_j (x_j - \mu_i)^T (x_j - \mu_i)\right) / m_i \right)^{1/2} \qquad j = 1..\, m_i \tag{2.8}$$

Distance between means of two cluster i and cluster j is defined as

$$D_{ij} = ((\mu_i - \mu_j)^T (\mu_i - \mu_j))^{1/2} \tag{2.9}$$

where

Si : Dispersion of cluster i.

Sj : Dispersion of cluster j.

Dij : Distance between means of cluster i and cluster j.

m_i *: Number of members of cluster i.*

x_i *: Input samples of cluster i.*

μ_i *: Mean of cluster i.*

k : Number of clusters.

The clustering quality value can be defined as the average cluster-to-cluster similarity value of all cluster-to-cluster similarity values.

$$R_{avg} = avg\ (Rij) \qquad i = 1..k \quad j = 1..k \tag{2.10}$$

A smaller clustering value of R_{avg} indicates a better clustering quality value. Among the two clustering quality metrics given in (2.3) and (2.7), the quality metric in (2.3) covers the overall data more than the one in (2.7). So, in the thesis the results for the clustering quality metric in (2.3).

As the classification performance measure class-to-class confusion matrices are widely used. These matrices show the actual and predicted classifications performed by the classification system. In such a matrix the entry in row i column j shows the number of samples classified as class j but in fact are the members of class i. Confusion matrices shows class-to-class classification performance however they do not yield a single value which is to show the overall performance of the classifier. In the literature there are some classification performance values used for this purpose. One of them is called KHAT (Wilkinson, 2005). This classification performance metric takes the class-to-class confusion matrix as input and returns a single value that presents the classification performance. KHAT value of a confusion matrix is given by:

$$KHAT = \frac{(N * (\sum_i X_{ii})) - (\sum_i (X_{i+} * X_{+i}))}{(N^2) - (\sum_i (X_{i+} * X_{+i}))} \qquad i = 1..r \qquad (2.11)$$

where

r : *Number of rows in the confusion matrix*

X_{ii} : *Number of observations in row i column i of the confusion matrix*

X_{i+} : *Marginal total of row i of the confusion matrix*

X_{+i} : *Marginal total of column i of the confusion matrix*

N : *Total number of samples in the confusion matrix*

KHAT formula takes into account not only the correct classifications but also the misclassifications.

Also the average of the correct classification rates of each class can also be used as classification metric and its formula is given below.

$$Recognition_{avg} = (\sum_i C_i) / k \qquad (2.12)$$

where

C_i = *Correct recognition rate for class i*

k = *Number of classes*

In fact $\text{Recognition}_{\text{avg}}$ given in (2.12) is the sum of the diagonal elements in confusion matrix divided by the number of classes.

2.7 Feature Extraction and Classification Methods

In this thesis, PCA, LDA, ICA and NMF methods are used for feature extraction, while KNN and SVM methods are used for classification. Our target recognition system consists of a feature extraction method and a classifer chosen from these methods. Methods are explained in the following sections.

2.7.1 PCA

PCA (Principal component analysis) is a non-parametric method that extracts relevant information from complex data sets. The main aim of PCA is to reduce the dimension of the data while preserving as much representative information as the original data (Shlens, 2005). PCA is a linear transformation that computes a matrix which transforms the high dimensional space to a lower dimensional space. PCA transforms the data along the directions where data varies the most. PCA is unsupervised, i.e. it does not deal with class information of the data.

Considering the vector x, PCA tries to find the matrix $T \in R^{KxN}$ for which $y = Tx$ where $y \in R^K$ is the transformed version of $x \in R^N$ such that $K \leq N$.

PCA method can be summerized as below:

- $x_1, x_2 \,_{..}\, x_L$ are the sample vectors whose dimension is N and will be reduced. L is the number of samples.
- Calculate the mean of the samples. $\mu = (\sum_j x_j) / L \quad j = 1..L$
- Subtract the mean from the samples. $\Phi_j = x_j - \mu$
- Calculate the matrix A. $A = [\Phi_1 \, \Phi_2 \,_{..}\, \Phi_L]$
- Calculate the covariance matrix $C = AA^T$
- Calculate the eigenvalues of C, $\Lambda_1 > \Lambda_2 >_{..} > \Lambda_N$
- Calculate the eigenvectors of C, $\Pi_1, \Pi_2, _{..}, \Pi_N$
- Eigenvectors determines the directions of the new space.

- Any training or test sample can be projected to the new space by $y_i = (x_i - \mu) [\Pi_1 \Pi_2 .. \Pi_K]$ where x_i is the sample and y_i is the transformed sample.
- Dimensionality reduction means loss of information. The dimension of the new space must be chosen such that the difference between y_i and x_i must be minimum.
- In order to minimize the difference between y_i and x_i , K must be chosen such that;
  $(\sum_i \Lambda_i) / (\sum_j \Lambda_j) >$ Threshold (For example 0.85)
  where i = 1 .. K and j = 1 .. N
- One advantage of PCA is that noisy directions can be eliminated from data representation.

2.7.2 LDA

LDA (Linear Discriminant Analysis) is a feature extraction method that utilizes the class information of the samples. LDA tries to find the directions in which separation of classes is good by computing the within class scatter S_w and between class scatter S_B (Shan, 2002).

Within class scatter S_w is given by the derivation:

$$S_w = \sum_i \sum_j (y_j - \mu_i) (y_j - \mu_i)^T \quad i = 1..k \quad j = 1..m_i \tag{2.13}$$

where

k : Number of classes

m_i : Number of samples that belongs to class i

μ_i : Mean of the samples in class i

Between class scatter S_B is given by derivation:

$$S_B = \sum_i (\mu_i - \mu) (\mu_i - \mu))^T \tag{2.14}$$

where

μ : Mean of the overall data set

LDA is a transformation that maximizes between class scatter while minimizing within class scatter. To perform this LDA finds the optimal transformation W to maximize J(W). J(W) is given by the derivation:

$$J(W) = (W^T S_B W) / (W^T S_W W) \tag{2.15}$$

To maximize J(W) the equation below must be solved.

$$S_B W = \Lambda S_W W \tag{2.16}$$

For the equation (2.16) to have a solution, S_W must be non-singular. Solving equation (2.16) requires finding the eigenvectors of $S_W^{-1} S_B$. In our target recognition system we reduced the dimension of the training and test samples to 32 with PCA before applying LDA.

2.7.3 ICA

ICA (Independent Component Anlaysis) is a recently developed linear transformation method that maximizes the statistical independence of the components of the new representation as much as possible (Hyvarinen, 1999). ICA can be defined in a general sense as a linear transformation method which finds a projection W for a random vector x such that s = Wx and components of s are statisticaly independent as much as possible. ICA is mainly used for blind source separation problem and it can also be used for feature extraction. ICA can be considered as a variant of PCA such that PCA makes the data uncorrelated whereas ICA makes the data statistically independent (Lathauwer, 2000). The aim of ICA is to make the transformed data non-gaussian Vasilescu (2005).

To implement ICA, the code in Ustun (2007) is used with modifications. Before executing ICA, we reduced the size of training and test samples to 32 with PCA.

2.7.4 NMF

NMF (Non-negative Matrix Factorization) is used in many areas. In algebra, large and complex problems can be divided to small simple subproblems by NMF. In pattern recognition NMF can be used for feature extraction and dimension reduction (Weixiang, 2006). Considering an nxm non-negative matrix V, the aim of NMF is to find two non-negative matrices W and H such that

$$V \approx W * H \tag{2.17}$$

where

$W \in R^{nxr}, H \in R^{rxm}$

Here, r is generally chosen smaller than n and can be as small as possible to reduce dimension (Xue, 2006). W and H are also non-negative.

To find matrices W and H, there are different methods in the literature. In the thesis we used the one that minimizes Divergence(V||WH) with respect to W and H, being subject to the constraints W ≥ 0 and H ≥ 0. In order to satisfy the non-negativity constraint for V, W and H, during the experiments we added the minimum value of V to all training and test samples. W and H can be intiated to random values. The update rules for W and H are given by derivations:

$$H_{a\mu} \leftarrow H_{a\mu} (\textstyle\sum_i (W_{ia} V_{i\mu} / (WH)_{i\mu})) / (\textstyle\sum_k W_{ka}) \tag{2.18}$$

$$W_{ia} \leftarrow W_{ia} (\textstyle\sum_\mu (H_{a\mu} V_{i\mu} / (WH)_{i\mu})) / (\textstyle\sum_v H_{av}) \tag{2.19}$$

Pseudo inverse of matrix W is multiplied by test samples and transpose of matrix H gives the NMF applied training samples. In our pattern recognition system before executing NMF, dimension of training and test samples are reduced to 32 with PCA.

2.7.5 KNN

KNN (K nearest neighbor) is a classifier that classifies test samples according to the class labels of training samples that are closest to the test sample in the feature space. The class label of the test sample is decided as the most common class label among the class labels of the K-nearest neighbors. It can be considered as the simplest classifier. In our target recognition system, test samples are classified according to the class labels of the 5 closest training samples. KNN can not be considered as a real time implementable classifier since at execution, for a test sample distances to all training samples are calculated rather than multiplying the sample with a matrix and deciding the class label. There is no training phase for this classifier.

2.7.6 SVM

A SVM (Support Vector Machine) is a classifier that separates the data into two groups by forming an N dimensional hyperplane. The aim of SVM is to find the optimal separating hyperplane so that different classes are on the different sides of the hyperplane. Support vectors are the samples which are the closest ones to the hyperplane. SVMs are used for handwritten digit recognition, object recognition, speaker identification, face detection, text categorization (Burgess, 1998). For the 2-dimensional case, an example separating hyperplane and support vectors are presented in Figure 2.10.

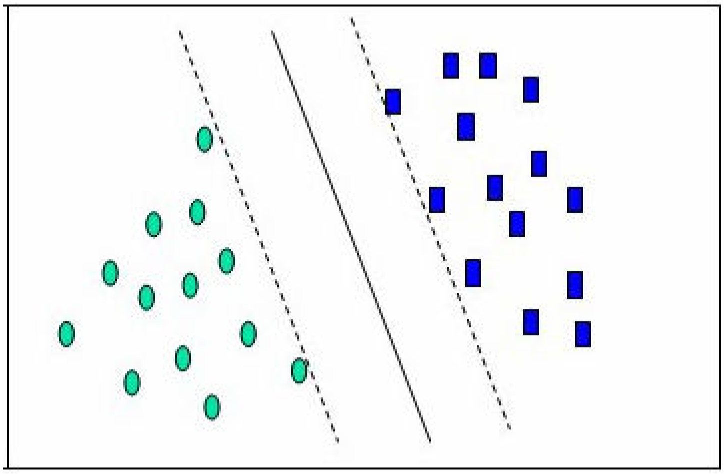

Figure 2.10 Separating hyperplane for 2 dimensions

In Figure 2.10 the green and blue labels shows the samples of two different classes. The continuos black line is the separating hyperplane and the samples that are closest to the two dashed lines are the support vectors. This is a compleletely separable condition i.e SVM separates all of the samples correctly to their classes, there is no overlapping. There can be non-separable cases in which SVM can not separate the classes and there will be training errors too. SVM finds the support vectors for which the margin between clusters is maximized. The aim of maximizing the margins is to reduce the testing errors. For the cases when the boundaries between the clusters are so complex that linear seperation is not possible, non-linear kernel functions can be used instead of linearly separating hyperplanes. Radial Basis Function is one of the most recommended and used one as the kernel function and we also used it in our code. The support vector machine code used in the thesis is given in Spider (2006).

CHAPTER 3

THE PROPOSED ATR SYSTEM

3.1 The General Structure of the ATR System

The block scheme of the target recognition system proposed in the thesis is shown in Figure 3.1. The system consists of N-bin Data Generation, Feature Extraction & Dimension Reduction and Classification stages which are explained in sections 3.2, 3.3 and 3.4 respectively.

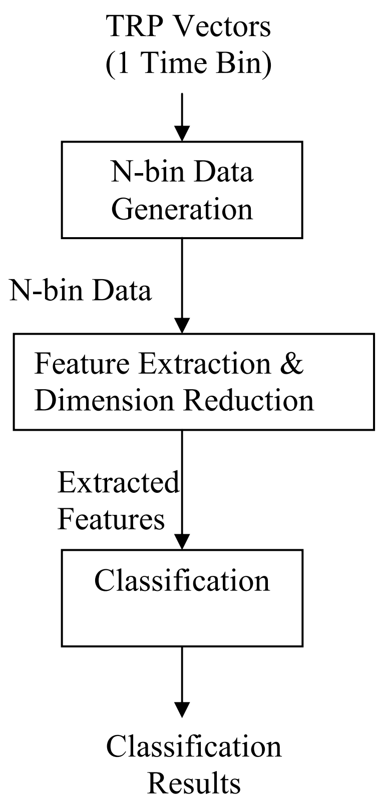

Figure 3.1 Block scheme of the target recognition system proposed

3.2 N-bin Data Generation

Some target classes have repetitions in time in their TRP vectors. To see these repetitions in time visually, 3-D plots of TRP vectors of target training classes were given in the figures from Figure 2.3 to Figure 2.9.

From the figures we can observe that TRP vectors of vehicles (car, truck, bus) are homogenic in time while target classes such as walking man, running man and helicopter have different vectors which repeat itself in time. To see these repetitions in detail furtherly 2-D time-bin – amplitude plots for walking man, running man and helicopter targets are shown below in Figure 3.2 to Figure 3.4. These plots are the projections of the 3-D plots in Figure 2.8, Figure 2.9 and Figure 2.7 into amplitude and time-bin axes. One of the main goals of this thesis is to take into consideration these repetitions in time in order to enhance classification performance.

