



**EVALUATION OF MULTIMODAL SENSORS FOR
CLASSIFICATION OF PARKINSON'S DISEASE
WITH SEVERITY LEVELS**

by

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LIST OF ABBREVIATIONS

PD	Parkinson Disease
WHO	World Health Organization
PWP	Patients with Parkinson
PDI	Peripheral Decarboxylase Inhibitor
EEG	Electroencephalogram
EMG	Electromyogram
UPDRS	Unified Parkinson's Disease Rating Scale
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
IMU	Inertial Measurement Unit
ADL	Activities of Daily Living
ANS	Autonomous Nervous System
CNS	Central Nervous System
CR	Crossing Rate
KLT	Karhunen-Loeve Transform
DNN	Dynamic Neural Network
DFT	Discrete Fourier Transform
PCA	Principal Component Analysis
MLBP	Multi-layer Back Propagation
PET	Positron Emission Tomography
SPECT	Single-photon Emission Computed Tomography
VBM	voxel-based morphometry
MOCAP	Multimodal Motion Capture
FFT	Fast Fourier Transform
LID	Levodopa-induced dyskinesia
MLP	Multilayer Perceptron
MIL	Multiple Instances Learning
APR	Axis-parallel Hyper-rectangle
NTP	Network Time Protocol
StSi	Stand-Sit
SiSt	Sit-Stand
MLP-NN	Multilayer Perceptron Neural Network
LM	Levenberg-Marquardt
SCG	Scaled Conjugate Gradient

ET	Essential Tremor
FoG	Freezing of Gait
LASSO	Bayesian Least Absolute Shrinkage and Selection Operator
MNB	MotionNode Bus
STFT	Short-Time Fourier Transform
DWT	Discrete Wavelet Transform
WPT	Wavelet Packet Transform
HHT	Hilbert-Huang Transform
EMD	Empirical mode decomposition
EWT	Empirical Wavelet Transform
EWPT	Empirical Wavelet Packet Transform
FFT	Fast Fourier Transform
HT	Hilbert Transform
IA	Instantaneous Amplitude
IF	Instantaneous Frequency
HOS	Higher Order Spectra
KNN	k -nearest Neighbour
PNN	Probabilistic Neural Network
ELM	Extreme Learning Machine
RBF	Radial Basis Function
ANOVA	Analysis of Variance
MMSE	Mini-Mental State Examination
BDI	Beck Depression Inventory
GUI	Graphical User Interface
DFB	Discrimination-function-based
RF	Random Forests
fKNN	Fuzzy K-Nearest Neighbour
SVM	Support Vector Machine
ANN	Artificial Neural Network
ShWe	Shannon wavelet entropy
ReWe	Renyi wavelet entropy
TsWe	Tsallis wavelet entropy

LIST OF SYMBOLS

Ω	Non redundant region
L	Number of points within the region
ϕ	Phase angle of the bispectrum
j	Decomposition level
N	Length of the analysis window
E_i	Energy of i -th sub-band signal
K	Total number of sub-band signals
α	Non-extensity index
d	Embedded dimension
τ	Time lag
l	Length of sequence to be compared
w	Width of fuzzy boundary of the exponential function
g	Gradient of fuzzy boundary of the exponential function
$B_i(f_1, f_2)$	Bispectrum in the bifrequency (f_1, f_2)
$*$	Complex conjugate
η	Spread factor
k	Number of neighbours
$\%$	Percentage
F -value	Critical value for the F-distribution
p -value	Probability of obtaining test statistical results
\pm	Plus minus
N	Number of participants

