بسم الله الرحمن الرحيم

شبكة المعلومات الجامعية

التوثيق الالكتروني والميكروفيلم

شبكة المعلومات الجامعية

جامعة عين شمس

التوثيق الالكتروني والميكروفيلم

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بالرسالة صفحات

لم ترد بالاصل

Menoufia University
Faculty of Electronic Engineering
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SHAPES RECOGNITION WITH NEURAL NETWORKS

A THESIS

Submitted for the Partial Fulfillment for the Degree of

MASTER OF SCIENCE

BY

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ARABIC SUMMARY ....

SUMMARY

In real-word applications, training data are not always complete. Some of these data may be incomplete or missing and others may be uncertain or ambiguous. First of all, one of the simplest and most realistic manners for representing incomplete or missing data is the interval representation, this means that the inputs are given by intervals instead of real numbers. Two approaches have been proposed before in [3], [13] to solve such problems. In the first approach [3], an architecture of interval neural networks and a learning algorithm as an extension of standard BP(Back-Propagation) algorithm have been proposed. However, in [3], a very complicated cost function was used in the learning algorithm, and the algorithm was applied only to the disjoint classes, and it had not been tested using overlapping classes. In this work, we have implemented the same algorithm of [3] for interval inputs, but using a simple cost function, very similar to that used in the standard BP algorithm [1, 2]. Using such simple cost function, we have obtained the same results as in [3]. Moreover, we have tested the developed algorithm using overlapping classes, and the testing results indicated that the algorithm is useful only for disjoint classes and it is not good for overlapping classes. In the second approach [13], a neural networks, that can utilize, the expert knowledge represented by fuzzy if-then rules as well as the numerical data, in the learning have been proposed. Although the proposed algorithm in [13] was dealing mainly with fuzzy numbers as inputs, the most important parts of fuzzy set theorem, resolution principle using α-cuts and the extension principle were not mentioned or studied in [13]. Moreover, the α-cuts were not introduced in the developed algorithm of [13]. Thus, in the present work, in the second approach, we have developed using the same algorithm in [13], we have studied in details, the concepts of α-cuts, resolution principle and the extension principle. On the other hand, we introduce α-cuts explicitly in our implementation. The testing results indicated that the α-cuts have a great influence on the output separation regions. Testing results indicated also that the developed algorithm has a very good classification capability for separating the overlapping fuzzy input data.

CHAPTER 1

INTRODUCTION

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INTRODUCTION

1.1 Introduction

Recently, interest in neural computation has been growing exponentially, since neural networks hold the promise of solving problems that proven to be extremely difficult for traditional digital computers. Not only neural networks are parallel computing devices and therefore fast, but also they are cable of learning by example.

One of the most significant development in the area of neural networks is the backpropagation (BP) learning algorithm [1, 2]. Its ability to fit complex, high-dimensional functions on the basis of simple training data has led to it being applied to a wide variety of problems in several areas including classification systems. The BP algorithm provides an easy and elegant way to train neural networks. It is mainly an iterative gradient algorithm designed to minimize the mean-squared error between the desired output and the actual output for a particular input to the network. Despite of the fact that the BP algorithm has been used as the learning algorithm successfully in many applications, there are two issues of concern need to be solved. The first is the possibility of being trapped at a local minimum in training. The second, the convergence rate is typically too slow even if learning can be achieved. A very long time is required to train large sized network structures and data sets. So, to overcome this problem, interval neural networks had been proposed in [3]. These interval neural networks in the present work are characterized by interval input vectors and interval output vectors. This means that the input and output data are given by intervals instead of real numbers.

1.2 Pattern Recognition

Pattern recognition is a search for structure in data, so the pattern recognition algorithms are often classified as either parametric or non-parametric [38]. For some classification tasks, pattern categories are known a priori to be characterized by a set of parameters. A parametric approach is to define the discriminant function by a class of probability densities defined by a relatively small number of parameters.

1.2.1 Configuration of the Pattern Recognition System

1.2.1.1 Tree phases in pattern recognition

In pattern recognition, we can divide an entire task into three phases: data acquisition, data preprocessing, and decision classification, as shown in Figure 1.1.