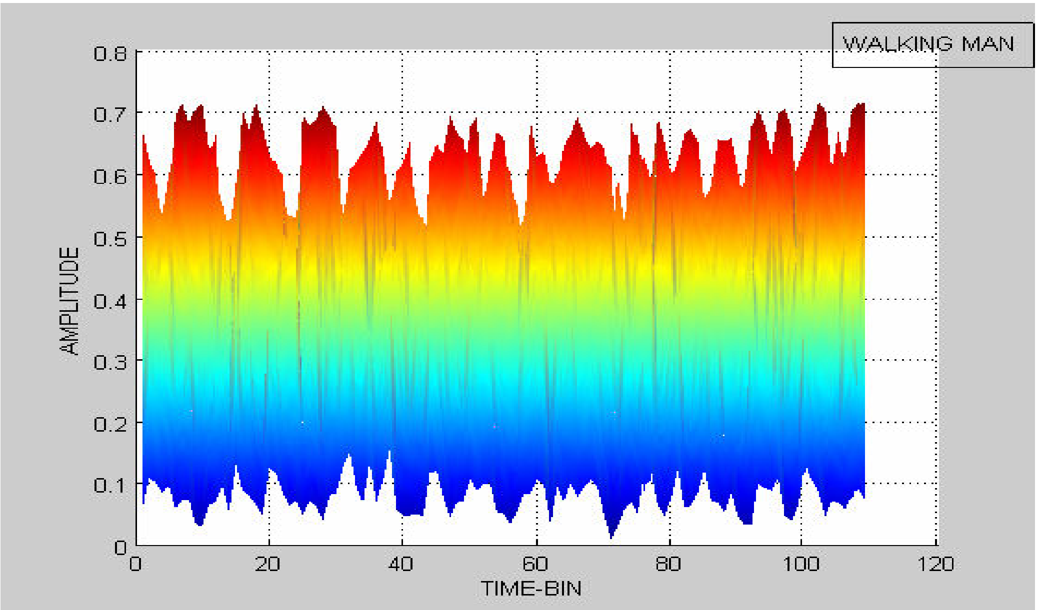

Figure 3.2 Time-bin – Amplitude plot for Walking Man training data

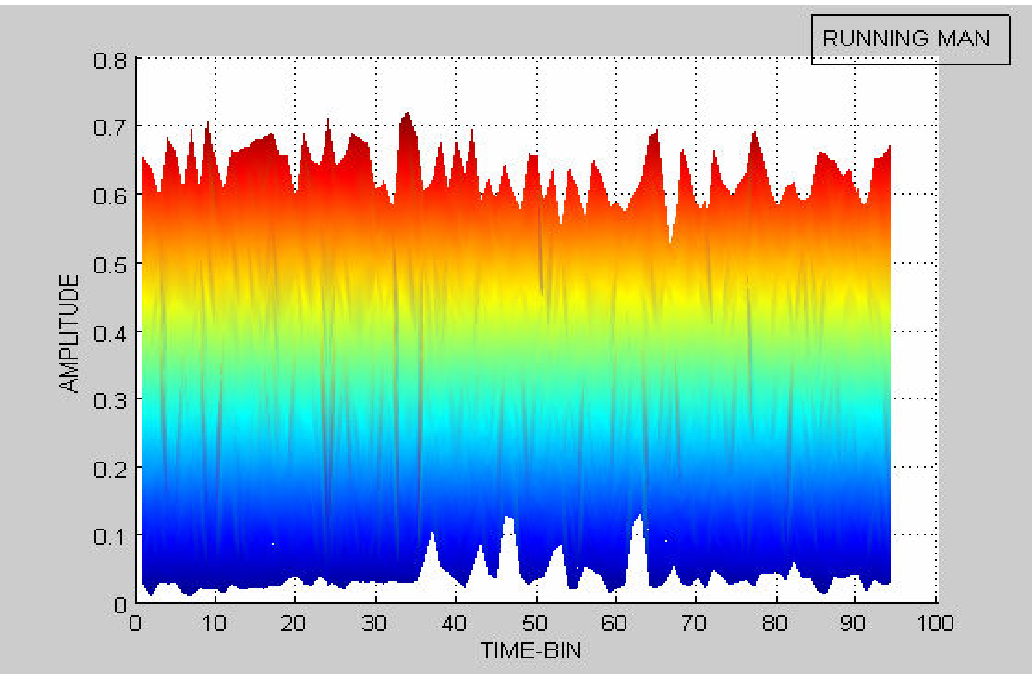

Figure 3.3 Time-bin – Amplitude plot for Running Man training data

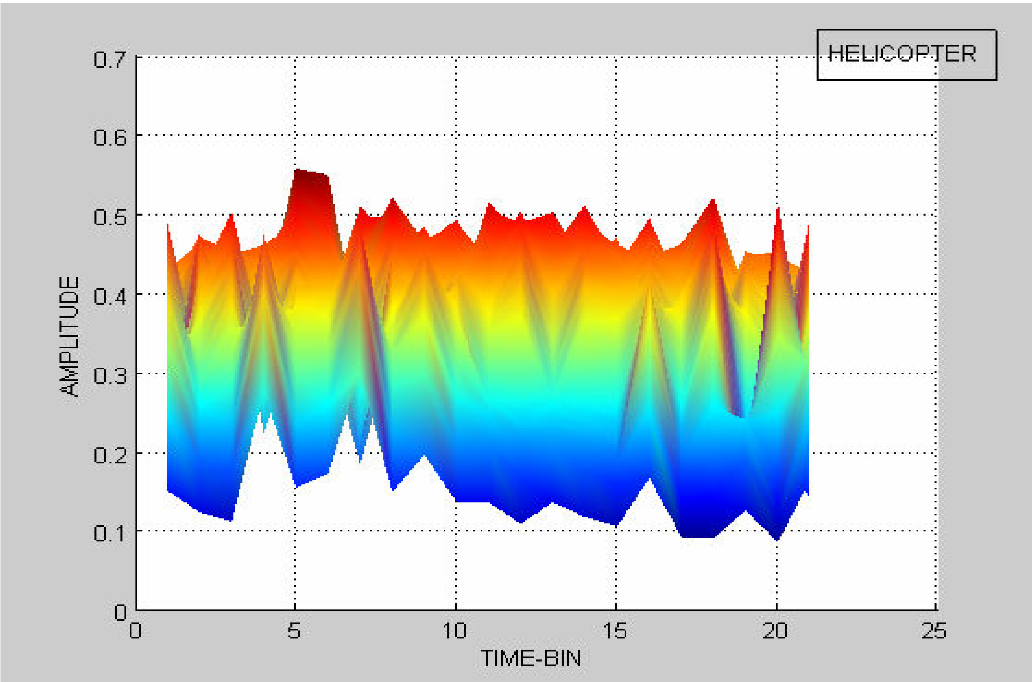

Figure 3.4 Time-bin – Amplitude plot for Helicopter training data

To take these repetitions into consideration, successive TRP vectors in time of a target can be concatenated and presented to the feature extraction part of the target recognition system. The N-bin Data Generation part of the target recognition system just concatenates previous N-1 TRP vectors with the current TRP vector and outputs this as the N time-bin sample.

3.3 Feature Extraction & Dimension Reduction

The second part of the target recognition system is feature extraction and dimension reduction part. PCA, LDA, ICA, NMF methods are used alternatively for feature extraction. Before applying LDA, ICA and NMF methods, we used PCA for dimension reduction. Data dimension is reduced with PCA to 32 before applying these algorihms. Feature extraction part is shown in Figure 3.5. After the feature extraction step not all the features of the samples are fed to the classifier, they are further reduced to proper dimension.

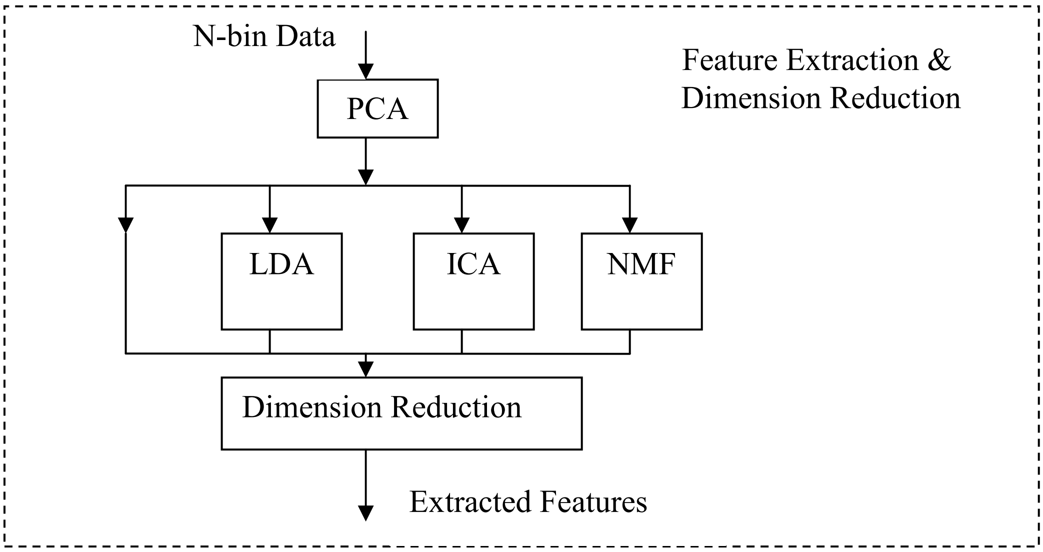

Figure 3.5 Feature Extraction & Dimension Reduction of the target recognition system

3.4 Classification

K-Nearest Neighbor and Support Vector Machine classifiers are used at the classification stage of the pattern recognition system. Multi-Layer Perceptron classifier is not used in classification because for target classes which have less training samples than other classes (tank and helicopter), poor classification performance results are obtained. KNN classifier is coded in MATLAB and we used an SVM tool that we found from the internet Spider (2006).

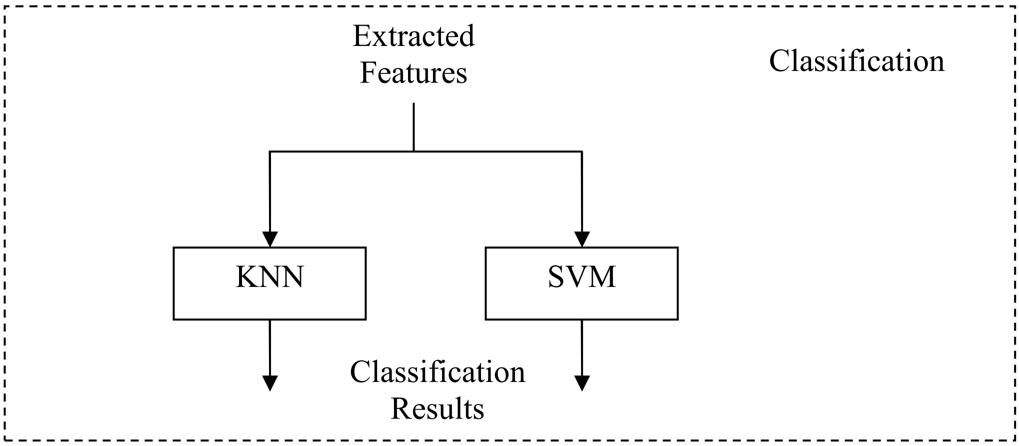

Figure 3.6 Classification stage of the pattern recognition system

3.5 Hierarchical Classification

Observing the training TRP vectors shown in Figure 2.3 to Figure 2.9, we see that some target classes have similar vectors compared to the other classes. While Car, Truck and Bus TRP vectors are similar to each other and make one group, the Walking Man and Running Man TRP vectors make another group. This grouping is shown schematically in Figure 3.7

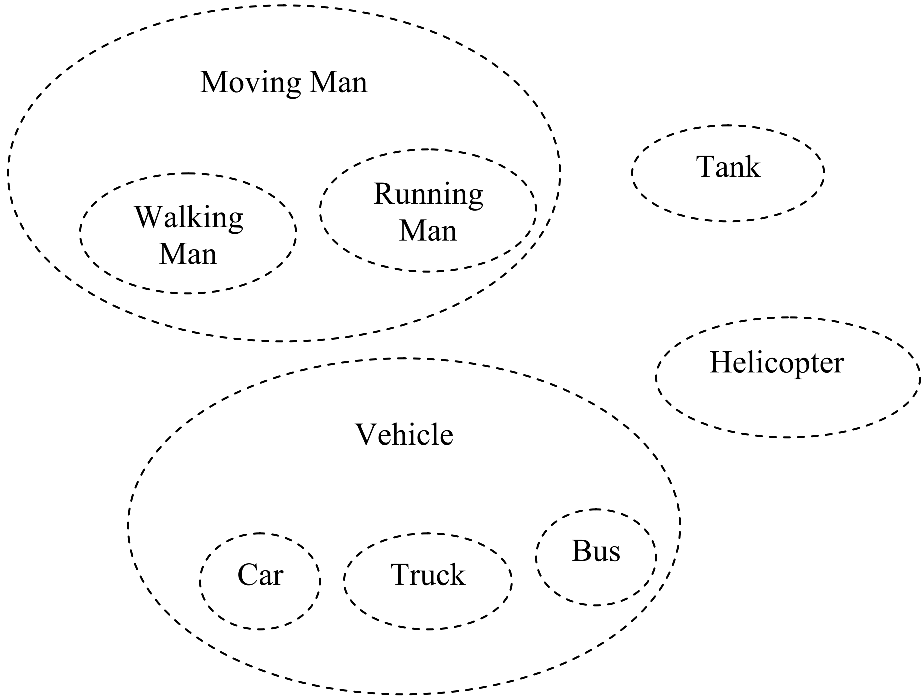

Figure 3.7 Hierarchical grouping of data according to their similarities

So, instead of trying to assign the target samples directly to 7 classes, we can first classify them to a smaller class set in which classes are of more general types (first level classification) and then the samples that belong to these classes can be further classified to the classes which are of more detailed types (second level classification). By applying such a classification system the classification performance can be improved. For our data, Car, Truck and Bus target samples form the vehicle target class set. Walking Man and Running Man target samples form the Moving Man target class set. In the first level of the classification the samples will be classified to Vehicle, Tank, Helicopter and Moving Man target classes, then in the second level of classification the samples classified as Vehicle will further be classified to Car, Truck and Bus target classes and samples classified as Moving Man will further be classified to Walking Man and

Running Man target classes. The overall hierarchical classification system for our target samples is shown in Figure 3.8.

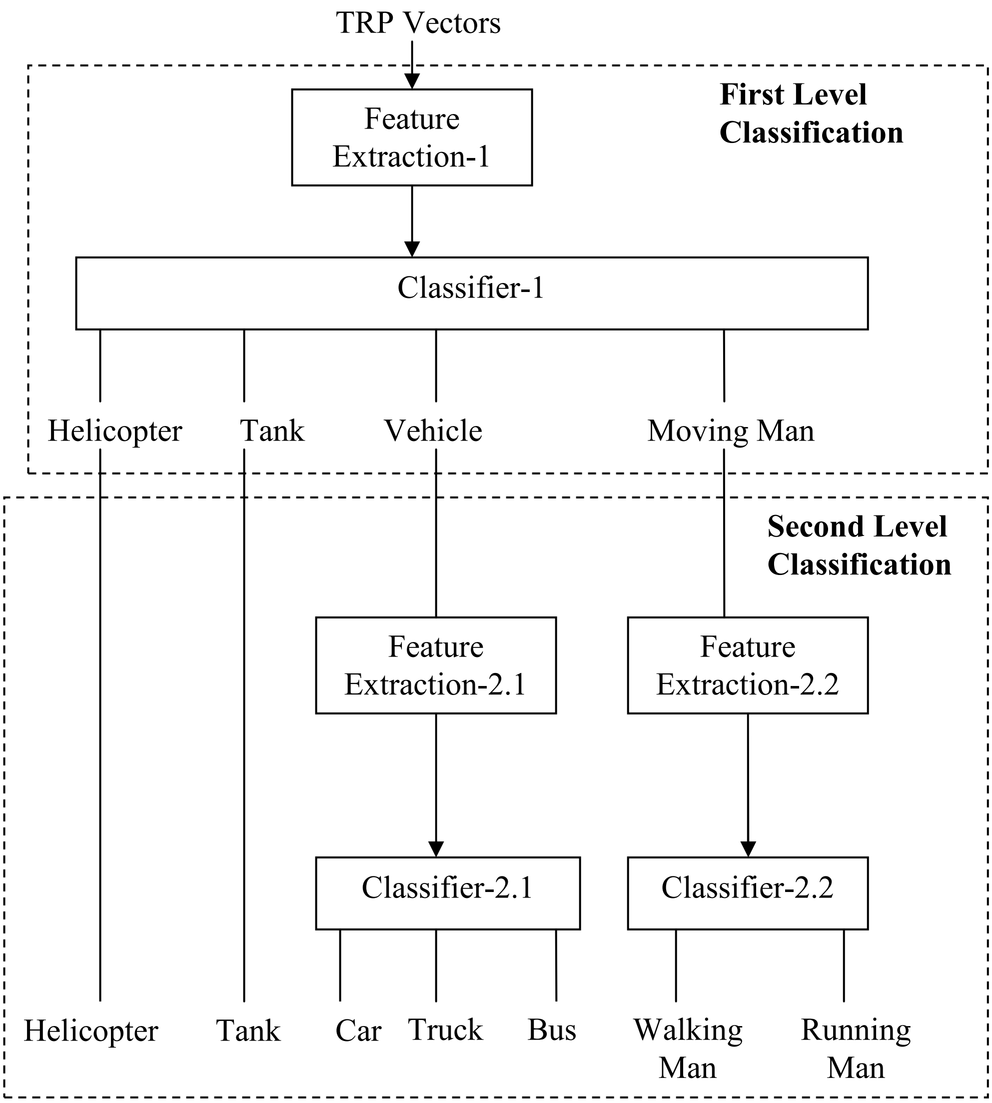

Figure 3.8 Hierarchical target recognition system

The Feature Extraction steps shown in Figure 3.8 can be PCA, LDA, ICA or NMF as before we used in Section 3.3 and the Classifier steps can ve SVM or KNN similarly as in Section 3.4. Vehicle, Tank, Helicopter and Moving Man target train and test samples are fed to the Feature Extraction-1 step. Feature Extraction-1 uses vehicle, tank, helicopter and moving man classes as base classes. Classifier-1 is also trained with extracted features of the training samples of these classes. After Classifier-1, all target test samples are classified to vehicle, tank, helicopter and moving man target classes.

TRP vectors of target test samples classified as Vehicle are then classified as Car, Truck, Bus after Feature Extraction-2.1 and Classifier-2.1 steps. Feature Extraction-2.1 step uses Car, Truck and Bus base classes. Classifier-2.1 is trained with the extracted features of target train samples belonging to the mentioned classes.

TRP vectors of target test samples classified as Moving Man are then classified as Walking Man and Running Man after Feature Extraction-2.2 and Classifier-2.2 steps. Feature Extraction-2.2 uses Walking Man and Running Man as base classes. Classifier-2.2 is trained with the extracted features of target train samples belonging to the mentioned classes.

The khat result tables and recognition rates of hierarchical classification for various time-bin and principal component values are presented in Chapter 4.

3.6 Clustering and Classification Performance Analysis

To evaluate the performance of target recognition system shown in Figure 3.1, Clustering Quality Evaluations and Classification Performance Evaluations metrics are applied which are described in 3.6.1 and 3.6.2 respectively.