Penilaian Multimodal Sensor Untuk Klasifikasi Tahap Keterukan Penyakit Parkinson

ABSTRAK

Penyakit Parkinson (PD) adalah sejenis gangguan progresif neurodegeneratif yang telah menjejaskan sebahagian besar populasi. Beberapa gejala PD termasuk gegaran, ketegaran, kelambatan pergerakan dan gangguan suara. Baru-baru ini, evolusi pelbagai alat untuk memantau PD telah merangsang minat penyelidik, yang membawa kepada kemungkinan untuk menggunakan teknologi yang dapat diguna pakai bagi membantu memantau keadaan pesakit dengan Parkinson (PWP) dan menghasilkan maklum balas klinikal yang berguna. Terdapat pelbagai inisiatif daripada penyelidik untuk mengesan PD, termasuk menggunakan (1) Protokol pengambilan data bukan isyarat iaitu diari pesakit, laporan, skala penarafan klinikal dan modaliti pengimejan atau melalui (2) teknik analisis isyarat iaitu isyarat bioelektrik (Isyarat EMG dan isyarat EEG); Isyarat data gerakan melalui sensor gerakan boleh pakai dan (4) Isyarat ucapan melalui sensor audio. Di antara semua inisiatif, mengesan perkembangan PD menggunakan sensor gerakan yang boleh pakai dan sensor audio, telah menimbulkan perhatian yang ketara oleh penyelidik disebabkan oleh potensinya yang sangat besar. Namun, kekuatan algoritma pemrosesan isyarat dan pengelasan isyarat adalah terhad terutamanya maklumat yang diperolehi daripada sensor gerakan yang boleh dipakai untuk mengelaskan PWP dengan tahap keterukan yang berbeza. Untuk isyarat ucapan, pelbagai kerja untuk membezakan PWP dan subjek sihat telah dijalankan, tetapi penyelidikan yang terhad ditumpukan pada pengelasan multi-kelas PD, dimana kebanyakan kerja terdahulu dijalankan berdasarkan klasifikasi binari, dengan peringkat awal dan akhir PD diperakukan secara sama rata. Oleh itu, dalam kajian ini, sistem pengiktirafan berdasarkan maklumat daripada sensor gerakan dapat dipakai dan sensor audio sebagai biomarker dicadangkan untuk pengesanan awalan PD dengan keupayaan klasifikasi multikelas. Tiga kelas tahap keterukan PD diambilkira - 'ringan', 'sederhana' dan 'teruk' daripada subjek sihat untuk memberikan hasil klasifikasi yang lebih penting untuk kegunaan klinikal. Pertama, isyarat daripada sensor gerakan yang boleh pakai dan sensor audio dihurai menggunakan transformasi yang dicadangkan iaitu transformasi wavelet empirikal (EWT) dan transformasi wavelet packet empirikal (EWPT). Seterusnya, beberapa ciri-ciri diekstrak daripada pekali isyarat yang telah dihurai. Prestasi algoritma dianalisis dengan menggunakan tiga klasifikasi - K-nearest neighbour (KNN), probabilistic neural network (PNN) and extreme learning machine (ELM). Pengesanan pendekatan yang dicadang menunjukkan keberkesanan tenaga wavelet, ciri berasaskan entropi dan Higher order Spectra (HOS) daripada penguraian EWT/EWPT untuk multi-kelas klasifikasi tahap keterukan PD dengan ketepatan purata tertinggi 96.95% daripada ELM RBF. Akhir sekali, sistem penyaringan yang bukan invasif untuk mengesan tahap keterukan PD telah dibangunkan menggunakan Matlab Graphical User Interface (GUI) Toolbox. Sistem GUI diharapkan dapat memudahkan para profesional perubatan untuk memantau perkembangan PD.

Evaluation of Multimodal Sensors for Classification of Parkinson's Disease with Severity Levels

