DISCRETE WAVELET PACKET TRANSFORM FOR ELECTROENCEPHALOGRAM BASED VALENCE-AROUSAL EMOTION RECOGNITION

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Abstrak

Pengecaman emosi berasaskan elektroensefalogram (EEG) telah mendapat perhatian yang tinggi.Hal ini disebabkan ianya adalah suatu kaedah tak invasif untuk mendapatkan isyarat daripada otak dan ianya boleh menunjukkan keadaan emosi secara terus. Walau bagaimanapun, isu-isu yang mencabar berkaitan pengecaman keadaan emosi berasaskan EEG ini adalah ianya memerlukan kaedah dan algoritma yang direka bentuk dengan baik dan proses untuk mendapatkan ciri-ciri yang diperlukan daripada isyarat EEG yang kompleks, tidak menentu dan berbilang saluran demi memperoleh prestasi pengelasan yang optimum. Tujuan kajian ini adalah untuk membongkar kaedah pengeluaran ciri dan kombinasi beberapa saluran elektrod yang melaksanakan pengecaman emosi valens-kebangkitan yang berasaskan EEG yang optimum. Berdasarkan hal ini, eksperimen telah dijalankan terhadap dua pengecaman emosi untuk mengelaskan keadaan emosi manusia kepada valens tinggi/rendah atau kebangkitan tinggi/rendah. Eksperimen yang pertama bertujuan untuk menilai prestasi Pengubahan Diskret Riak Paket (DWPT) sebagai satu kaedah pengeluaran ciri. Eksperimen kedua adalah bertujuan untuk mengenalpasti kombinasi saluran-saluran elektrod yang mengecam emosi dengan optimum berdasarkan model valens-kebangkitan dalam pengecaman emosi EEG. Dalam menilai hasil kajian ini, satu penanda aras digunakan untuk melaksanakan pengelasan emosi. Dalam eksperimen pertama, ciri-ciri entropi bagi jalur teta, alfa, beta dan gama dikeluarkan melalui 10 saluran EEG iaitu Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, dan O2 menggunakan DWPT dengan Mesin Jejarian Asas Fungsi-Sokongan Vektor (RBF-SVM) digunakan sebagai pengelas. Dalam eksperimen kedua, eksperimen pengelasan diulang dengan menggunakan 4 saluran frontal EEG Fp1, Fp2, F3 dan F4. Keputusan eksperimen pertama menunjukkan ciri-ciri entropi yang dikeluarkan dengan menggunakan DWPT adalah lebih baik daripada ciri-ciri kuasa jalur. Manakala keputusan eksperimen pengelasan kedua menunjukkan kombinasi 4 saluran frontal lebih signifikan daripada kombinasi 10 saluran.

Kata kunci: Pengubahan Diskret Riak Paket, Elektroensefalogram, Pengecaman emosi, Entropi, Fungsi Jejarian Asas, Mesin vektor sokongan.

Abstract

Electroencephalogram (EEG) based emotion recognition has received considerable attention as it is a non-invasive method of acquiring physiological signals from the brain and it could directly reflect emotional states. However, the challenging issues regarding EEG-based emotional state recognition is that it requires well-designed methods and algorithms to extract necessary features from the complex, chaotic, and multichannel EEG signal in order to achieve optimum classification performance. The aim of this study is to discover the feature extraction method and the combination of electrode channels that optimally implements EEG-based valence-arousal emotion recognition. Based on this, two emotion recognition experiments were performed to classify human emotional states into high/low valence or high/low arousal. The first experiment was aimed to evaluate the performance of Discrete Wavelet Packet Transform (DWPT) as a feature extraction method. The second experiment was aimed at identifying the combination of electrode channels that optimally recognize emotions based on the valence-arousal model in EEG emotion recognition. In order to evaluate the results of this study, a benchmark EEG dataset was used to implement the emotion classification. In the first experiment, the entropy features of the theta, alpha, beta, and gamma bands through the 10 EEG channels Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2 were extracted using DWPT and Radial Basis Function-Support Vector Machine (RBF-SVM) was used as the classifier. In the second experiment, the classification experiments were repeated using the 4 EEG frontal channels Fp1, Fp2, F3, and F4. The result of the first experiment showed that entropy features extracted using DWPT are better than bandpower features. While the result of the second classification experiment shows that the combination of the 4 frontal channels is more significant than the combination of the 10 channels.

Keywords: Discrete wavelet packet transform, Electroencephalogram, Emotion recognition, Entropy, Radial basis function, Support vector machine.

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List of Abbreviations

ANN-	Artificial Neural Networks
ANS-	Autonomic Nervous System
CNS-	Central Nervous System
DEAP-	A Database for Emotion Analysis Using Physiological Signals
DWT-	Discrete Wavelet Transform
DWPT-	Discrete Wavelet Packet Transform
EEG -	Electroencephalogram
EOG -	Electrooculogram
ERP-	Event Related Potentials
FD-	Fractal Dimension
fNIRS -	Functional Near-Infrared Spectroscopy
GA-	Genetic Algorithm
IADS-	International Affective Digitized Sounds
IAPS-	International Affective Picture System
KNN-	K-Nearest Neighbour
LDA-	Linear Discriminant Analysis
NB -	Naïve Bayes
PCA-	Principal Component Analysis
PSD-	Power Spectral Density
RPA-	Recurrence Plot Analysis
RBF-	Radial Basis Function-Support Vector Machine
SAM-	Self-Assessment Manikins
SVM-	Support Vector Machine

CHAPTER ONE

INTRODUCTION

1.1 Introduction

Human beings express various emotions during daily activities and interactions with other people. In human daily interactions, these emotions are recognized through facial expression, voice, or body gesture. The task of recognizing emotions is simple for human, however computers capability of recognizing human emotions is still diminished (Amaral, Ferreira, Aquino, and Castro (2013).

In affective computing, facial expressions, body gestures, and vocal intonation have been used to recognize human emotions (Fu, Yang, and Hou, 2011). However, due to the fact that human can control the facial expressions, body gestures, and vocal intonation voluntarily, various studies have used physiological bio-signals from the peripherals of the human body to recognize emotions (Kim, Bang, and Kim, 2004; Kim and André, 2006; Kim and André, 2008; Picard, Vyzas, and Healey, 2001). The electrical signals from the brain itself acquired by Electroencephalograms (EEG) are recently used to recognize human emotions (Jatupaiboon, Pan-ngum, and Israsena, 2013; Lin, Wang, Jung, Wu, Jeng, Duann and Chen, 2010; Wang, Nie, and Lu, 2011).

The non-linearity, non-stationary, and chaotic properties of the EEG signals have created great problems that lead to thorough signal processing and analysis (Sanei and Chambers, 2008). In other words, to achieve optimal results, there is a need to systematically choose the methods and techniques that will be applied when

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