3.6.1 Clustering Quality Evaluation

Before observing the overall target recognition system classification performance, we used simply the PCA method for 1 time-bin, 5 time-bin and 10 time-bin data in order to see the affect of repetitions in time. In our normalized data set, a single time bin contains 63 data points in the frequency domain. So, data dimensions for 1 bin data, 5 bin data and 10 bin data are 63, 315 and 630 respectively. In the dimension reduction step we reduced the size of extracted features to 2 for visual examination. The separation of target classes for train and test data with respect to these 2 extracted features is shown in Chapter 4.

Observing the affect of using repetitions in time visually by using 2-D plots of the 2-dimensional extracted features gives us an intuition on how the samples are distribured over the feature space when different numbers of bins are used. However expressing it mathematically is a better way. For this purpose we used the clustering quality metrics in (2.3) and (2.7). After N-bin Data Generation and Feature Extraction & Dimension Reduction steps, we calculated the values of these clustering quality metrics on the feature vectors obtained. Clustering quality values are calculated for various time-bin data and for various numbers of principal components (By the number principal components we refer to the dimension of feature vectors after the N-bin Data Generation and Feature Extraction & Dimension Reduction steps.). Values calculated according to the metric in (2.3) are presented in Chapter 4.

3.6.2 Classification Performance Evaluation

By feeding our test TRP vectors to the target recognition system shown in Figure 3.1 and which is trained with our training TRP vectors, we obtained class-to-class confusion matrices. To express the classification performance as a single value, KHAT classification performance metric is used, which is described in section 2.6. Class-to-class confusion matrices are input to the KHAT function and KHAT function returns a single value that represents the classification performance. A higher value represents a better classification. Maximum value of KHAT is 1 which means that there are no misclassifications. KHAT values and Recognition Rates for different number of time bins and number of principal components are presented in Chapter 4.

CHAPTER 4

EXPERIMENTAL RESULTS

In this chapter clustering quality results and classification performance results which were explained in Chapter 3 are presented.

4.1 Clustering Quality Results

To see the effects of using repetitions in the TRP vectors before performing all of the target recognition system steps, we applied PCA feature extraction method to 1, 5 and 10 time-bin data for target training and test data sets. When applying PCA to training and test data sets, the coefficients calculated for the training data set are used. After applying PCA, we presented the 2-D plots of the first two principal components having the largest eigen values through Figure 4.1 to Figure 4.6.

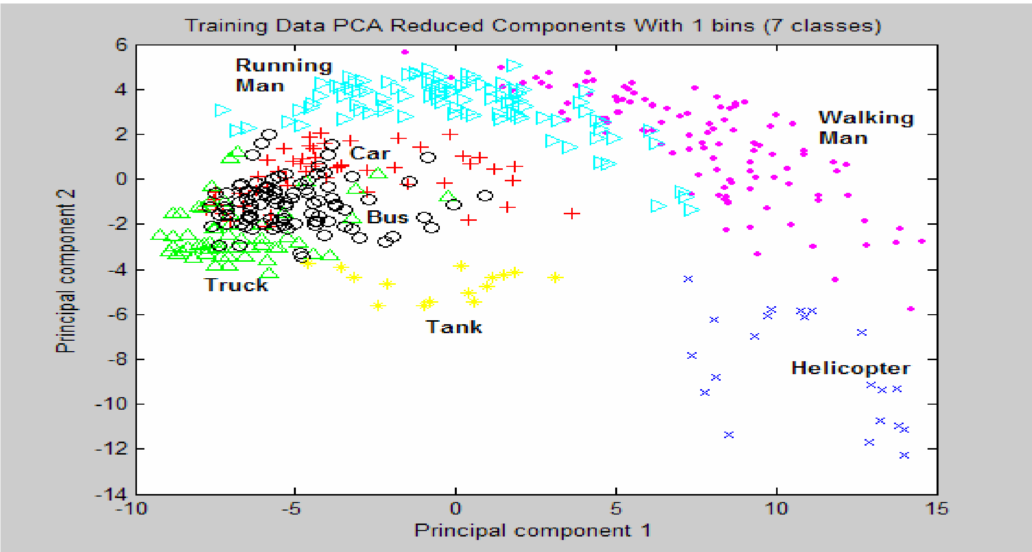

Figure 4.1 Target clusters of train data set for 1 bin data with PCA reduced components.

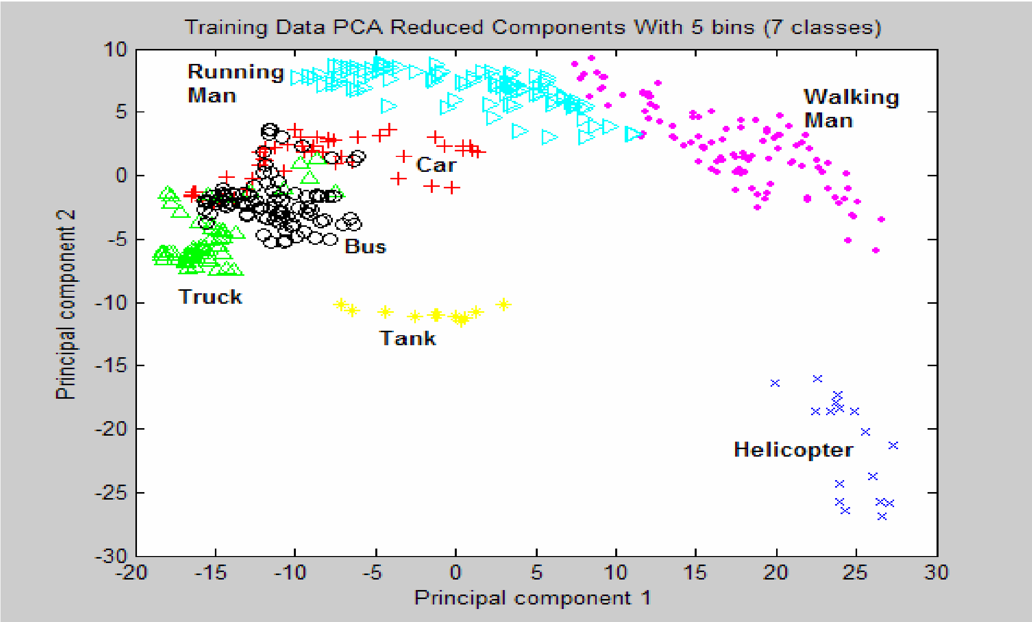

Figure 4.2 Target clusters of train data set for 5 bin data with PCA reduced components.

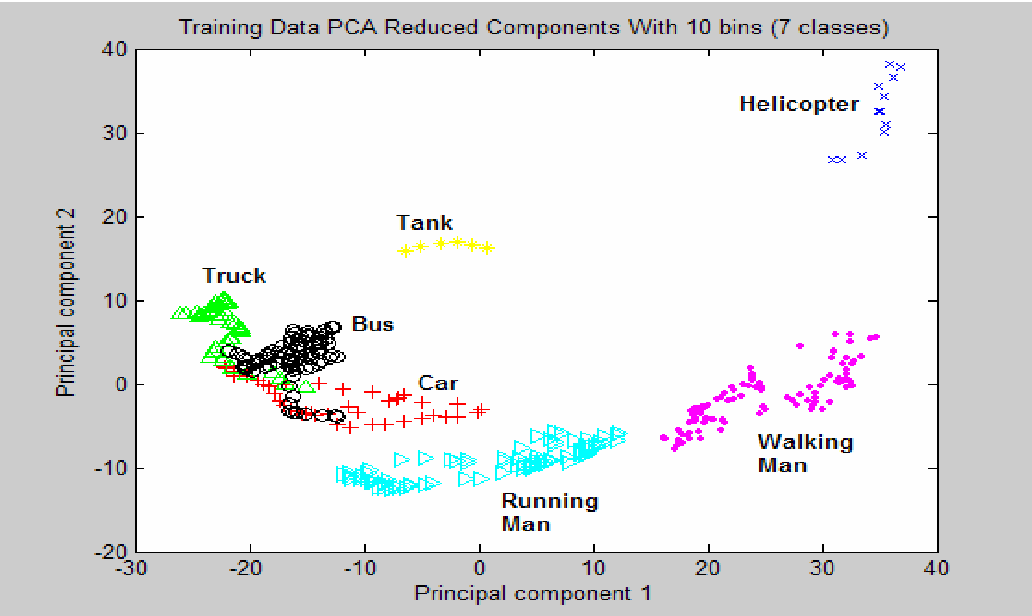

Figure 4.3 Target clusters of train data set for 10 bin data with PCA reduced components.

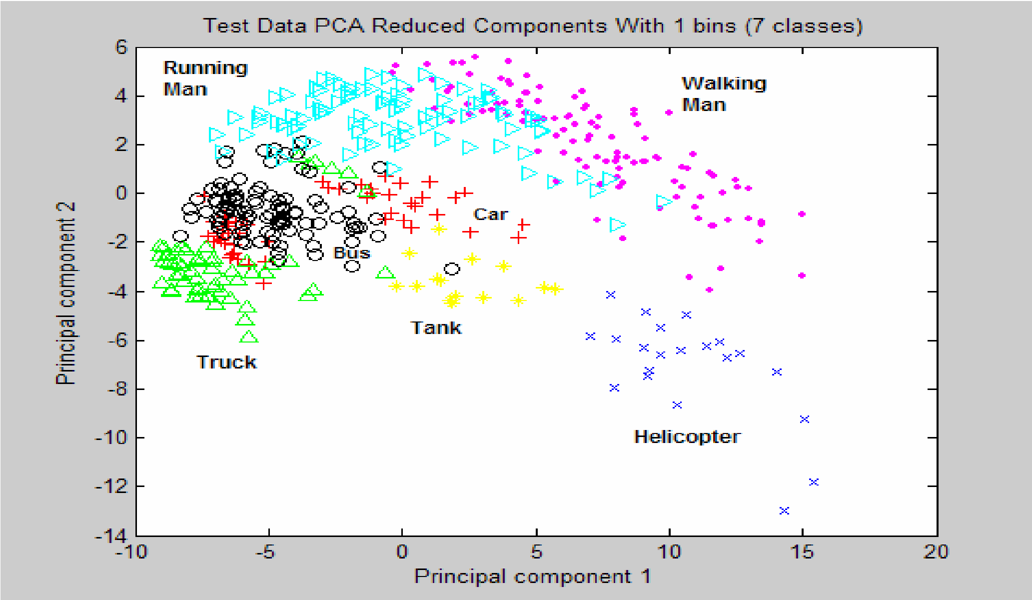

Figure 4.4 Target clusters of test data set for 1 bin data with PCA reduced components.

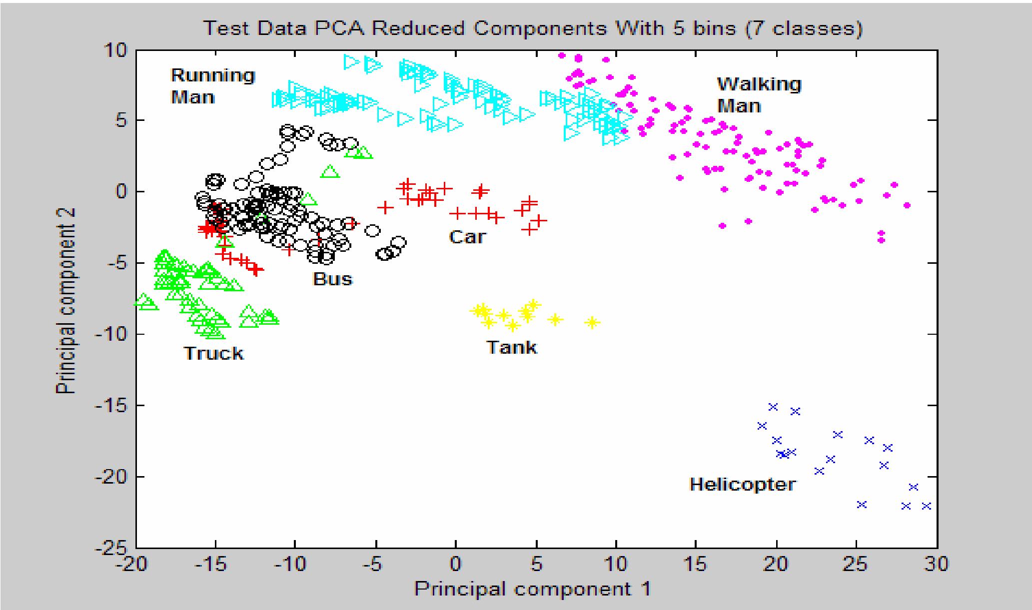

Figure 4.5 Target clusters of test data set for 5 bin data with PCA reduced components

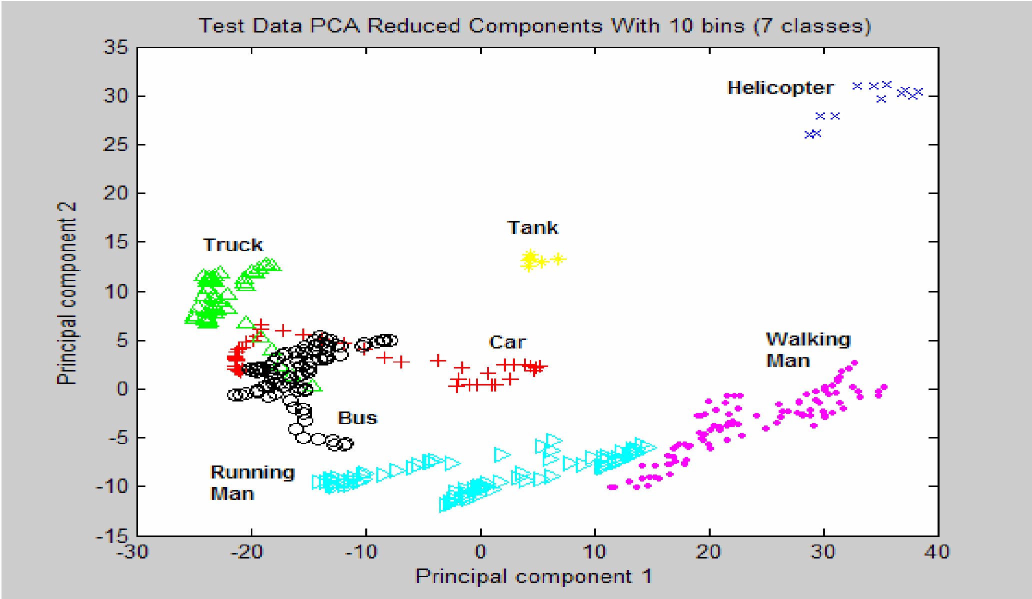

Figure 4.6 Target clusters of test data set for 10 bin data with PCA reduced components.

As we can see from Figure 4.1, Figure 4.2 and Figure 4.3 target classes are separated from each other and class members of the same class become closer to each other while they are separated from other classes as the number of bins used increases. Walking Man and Running Man classes become separated from CAR, TRUCK and BUS classes. Number of overlapping samples between Walking Man and Running Man classes is reduced as the number of bins is increased. There are no overlapping samples between Running Man and Vehicle classes for multiple numbers of bins. For 10 bin data there are no overlapping samples between classes except between vehicle classes. These results are obtained using only 2 prinpical componets. A better separation can be obtained with a higher number of principal components, however it is not easy to show the separation visually with more than 2 principal components. In order to observe the seperation in other dimensions, clusterings of PCA applied 1 time-bin training data are presented in Figure 4.7 and Figure 4.8 . These figures present the clusterings with respect to first-third and second-third principal components.