ABSTRACT

Parkinson's disease (PD) is a progressive neurodegenerative disorder that has affected a large part of the population. Several symptoms of PD include tremor, rigidity, slowness of movements and vocal impairments. Recently, the evolution of numerous tools for monitoring PD has stimulated the interest of researchers, leading to the possibility of utilising wearable technology to assist in monitoring patient with Parkinson (PWP) state and generate valuable clinical feedback. There have been various initiatives from researchers for PD detection, which includes using (1) Non-signal data acquisition protocols i.e. patients' diaries, self-reports, clinical rating scales and imaging modalities or through (2) Signal analysis techniques i.e. Bioelectrical signals (EMG signals and EEG signals), motion data signals via wearable motion sensors and speech signals via audio sensor. Among all the initiatives, detecting PD progression using wearable motion sensors and audio sensor has raised significant attention by researchers due to its enormous potentials. However, current signal processing and classification algorithms have limited capability and performance especially involving information obtained from wearable motion sensors for classification of PWP with different severity levels. Additionally, even though there were many works for distinguishing PWP and healthy controls via audio sensor, there are limited researches focusing on multiclass classification of PD. Most of the previous works were conducted based on a binary classification, resulting in early PD stage and the advanced ones being treated equally. Therefore, in this research, a recognition system based on wearable motion sensors and audio sensor information as biomarkers for initial PD detection with the ability for multiclass classification was developed. Three classes of PD severity levels were considered – 'mild', 'moderate' and 'severe' from healthy controls to give the classification results more accurate for clinical use. First, the signals from wearable motion sensors and audio sensor were decomposed by the proposed algorithms known as empirical wavelet transform (EWT) and empirical wavelet packet transform (EWPT) respectively. Then, several features were extracted from the coefficients of all decomposed signals. The performance of the algorithm was validated using three classifiers – K-nearest neighbour (KNN), probabilistic neural network (PNN) and extreme learning machine (ELM). Validation of the proposed algorithms demonstrated the effectiveness of wavelet energy, entropy-based and Higher Order Spectra (HOS) - based features from the EWT/ EWPT decomposition for multiclass PD severity levels classification with the highest average accuracy of 96.95% from ELM RBF kernel classifier. Finally, a non-invasive screening system using the proposed algorithm for detection of PD severity levels was also developed using Matlab Graphical User Interface (GUI) Toolbox. It is hoped, the GUI system eases medical professionals to monitor the progression of PD.

CHAPTER 1 : INTRODUCTION

1.1 Introduction

This chapter presents an introduction to Parkinson Disease (PD), discussion on conventional techniques used for the detection of PD, limitations of existing techniques and the significance of this research work. The main objective of the research work and the organization of the thesis are also elaborated in the subsequent sections.

1.2 Research Background

In the past decades, quantitative observation of human motor mechanisms and movement disability has been an active research field evolving from large ubiquitous computer technologies, context-aware computing to solid-state micro sensors and telecommunication due to the advancement in sensor technologies. There are number of beneficial applications, such as human daily activity recognition pattern/behaviour discovery, healthcare monitoring, elderly care management and human-computer interaction. In principle, the applications provide great public benefits linked to human real life, with much attention-grabbing advances towards healthcare technologies management of patients affected by chronic diseases (Casale, Pujol, & Radeva, 2011; Choudhury et al., 2008; Kim, Helal, & Cook, 2010).

The accessibility of advanced sensor technologies has also provided healthcare industry the ability to measure human motor performance in great details and with good precision, for examples physiological monitoring in diagnosis of individuals with neurological diseases and human home-base sensing for assistance in falls prevention. Another promising application is the development and deployment of wearable systems for investigating various pathologies of human motor performance and patient's remote monitoring, which will greatly enhance the capabilities of healthcare system. (Patel, Park, Bonato, Chan, & Rodgers, 2012).

According to World Health Organization (WHO), Malaysia has been driven by remarkable improvements in term of health, extended life expectancy, lower mortality rate and falling of fertility rate resembling other developing countries (Mafauzy, 2000). The declined in fertility rate and improvement in health and longevity has brought fluctuations in the demographic profile of its population due to improvement in medical care and better living conditions. The expansion of life expectancy cause the elderly population to grow faster, which is one of the primary concerns of medical and health practitioners. The older generations are generally less healthy than the younger ones, with addition to physical and social changes, hence leading to a growing number of individuals affected by numerous types of acute and chronic diseases, such as neurological diseases. (Durrani, 2016; Organization, 2011; Sim, 2001).

Parkinson disease (PD) is ranked in second place for the most common chronic progressive neurodegenerative disorder in the world after Alzheimer's disease, which affected approximately 3% of world populations above 65 years (Tanner & Goldman, 1996). Based on the statistic by the WHO, it was predicted that 7 to 10 million

individuals worldwide are living with PD up to now. In the next 25 years, this number is estimated to increase worldwide due to the rising proportion of elderly people in the population. The occurrence of PD upsurges with age and the syndrome rate rises sharply after age of 60 (Goodman, 1996; Patel et al., 2006). These scenarios pose a significant public health challenge as age is the leading key risk feature for the onset of PD. It is important to note that, PD has greater influences in North America and Europe countries compared to Africa or Asian countries and men are 1.5 times more likely to have PD compared to women. In Malaysia, based on the Malaysian PD Foundation 2018 report, the total number of patients with Parkinson (PWP) were approximately 15000 to 20000 and this number is expected to rise. Hence, it is important for PD management approaches aimed at early detection and treatment so as to improve the quality of life for Patients with Parkinson (PWP) (Aarli, Dua, Janca, & Muscetta, 2006; Stroke & Health, 2014).

