

**EEG SIGNAL CLASSIFICATION USING FUZZY-ROUGH NEAREST
NEIGHBOURS (FRNN) MODEL FOR PERSON AUTHENTICATION**

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DECLARATION

I hereby declare that this project report entitled
**EEG SIGNAL CLASSIFICATION USING FUZZY-ROUGH NEAREST
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is written by me and is my own effort and that no part has been plagiarized
without citations.

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SUPERVISOR : _____ Date: _____
(DR. CHOO YUN HUOY)

DEDICATION

To my beloved parents, Mr. Liew Ted Kion and Mrs. Lee Chiu Lin, your love and support are my greatest inspiration upon accomplish this project.

To my dearest supervisor, Dr. Choo Yun Huoy for being responsible, receptive and always by my side to encourage and motivate me.

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ABSTRACT

EEG signals especially Visual Evoked Potential (VEP) is unique but highly uncertain and difficult to process. Thus, identify the appropriate feature vector and prediction model are essential to implement this modality for person authentication purposes. The research on analyzing VEP for person authentication using soft computing modeling is very limited and hardly emphasizes on uncertainty methods even though uncertainty modeling has been proven efficient in many other domains. Fuzzy-Rough Nearest Neighbours (FRNN) model is outstanding to model uncertainty in element belongings under an imperfect data condition. This advantage is vital for person authentication modeling using VEP, but there is a lack of research work focusing in this direction. Hence, the objectives of this project are to identify the VEP active electrodes and significant feature vectors for authentication modeling, and to evaluate the performance of the proposed Fuzzy-Rough Nearest Neighbours (FRNN) model for person authentication classification. This project followed the experimental methodology including the preliminary studies, data preparation, EEG signals feature extraction, experimentation and result analysis. Mean, cross-correlation and coherence are the feature vectors that extracted from the lateral and midline electrodes. The classification results of FRNN using implicator and t-norm were promising against its comparison techniques of D-kNN and FLR especially in the measurement of AUC. Nevertheless, feature selection is suggested in the future work to minimize the dimension of data in order to achieve a better generalized feature space in the authentication framework.

ABSTRAK

Visual Evoked Potential (VEP) yang terdapat dalam isyarat EEG adalah unik tetapi sentiasa berubah dan sukar untuk diproses. Oleh itu, pengenalpastian ciri-ciri vektor yang sesuai adalah sangat penting untuk tujuan pengesanan orang. Analisis VEP yang menggunakan model “soft computing” adalah terhad dan tidak menekankan kepada masalah ketidakpastian walaupun model-model ini telah terbukti efektif dalam pelbagai bidang lain. Model Fuzzy-Rough Nearest Neighbour (FRNN) dapat membentuk model ketidakpastian walaupun dengan data-data yang tidak sempurna. Kelebihan ini adalah penting untuk proses pengesanan model melalui VEP. Namun, penyelidikan kurang diberi perhatian melalui kaedah ini. Oleh itu, objektif projek ini adalah untuk mengenalpasti elektrod aktif VEP dan ciri-ciri vektor yang sesuai dalam pengesanan orang ini. Selain itu, projek ini akan menilai prestasi FRNN yang dicadangkan. Projek ini mengikuti kaedah eksperimen termasuk kajian awal, penyediaan data, ciri-ciri pengekstrakan isyarat EEG, eksperimen dan analisis keputusan. Purata, kolerasi-bersilang dan kekuatan yang diambil daripada elektrod sisi dan elektrod garis tengah. Pengklasifikasian keputusan FRNN melalui implikator dan t-norma member kesan ke atas teknik perbandingan D-kNN dan FLR dalam ukuran AUC. Walaubagaimanapun, pemilihan ciri-ciri adalah lebih relevan untuk digunakan dalam masa hadapan untuk meminimakan dimensi data untuk mencapai ruang ciri umum yang lebih baik dalam rangka pengesanan.