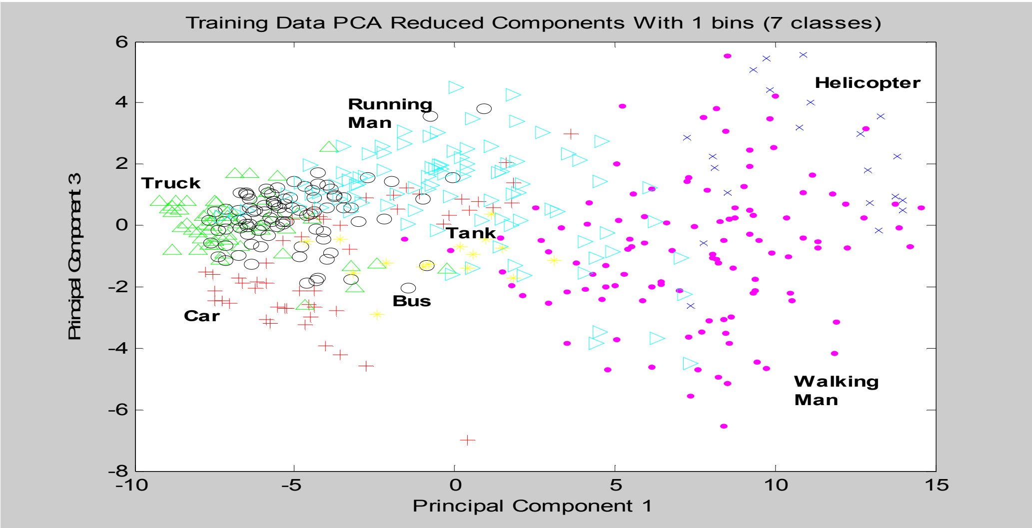

Figure 4.7 Target clusters of PCA applied training data set for 1 bin data with respect to first and third principal components

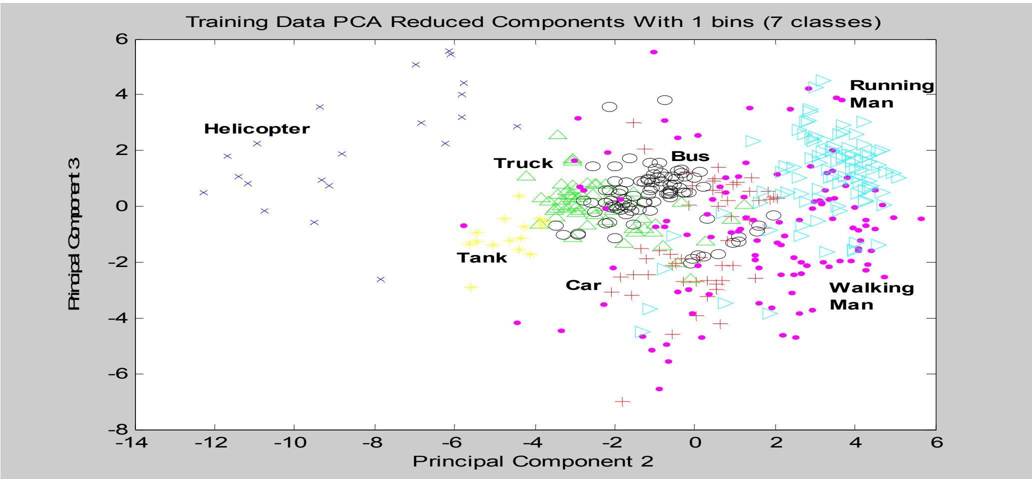

Figure 4.8 Target clusters of PCA applied training data set for 1 bin data with respect to second and third principal components

In Figure 4.9 and Figure 4.10 target clusters of PCA applied 10 time-bin data are presented. These figures present the clusterings with respect to first-second and second-third principal components.

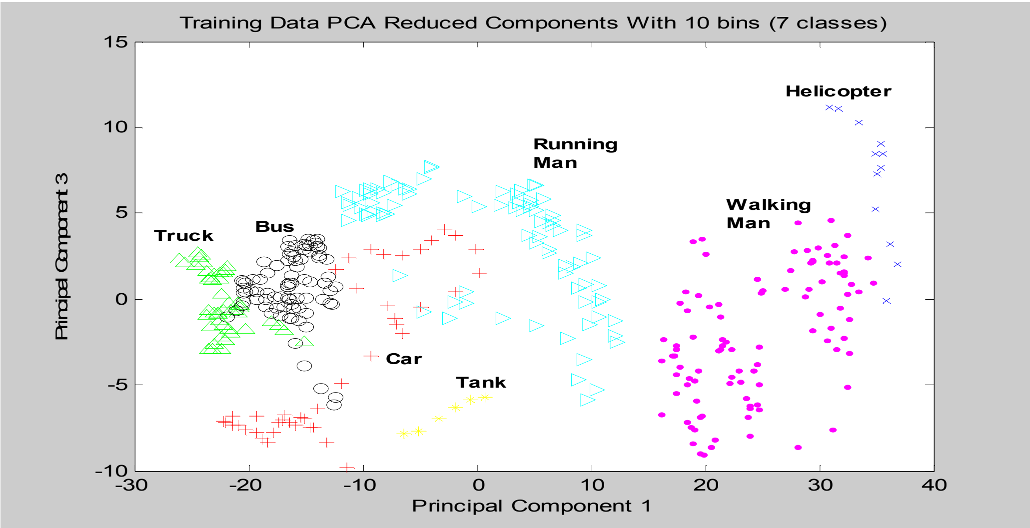

Figure 4.9 Target clusters of PCA applied training data set for 10 bin data with respect to first and third principal components

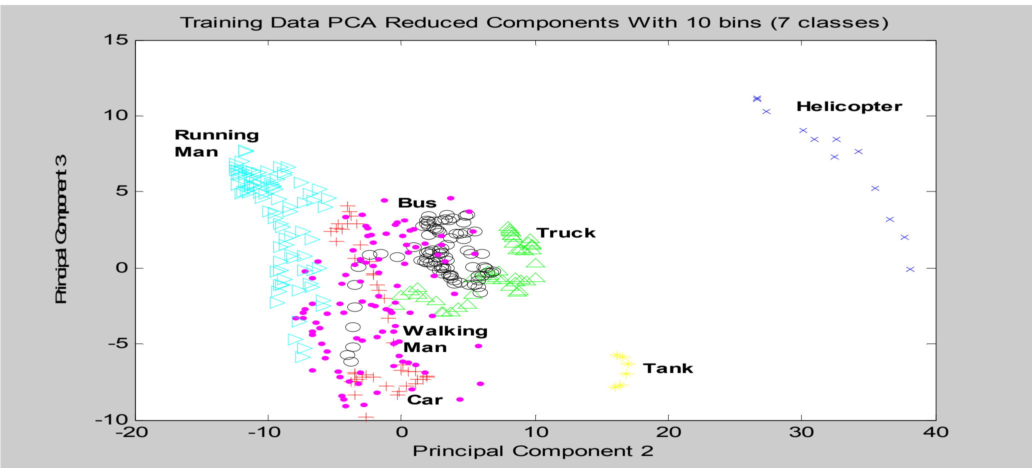

Figure 4.10 Target clusters of PCA applied training data set for 10 bin data with respect to second and third principal components

By the 2-D plots of 2 extracted features of PCA applied training and test data, we observed that using repetitions in time provides better clustering. However it must be expressed mathematically. To express it mathematically, after generating N time-bin data, we applied PCA, LDA, ICA and NMF transformations to test and training data for various numbers of time-bins. After feeding the extracted and reduced features to the clustering quality metric in (2.3) for various number of principal components, we obtained clustering quality results. Clustering quality values are calculated for various time-bin data and for various numbers of principal components. These results are presented through Table 4.1 to Table 4.8.

Table 4.1 Clustering quality values of training samples for 2 principal components (For different number of time bins)

Clustering quality for training data		Feature Extraction Method			
		PCA	**LDA**	**ICA**	**NMF**
Number Of Time Bins	**1**	0,24	0,14	0,15	24,45
	2	0,19	0,09	0,14	13,23
	3	0,15	0,06	0,11	20,58
	4	0,13	0,05	0,09	24,11
	5	0,12	0,04	0,08	15,22
	6	0,11	0,04	0,08	21,17
	7	0,10	0,03	0,07	24,69
	8	0,09	0,03	0,07	22,26
	9	0,09	0,03	0,06	16,51
	10	0,09	0,02	0,06	8,34

Table 4.2 Clustering quality values of test samples for 2 principal components

Clustering quality for test data		Feature Extraction Method			
		PCA	**LDA**	**ICA**	**NMF**
Number Of Time Bins	**1**	0,31	0,19	0,20	21,51
	2	0,25	0,11	0,18	15,54
	3	0,22	0,09	0,15	17,31
	4	0,19	0,07	0,13	27,12
	5	0,17	0,06	0,12	15,32
	6	0,16	0,05	0,11	27,15
	7	0,15	0,04	0,11	20,49
	8	0,14	0,04	0,11	19,99
	9	0,14	0,04	0,10	16,56
	10	0,14	0,03	0,10	8,72

Table 4.3 Clustering quality values of training samples for 3 principal components

Clustering quality for training data		Feature Extraction Method			
		PCA	**LDA**	**ICA**	**NMF**
Number Of Time Bins	**1**	0,30	0,14	0,16	16,64
	2	0,23	0,11	0,13	11,89
	3	0,19	0,09	0,11	12,15
	4	0,17	0,07	0,09	22,43
	5	0,16	0,06	0,08	17,81
	6	0,15	0,05	0,08	11,34
	7	0,14	0,04	0,07	17,88
	8	0,12	0,04	0,07	13,16
	9	0,12	0,04	0,06	12,82
	10	0,11	0,03	0,06	9,89

Table 4.4 Clustering quality values of test samples for 3 principal components

Clustering quality for test data		Feature Extraction Method			
		PCA	**LDA**	**ICA**	**NMF**
Number Of Time Bins	**1**	0,35	0,22	0,21	13,18
	2	0,28	0,16	0,18	11,09
	3	0,24	0,12	0,15	11,27
	4	0,22	0,10	0,14	17,20
	5	0,21	0,08	0,12	17,40
	6	0,20	0,07	0,12	10,08
	7	0,18	0,06	0,11	18,69
	8	0,17	0,06	0,11	11,32
	9	0,16	0,05	0,10	12,10
	10	0,15	0,05	0,10	10,33

Table 4.5 Clustering quality values of training samples for 4 principal components

Clustering quality for training data		Feature Extraction Method			
		PCA	**LDA**	**ICA**	**NMF**
Number Of Time Bins	**1**	0,35	0,17	0,16	18,80
	2	0,28	0,15	0,13	19,69
	3	0,24	0,11	0,11	13,10
	4	0,22	0,09	0,09	18,12
	5	0,20	0,08	0,08	13,49
	6	0,18	0,07	0,07	15,16
	7	0,17	0,06	0,07	10,95
	8	0,16	0,05	0,07	15,65
	9	0,15	0,05	0,06	11,14
	10	0,14	0,04	0,06	9,68

Table 4.6 Clustering quality values of test samples for 4 principal components

Clustering quality for test data		Feature Extraction Method			
		PCA	**LDA**	**ICA**	**NMF**
Number Of Time Bins	**1**	0,39	0,27	0,21	13,48
	2	0,33	0,21	0,18	21,17
	3	0,29	0,15	0,15	11,51
	4	0,27	0,12	0,13	15,01
	5	0,25	0,10	0,13	12,14
	6	0,23	0,08	0,11	12,01
	7	0,22	0,07	0,11	10,73
	8	0,21	0,07	0,11	16,48
	9	0,20	0,06	0,10	12,16
	10	0,19	0,06	0,10	9,77

Table 4.7 Clustering quality values of training samples for 5 principal components

Clustering quality for training data		Feature Extraction Method			
		PCA	**LDA**	**ICA**	**NMF**
Number Of Time Bins	**1**	0,37	0,21	0,16	12,74
	2	0,31	0,17	0,13	13,90
	3	0,26	0,13	0,10	16,40
	4	0,24	0,11	0,09	12,71
	5	0,23	0,09	0,08	11,03
	6	0,22	0,08	0,07	13,45
	7	0,20	0,07	0,07	9,91
	8	0,19	0,06	0,07	11,81
	9	0,19	0,06	0,06	12,07
	10	0,18	0,05	0,06	11,85

Table 4.8 Clustering quality values of test samples for 5 principal components

Clustering quality for test data		Feature Extraction Method			
		PCA	**LDA**	**ICA**	**NMF**
Number Of Time Bins	**1**	0,41	0,31	0,21	12,56
	2	0,35	0,24	0,18	13,92
	3	0,31	0,18	0,15	13,86
	4	0,30	0,14	0,13	12,22
	5	0,28	0,12	0,12	10,71
	6	0,27	0,10	0,11	11,96
	7	0,26	0,09	0,11	10,49
	8	0,25	0,08	0,10	12,00
	9	0,24	0,07	0,10	13,11
	10	0,23	0,07	0,10	11,53

Due to the clustering quality description in (2.3), a smaller value represents a better clustering quality. As we can see from Table 4.1 to Table 4.8, increasing the number of time-bins provides a better clustering quality for all feature extraction methods. Among the feature extraction algorithms applied, LDA provides the best clustering quality and NMF provides the worst clustering quality. As an example, for Training Data of 10 time-bins which is reduced to 5 principal components with feature extraction, we get 11.53, 0.18, 0.06 and 0.05 clustering quality values for NMF, PCA, ICA and LDA respectively. However, this does not mean that in our target recognition system best classification results will be obtained when LDA is used at the feature extraction stage. These results just mean that best geometrical separation is obtained with LDA and worst geometrical separation is obtained by NMF. For NMF clustering quality can be increased by increasing the number of principal components.

Increasing the number of principal components does not change the clustering quality values of ICA. Intuitively, ICA can be regarded as the best method in extracting the most significant and meaningful part of the data with minimum number of principal components. For other methods the clustering quality value depends on the number of principal components taken. The dependence of the clustering quality on the number of principal components can be regarded as a disadvantage.

4.2 Classification Performance Results

In this section, classification performance results of target recognition system in Figure 3.1 are given. Our classification performance metric KHAT is explained in section 2.6. KHAT is a derivation that takes misclassifications into consideration. We also give the Average Recognition Rate results as a performance metric, which is the average of the correct classification rates for each class. The KHAT and Average Recognition Rate results are given in Table 4.9 through table 4.25. Regarding the four feature extraction methods (PCA, LDA, ICA and NMF) and two classification methods (SVM, KNN) used, there are 8 configurations of our target recognition system. By configuration, we refer the feature extraction method and classification method used. These configurations are PCA+KNN, PCA+SVM, LDA+KNN, LDA+SVM, ICA+KNN, ICA+SVM, NMF+KNN, NMF+SVM. For example PCA+KNN means that we use PCA at feature extraction stage of our target recognition system and KNN at the classifier stage of our target recognition system. The configurations used are given at the upper left hand corner of the tables. Also for each type of configuration, minimum, maximum and average value of the table are given below the table.

Since W and H matrices in (2.18) and (2.19) are intialized to random values and updated with equations (2.18) and (2.19), NMF can give different classification performances for different experiments with the same sample training and test data set. In order to obtain reliable classification results with NMF, average of classification performances of 10 experiments with different random initial values are obtained for the configurations in which NMF is used in the feature extraction step.

Table 4.9 Khat values for confusion matrices of PCA and KNN applied on test data for different number of time-bins and different number of principal components.

