

# Image Cover Sheet

**CLASSIFICATION**

UNCLASSIFIED

**SYSTEM NUMBER**

131304

**TITLE**

MULTI-SENSOR DATA FUSION FOR TARGET ACQUISITION

**System Number:****Patron Number:****Requester:****Notes:** Paper #5 contained in Parent Sysnum #129006**DSIS Use only:****Deliver to:** DK

Multi-sensor data fusion for target acquisition  
CRAD SIPWG  
Workshop on Neural Networks

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May 1992

In the past few years, DREV has undertaken the study and development of intelligent systems for application in area defence weapons (ADW), intelligent mines, battlefield surveillance systems and peacekeeping missions. The current problem is to be able to acquire and identify noncooperative vehicles using a number of sensors (e.g. geophones, microphones and electromagnetic sensors). By making use of a host of signals, the aim is to provide as fine a level of discrimination as possible. This approach, commonly referred to as *data fusion*, is an area of interest in many applications and very diverse disciplines.

In a first step, it is necessary to determine the signal features which will serve to discriminate between the vehicles. Once an appropriate set of features has been selected, the neural net is a proposed method for classifying and/or identifying the various signatures, and come to a decision on the identity of the unknown vehicle. The neural network should prove well suited for the expected variability of the signatures of vehicles due to the noise and uncertainties of a combat environment.

Currently at DREV, in parallel with the search for appropriate signal features, work is about to begin in the simulation of neural nets by first repeating some previously published results to gain a practical understanding of the artificial neural net, study the various network topologies and the various training algorithms.

Among the simulations to be run are:

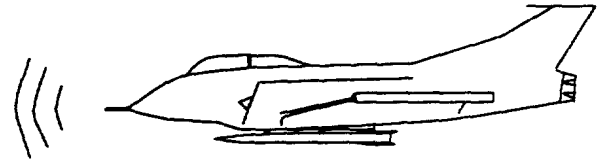
1. character recognition: given an array of pixels, a neural net is trained on a standard alphabet of characters, and then tested for recognition of corrupted versions of these characters;
2. adaptive antennas: a phased-array antenna controlled by a neural net is made to adaptively produce a peak and a null in its radiation pattern in specific directions.

Expertise gained in performing these simulations and others will be useful in designing a neural net for the classification/identification of vehicle signatures.

## Data Fusion for Vehicle Identification

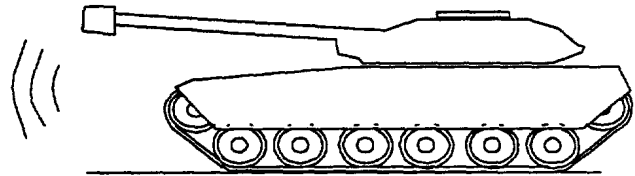
### **Aim:**

Acquire/identify vehicles using a multi-sensor system.



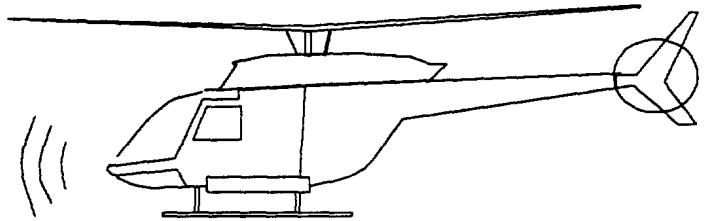
### **Signatures of interest:**

- Acoustic emissions
- Seismic emissions
- Electric emissions
- Magnetic emissions