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
AUC	-	Area under ROC curve
BCI	-	Brain Computer Interfaces
D-kNN	-	Discernibility Nearest Neighbours
EEG	-	Electroencephalography
FIS	-	Fuzzy Inference System
FLR	-	Fuzzy Lattice Reasoning
FNN	-	Fuzzy Nearest Neighbours
FRNN	-	Fuzzy-Rough Nearest Neighbours
FRNN-O	-	Fuzzy-Rough Ownership Function
KNN	-	K-Nearest Neighbours
MLP	-	Multi-layered Perceptron
PIN	-	Personal Identification Number
ROC	-	Receiver Operating Characteristic
SVM	-	Support Vector Machine
VEP	-	Visual Evoked Potential
VQNN	-	Vaguely Quantified rough-set based Nearest Neighbour
WEKA	-	Waikato Environment for Knowledge Analysis

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CHAPTER I

INTRODUCTION

1.1 Project Background

An authentication or verification systems involves accepting or rejecting the identity that claimed by a particular individual, which is one-to-one matching. In contrast, an identification system attempts to establish the identity of a given person out of a closed pool of N people, which is one-to-N matching (Marcel and Millan, 2007). Feature extraction and preprocessing steps are the same for both authentication and identification before classification. However, person authentication is the main focus in this project. There are several types of methods that can be used for person authentication such as knowledge based, token based and biometrics. Password and Personal Identification Number (PIN) are the examples of knowledge based authentication while signature is the example of token based authentication. Biometrics system such as fingerprint authentication system depends on the surface of the finger. With the shortcomings from the authentication methods mentioned, an authentication system which used EEG signals will be used as the features of person authentication.

Electroencephalography (EEG) signals are brain activities that recorded from electrodes mounted on the scalp. EEG signals are the product of ionic current flows that happens in the brain's neurons. EEG is the most practical capturing method that can be used in biometrics due to the advances in its hardware devices. It is unique, confidential and cannot be duplicated. There is a research showing that the EEG signals of a person is different from person to person, even when they are performing the same task or thought when responding to same visual stimuli (Zuquete *et al.*, 2010).

EEG signals are hard to recreate because these may influenced by some sources of noise, such as environmental noise and physiological noise. Since it is hard to reproduce same EEG signals from a person, therefore, uncertainty method such as fuzzy set theory and rough set theory are needed to classify the signals. Apart from that, K-Neasrest Neighbors (KNN) algorithm is a well-known classification technique as it assigns a test object to the decision class. Thus, the combination of fuzzy set theory, rough set theory and KNN called Fuzzy-Rough Nearest Neighbour (FRNN) is chosen to classify EEG signals. FRNN is a technique that used nearest neighbors to construct fuzzy lower and upper approximations of the decision classes (Jensen and Cornelis, 2011). The classification results of FRNN using implicator and t-norm were promising against its comparison techniques of D-kNN and FLR especially in the measurement of AUC.

The feature extraction step is needed before perform classification. The main focus is to extract feature vector from raw data for the purpose of classification.

1.2 Problem Statement

Person authentication plays an important role in security. One of the person authentication methods is EEG signals. EEG signals are very unique in their own way as the signals are only transmitted by a living human being. Thus, it is acceptable to have different range of the signal at every moment and stimuli as per person which makes it impossible to duplicate or swiped. EEG signals especially Visual Evoked Potential (VEP) is unique but highly uncertain and difficult to process. Thus, identify the appropriate feature vector and prediction model are essential to implement this modality for person authentication purposes. The research on analyzing VEP for person authentication using soft computing modelling is very limited and hardly emphasizes on uncertainty methods even though uncertainty modelling has been proven efficient in many other domains. Fuzzy set and rough set are the best solution dealing with uncertainty and manipulating imperfect data (Singh et al., 2011). A combination of both notions, the Fuzzy-Rough Nearest Neighbour (FRNN) model is outstanding to model uncertainty in element belongings under an imperfect data condition. This advantage is vital for person authentication modeling using VEP, but there is a lack of research work focusing in this direction.

1.3 Objectives

This project embarks on the following objectives:

1. To identify VEP active electrodes for channel selection.
2. To identify feature vectors for EEG signal authentication modelling.

3. To propose the Fuzzy-Rough Nearest Neighbour (FRNN) model for person authentication classification.

1.4 Scope

This project focuses mainly on person authentication using EEG signals. The importance electrodes for VEPs are midline and lateral electrodes. Features extraction will be the main focus since the feature values is considered a different observation for the purpose of classification. Besides that, Kleene-Dienes will be used as implicator and t-norm for both FRNN and D-kNN models. On the other hand, the size of threshold that used for FLR model is 0.1.