Khat Results PCA + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,69	0,81	0,86	0,84	0,84	0,86	0,87	0,88	0,88	0,88	0,88	0,89	0,89	0,88
	2	0,75	0,86	0,86	0,85	0,86	0,86	0,88	0,88	0,88	0,88	0,90	0,90	0,90	0,90
	3	0,78	0,90	0,87	0,87	0,88	0,88	0,88	0,89	0,89	0,90	0,89	0,90	0,90	0,90
	4	0,80	0,87	0,90	0,89	0,88	0,89	0,89	0,90	0,91	0,91	0,91	0,91	0,91	0,91
	5	0,82	0,88	0,91	0,89	0,88	0,88	0,88	0,91	0,91	0,91	0,91	**0,92**	**0,92**	**0,92**
	6	0,82	0,88	**0,92**	0,89	0,89	0,89	0,91	0,90	0,91	0,91	0,91	0,91	**0,92**	**0,92**
	7	0,81	0,87	**0,92**	0,90	0,90	0,90	**0,92**	0,91	0,91	0,91	0,91	**0,92**	**0,92**	**0,92**
	8	0,82	0,89	0,89	**0,92**	0,91	0,90	0,91	0,91	0,91	0,91	**0,92**	**0,92**	**0,92**	**0,92**
	9	0,79	0,88	0,88	**0,92**	**0,92**	0,91	**0,92**	0,91	**0,92**	0,91	0,91	**0,92**	**0,92**	**0,92**
	10	0,81	0,87	0,89	0,91	0,91	0,90	0,90	0,90	0,91	0,91	0,91	**0,92**	0,91	0,91

Best Khat Value = 0.92, Worst Khat Value = 0.69, Average Khat Value = 0.89

Table 4.10 Average recognition rates of PCA and KNN applied on test data for different number of time-bins and different number of principal components

Average Recognition Rates PCA + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,75	0,85	0,89	0,87	0,87	0,89	0,89	0,90	0,90	0,90	0,90	0,91	0,91	0,90
	2	0,79	0,89	0,88	0,88	0,89	0,89	0,90	0,91	0,90	0,90	0,91	0,91	0,91	0,91
	3	0,82	0,92	0,89	0,89	0,90	0,91	0,91	0,91	0,91	0,92	0,91	0,92	0,92	0,92
	4	0,84	0,90	0,92	0,91	0,90	0,91	0,91	0,92	0,92	0,93	0,93	0,93	0,93	0,93
	5	0,86	0,90	0,93	0,91	0,90	0,91	0,91	0,93	0,93	0,93	0,93	0,93	0,93	0,93
	6	0,86	0,90	0,93	0,91	0,91	0,91	0,92	0,92	0,93	0,93	0,93	0,93	**0,94**	**0,94**
	7	0,84	0,90	**0,94**	0,92	0,92	0,92	0,93	0,93	0,93	0,93	0,93	**0,94**	**0,94**	**0,94**
	8	0,85	0,91	0,91	0,93	0,93	0,92	0,93	0,93	0,93	0,93	**0,94**	**0,94**	**0,94**	**0,94**
	9	0,83	0,90	0,90	0,93	0,93	0,93	0,93	0,93	0,93	0,93	0,93	0,93	**0,94**	**0,94**
	10	0,85	0,90	0,91	0,93	0,93	0,92	0,92	0,92	0,93	0,93	0,93	0,93	0,93	0,93

Best Recognition Rate = 0.94, Worst Recognition Rate= 0.75, Average Recognition Rate = 0.91

Table 4.11 Khat values for confusion matrices of PCA and SVM applied on test data

Khat Results PCA + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,62	0,73	0,78	0,83	0,82	0,85	**0,87**	**0,87**	**0,87**	**0,87**	**0,87**	0,86	0,86	0,86
	2	0,64	0,81	0,82	0,83	0,81	0,82	0,80	0,79	0,79	0,79	0,79	0,79	0,76	0,76
	3	0,63	0,81	0,86	0,85	0,82	0,80	0,78	0,75	0,72	0,70	0,71	0,71	0,69	0,67
	4	0,68	0,79	**0,87**	0,82	0,80	0,75	0,71	0,66	0,66	0,64	0,63	0,62	0,61	0,61
	5	0,61	0,77	0,84	0,78	0,75	0,70	0,67	0,63	0,62	0,59	0,58	0,56	0,55	0,54
	6	0,61	0,71	0,81	0,75	0,72	0,68	0,65	0,60	0,57	0,55	0,54	0,53	0,51	0,50
	7	0,61	0,74	0,80	0,70	0,68	0,63	0,61	0,56	0,54	0,53	0,50	0,47	0,45	0,44
	8	0,66	0,75	0,74	0,68	0,63	0,61	0,56	0,54	0,48	0,45	0,43	0,42	0,41	0,38
	9	0,63	0,76	0,69	0,68	0,61	0,57	0,51	0,47	0,41	0,41	0,39	0,37	0,35	0,34
	10	0,53	0,77	0,70	0,66	0,58	0,53	0,46	0,38	0,35	0,34	0,33	0,31	0,31	0,29

Best Khat Value = 0.87, Worst Khat Value = 0.29, Average Khat Value = 0.65

Table 4.12 Average recognition rates of PCA and SVM applied on test data

Average Recognition Rates		Number Of Principal Components													
PCA + SVM		**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
	1	0,69	0,78	0,82	0,86	0,86	0,88	0,89	**0,90**	**0,90**	0,89	0,89	0,89	0,89	0,88
	2	0,71	0,84	0,85	0,87	0,85	0,85	0,84	0,83	0,83	0,83	0,83	0,83	0,81	0,81
	3	0,70	0,84	0,89	0,88	0,86	0,84	0,82	0,80	0,78	0,77	0,77	0,77	0,76	0,74
	4	0,74	0,83	**0,90**	0,86	0,84	0,81	0,78	0,74	0,73	0,72	0,71	0,70	0,70	0,70
Number	**5**	0,68	0,82	0,87	0,83	0,80	0,77	0,75	0,71	0,70	0,69	0,67	0,66	0,65	0,64
Of	**6**	0,69	0,77	0,85	0,80	0,78	0,75	0,73	0,69	0,67	0,66	0,64	0,64	0,62	0,62
Time	**7**	0,69	0,80	0,84	0,77	0,75	0,71	0,70	0,66	0,65	0,64	0,62	0,60	0,58	0,57
Bins	**8**	0,73	0,80	0,79	0,76	0,72	0,70	0,66	0,64	0,61	0,58	0,56	0,56	0,55	0,53
	9	0,70	0,81	0,76	0,75	0,70	0,67	0,63	0,59	0,55	0,55	0,54	0,52	0,51	0,50
	10	0,62	0,82	0,77	0,74	0,68	0,64	0,59	0,53	0,51	0,50	0,50	0,49	0,48	0,47

Best Recognition Rate = 0.90, Worst Recognition Rate= 0.47, Average Recognition Rate = 0.73

As we can see from Table 4.9, classification khat results for PCA+KNN don't increase much by increasing the number of principal components or number the number of time-bins when the number of principal components is bigger than 4. For a constant number of principal components, increasing the number of time-bins generally increases classification performance. The difference between classification performances of small number of time bins and large number of time bins for small number of principal components is higher than the difference for large number of principal components. Also for PCA+KNN there is saturation in the classification performance after the number of time-bins 3. Increasing the number of time-bins for PCA+KNN does not increase the classification performance so much. This can be due to the lack of enough number of pricipal components for high number of time-bins. To understand this for PCA+KNN the number of principal components is chosen proportional to the number of time bins. The number of principal components is chosen as %10 of the original sample size for each time bin data. The classification performance results of this trial are shown in Table 4.13.

As we can see from Table 4.11, PCA+SVM classification performance is lower than PCA+KNN performance when the number of time-bins is 1. Also increasing the number of time bins and increasing the number of principal components decreases classification performance. We can conclude that using PCA+SVM is not suitable for our target classification system.

Table 4.13 Khat values for PCA and KNN applied test data
(Number of Principal Components is % 10 of the original sample size)

Number Of Time Bins	Classification Performance
1	0,84
2	0,90
3	0,92
4	0,93
5	0,93
6	0,93
7	0,93
8	0,92
9	0,92
10	0,91

We see that, to utilize the repetitions in the data for PCA, the number of principal components must be chosen proportional to the number of time-bins. Also after a point, increasing the number of time-bins so much can degrade the system performance. A time-bin number of 5 or is 6 is adequate to improve the classification performance.

As we can see from Table 4.11, when the number of principal components is high, increasing the number of time-bins causes a tremendous decrease in the classification performance. For example when the number of principal components is 15, khat value for 1 time-bin is % 86, while khat value for 5 time-bin is % 54. Without considering the within class and between class information, PCA finds the directions where all data shows the maximum variance, so we can not guarantee that good classification results will be obtained by SVM. Regarding the bad classfication performance with PCA+SVM, we can conclude that PCA transforms the data to a space which is improper for SVM. To prove that PCA transforms the data to a space which is improper for SVM, we omitted the feature extraction step and fed the 5 time-bin TRP vectors to the SVM classifier. With PCA+SVM we obtained %54 classification performance whereas with only SVM we obtained %90 classification performance.

Table 4.14 Khat values of LDA and KNN applied on test data

Khat Results		Number Of Principal Components													
LDA + KNN		**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,53	0,71	0,79	0,78	0,80	0,79	0,79	0,80	0,79	0,78	0,79	0,80	0,81	0,81
	2	0,67	0,73	0,79	0,76	0,83	0,84	0,84	0,85	0,86	0,85	0,85	0,85	0,85	0,85
	3	0,76	0,77	0,80	0,76	0,83	0,84	0,84	0,85	0,85	0,85	0,84	0,84	0,84	0,85
	4	0,67	0,75	0,76	0,82	0,87	0,87	0,87	0,87	0,86	0,86	0,86	0,87	0,87	0,86
	5	0,60	0,70	0,79	0,82	0,89	0,89	0,89	0,90	0,90	0,90	0,90	0,90	0,91	0,90
	6	0,67	0,74	0,84	0,86	0,92	0,91	0,91	0,91	0,91	0,91	0,92	0,92	0,92	0,92
	7	0,63	0,77	0,82	0,87	0,93	0,92	0,92	0,93	0,93	0,93	0,93	0,93	0,93	0,93
	8	0,76	0,82	0,85	0,91	0,92	0,92	0,92	0,92	0,92	0,92	0,92	0,92	0,92	0,92
	9	0,78	0,84	0,87	0,92	0,93	0,93	0,92	0,93	0,93	0,93	0,92	0,93	0,92	0,92
	10	0,81	0,87	0,89	0,93	0,93	0,93	0,93	0,93	0,93	0,93	0,93	0,93	**0,94**	0,93

Best Khat Value = 0.94, Worst Khat Value = 0.53, Average Khat Value = 0.86

Table 4.15 Average recognition rates of LDA and KNN applied on test data

Average Recognition Rates LDA + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,61	0,77	0,83	0,82	0,84	0,83	0,83	0,83	0,83	0,82	0,83	0,84	0,85	0,85
	2	0,73	0,78	0,83	0,81	0,86	0,87	0,87	0,88	0,89	0,88	0,88	0,88	0,88	0,88
	3	0,81	0,82	0,84	0,80	0,86	0,87	0,87	0,88	0,88	0,88	0,87	0,87	0,87	0,88
	4	0,73	0,80	0,81	0,85	0,89	0,90	0,90	0,89	0,89	0,89	0,89	0,90	0,90	0,89
	5	0,68	0,76	0,83	0,86	0,91	0,91	0,91	0,92	0,92	0,92	0,92	0,92	0,93	0,92
	6	0,74	0,79	0,87	0,88	0,93	0,93	0,93	0,93	0,93	0,93	0,93	0,94	0,94	0,94
	7	0,70	0,81	0,85	0,90	0,94	0,94	0,94	0,94	0,94	0,94	0,94	0,94	0,94	0,94
	8	0,81	0,86	0,88	0,93	0,94	0,94	0,94	0,93	0,94	0,94	0,94	0,94	0,94	0,94
	9	0,83	0,87	0,90	0,94	0,94	0,94	0,94	0,94	0,94	0,94	0,94	0,94	0,94	0,94
	10	0,84	0,89	0,91	0,94	0,94	0,94	0,94	0,94	**0,95**	0,94	**0,95**	**0,95**	**0,95**	**0,95**

Best Recognition Rate = 0.95, Worst Recognition Rate= 0.61, Average Recognition Rate = 0.88

Table 4.16 Khat values of LDA and SVM applied on test data

Khat Results LDA + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,52	0,57	0,61	0,61	0,71	0,68	0,65	0,65	0,69	0,67	0,70	0,72	0,76	0,75
	2	0,68	0,66	0,71	0,67	0,78	0,77	0,80	0,76	0,81	0,81	0,82	0,82	0,83	0,83
	3	0,74	0,70	0,75	0,73	0,73	0,75	0,83	0,85	0,82	0,83	0,83	0,88	0,86	0,88
	4	0,63	0,71	0,60	0,83	0,80	0,81	0,81	0,85	0,87	0,83	0,82	0,86	0,87	0,88
	5	0,62	0,67	0,75	0,87	0,92	0,89	0,87	0,87	0,89	0,89	0,92	0,91	0,92	0,92
	6	0,65	0,62	0,76	0,89	0,89	0,91	0,90	0,91	0,90	0,91	0,91	0,93	0,92	0,93
	7	0,61	0,79	0,75	0,96	0,95	0,96	0,96	0,93	0,93	0,94	0,95	0,96	0,96	0,96
	8	0,72	0,73	0,78	0,93	0,99	0,95	0,95	0,94	0,94	0,96	0,97	0,97	0,96	0,96
	9	0,69	0,78	0,69	0,93	0,93	0,94	0,95	0,97	0,97	0,96	**0,98**	**0,98**	**0,98**	**0,98**
	10	0,71	0,78	0,87	0,96	0,96	0,93	0,95	0,94	0,96	0,96	0,96	0,96	0,96	0,96

Best Khat Value = 0.98, Worst Khat Value = 0.52, Average Khat Value = 0.84

Table 4.17 Average recognition rates of LDA and SVM applied on test data

Average Recognition Rates LDA + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,61	0,64	0,68	0,69	0,76	0,74	0,71	0,72	0,75	0,74	0,76	0,77	0,81	0,80
	2	0,74	0,72	0,76	0,74	0,83	0,81	0,84	0,81	0,84	0,84	0,86	0,86	0,86	0,86
	3	0,79	0,76	0,80	0,78	0,78	0,80	0,86	0,88	0,86	0,86	0,86	0,90	0,89	0,90
	4	0,70	0,77	0,68	0,86	0,83	0,85	0,85	0,88	0,90	0,86	0,86	0,89	0,90	0,90
	5	0,70	0,73	0,80	0,90	0,93	0,91	0,89	0,89	0,91	0,92	0,93	0,93	0,94	0,93
	6	0,71	0,69	0,81	0,91	0,91	0,93	0,92	0,93	0,92	0,93	0,93	0,94	0,94	0,94
	7	0,69	0,83	0,80	0,97	0,96	0,97	0,97	0,94	0,95	0,95	0,96	0,97	0,97	0,96
	8	0,77	0,78	0,83	0,95	0,99	0,96	0,96	0,95	0,95	0,97	0,97	0,97	0,97	0,97
	9	0,75	0,82	0,75	0,94	0,94	0,95	0,96	0,97	0,97	0,97	**0,98**	**0,98**	**0,98**	**0,98**
	10	0,77	0,82	0,90	0,97	0,97	0,95	0,96	0,96	0,97	0,97	0,97	0,97	0,97	0,97

Best Recognition Rate = 0.98, Worst Recognition Rate= 0.61, Average Recognition Rate = 0.87

As we can see from Table 4.14, increasing the number of time bins for LDA + KNN causes a tremendous change in the classsification performance. When the number of principal components is 2, the classification performance is % 53 for 1 time-bin data and classification performance is % 81 for 10 time-bin data. When the number of principal components is 15, classification performance is %81 for 1 time-bin data and classification performance is %93 for 10 time-bin data. Even a classification performance improvement of %12 is obtained for large number of principal components by increasing the number of time bins.

As we can see from Table 4.16, increasing the number of time-bins for LDA+SVM also causes a tremendous change in the classification performance. When the number of principal components is 2, the classification performances for 1 time-bin data and for 10 time-bin data are %52 and %71. When the number of principal components is 15, the classifications performances for 1 time-bin data and 10 time-bin data are %75 and %96 respectively. The maximum classification performance obtained with LDA+SVM is %98 which outperforms PCA+KNN. PCA+KNN classification performance is better for small number of principal components and small number of time bins than LDA+SVM, however LDA+SVM classification performance is much better than PCA+KNN for large number of principal components and large number of time bins.