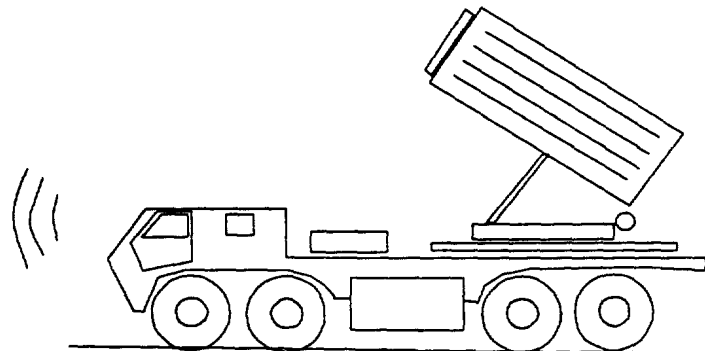
### **Characteristics:**

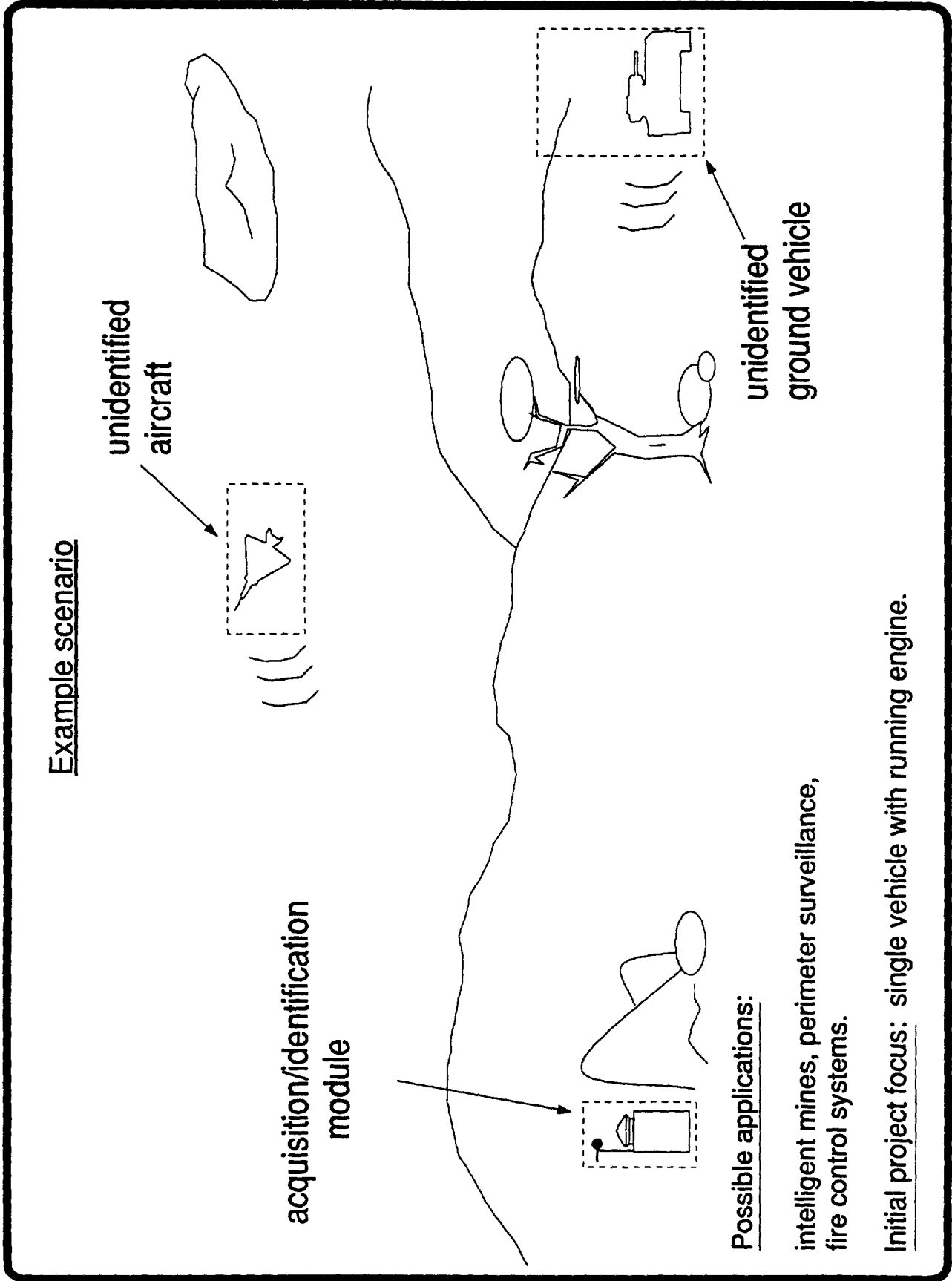
- passive detection
- non-imaging processing



### **Vehicle groups:**

- winged aircraft
- tracked vehicle
- helicopter
- wheeled vehicle





## Vehicle identification process

1) Selection of discriminating features:

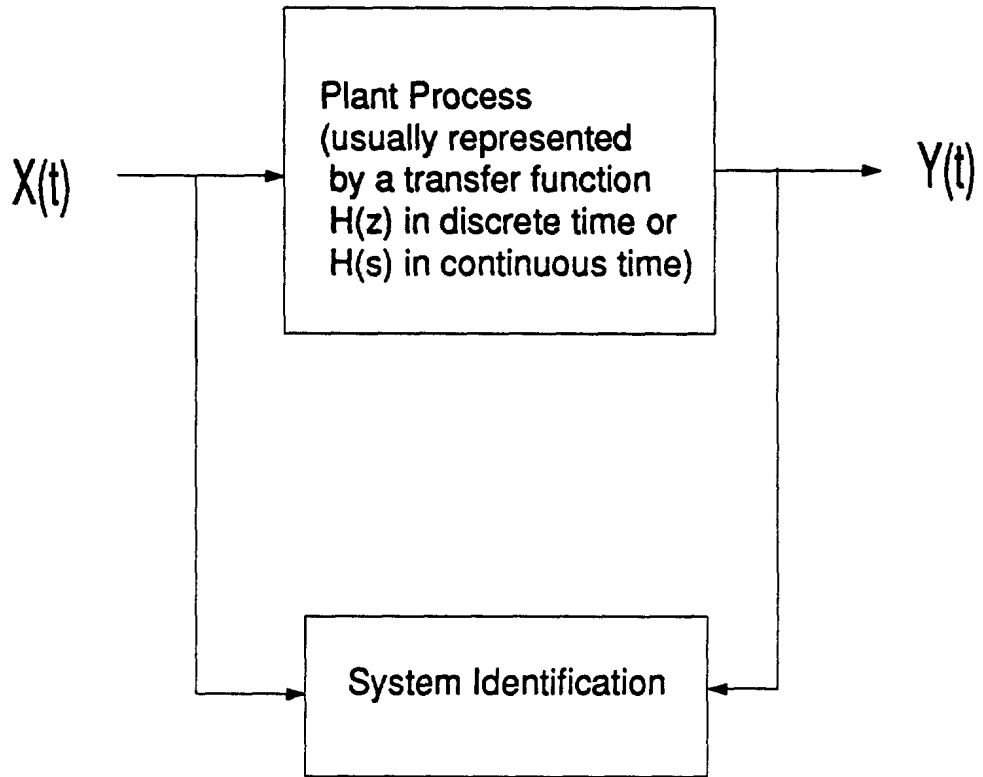
signature gathering, signal/system modeling.