1.3 Problem Statement

With the latest improvement in healthcare technology, techniques for PD assessment are relatively restricted. At present, PWP assessment can be accomplished through 2 main approaches, either through non-signal protocols or signals analysis techniques. Among them, detecting PD progression using motion data and speech signals has stimulated the attention of numerous researchers as slowness in movement, involuntary/shaking movements, postural instability and speech impairment were the most common presenting PD symptoms (Almeida et al., 2019; Braga, Madureira, Coelho, & Ajith, 2019; Lonini et al., 2018; Pardoel, Kofman, Nantel, & Lemaire, 2019; Vaiciukynas, Verikas, Gelzinis, & Bacauskiene, 2017).

Wearable motion sensors have been generally proposed for the assessment of PWP daily life activities and changes in PD symptoms/motor complications, using uni-modal or bi-modal sensor such as accelerometer, gyroscope and magnetometer sensor. These sensors have turned out to be miniature, robust, totally unobstructive in facilitating PD assessment (LeMoyne, Mastroianni, & Grundfest, 2013; Matteo Pastorino et al., 2011; Patel et al., 2012; Salarian, Russmann, Vingerhoets, Burkhard, & Aminian, 2007; Zabaleta, Keller, & Fimbel, 2008). However, current research on the wearable sensor platform do not focus much on combination of multiple wearable sensors for assessment of PD. At the same time, the strength of present signal processing and classification algorithms was not evaluated on information obtained from the wearable motion sensors for classification of PWP with different severity levels from healthy controls. (M B ählin et al., 2010; H. L. Chen et al., 2013; Pastor-Sanz, Cancela, Waldmeyer, Pansera, & Pastorino, 2011; Patel et al., 2010).

While for speech signals via audio sensor, research also shown that speech signal is a useful biomarker for PD assessment based on the sources of medical indication that speech impairment is one of the initial indications of the onset of PD, with approximately 90% of PWP show speech impairments. Although the fact that there have been various studies involving the application of speech signals for distinguishing PWP and healthy controls, there is still vagueness in different developmental stages conducted for speech analysis that emphasis on multiclass classification of PD severity levels. Most of the previous studies were conducted based on a binary classification (PD vs non-PD), resulting in early PD stage and the advanced stages being treated equally (Alemami & Almazaydeh, 2014; H. L. Chen et al., 2013; Tsanas, 2012; Tsanas, Little, Fox, & Ramig, 2014).

Additionally, integration of data from more than one sensor has the potential to provide more reliable information for assessments of PWP, and it is expected to provide a significant progress for continuously supervising the PWP's. This has increased substantial attention of looking for a statistical mapping between speech properties and application of wearable motion sensors, on the basis of clinical indication, suggesting that the earliest PD symptoms in the vast majority of PWP are slowness (82.4%), tremor (82%), difficulty in walking (77.1%) and speech difficulty (84%). The combination of wearable motion sensors (accelerometer, gyroscope and magnetometer) forms an inertial measurement unit (IMU) that can provides quick, accurate position and orientation determination with a low amount of drift over time. While, speech signal recording via audio sensor is regarded as one of the easiest and non-invasive solutions, which is an essential advantage of introducing it as one of the notable biomarkers for detection of PD.

Hence, in this study, the attention is made on proposing a recognition system with the combination of wearable motion sensors (motion data signals) and audio sensor (speech signals) information as biomarkers for PD assessment, which is ability to perform multiclass classification i.e. differentiating between PD severity levels (mild, moderate and severe) from healthy controls.

1.4 Research Objectives

This research aims to develop a recognition system for differentiating PD severity levels (i.e. mild, moderate and severe). For successful implementation of the PD recognition, the following objectives were outlined for this research.