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شبكة المعلومات الجامعية التوثيق الالكتروني والميكروفيلم





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قسو

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شبكة المعلومات الحامعية



بالرسالة صفحات لم ترد بالأصل



FACULTY OF ENGINEERING ALEXANDRIA UNIVERSITY

IMPROVING THE STATISTICAL PARAMETRIC GAUSSIAN CLASSIFIER USING NEURAL NETWORKS

A thesis submitted to the

Department of Computer Science and Automatic Control in partial fulfillment of the requirements for the degree of

Master of Science

By

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To My Beloved Parents and Sisters

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PREFACE

The statistical approach to pattern recognition is among the early approaches applied in this field of research. Parametric statistical classifiers design techniques have been extensively studied, in general, and Gaussian classifiers, in particular, due to its analytical tractability [10]. However, some assumptions inherent in the design of the Gaussian classifier result in suboptimal classifier [9].

Recently [33], it was demonstrated, both theoretically and experimentally, that a neural network pattern classifier generates the empirical distribution of the sample data which are used to train the network. This thesis takes advantage of this fact and improves a Gaussian classifier using an isomorphic sigma-pi neural network [9].

This study contains four chapters, and three appendices. Their contents are as follows:

<u>Chapter I:</u> Presents different approaches to pattern recognition. Special attention is given to classifiers designed using the decision theoretic approach such as neural networks classifiers and traditional statistical classifiers. Both of these classifiers are discussed in more detail.

Chapter II: Presents the main drawbacks of the basic parametric Gaussian classifier and a method for mapping it to a Gaussian isomorphic neural network (GIN) and mapping the GIN back to a Gaussian classifier. Backpropagation learning is reviewed and a modification is suggested to overcome network paralysis. The algorithms used in classification are stated along with their data structures, storage and time complexities.

Chapter III: The hybrid statistical neural network classifier proposed in chapter II is tested using a generated multivariate normal distributed data and two well known data sets (The Fisher's iris data and the british towns data). Also, a detailed design of a sonar target recognition system is presented including a review on sonar, data acquisition, feature extraction and results.

<u>Chapter IV:</u> Concludes the present work and discusses some possible directions for future research work.

Appendix A: Presents the Gaussian elimination algorithm for evaluating the determinant and the inverse of a matrix. Also, unstable or ill-conditioned systems are discussed.

<u>Appendix</u> <u>B:</u> Presents Linear prediction and a special attention is given to the all-pole model.

Appendix C: Lists of Fisher's iris data, british towns data and sonar data are given.

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