2) Classification of those features:

developing a systematic process by which the observed signal features are to be classified in order to arrive at a decision about the identity of the unknown vehicle.

Among the suggested solutions are expert systems, fuzzy logic and artificial neural networks. The latter will be the first to be investigated as a solution to the problem of classifying vehicle signatures.

## Classical system identification

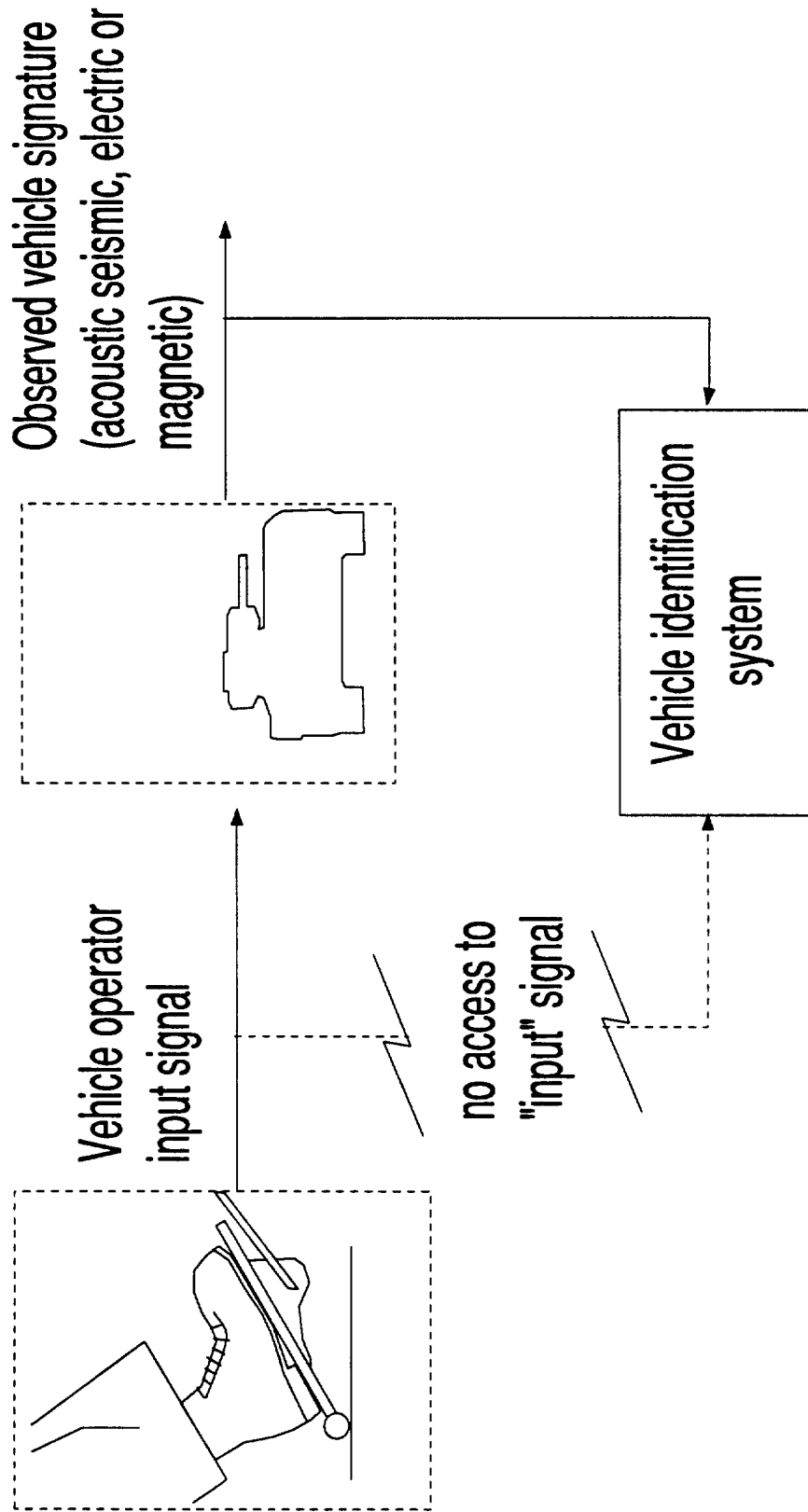


Plant process  $H$  is identified or approximated using only the observed input and output signals  $x(t)$  and  $y(t)$ .