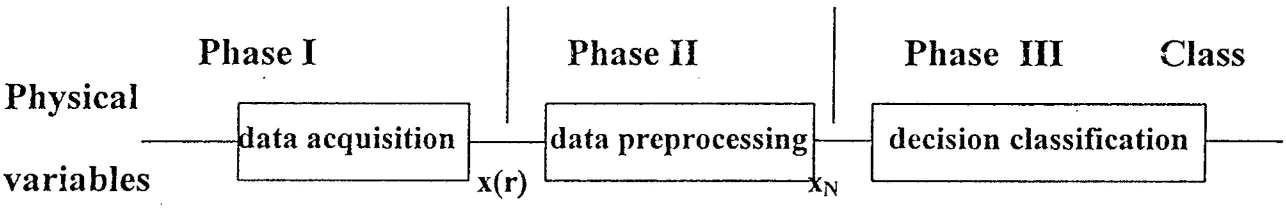

Figure 1.1: Conceptual representation of a pattern recognition problem

In the data acquisition phase, analog data from the physical world are gathered through a transducer and converted to digital format suitable for computer processing. In this stage, the physical variables are converted into a set of measured data, indicated in the Figure by electric signals, x(r), if the physical variables are sound (or light intensity) and the transducer is a microphone (or photocells). The measured data are then used as the input to the second phase (data preprocessing) and grouped into a set of characteristic feature (x_N) as output. The third phase is actually a classifier which is in the form of a set of decision functions. With this set of features (x_N) the object may be classified. Figure 1.2 is a schematic diagram of an actual aerial multispectral scanner and data analysis system. The set of [illegible]a at B, C, and D are in the pattern space, feature space, and classification space, respectively.

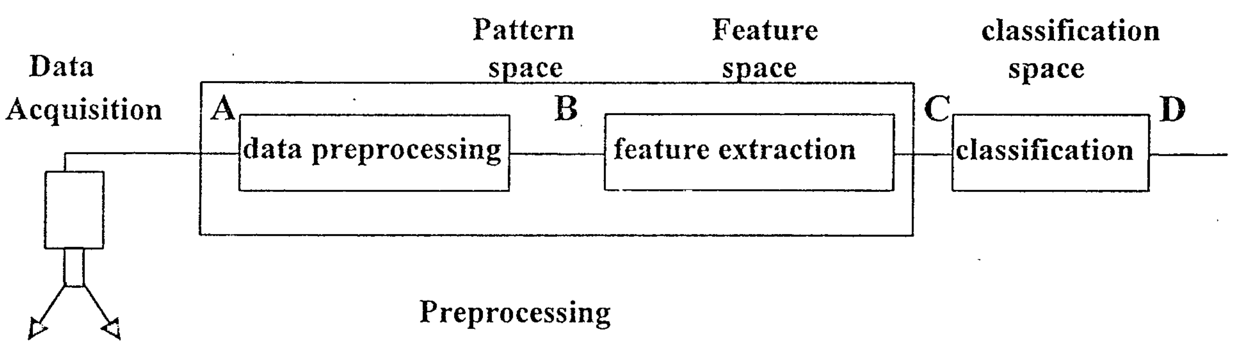

Figure 1.2: multispectral scanner and data analysis system [38]

1.3 Comparison between neural networks classifier and other conventional classifiers:

It useful to compare the similarities and difference between the classification using neural networks (NNs) and other classifiers. Multi-layer perceptron (MLP) classifiers with continuous valued inputs and trained with the backpropagation algorithm can perform as well as and some better than conventional classifiers as Bayesian calssifier, quadratic Gaussion classifier and K-nearest neighbor (K-NN) classifier see [39]. From the results of experiments in [39], the MLP classifier using BP algorithm for training NNs, the convergence time and also the percentage error rate are less than other conventional classifiers. Moreover the performance of MLP classifier is the best than other conventional classifiers.

1.4 Training data in neural networks

The neural networks model is capable of handling a real numbers of input features presented in quantitative form, where an input feature is either present or absent and each pattern belongs to either one class or another. They do not consider cases where an input feature may possess a property with a certain degree of confidence, or where a pattern may belong to more than one class with a finite degree of "belongingness". But in real-world applications, training data are not always complete. Some oh these data may be incomplete or missing and others may be uncertain or ambiguous. So, the simplest and most realistic manners for representing incomplete or missing data is the interval representation, this mean that the input features are given by intervals instead of real numbers. So, for handling interval data in neural networks, the backpropagation algorithm in [1, 2], was extended to the case of interval input vectors [3]. In conventional classification problems, all input values of each sample are completely known and represented by a real vector. In many applications tasks of neural networks, the ability to deal with missing or uncertain input is crucial [4]. The interval neural networks have the highest fitting ability for training data and the highest generalization ability to new interval input vector.