Table 4.18 Khat values of ICA and KNN applied on test data

Khat Results		Number Of Principal Components													
ICA + KNN		**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,73	0,74	0,76	0,76	0,78	0,78	0,78	0,79	0,78	0,78	0,78	0,78	0,78	0,78
	2	0,79	0,80	0,80	0,81	0,82	0,80	0,80	0,79	0,80	0,80	0,80	0,80	0,80	0,80
	3	0,79	0,80	0,80	0,81	0,82	0,82	0,82	0,82	0,81	0,81	0,81	0,82	0,81	0,82
	4	0,81	0,81	0,80	0,81	0,81	0,81	0,81	0,81	0,81	0,81	0,81	0,81	0,81	0,81
	5	0,82	0,82	0,83	0,83	0,83	0,83	0,82	0,83	0,82	0,81	0,81	0,81	0,81	0,81
	6	0,81	0,82	0,81	0,81	0,83	0,82	0,81	0,82	0,81	0,81	0,81	0,82	0,82	0,82
	7	**0,84**	**0,84**	0,83	0,83	0,83	**0,84**	**0,84**	**0,84**	**0,84**	0,83	**0,84**	**0,84**	**0,84**	**0,84**
	8	**0,84**	**0,84**	0,83	0,82	0,82	0,82	0,81	0,81	0,81	0,81	0,82	0,81	0,82	0,82
	9	0,83	0,83	0,82	0,83	0,83	0,83	**0,84**	0,83	0,83	0,83	0,83	**0,84**	0,83	0,83
	10	0,83	0,82	0,82	0,81	0,82	0,82	0,81	0,81	0,82	0,82	0,82	0,82	0,81	0,82

Best Khat Value = 0.84, Worst Khat Value = 0.73, Average Khat Value = 0.81

Table 4.19 Average recognition rates of ICA and KNN applied on test data

Average Recognition Rates		Number Of Principal Components													
ICA + KNN		**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
	1	0,78	0,79	0,80	0,80	0,82	0,82	0,82	0,83	0,82	0,82	0,82	0,82	0,82	0,82
	2	0,83	0,84	0,84	0,85	0,85	0,84	0,84	0,83	0,83	0,84	0,84	0,84	0,84	0,84
	3	0,83	0,84	0,84	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,85
	4	0,84	0,85	0,84	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,85
Number	**5**	0,86	0,85	0,86	**0,87**	**0,87**	0,86	0,86	0,86	0,86	0,85	0,85	0,85	0,85	0,85
Of	**6**	0,85	0,85	0,85	0,85	0,86	0,86	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,85
Time	**7**	**0,87**	**0,87**	0,86	0,86	**0,87**	**0,87**	**0,87**	**0,87**	**0,87**	0,86	**0,87**	**0,87**	**0,87**	**0,87**
Bins	**8**	**0,87**	**0,87**	0,86	0,86	0,85	0,86	0,85	0,85	0,85	0,85	0,86	0,85	0,85	0,86
	9	**0,87**	0,86	0,86	0,86	0,86	0,86	**0,87**	**0,87**	**0,87**	**0,87**	**0,87**	**0,87**	**0,87**	**0,87**
	10	0,86	0,86	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,85	0,86	0,85	0,85	0,86

Best Recognition Rate = 0.87, Worst Recognition Rate= 0.78, Average Recognition Rate = 0.85

Table 4.20 Khat values of ICA and SVM applied on test data

Khat Results ICA + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,79	0,79	0,82	0,82	0,84	0,85	0,85	0,83	0,83	0,83	0,82	0,83	0,83	0,84
	2	0,79	0,81	0,81	0,85	0,85	0,87	0,87	0,88	0,88	0,87	0,87	0,87	0,86	0,86
	3	0,82	0,81	0,81	0,85	0,86	0,87	0,88	0,89	0,88	0,88	0,88	0,89	0,89	0,89
	4	0,84	0,84	0,83	0,87	0,88	0,89	0,90	0,90	0,89	0,88	0,89	0,89	0,88	0,88
	5	0,84	0,85	0,86	0,88	0,87	0,87	0,88	0,88	0,88	0,87	0,87	0,88	0,86	0,88
	6	0,82	0,82	0,83	0,83	0,84	0,84	0,84	0,87	0,87	0,88	0,89	0,89	0,89	0,88
	7	0,82	0,80	0,81	0,85	0,92	0,91	0,90	0,89	0,86	0,87	0,90	0,89	0,90	0,90
	8	0,81	0,82	0,82	0,82	0,86	0,89	0,89	0,88	0,91	0,90	0,92	0,93	0,92	0,93
	9	0,83	0,82	0,82	0,80	0,81	0,86	0,85	0,89	0,88	0,91	0,92	0,93	0,92	0,94
	10	0,83	0,82	0,82	0,80	0,83	0,88	0,89	0,90	0,94	0,94	0,94	0,94	0,96	**0,97**

Best Khat Value = 0.97, Worst Khat Value = 0.79, Average Khat Value = 0.87

Table 4.21 Average recognition rates of ICA and SVM applied on test data

Average Recognition Rates		Number Of Principal Components													
ICA + SVM		**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
	1	0,83	0,83	0,86	0,86	0,87	0,88	0,88	0,86	0,86	0,86	0,86	0,86	0,86	0,87
	2	0,83	0,85	0,85	0,87	0,88	0,89	0,90	0,90	0,90	0,90	0,89	0,89	0,89	0,89
	3	0,85	0,85	0,85	0,88	0,89	0,89	0,90	0,91	0,91	0,90	0,90	0,91	0,91	0,91
	4	0,87	0,87	0,86	0,90	0,90	0,91	0,92	0,92	0,91	0,91	0,91	0,91	0,90	0,90
Number	**5**	0,87	0,88	0,88	0,90	0,90	0,89	0,90	0,91	0,90	0,90	0,90	0,90	0,89	0,90
Of	**6**	0,86	0,85	0,86	0,87	0,87	0,87	0,87	0,90	0,90	0,91	0,91	0,91	0,91	0,90
Time	**7**	0,86	0,84	0,84	0,88	0,94	0,93	0,92	0,91	0,89	0,90	0,92	0,91	0,92	0,92
Bins	**8**	0,85	0,86	0,86	0,86	0,89	0,91	0,91	0,90	0,93	0,92	0,93	0,94	0,93	0,95
	9	0,87	0,86	0,86	0,84	0,85	0,89	0,88	0,91	0,91	0,93	0,94	0,94	0,94	0,95
	10	0,86	0,86	0,86	0,84	0,86	0,91	0,91	0,92	0,95	0,95	0,96	0,95	**0,97**	**0,97**

Best Recognition Rate = 0.97, Worst Recognition Rate= 0.83, Average Recognition Rate = 0.89

As we can see from Table 4.18, for constant number of time bins the classification performance of ICA+KNN does not change much by increasing the number of principal components. When the number of principal components is constant, a classification performance improvement of % 4 to % 10 is obtained for different number of principal components. The classification performance of ICA+KNN is satisfactory but could not compete with the classification performance of LDA+SVM or LDA+KNN.

As we can see from the Table 4.20, the minimum classification performance of ICA+SVM is %79. ICA+SVM outperforms LDA+SVM, LDA+KNN and PCA+KNN in minimum classification performance. Comparing to ICA+KNN, increasing the number of principal components improves classification performance of ICA+SVM tremendously. When the number of principal components is 2, the classification performances for 1 time-bin data and 10 time-bin data are %79 and %83 respectively. When the number of principal components is 15, the classification performances for 1 time-bin data and 10 time-bin data are %84 and %97 respectively. The maximum classification performance obtained with ICA+SVM is %97 which is very close to the maximum classification performance of LDA+SVM of %98. Regarding that the classification performance of LDA+SVM is not satisfactory enough for small numbers of principal components and small number of time bins, we can conclude that using ICA in the feature extraction stage and using SVM in the classifier stage is the best choice for our target recognition system.

Table 4.22 Khat values of NMF and KNN applied on test data

Khat Results NMF + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,21	0,35	0,55	0,59	0,61	0,67	0,71	0,71	0,74	0,77	0,76	0,78	0,80	0,81
	2	0,29	0,45	0,57	0,63	0,69	0,72	0,72	0,79	0,76	0,78	0,82	0,85	0,85	0,86
	3	0,39	0,42	0,48	0,68	0,65	0,72	0,77	0,76	0,83	0,80	0,86	0,85	0,86	0,87
	4	0,33	0,43	0,54	0,57	0,66	0,75	0,79	0,82	0,83	0,81	0,84	0,87	0,87	0,87
	5	0,42	0,41	0,69	0,64	0,65	0,78	0,80	0,81	0,86	0,82	0,87	0,87	0,86	**0,89**
	6	0,46	0,50	0,62	0,66	0,61	0,76	0,79	0,81	0,85	0,84	0,85	0,86	0,86	0,88
	7	0,47	0,45	0,50	0,69	0,61	0,76	0,78	0,80	0,84	0,86	0,85	0,87	**0,89**	**0,89**
	8	0,36	0,46	0,56	0,59	0,75	0,73	0,76	0,78	0,82	0,87	0,87	0,86	0,88	0,88
	9	0,30	0,56	0,57	0,61	0,75	0,74	0,81	0,83	0,83	0,84	0,86	0,87	0,88	0,88
	10	0,49	0,52	0,55	0,70	0,73	0,72	0,82	0,83	0,82	0,84	0,86	0,85	0,88	0,88

Best Khat Value = 0.89, Worst Khat Value = 0.21, Average Khat Value = 0.72

Table 4.23 Average recognition rates of NMF and KNN applied on test data

Average Recognition Rates NMF + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,36	0,47	0,63	0,67	0,69	0,74	0,76	0,77	0,79	0,82	0,81	0,82	0,84	0,84
	2	0,43	0,56	0,65	0,70	0,75	0,77	0,77	0,83	0,81	0,82	0,86	0,88	0,88	0,89
	3	0,50	0,53	0,58	0,74	0,72	0,78	0,81	0,80	0,87	0,84	0,89	0,88	0,89	0,90
	4	0,46	0,54	0,63	0,65	0,73	0,80	0,83	0,85	0,86	0,85	0,87	0,89	0,89	0,90
	5	0,53	0,52	0,75	0,71	0,71	0,83	0,84	0,84	0,89	0,85	0,89	0,90	0,89	**0,91**
	6	0,56	0,60	0,69	0,73	0,68	0,80	0,83	0,85	0,88	0,87	0,88	0,89	0,89	0,90
	7	0,57	0,55	0,60	0,75	0,69	0,81	0,82	0,84	0,87	0,89	0,88	0,89	**0,91**	**0,91**
	8	0,49	0,57	0,65	0,67	0,80	0,79	0,81	0,83	0,86	0,89	0,89	0,89	**0,91**	**0,91**
	9	0,44	0,64	0,66	0,69	0,80	0,79	0,85	0,86	0,86	0,87	0,89	0,89	0,90	0,90
	10	0,60	0,61	0,64	0,76	0,78	0,78	0,85	0,87	0,86	0,87	0,89	0,88	0,90	0,90

Best Recognition Rate = 0.91, Worst Recognition Rate= 0.36, Average Recognition Rate = 0.77

Table 4.24 Khat values of NMF and SVM applied on test data

Khat Results NMF + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,33	0,40	0,59	0,59	0,62	0,69	0,69	0,73	0,77	0,75	0,77	0,79	0,79	0,80
	2	0,38	0,49	0,62	0,63	0,70	0,70	0,73	0,78	0,77	0,78	0,83	0,87	0,88	0,89
	3	0,41	0,49	0,54	0,65	0,68	0,70	0,75	0,76	0,84	0,81	0,85	0,88	0,89	0,89
	4	0,39	0,48	0,53	0,64	0,68	0,72	0,78	0,80	0,84	0,85	0,84	0,88	0,89	0,90
	5	0,43	0,48	0,64	0,66	0,68	0,76	0,79	0,83	0,84	0,85	0,88	0,92	0,91	0,93
	6	0,43	0,50	0,64	0,66	0,65	0,70	0,81	0,80	0,86	0,87	0,89	0,92	0,93	0,92
	7	0,45	0,53	0,58	0,69	0,67	0,76	0,81	0,81	0,85	0,85	0,87	0,91	0,92	0,93
	8	0,41	0,47	0,61	0,60	0,67	0,71	0,75	0,77	0,83	0,88	0,90	0,91	0,91	0,93
	9	0,36	0,55	0,59	0,59	0,72	0,72	0,79	0,84	0,85	0,87	0,90	0,92	0,94	**0,97**
	10	0,52	0,53	0,54	0,66	0,71	0,78	0,81	0,85	0,83	0,86	0,90	0,92	0,94	0,95

Best Khat Value = 0.97, Worst Khat Value = 0.33, Average Khat Value = 0.74

Table 4.25 Average recognition rates of NMF and SVM applied on test data

Average Recognition Rates NMF + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,47	0,52	0,67	0,67	0,69	0,75	0,75	0,78	0,81	0,80	0,82	0,83	0,83	0,84
	2	0,51	0,59	0,69	0,70	0,76	0,76	0,78	0,82	0,81	0,83	0,86	0,90	0,90	0,91
	3	0,53	0,59	0,63	0,72	0,74	0,76	0,80	0,81	0,87	0,85	0,88	0,90	0,91	0,91
	4	0,51	0,58	0,62	0,71	0,74	0,78	0,82	0,84	0,87	0,88	0,87	0,90	0,91	0,92
	5	0,54	0,58	0,71	0,72	0,74	0,80	0,83	0,86	0,87	0,88	0,90	0,93	0,93	0,94
	6	0,54	0,60	0,71	0,73	0,72	0,76	0,85	0,84	0,88	0,90	0,91	0,93	0,94	0,94
	7	0,56	0,62	0,66	0,75	0,74	0,81	0,85	0,85	0,88	0,88	0,90	0,93	0,94	0,94
	8	0,54	0,57	0,69	0,68	0,74	0,76	0,80	0,82	0,86	0,90	0,92	0,93	0,93	0,95
	9	0,49	0,65	0,68	0,68	0,78	0,78	0,83	0,87	0,88	0,89	0,92	0,94	0,95	**0,97**
	10	0,62	0,63	0,64	0,73	0,77	0,82	0,85	0,88	0,86	0,89	0,92	0,94	0,95	0,96

Best Recognition Rate = 0.97, Worst Recognition Rate= 0.47, Average Recognition Rate = 0.79

As we can see from Table 4.22 NMF+KNN does not provide us good classification performance results for small numbers of principal components. The number of principal components must be at least 5 to get a classification performance of %70.

As we can see from Table 4.24, the classification performance of NMF+SVM is better than classification performance of NMF+KNN. Like NMF+KNN, NMF+SVM provides poor classification performance for small number of time bins and small number of principal components. However, for large values of principal components and time bins NMF+SVM provides good performance. The maximum classification performance obtained with NMF+SVM is %97. The classification performances of NMF+KNN and NMF+SVM can be considered as the worst classification performances among the feature extraction algoritms applied.

We can conclude that NMF is not good at extracting the significant features of data. With ICA+SVM the classification performance is %79 with a principal component value of 2 and time bin value of 1, however with NMF+SVM the classification performance value is only %33 with the same number of principal components and number of time-bins. Regarding Table 4.22, when the number of time bins 1, the classification performance increases from %21 to %81 with the increase of the number of principal components from 2 to 15.

Despite taking average of 10 experiments with different random initial values for NMF, there are some cases for which reliable classification performance results can not be obtained. In Table 4.22, when the number of principal components is 5, increasing the number of time bins can cause fluctuations. For example khat value for 3 time-bins is %68, while khat value for 4 time-bins is %57. Also khat value for 9 time-bins is %61 and khat value for 10 time-bins is %70. This is due to the fact that NMF can give different results for different iterations.

4.3 Hierarchical Classification Performance Results

In this section the classification performance results for the hierarchical target recognition system shown in Figure 3.8 are presented. Classification performance results calculated are KHAT (2.11) and Average Recognition Rate (2.12). Classification performance results are calculated for various numbers of time-bins and various numbers of principal components. These results are presented through Table 4.26 to Table 4.41.