### Applications:

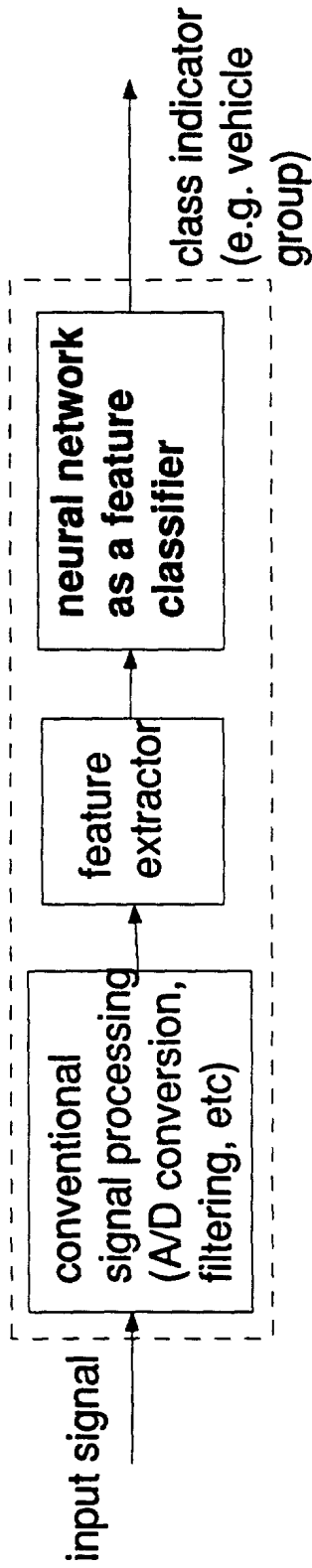
adaptive systems(i.e. controller design for time-varying systems)

# Vehicle identification



## Artificial neural network application

vehicle identification system



### Current Work:

- 1) Signal processing and feature selection/extraction
- 2) neural network simulations



## Neural network simulations

Before attempting to use neural networks on the problem of vehicle identification, a practical expertise base will be built by first replicating some published results on the topic of neural networks.

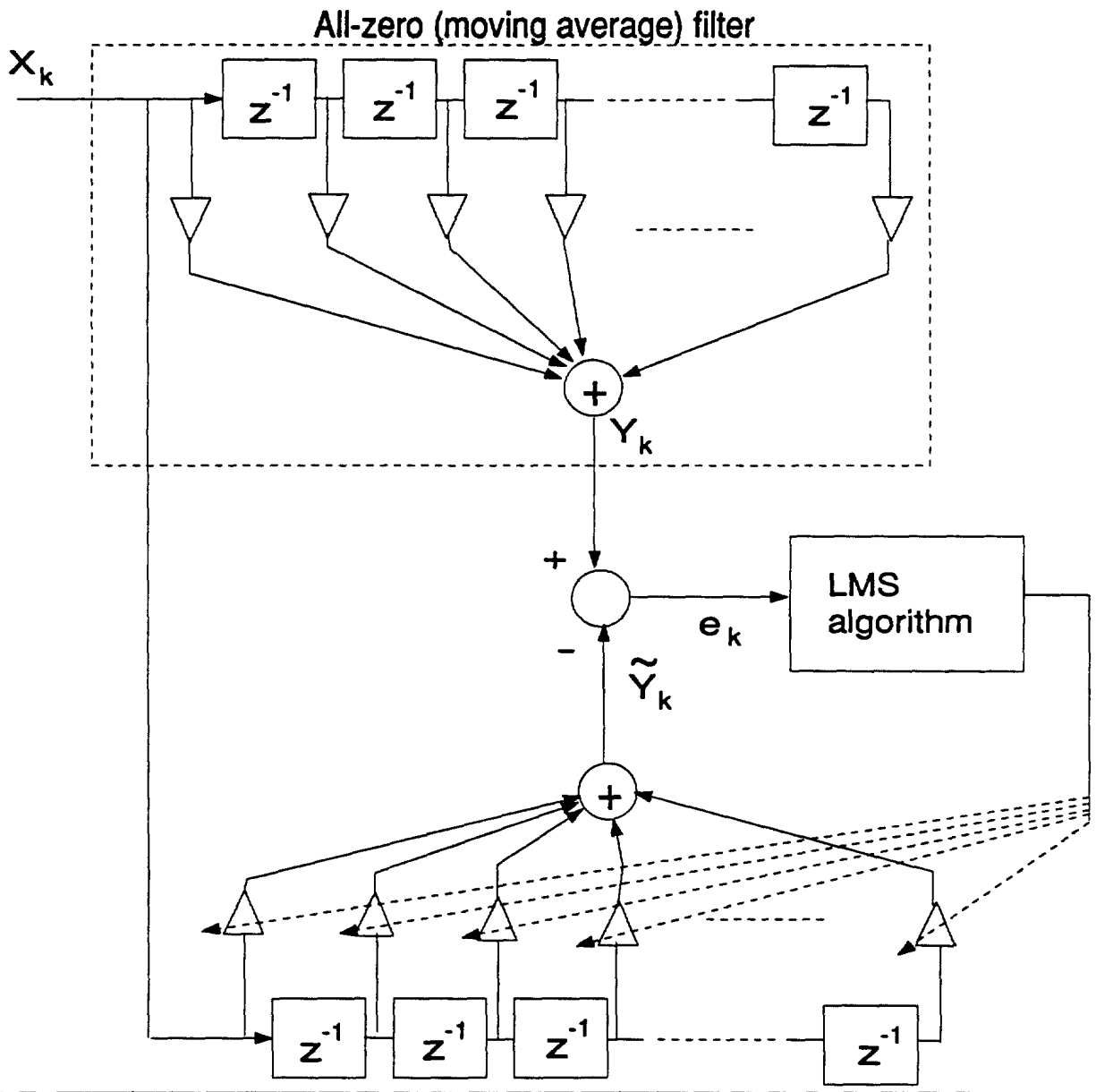
The following simulations are among the projected applications of neural networks which have been started or will be simulated at DREV. This work is carried out in parallel with that of finding appropriate signal features enabling the discrimination of vehicles. The first two applications of neural networks are reported on in this presentation:

- 1) Application of the Adaline and the Least-Mean-Square (LMS) algorithm as a system identifier.
  