1.5 Project Significance

The project significance for this project is to propose person authentication modelling using EEG signals. Apart from that, three methods such as FRNN, D-kNN and FLR are chosen from Waikato Environment for Knowledge Analysis (WEKA) to classify EEG signals.

1.6 Expected Output

At the end of this project, the expected output is to get a set of coding for feature extraction of EEG signals and a best classifier will be determined in order to classify EEG signals classification result for person authentication.

1.7 Conclusion

As a conclusion, FRNN model is proposed and then compared with D-kNN and FLR models in classification of EEG data based on the feature vectors that have extracted. It is believed that with the combination of fuzzy set, rough set and KNN model, which is FRNN model can produce a better result compared to the others in term of accuracy and AUC measurements.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

In this chapter, a literature review of the person authentication models with different biometric features and a literature review on a various types of artificial intelligence techniques to classify the EEG signals have been studied. It is because artificial intelligence techniques are believed to get better result in accuracy and use less time to classify the EEG signals. This chapter contains seven sections. The first section presents different types of person authentication models and the second section presents the importance of EEG signals in person authentication modeling. The third section described about feature extraction of the EEG signals. The fourth section provides the literature review on fuzzy-rough based. The fifth section will be discussed about the evaluation and performance and the sixth section is discussing about the EEG dataset that have used in other research. Lastly, the conclusion will be provided in the seventh section.

2.2 Person Authentication and Person Identification

Person authentication or verification is different from person identification. Person authentication system gives a yes or no answer for the person that claimed by a person (one-to-one matching). In contrast, person identification system gives the identity of an individual from a group of person that being evaluated (one-to-N matching) (Marcel and Millán, 2007). The steps of data preprocessing and feature extraction are sharing the same for authentication and identification. This project focused mainly on person authentication but not person identification. Applications of person authentication such as airport checking, building gate control are widely used.

Several types of methods can be used to authenticate human beings from others. Traditional methods such as knowledge-based and token based are usually used by human. Password is one of the examples for knowledge-based while signature is the example of token based. Most of the people still prefer to use signature and passwords as an authentication way because both of these methods are easier and do not need any maintenance. Unfortunately, password model and signature are considered the weakest authentication model because password can be stolen and guessed easily by shoulder surfing and signature can be forged easily. There is a research in Lashkari *et al.* (2009) enumerates 16 current challenges that passwords face today.

Biometric authentication system was introduced to overcome traditional authentication methods. The major difference between biometric and traditional authentication method is the way of authenticate a person is based on the physical characteristic. The features that can be measured for person authentication system are fingerprint, face, voice, hand geometry and iris recognition. The advantage of using biometrics as authentication system is unique. In 14th century, there was a Chinese used foot prints and palm prints to identify babies (Arreymbi *et al.*, 2011).

Fingerprint authentication system considers one of the most popular and oldest biometrics authentication systems. However, due to the advancement of technologies and evilness of human beings, fingerprint can be imitated which bring down the uniqueness of it. Apart from that, fingerprint system is depending on the surface of our finger. It is unable to get their fingerprint perfectly if the people with certain physical disabilities or severe injuries such as missing hands or burned fingers. Other than that, fingerprint nowadays is not secure due to the advancement of technology. There is some research showing that fingerprint can be forged and various algorithms are being developed to detect fingerprint forgery (Shin *et al.*, 2010). According to Easton *et al.*, there are six steps to forge fingerprint by using superglue.

Face recognition model is not reliable because the human face structure will evolved and change throughout the lifecycle of human due to genetic or environmental factors. Besides that, face recognition is not a perfect biometric authentication method because it depends on light, facial expression, resolution and form of hair of an individual (Babich, 2012).

Voice also acts as a biometric method in person authentication because every person has different pitch and it is unique. The sound is produced when air leaves the body of an individual through oral cavity (mouth), nasal cavity (nose) and larynx. Obstructions such as lips, teeth, tongue, size and position are used to produce sound (Babich, 2012). However, the voice can be easily recorded due to the advancement of technology and used for unauthorized PC or network. In addition, voice recognition can be easily affected by environmental factors like background noise. It might take hours to record the voice but the system tends to make error.

Hand geometry recognition system was popular in 10 years ago but nowadays it is seldom used (Babich, 2012). This recognition system is based on the shape of the hand of an individual which differs from another person. Unfortunately, hand geometry is not unique. It is because the measurements of this method are measuring and