Table 4.26 Khat values of PCA and KNN applied on test data

Khat Results Hierarchical PCA + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,76	0,82	0,86	0,87	0,86	0,89	0,89	0,90	0,89	0,88	0,90	0,89	0,89	0,89
	2	0,79	0,84	0,87	0,89	0,90	0,90	0,90	0,90	0,90	0,90	0,90	0,90	0,90	0,90
	3	0,79	0,86	0,87	0,90	0,91	0,91	0,90	0,93	0,92	0,91	0,92	0,92	0,93	0,92
	4	0,78	0,85	0,87	0,87	0,91	0,91	0,91	0,92	**0,94**	0,93	**0,94**	**0,94**	**0,94**	**0,94**
	5	0,77	0,86	0,88	0,88	0,92	0,92	0,92	0,91	0,92	0,93	0,92	0,93	0,93	0,93
	6	0,81	0,81	0,87	0,87	0,89	0,91	0,91	0,91	0,91	0,92	0,92	0,93	0,93	**0,94**
	7	0,83	0,82	0,87	0,89	0,89	0,93	0,93	0,93	0,92	0,93	**0,94**	0,93	0,93	0,93
	8	0,83	0,82	0,88	0,91	0,90	0,93	0,92	0,92	0,92	0,92	0,92	0,93	0,93	**0,94**
	9	0,83	0,87	0,88	0,93	0,93	**0,94**	0,93	0,92	0,92	0,92	0,92	0,93	0,93	0,93
	10	0,85	0,89	0,88	0,93	0,93	**0,94**	0,93	0,93	0,92	0,92	0,92	0,93	0,92	0,92

Best Khat Value = 0.94, Worst Khat Value = 0.76, Average Khat Value = 0.90

Table 4.27 Average recognition rates of PCA and KNN applied on test data

Average Recognition Rates Hierarchical PCA + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,80	0,85	0,88	0,90	0,89	0,91	0,91	0,92	0,91	0,90	0,92	0,91	0,91	0,91
	2	0,83	0,87	0,90	0,91	0,92	0,92	0,91	0,91	0,92	0,92	0,92	0,92	0,91	0,92
	3	0,83	0,89	0,90	0,92	0,93	0,93	0,92	**0,95**	0,94	0,93	0,93	0,94	0,94	0,93
	4	0,82	0,88	0,89	0,89	0,93	0,93	0,93	0,94	**0,95**	**0,95**	**0,95**	**0,95**	**0,95**	**0,95**
	5	0,81	0,88	0,90	0,90	0,93	0,93	0,93	0,93	0,93	0,94	0,94	0,94	0,94	**0,95**
	6	0,85	0,85	0,90	0,90	0,91	0,93	0,93	0,93	0,93	0,93	0,94	0,94	0,94	**0,95**
	7	0,87	0,85	0,90	0,92	0,91	0,94	0,94	0,94	0,94	0,94	**0,95**	**0,95**	**0,95**	**0,95**
	8	0,87	0,85	0,90	0,93	0,92	0,94	0,94	0,94	0,94	0,94	0,94	0,94	0,94	**0,95**
	9	0,86	0,90	0,91	0,94	0,94	**0,95**	0,94	0,94	0,94	0,94	0,94	0,94	0,94	**0,95**
	10	0,88	0,92	0,91	**0,95**	**0,95**	**0,95**	**0,95**	**0,95**	0,94	0,93	0,94	0,94	0,94	0,94

Best Recognition Rate = 0.95, Worst Recognition Rate= 0.80, Average Recognition Rate = 0.92

Table 4.28 Khat values of PCA and SVM applied on test data

Khat Results Hierarchical PCA + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,66	0,71	0,82	0,85	0,84	0,85	0,85	**0,86**	0,84	0,83	0,84	0,82	0,81	0,81
	2	0,69	0,75	0,82	0,84	0,81	0,78	0,76	0,71	0,71	0,69	0,67	0,66	0,64	0,61
	3	0,70	0,76	0,79	0,75	0,71	0,68	0,64	0,62	0,59	0,54	0,49	0,45	0,42	0,38
	4	0,71	0,80	0,75	0,69	0,64	0,59	0,52	0,46	0,44	0,38	0,34	0,32	0,31	0,30
	5	0,67	0,76	0,69	0,62	0,56	0,47	0,44	0,37	0,33	0,30	0,29	0,28	0,28	0,27
	6	0,62	0,69	0,64	0,55	0,48	0,44	0,40	0,33	0,30	0,28	0,28	0,26	0,26	0,26
	7	0,72	0,66	0,62	0,51	0,45	0,41	0,35	0,31	0,29	0,27	0,26	0,25	0,25	0,24
	8	0,75	0,69	0,57	0,46	0,41	0,35	0,32	0,28	0,27	0,25	0,25	0,24	0,23	0,23
	9	0,73	0,71	0,55	0,45	0,38	0,34	0,29	0,26	0,24	0,24	0,23	0,22	0,22	0,21
	10	0,70	0,68	0,53	0,40	0,36	0,32	0,28	0,25	0,22	0,21	0,21	0,20	0,19	0,19

Best Khat Value = 0.86, Worst Khat Value = 0.19, Average Khat Value = 0.50

Table 4.29 Average recognition rates of PCA and SVM applied on test data

Average Recognition Rates Hierarchical PCA + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,72	0,76	0,85	**0,88**	0,87	**0,88**	**0,88**	**0,88**	0,87	0,87	0,87	0,86	0,85	0,85
	2	0,74	0,80	0,86	0,87	0,85	0,83	0,81	0,77	0,77	0,76	0,74	0,73	0,71	0,70
	3	0,75	0,81	0,83	0,80	0,77	0,75	0,72	0,71	0,68	0,64	0,61	0,58	0,56	0,53
	4	0,77	0,84	0,80	0,75	0,72	0,68	0,63	0,59	0,57	0,53	0,50	0,48	0,48	0,47
	5	0,74	0,81	0,75	0,70	0,66	0,60	0,57	0,52	0,49	0,47	0,46	0,45	0,45	0,45
	6	0,69	0,75	0,72	0,65	0,60	0,57	0,55	0,49	0,47	0,46	0,45	0,44	0,44	0,44
	7	0,78	0,73	0,70	0,62	0,58	0,55	0,51	0,48	0,47	0,45	0,44	0,44	0,44	0,43
	8	0,80	0,76	0,67	0,59	0,55	0,51	0,48	0,46	0,45	0,44	0,44	0,43	0,42	0,42
	9	0,78	0,77	0,66	0,58	0,53	0,50	0,47	0,45	0,43	0,43	0,42	0,42	0,42	0,41
	10	0,77	0,74	0,64	0,55	0,52	0,49	0,46	0,44	0,42	0,41	0,41	0,40	0,40	0,40

Best Recognition Rate = 0.88, Worst Recognition Rate= 0.40, Average Recognition Rate = 0.62

Table 4.30 Khat values of LDA and KNN applied on test data

Khat Results Hierarchical LDA + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,69	0,73	0,70	0,70	0,70	0,73	0,74	0,75	0,76	0,76	0,74	0,76	0,79	0,79
	2	0,78	0,79	0,79	0,80	0,80	0,82	0,81	0,81	0,80	0,80	0,80	0,83	0,81	0,82
	3	0,81	0,83	0,83	0,82	0,81	0,82	0,81	0,82	0,84	0,83	0,84	0,84	0,85	0,85
	4	0,86	0,88	0,89	0,88	0,89	0,88	0,89	0,89	0,89	0,89	0,90	0,91	0,90	0,89
	5	0,91	0,93	0,92	0,92	0,92	0,92	0,92	0,92	0,92	0,91	0,91	0,92	0,92	0,92
	6	0,94	0,94	0,95	0,95	0,95	0,95	0,95	0,95	0,94	0,94	0,94	0,94	0,94	0,94
	7	0,93	0,94	0,94	0,94	0,94	0,93	0,94	0,94	0,95	0,95	0,95	0,95	0,94	0,94
	8	0,93	0,95	0,96	0,97	0,96	0,97	0,97	0,97	0,97	0,97	0,97	0,97	0,96	0,97
	9	0,95	0,96	0,97	0,97	**0,98**	0,97	0,97	0,97	0,97	**0,98**	**0,98**	**0,98**	**0,98**	**0,98**
	10	0,96	0,96	0,96	0,96	0,96	0,96	0,95	0,95	0,95	0,95	0,96	0,96	0,95	0,96

Best Khat Value = 0.98, Worst Khat Value = 0.69, Average Khat Value = 0.90

Table 4.31 Average recognition rates of LDA and KNN applied on test data

Average Recognition Rates Hierarchical LDA + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,75	0,78	0,76	0,76	0,76	0,78	0,79	0,79	0,80	0,81	0,79	0,80	0,83	0,83
	2	0,82	0,83	0,83	0,83	0,83	0,85	0,84	0,85	0,84	0,84	0,83	0,86	0,85	0,85
	3	0,85	0,86	0,86	0,86	0,85	0,85	0,85	0,85	0,87	0,86	0,87	0,87	0,88	0,88
	4	0,89	0,90	0,91	0,90	0,91	0,90	0,91	0,91	0,91	0,91	0,92	0,92	0,92	0,91
	5	0,93	0,94	0,94	0,94	0,94	0,93	0,94	0,93	0,93	0,93	0,93	0,94	0,94	0,94
	6	0,96	0,96	0,96	0,96	0,96	0,96	0,96	0,96	0,95	0,96	0,95	0,95	0,95	0,95
	7	0,95	0,95	0,95	0,95	0,95	0,95	0,95	0,95	0,96	0,96	0,96	0,96	0,95	0,95
	8	0,94	0,96	0,97	0,97	0,97	0,97	0,97	**0,98**	**0,98**	**0,98**	0,97	0,97	0,97	0,97
	9	0,96	0,97	**0,98**	**0,98**	**0,98**	**0,98**	**0,98**	**0,98**	**0,98**	**0,98**	**0,98**	**0,98**	**0,98**	**0,98**
	10	0,97	0,97	0,97	0,97	0,97	0,97	0,96	0,96	0,96	0,96	0,97	0,97	0,96	0,97

Best Recognition Rate = 0.98, Worst Recognition Rate= 0.75, Average Recognition Rate = 0.92

Table 4.32 Khat values of LDA and SVM applied on test data

Khat Results Hierarchical LDA + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,67	0,72	0,71	0,64	0,64	0,66	0,69	0,70	0,72	0,71	0,72	0,73	0,73	0,73
	2	0,72	0,77	0,77	0,78	0,77	0,79	0,77	0,81	0,80	0,81	0,82	0,83	0,83	0,81
	3	0,75	0,80	0,81	0,81	0,81	0,80	0,80	0,79	0,81	0,81	0,82	0,81	0,81	0,82
	4	0,87	0,90	0,88	0,88	0,89	0,88	0,87	0,87	0,85	0,85	0,84	0,85	0,85	0,85
	5	0,92	0,93	0,93	0,93	0,91	0,91	0,92	0,91	0,91	0,92	0,91	0,90	0,90	0,89
	6	0,92	0,93	0,93	0,93	0,94	0,93	0,94	0,94	0,92	0,91	0,91	0,92	0,92	0,92
	7	0,94	0,94	0,94	0,94	0,94	0,93	0,93	0,94	0,93	0,92	0,91	0,90	0,91	0,90
	8	0,93	0,95	0,94	0,95	0,94	0,94	0,93	0,93	0,93	0,93	0,93	0,93	0,93	0,93
	9	0,93	0,96	**0,97**	**0,97**	0,96	0,95	0,93	0,94	0,94	0,94	0,94	0,94	0,94	0,93
	10	0,94	0,96	0,95	0,95	0,94	0,94	0,94	0,94	0,93	0,93	0,93	0,93	0,93	0,93

Best Khat Value = 0.97, Worst Khat Value = 0.64, Average Khat Value = 0.87

Table 4.33 Average recognition rates of LDA and SVM applied on test data

Average Recognition Rates Hierarchical LDA + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,73	0,78	0,77	0,71	0,71	0,72	0,75	0,76	0,77	0,76	0,78	0,78	0,78	0,78
	2	0,77	0,81	0,81	0,82	0,81	0,83	0,82	0,84	0,84	0,84	0,85	0,86	0,86	0,85
	3	0,80	0,84	0,85	0,85	0,84	0,84	0,84	0,83	0,84	0,85	0,85	0,85	0,85	0,85
	4	0,89	0,92	0,90	0,90	0,91	0,90	0,90	0,90	0,88	0,88	0,87	0,88	0,88	0,88
	5	0,93	0,95	0,94	0,94	0,93	0,93	0,94	0,93	0,93	0,93	0,93	0,92	0,92	0,91
	6	0,94	0,94	0,94	0,94	0,95	0,95	0,96	0,95	0,94	0,93	0,93	0,93	0,94	0,93
	7	0,95	0,95	0,95	0,95	0,95	0,95	0,95	0,95	0,94	0,94	0,93	0,92	0,93	0,92
	8	0,94	0,96	0,95	0,96	0,95	0,95	0,95	0,95	0,95	0,95	0,95	0,95	0,95	0,94
	9	0,95	0,97	0,97	**0,98**	0,97	0,96	0,95	0,95	0,95	0,95	0,95	0,95	0,95	0,95
	10	0,96	0,97	0,96	0,96	0,96	0,95	0,95	0,95	0,95	0,94	0,94	0,94	0,95	0,95

Best Recognition Rate = 0.98, Worst Recognition Rate= 0.71, Average Recognition Rate = 0.90

Table 4.34 Khat values of ICA and KNN applied on test data

Khat Results Hierarchical ICA + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,74	0,77	0,80	0,80	0,80	0,80	0,80	0,81	0,81	0,80	0,81	0,81	0,81	0,81
	2	0,75	0,82	0,83	0,84	0,85	0,85	0,86	0,85	0,84	0,84	0,84	0,84	0,84	0,84
	3	0,77	0,81	0,81	0,83	0,85	0,84	0,85	0,85	0,85	0,86	0,86	0,85	0,85	0,85
	4	0,78	0,82	0,81	0,82	0,83	0,83	0,82	0,83	0,83	0,83	0,84	0,84	0,84	0,85
	5	0,80	0,83	0,84	0,85	0,86	0,86	0,85	0,86	0,85	0,85	0,85	0,85	0,85	0,86
	6	0,82	0,83	0,83	0,84	0,85	0,85	0,85	0,86	0,86	0,85	0,85	0,85	0,86	0,86
	7	0,82	0,85	0,85	0,86	0,85	0,85	0,86	0,86	**0,87**	0,86	0,86	0,86	**0,87**	0,86
	8	0,84	0,85	0,82	0,84	0,83	0,83	0,83	0,84	0,83	0,85	0,85	0,85	0,85	0,86
	9	0,84	0,85	0,86	0,86	0,85	0,84	0,85	0,85	**0,87**	**0,87**	**0,87**	**0,87**	**0,87**	**0,87**
	10	0,84	0,86	0,84	0,84	0,84	0,83	0,83	0,83	0,85	0,85	0,85	0,86	0,86	0,86

Best Khat Value = 0.87, Worst Khat Value = 0.74, Average Khat Value = 0.84

Table 4.35 Average recognition rates of ICA and KNN applied on test data

Average Recognition Rates Hierarchical ICA + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,79	0,81	0,84	0,84	0,84	0,84	0,84	0,85	0,84	0,84	0,84	0,84	0,84	0,84
	2	0,80	0,86	0,86	0,87	0,87	0,88	0,88	0,88	0,87	0,87	0,87	0,87	0,87	0,87
	3	0,81	0,84	0,85	0,86	0,88	0,87	0,88	0,88	0,88	0,88	0,88	0,88	0,88	0,88
	4	0,82	0,85	0,85	0,85	0,86	0,86	0,85	0,86	0,86	0,86	0,87	0,87	0,87	0,88
	5	0,83	0,86	0,87	0,88	0,88	0,88	0,88	0,88	0,88	0,88	0,88	0,88	0,88	0,88
	6	0,86	0,87	0,87	0,87	0,88	0,88	0,88	0,89	0,89	0,88	0,88	0,88	0,89	0,88
	7	0,85	0,88	0,88	0,89	0,88	0,88	0,89	0,89	0,89	0,89	0,89	0,89	0,89	0,89
	8	0,87	0,88	0,85	0,87	0,86	0,86	0,86	0,87	0,87	0,88	0,88	0,88	0,88	0,89
	9	0,87	0,88	0,89	0,89	0,88	0,87	0,88	0,88	0,89	**0,90**	**0,90**	**0,90**	**0,90**	**0,90**
	10	0,87	0,89	0,87	0,88	0,88	0,87	0,87	0,87	0,88	0,88	0,88	0,89	0,89	0,89

Best Recognition Rate = 0.90, Worst Recognition Rate= 0.79, Average Recognition Rate = 0.87

Table 4.36 Khat values of ICA and SVM applied on test data

Khat Results Hierarchical ICA + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,73	0,74	0,82	0,85	0,87	0,85	0,87	0,86	0,86	0,86	0,87	0,87	0,86	0,87
	2	0,73	0,78	0,82	0,81	0,86	0,84	0,85	0,88	0,88	0,89	0,90	0,90	0,88	0,85
	3	0,78	0,83	0,79	0,85	0,85	0,88	0,88	0,90	0,88	0,88	0,90	0,90	0,90	0,91
	4	0,78	0,82	0,82	0,79	0,83	0,84	0,88	0,90	0,90	0,90	0,90	0,90	0,90	0,90
	5	0,77	0,80	0,80	0,81	0,84	0,88	0,91	0,90	0,91	0,90	0,90	0,91	0,91	0,91
	6	0,79	0,81	0,80	0,80	0,88	0,90	0,91	0,91	0,91	0,88	0,88	0,89	0,89	0,89
	7	0,77	0,79	0,81	0,85	0,87	0,87	0,88	0,90	0,91	0,90	0,90	0,90	0,90	0,90
	8	0,81	0,85	0,83	0,84	0,88	0,89	0,90	0,89	0,90	0,91	0,90	0,89	0,89	0,89
	9	0,86	0,87	0,89	0,90	0,93	0,92	0,91	0,91	0,89	0,89	0,90	0,88	0,90	0,92
	10	0,82	0,87	0,90	0,92	0,93	**0,94**	0,93	0,90	0,90	0,91	0,90	0,91	0,91	0,92