- 2) A layered neural network used for character recognition
  
- 3) A neural network used as an adaptive controller for an antenna array -- allows on-line control of the array's radiation pattern.

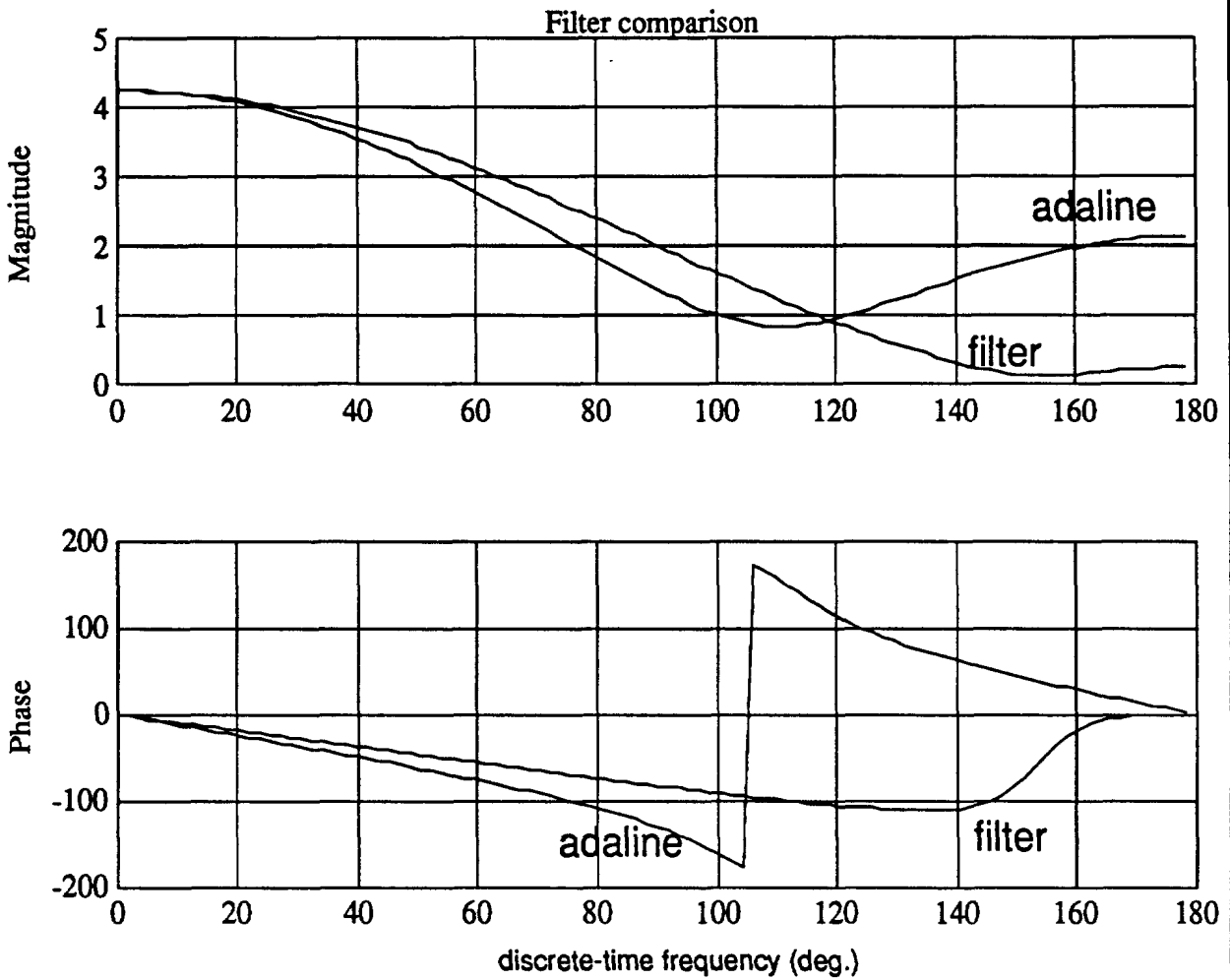
### The ADALINE as a system identifier

Aim: Focus on the behaviour of the LMS algorithm when used to identify a known system.

