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AN ENHANCED MODEL FOR USING ELECTROCARDIOGRAM (ECG) SIGNALS AS HUMAN BIOMETRIC

THESIS

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بسم الله الرحمن الرحيم

﴿ المحد الله الذي محانا المذا و ما كنا لنمتدي لولا أن محانا الله ﴾
حدي الله العظيم

جزء من الآية (٤٣) - سورة الأعراف

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DEDICATION

I would like to dedicate this thesis to my mother, my father, my sisters and my brothers who provide me with love, care and support.

PUBLISHED WORK

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- Anwar E.Ibrahim, Salah Abdel-Mageid, Nadra Nada, Marwa A. Elshahed, " ECG Signals for Human Identification Based on Fiducial and Non-Fiducial Approaches", International Journal of Advanced Computer Research (IJACR), (accepted).

ABSTRACT

Biometrics is an interesting study due to the amazing progress in security technology and defined as a method of recognizing humans based on a physiological characteristics (as *ECG. etc...*) face. fingerprints, DNA. behavioral or characteristics (as voice, gait, keystroke, signature, etc...). The term biometrics comes from the Greek words 'bio' (life) and 'metrics' (measurement), so biometrics means life measurement. Electrocardiogram (ECG) signal analysis is an active research area for diagnoses which is a method to measure the change in electrical potential of the heart over time. This work investigates in ECG signals as a biometric trait which based on uniqueness represented by physiological and geometrical of ECG signal. Biometric systems based ECG classified into two categories fiducial and non-fiducial approaches depend on the feature extraction methods.

In this work, a proposed non-fiducial identification system is presented with a comparative study using Radial Basis Function (RBF) neural network, Back Propagation (BP) neural network and Support Vector Machine (SVM) as classification methods. The Discrete Wavelet Transform method is applied to

extract features from the ECG signal. Two datasets are used in this work (ECG-ID and MIT-BIH) databases. The experimental results show that using RBF neural network gives higher identification rate than other used classifiers. Also, the system accuracy by using the neural network as a classifier is better than that using the support vector machine for the first and the second datasets. The obtained results show that decreasing the number of subjects the system performance using SVM is improved. Furthermore, integrating the two classifiers RBF and BP achieves a higher human identification rate.

Also, we present an ECG human identification system with different feature extraction methods as Daubechies wavelets ('db3', 'db8' and 'db10'), Symlets wavelet 'sym7' and Biorthogonal wavelet 'bior2.6'. A combination of RBF and BP neural network is used as a classifier compared with SVM. The experimental results show that using Daubechies wavelet 'db8' achieves the higher identification rate than the others used methods with the combined classifier. The proposed system performance is improved by adding fiducial features (R-R intervals) to the used non-fiducial features.

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LIST OF ABBREVIATION

ECG Electrocardiogram

EEG Electroencephalogram

PPG phonocardiogram

BVP Blood Volume Pressure

FAR False Acceptance Rate

FRR False Rejection Rate

RBF Radial Basis Function neural network

BP Back Propagation neural network

SVM Support Vector Machine

DWT Discrete Wavelet Transform

PCA Principle Component Analysis

LDA Linear Discriminant Analysis

WPD Wavelet Packet Decomposition

LPC Linear Predictive Coding

TM Template Matching

FFT Fast Fourier Transform

AC Autocorrelation

Chapter One

INTRODUCTION