Best Khat Value = 0.94, Worst Khat Value = 0.73, Average Khat Value = 0.87

Table 4.37 Average recognition rates of ICA and SVM applied on test data

Average Recognition Rates Hierarchical ICA + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,78	0,79	0,85	0,88	0,89	0,88	0,89	0,89	0,89	0,89	0,89	0,89	0,89	0,89
	2	0,78	0,82	0,85	0,84	0,89	0,87	0,87	0,90	0,90	0,91	0,92	0,92	0,90	0,88
	3	0,82	0,86	0,83	0,88	0,87	0,90	0,91	0,92	0,90	0,91	0,92	0,92	0,92	0,93
	4	0,82	0,85	0,86	0,83	0,86	0,87	0,90	0,92	0,92	0,92	0,92	0,92	0,92	0,92
	5	0,82	0,84	0,83	0,85	0,87	0,90	0,93	0,92	0,93	0,92	0,92	0,93	0,92	0,93
	6	0,83	0,85	0,84	0,84	0,90	0,92	0,93	0,93	0,93	0,90	0,90	0,91	0,91	0,91
	7	0,82	0,83	0,84	0,88	0,89	0,89	0,90	0,92	0,93	0,92	0,92	0,92	0,92	0,92
	8	0,84	0,88	0,87	0,87	0,90	0,92	0,92	0,91	0,92	0,92	0,92	0,91	0,91	0,91
	9	0,88	0,89	0,91	0,92	0,94	0,93	0,93	0,93	0,92	0,91	0,92	0,90	0,92	0,94
	10	0,85	0,90	0,92	0,93	0,94	**0,95**	**0,95**	0,92	0,92	0,93	0,92	0,93	0,93	0,94

Best Recognition Rate = 0.95, Worst Recognition Rate= 0.78, Average Recognition Rate = 0.89

Table 4.38 Khat values of NMF and KNN applied on test data

Khat Results Hierarchical NMF + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,36	0,36	0,50	0,53	0,62	0,68	0,72	0,71	0,76	0,80	0,72	0,79	0,80	0,81
	2	0,25	0,31	0,50	0,58	0,68	0,66	0,70	0,77	0,80	0,81	0,84	0,82	0,86	0,88
	3	0,49	0,47	0,55	0,61	0,73	0,73	0,76	0,81	0,83	0,77	0,86	0,86	0,87	0,90
	4	0,30	0,54	0,64	0,70	0,65	0,67	0,77	0,78	0,78	0,80	0,87	0,85	0,88	0,89
	5	0,30	0,45	0,57	0,61	0,65	0,76	0,80	0,84	0,79	0,84	0,87	0,87	0,90	0,91
	6	0,27	0,47	0,59	0,68	0,77	0,73	0,76	0,85	0,82	0,81	0,87	0,86	0,89	0,90
	7	0,36	0,43	0,58	0,63	0,70	0,77	0,80	0,78	0,85	0,82	0,87	0,89	0,89	0,90
	8	0,36	0,49	0,54	0,58	0,70	0,74	0,76	0,83	0,84	0,88	0,91	0,89	0,90	0,92
	9	0,38	0,50	0,60	0,75	0,65	0,73	0,82	0,83	0,86	0,89	0,88	0,88	0,91	0,92
	10	0,42	0,42	0,76	0,68	0,75	0,75	0,81	0,80	0,82	0,88	0,87	0,89	0,92	**0,94**

Best Khat Value = 0.94, Worst Khat Value = 0.25, Average Khat Value = 0.72

Table 4.39 Average recognition rates of NMF and KNN applied on test data

Average Recognition Rates Hierarchical NMF + KNN		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,48	0,48	0,60	0,62	0,69	0,74	0,77	0,77	0,81	0,84	0,78	0,83	0,84	0,85
	2	0,39	0,44	0,60	0,66	0,74	0,72	0,75	0,81	0,84	0,85	0,87	0,86	0,89	0,90
	3	0,59	0,57	0,64	0,68	0,78	0,78	0,80	0,85	0,87	0,82	0,89	0,89	0,90	0,92
	4	0,43	0,63	0,71	0,76	0,72	0,73	0,81	0,83	0,82	0,84	0,89	0,88	0,90	0,91
	5	0,44	0,56	0,65	0,68	0,71	0,81	0,84	0,87	0,83	0,87	0,90	0,90	0,92	0,93
	6	0,41	0,57	0,67	0,75	0,82	0,79	0,81	0,88	0,86	0,85	0,89	0,88	0,91	0,92
	7	0,49	0,54	0,66	0,70	0,76	0,82	0,84	0,83	0,88	0,85	0,89	0,91	0,91	0,92
	8	0,49	0,60	0,63	0,66	0,76	0,79	0,81	0,87	0,88	0,91	0,93	0,91	0,92	0,94
	9	0,51	0,60	0,68	0,80	0,72	0,78	0,86	0,86	0,88	0,91	0,91	0,90	0,93	0,93
	10	0,54	0,53	0,81	0,74	0,80	0,80	0,85	0,84	0,85	0,91	0,90	0,91	0,94	**0,95**

Best Recognition Rate = 0.95, Worst Recognition Rate= 0.39, Average Recognition Rate = 0.78

Table 4.40 Khat values of NMF and SVM applied on test data

Khat Results Hierarchical NMF + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,31	0,49	0,52	0,57	0,62	0,65	0,67	0,68	0,74	0,74	0,74	0,76	0,76	0,77
	2	0,33	0,43	0,51	0,58	0,65	0,65	0,73	0,78	0,79	0,81	0,84	0,88	0,90	0,90
	3	0,45	0,45	0,48	0,56	0,63	0,67	0,72	0,78	0,82	0,83	0,85	0,89	0,90	0,91
	4	0,38	0,44	0,50	0,63	0,66	0,68	0,78	0,80	0,82	0,84	0,89	0,88	0,92	0,92
	5	0,33	0,47	0,52	0,57	0,61	0,72	0,77	0,79	0,82	0,84	0,87	0,90	0,90	0,90
	6	0,36	0,48	0,54	0,63	0,71	0,67	0,72	0,82	0,84	0,87	0,88	0,89	0,91	0,92
	7	0,33	0,40	0,56	0,56	0,69	0,73	0,78	0,81	0,86	0,87	0,89	0,91	0,90	0,91
	8	0,40	0,42	0,48	0,54	0,63	0,72	0,78	0,81	0,84	0,88	0,91	**0,93**	0,92	0,92
	9	0,38	0,46	0,52	0,55	0,61	0,75	0,82	0,82	0,86	0,89	0,91	0,92	0,92	0,92
	10	0,34	0,41	0,51	0,58	0,69	0,73	0,80	0,80	0,83	0,89	0,88	0,90	0,92	0,91

Best Khat Value = 0.93, Worst Khat Value = 0.31, Average Khat Value = 0.71

Table 4.41 Average recognition rates of NMF and SVM applied on test data

Average Recognition Rates Hierarchical NMF + SVM		Number Of Principal Components													
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Number Of Time Bins	**1**	0,45	0,59	0,62	0,65	0,69	0,72	0,73	0,74	0,79	0,79	0,79	0,80	0,81	0,81
	2	0,47	0,54	0,60	0,66	0,72	0,71	0,78	0,82	0,83	0,85	0,87	0,90	0,92	0,92
	3	0,56	0,56	0,58	0,64	0,70	0,74	0,78	0,82	0,85	0,86	0,88	0,91	0,92	0,93
	4	0,50	0,55	0,60	0,70	0,73	0,75	0,82	0,84	0,85	0,87	0,91	0,90	0,93	**0,94**
	5	0,46	0,57	0,61	0,65	0,69	0,77	0,81	0,83	0,85	0,87	0,90	0,92	0,92	0,92
	6	0,49	0,58	0,63	0,70	0,77	0,74	0,77	0,86	0,87	0,90	0,90	0,92	0,93	0,93
	7	0,47	0,51	0,64	0,65	0,75	0,78	0,83	0,85	0,89	0,90	0,91	0,92	0,92	0,93
	8	0,52	0,54	0,58	0,63	0,70	0,77	0,82	0,85	0,88	0,91	0,93	**0,94**	**0,94**	**0,94**
	9	0,50	0,57	0,62	0,65	0,69	0,80	0,85	0,86	0,89	0,91	0,93	**0,94**	0,93	**0,94**
	10	0,48	0,53	0,61	0,66	0,76	0,79	0,84	0,84	0,86	0,91	0,91	0,92	0,93	0,93

Best Recognition Rate = 0.94, Worst Recognition Rate= 0.45, Average Recognition Rate = 0.77

Observing the classification performance tables of normal classification and hierarchical classification, we can conclude that hierarchical classification does not provide classification performance improvement for all feature extraction and classification methods. Hierarchical classification improves classification performance around %3-4 for LDA+KNN and LDA+SVM. Hierarchical classification does not improve performance for PCA+SVM, ICA+SVM, NMF+KNN, NMF+SVM. We can conclude that hierarchical classification does not improve performance when SVM or NMF is used. Also a classification performance improvement of %2 is obtained for PCA+KNN, ICA+KNN. Hierarchical classification improves performance when KNN is used.

4.4 Confusion Matrices

Khat values and average recognition rates for different number of time-bins and principal components were given through Table 4.9 to Table 4.25 for normal classification. Observing these tables we can see that best classification results are obtained with LDA+SVM and ICA+SVM. From Table 4.17, we see that an average recognition rate of %98 is obtained with LDA+SVM when the number of time bins is 9 and number of principal components is 12. The recognition rate obtained with LDA+SVM is %76, when the number of time bins is 1 and number of principal components is 12. To see the performance improvement by increasing the number of time-bins, confusion matrices for these two cases are given in Table 4.42 and Table 4.43 .

Table 4.42 Confusion matrix of LDA+SVM for 1 time-bin and 12 principal components

	Car	Truck	Bus	Tank	Helicopter	Walking Man	Running Man
Car	17	1	33	0	0	1	0
Truck	5	28	2	3	0	18	1
Bus	2	7	80	2	0	2	1
Tank	0	4	0	3	0	8	0
Helicopter	0	0	0	0	20	1	0
Walking Man	0	0	0	0	0	103	6
Running Man	5	0	0	0	0	4	85

Table 4.43 Confusion matrix of LDA+SVM for 9 time-bin and 12 principal components

	Car	Truck	Bus	Tank	Helicopter	Walking Man	Running Man
Car	37	3	4	0	0	0	0
Truck	0	49	0	0	0	0	0
Bus	0	0	86	0	0	0	0
Tank	0	0	0	7	0	0	0
Helicopter	0	0	0	0	13	0	0
Walking Man	0	0	0	0	0	101	0
Running Man	0	0	0	0	0	0	86

From Table 4.21, we see that an average recognition rate of %97 is obtained with ICA+SVM when the number of time bins is 10 and number of principal components is 15. The recognition rate obtained with ICA+SVM is %87, when the number of time bins is 1 and number of principal components is 15. To see the performance improvement by increasing the number of time-bins, confusion matrices for these two cases are given in Table 4.44 and Table 4.45 .

Table 4.44 Confusion matrix of ICA+SVM for 1 time-bin and 15 principal components

	Car	Truck	Bus	Tank	Helicopter	Walking Man	Running Man
Car	32	13	5	2	0	0	0
Truck	5	51	1	0	0	0	0
Bus	11	2	81	0	0	0	0
Tank	0	0	0	10	0	0	5
Helicopter	0	0	0	0	20	1	0
Walking Man	0	0	0	0	0	109	0
Running Man	6	0	2	0	0	5	81

Table 4.45 Confusion matrix of ICA+SVM for 10 time-bins and 15 principal components

	Car	Truck	Bus	Tank	Helicopter	Walking Man	Running Man
Car	37	0	6	0	0	0	0
Truck	0	47	1	0	0	0	0
Bus	0	0	83	2	0	0	0
Tank	0	0	0	6	0	0	0
Helicopter	0	0	0	0	12	0	0
Walking Man	0	0	0	0	0	100	0
Running Man	3	0	1	0	0	0	81

4.5 Classification Performance Summary

The summary of the classification performance results is given in Table 4.42. This summary table contains the best, worst and average classification performances of the tables Table 4.9 through Table 4.41.

Table 4.46 Summary of classification performance tables

		Normal Classification						Hierarchical Classification					
		KHAT VALUE			RECOGNITION RATE			KHAT VALUE			RECOGNITION RATE		
CLASSIFICATION	FEATURE EXTRACTION	Best	Worst	Average	Best	Worst	Average	Best	Worst	Average	Best	Worst	Average
KNN	PCA	0.92	0.69	0.89	0.94	0.75	0.91	0.94	0.76	0.90	0.95	0.80	0.92
	LDA	0.94	0.53	0.86	0.95	0.61	0.88	0.98	0.69	0.90	0.98	0.75	0.92
	ICA	0.84	0.73	0.81	0.87	0.78	0.85	0.87	0.74	0.84	0.90	0.79	0.87
	NMF	0.89	0.21	0.72	0.91	0.36	0.77	0.94	0.25	0.72	0.95	0.39	0.78
SVM	PCA	0.87	0.29	0.65	0.90	0.47	0.73	0.86	0.19	0.50	0.88	0.40	0.62
	LDA	0.98	0.52	0.84	0.98	0.61	0.87	0.97	0.64	0.87	0.98	0.71	0.90
	ICA	0.97	0.79	0.87	0.97	0.83	0.89	0.94	0.73	0.87	0.95	0.78	0.89
	NMF	0.97	0.33	0.74	0.97	0.47	0.79	0.93	0.31	0.71	0.94	0.45	0.77

CHAPTER 5

CONCLUSION

In this thesis improving the classification performance of the target recognition system designed in Erdogan (2002) is studied. Classification performance improvement is done by the following methods:

- Utilizing the repetitions in time in the TRP vectors of some target classes (walking man, running man and helicopter).
- Using different feature extraction (PCA, LDA, ICA and NMF) and classifier (KNN, SVM) combinations.
- Hierarchical Classification.

We observed that best classification performance results are obtained with LDA+SVM and ICA+SVM. ICA+SVM provides a minimum recognition rate of %83 and maximum recognition rate of %97. Also maximum recognition rate of LDA+SVM is %98, however ICA+SVM outperforms LDA+SVM at minimum recognition performance, the minimum recognition rate for LDA+SVM is %61. For all feature extraction and classification method combinations increasing the number of time bins also increases classification performance except PCA+SVM. For higher number of time bins and principal components NMF+KNN and NMF+SVM provides good classification performance (maximum recognition rates of %90 and %96 respectively), however NMF performance is not good for small number of time bins and principal components. Also NMF is not real time implementable; it takes too much time to extract features. Among the feature extraction methods ICA is the most useful one to extract the important features of the input data with the minimum number of principal components. A recognition rate of %83 is obtained when the number of time bins is 1 and the number of principal components is 2. Also SVM provides better performance than KNN.

Hierarchical classification does not improve classification performance except LDA method. But this improvement becomes insignificant when the number of principal components is high. When the number of principal components is 2 and number of time bins is 1, LDA+SVM provides a recognition rate of %61 for normal classification and %73 for hierarchical classification. When the number of principal components is 2 and number of time bins is 10, LDA+SVM provides a classification performance of %77 for normal classification and % 96 for hierarchical classification. Hierarchical classfication can be used to increase the performance of LDA, but there is no need to use such a method for ICA since hierarchical classification makes our target recognition system more complex.

Future research may consider the optimal target recognition system in which each type of misclassification brings different costs to the system. Since the radar used is a military radar, the classification of a car target as running man is more dangerous than classifying a walking man target as running man. The future work can study on a target recognition system which will minimize such dangerous misclassifications. Also multiple target situations are not handled in the thesis, they can be considered at a future work.

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APPENDIX A

ASKARAD TECHNICAL SPECIFICATIONS

Figure A.1 ASKARAD

Description:

ASKARAD ASELSAN Ground Surveillance and Artillery Fire Adjustment Radar is a radar system combining long range and precision in an easy to use system.

ASKARAD provides surveillance, target acquisition and classification, target tracking and artillery fire adjustment function within are unit.

Target Detection Ranges:

Vehicle Convoy : 38 km

Heavy Vehicle (Tank): 30 km

Helicopters : 25 km

Light Vehicle (Jeep) : 20 km

Soldiers : 15 km

155 mm shell burst : 15 km

105 mm shell burst : 8 km

Features:

Ground and coastal surveillance

Target acquisition and classification

Audible alarm

Automatic target tracking

Artillery fire adjustment

Guidance of small ground or airborne attack units

Helicopter navigational aid

Integration with command - control (C^2) systems

Technical Specifications:

Frequency : X - Band

Channel : 10

Transmitter Power : >5kW peak

Accuracy

Range : ± 10 m

Azimuth : ± 2 mils

Power Consumption

Transmit :< 290 W @ 24 VDC

Stand-by :< 120 W @ 24 VDC

Environmental Standard : MIL-STD-810D

Operating Temperature : -30°C to +55°C

EMI/RFI Specification : MIL-STD-461C