LMS: 
$$\vec{W}_{k+1} = \vec{W}_k + 2 \mu e_k \vec{X}_k$$



## Filter identification



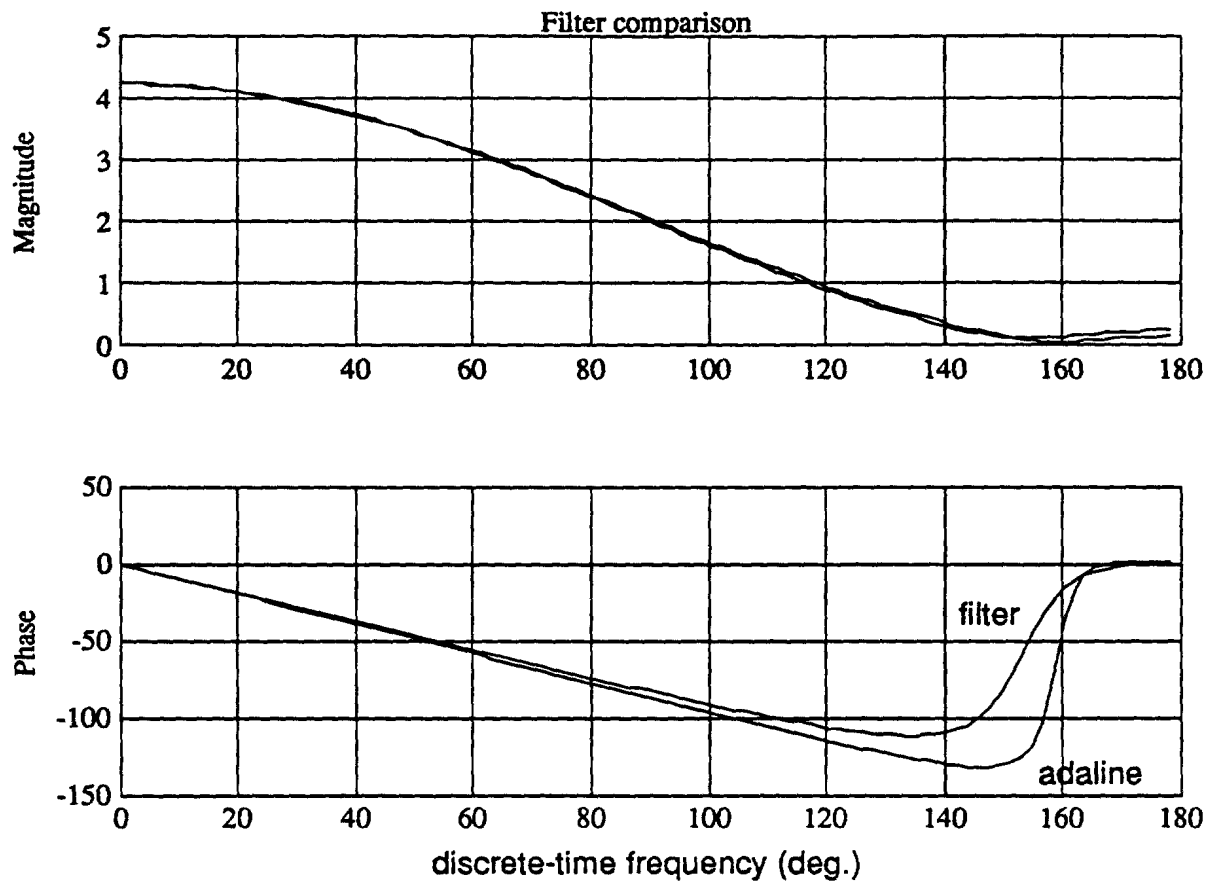
adaline order: 3

startup weight vector: 1, 1.9., 0.9

test signal:  $x = \exp(-0.1 t)$

$\mu=0.01$

## Filter identification



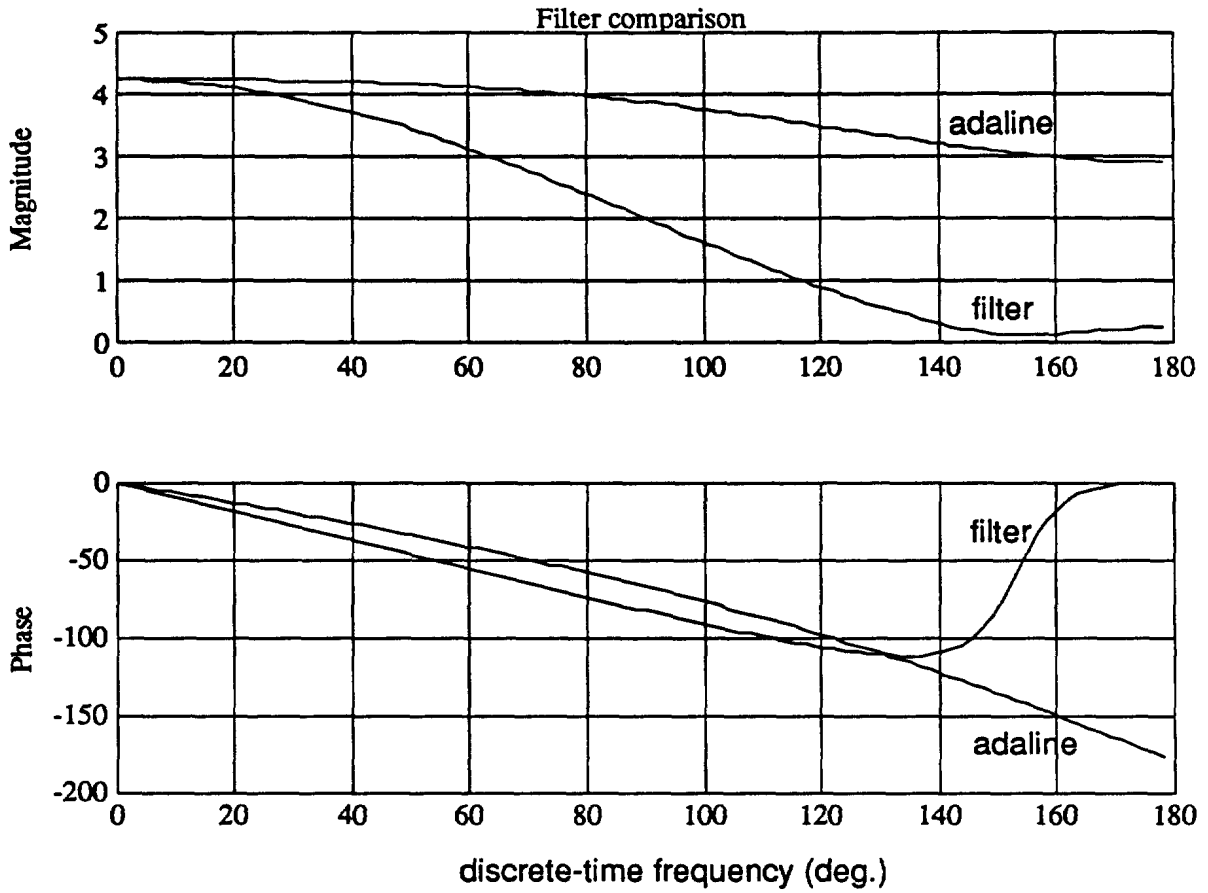
adaline order: 3

startup weight vector: 1, 1.9., 0.9

test signal:  $x = \exp(-0.1 t)$

$\mu=0.01$

## Filter identification



adaline order: 3

startup weight vector: .5, 3, -1

test signal:  $x = \exp(-0.1 t)$

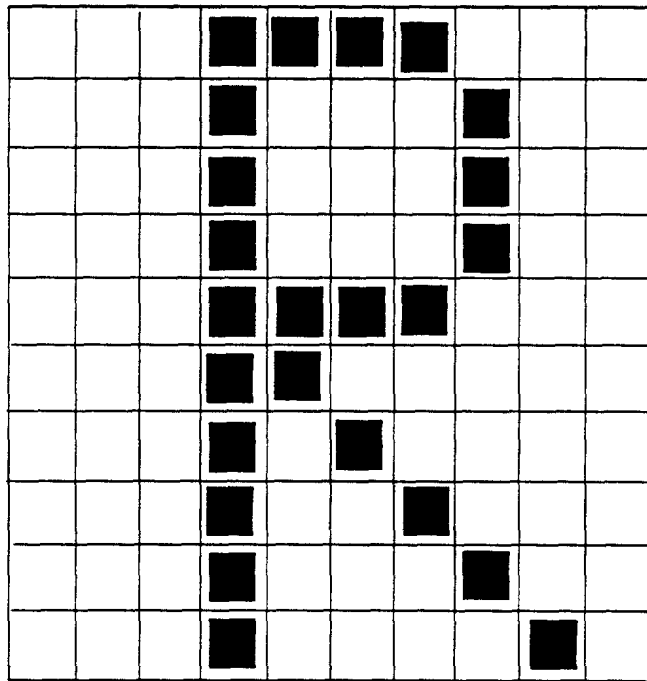
$\mu=0.01$

## Character Recognition with a neural network

Aim: Use the neural network as pattern classifier

Structure: 1) single adaline with sigmoid function

2) layered neural network



pixel values are binary:

+1 and 0      or      +1 and -1

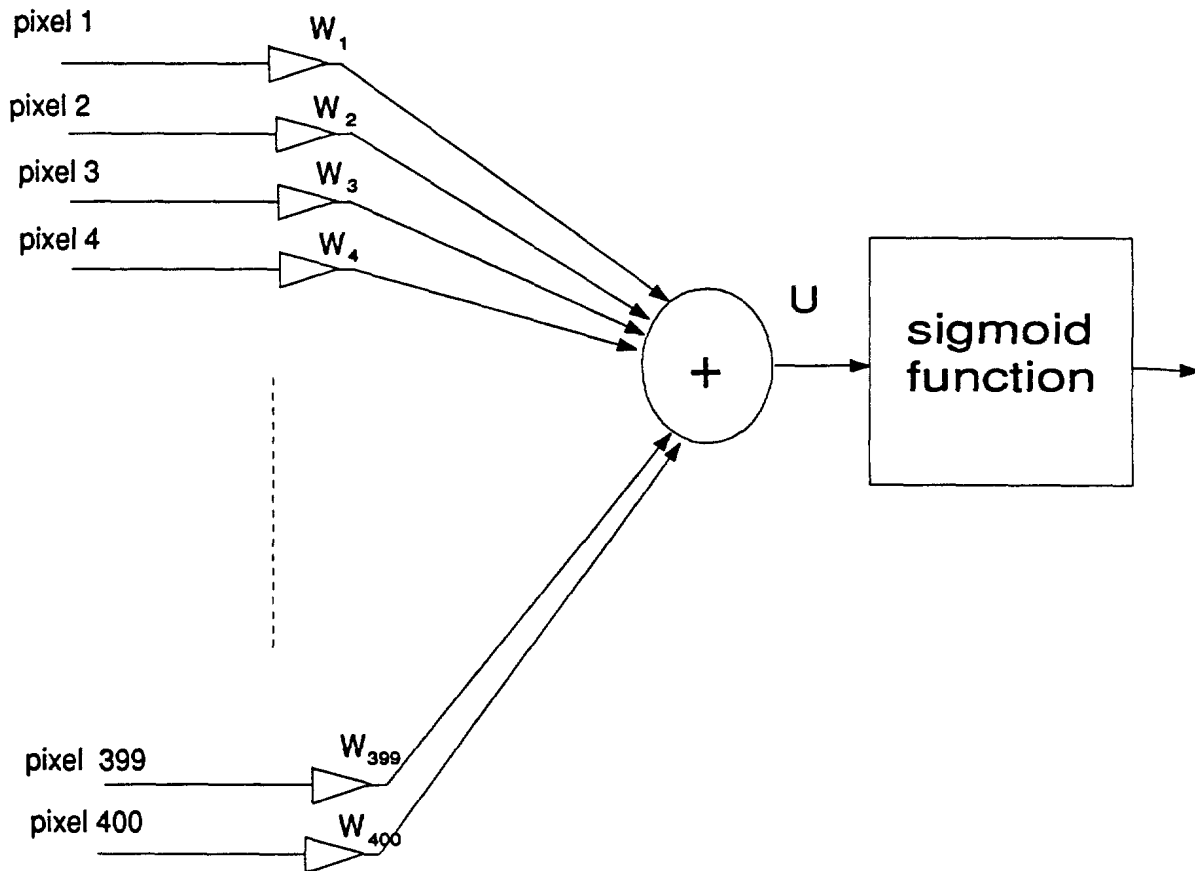
## Character Recognition with a neural network

1) single adaline:

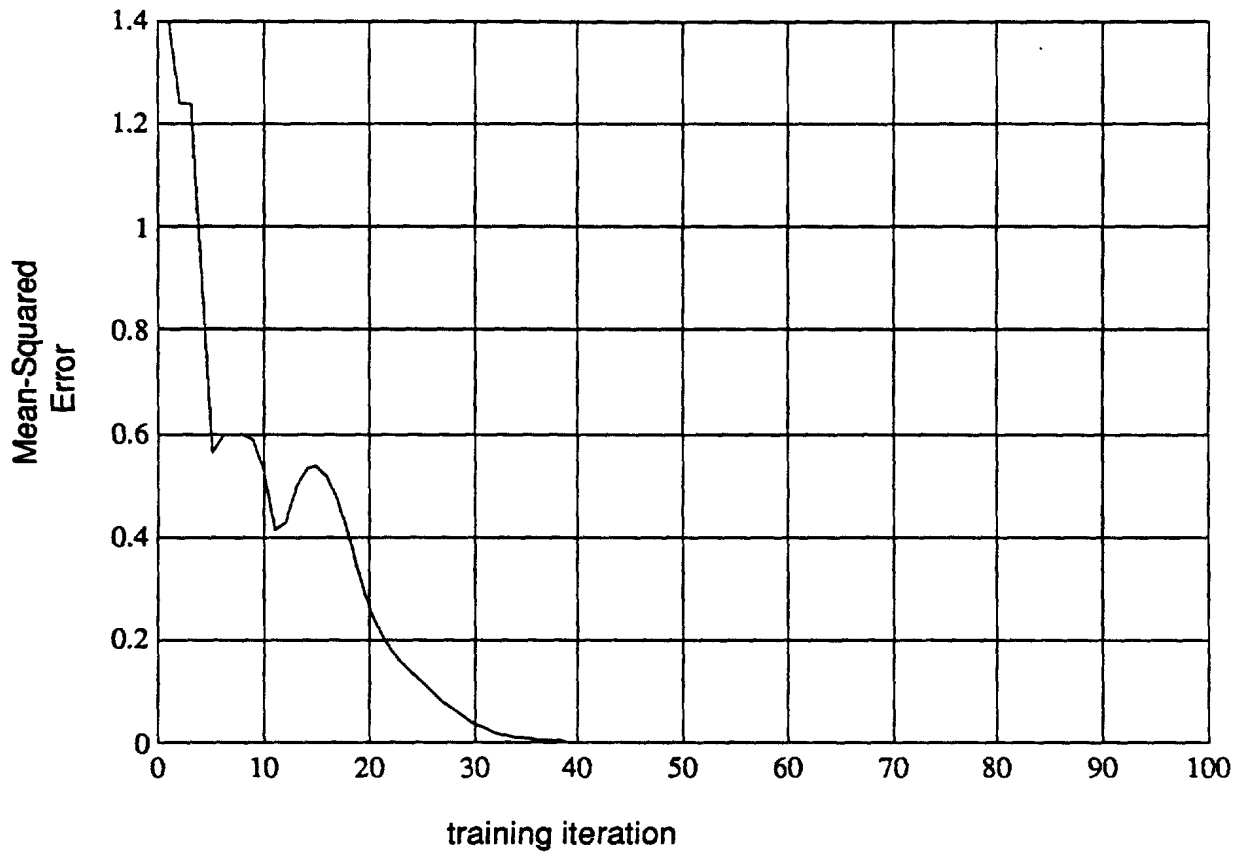
grid: 20 X 20

algorithm: LMS

sigmoid function:  $\tanh(u)$  or  $1 / (1 + \exp(-u))$



## Character Recognition



## Pattern Match

char #	target	adaline out	error(target-adaline)
1 ( C )	0.2000	0.1974	0.0026
2 ( R )	0.4000	0.3799	0.0201
3 ( D )	0.0000	-0.0000	0.0000
4 ( V )	-0.2000	-0.1974	-0.0026
5 ( E )	-0.4000	-0.3799	-0.0201

mu=0.001

MSE : 0.000164

sigmoid function: tanh(u)