IMPLEMENTATION OF FEATURE SELECTION AND WEIGHTING METHODS FOR EMOTION RECOGNITION FROM HUMAN ACTIONS

by

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TABLE OF CONTENT

DECLARATION OF THESIS i

ACKNOWLEDGEMENTS ii

TABLE OF CONTENT iii

LIST OF TABLES vii

LIST OF FIGURES x

LIST OF ABBREVIATIONS xiii

LIST OF SYMBOLS xv

ABSTRAK xvi

ABSTRACT xvii

CHAPTER 1 INTRODUCTION 1

1.1 Towards the Emotional Intelligence Machines 1

1.2 Research Problem and Challenges 4

1.3 Research Aims and Objective 5

1.4 Scope of the Research 5

1.5 Thesis Outline 6

CHAPTER 2 LITERATURE REVIEW 8

2.1 Model of Emotion 8

2.2 Modalities and Prospective View of the Emotion Intelligence Machine 11

2.2.1 Facial Expression 12

2.2.2 Physiological Signal 13

2.2.3 Speech Signal 14

2.2.4 Body Expression 16

2.3 Emotion recognition from body expression 18

2.3.1 Emotional Data Collection 19

2.3.2 Emotional Feature Extraction 28

2.3.4 Dimensional Reduction 29

2.3.5 Classification of Emotional State 32

2.4 Summary 32

CHAPTER 3 METHODOLOGY 34

3.1 Biological Motion Library (BML) Database 34

3.2 Global Transformation 37

3.3 Segmentation of walking action 38

3.3.1 Identification of the informative joint 40

3.3.2 Smoothening and removing of low energy signal using threshold value 41

3.3.3 Segmentation of single stride length 42

3.4 Feature extraction 42

3.5 Body component analysis 45

3.6 Feature validation 46

3.7 Feature selection and reduction 48

3.7.1 Relief-F 48

3.7.2 Fast Correlation-Based Filter 50

3.7.3 Correlation-Based Feature Selection 51

3.7.4 Principal Component Analysis 52

3.7.5 Linear Discriminant Analysis 54

3.8 Proposed Feature Weighting Method 56

3.8.1 Feature Weighting based on Fuzzy C-Means (FWFCM) 57
3.8.1.1 Calculation of cluster centres using the FCM method 57
3.8.2 Feature Weighting-based on Binary Encoded Output 61
3.9 Classification Methods 65
3.9.1 K-Nearest Neighbour 65
3.9.2 Fuzzy K-Nearest Neighbour 66
3.9.3 Probabilistic Neural Network 67
3.10 Classifier Performance Evaluation and Measures 69
3.11 Summary 73
CHAPTER 4 RESULTS & DISCUSSION 74
4.1 Body Component Analysis 74
4.2 Classification performance of all selected features 77
4.3 Feature selection and reduction 82
4.3.1 Analysis of the feature selection method 83
4.3.2 Feature Selection and Reduction Validation Result 90
4.3.3 Classification of feature selection and reduction method in discriminate emotional states 94
4.3.3.1 Comparison of the performance of the Feature Selection and Reduction Methods 94
4.3.3.2 Comparison of the performance between the emotional states and actions 99
4.4 Implementation of the Feature Weighting Method 104
4.4.1 Importance of feature weighting method 105

4.4.2 Classification of feature weighting method for emotion states discriminate 110

4.5 Comparison with previous works and research finding 112

4.6 Summary 116

CHAPTER 5 CONCLUSION AND RECOMMENDATION 119

5.1 Contribution 119

5.2 Limitation and future recommendations 120

REFERENCES 122

APPENDICES 130

Appendix A: Kinematic deviation of signal 131

Appendix B: Raw Feature Validation 135

Appendix C: Informative feature lists 144

Appendix C.1: Informative feature selection using Relief-F 144

Appendix C.2: Informative feature selection using FCBF 146

Appendix C.3: Informative feature selection using CFS 147

Appendix D: Feature Selection and Reduction Validation 150

Appendix E: Classifier parameter 154

Appendix F: Classification result of emotion using feature selection and reduction method 156

Appendix G: Feature Weighting Validation 168

Appendix H: Classification result of every emotion using feature weighting method 173

LIST OF PUBLICATIONS 185

LIST OF TABLES

NO.		PAGE
2.1	Summary of existing database referred to emotional or affective state.	21
2.2	Design details analysis of emotion features and methods in human actions.	26
3.1	Representation of Features Set.	45
3.2	Overall accuracy rate (%) of each weight in different actions through subject dependent using KNN classifier.	49
3.3	Binary codes for outputs of emotion in dataset.	61
3.4	Example of a dataset to illustrate the work of the FWBEO.	62
3.5	Total data set utilized for training and testing the classifier in subject dependent cases.	70
3.6	Total subjects utilized for training and testing the classifier in subject independent cases.	70
3.7	Total data set utilized for training and testing the classifier in gender dependent cases.	71
4.1	Overall accuracy (% ± std. dev) result of the emotion recognition in knocking, throwing, lifting and walking action using different classifiers.	76
4.2	Number of features selected.	83
4.3	Comparison work of emotion recognition in human action using same database.	115
B.0.1	Raw feature validation using one-way ANOVA for knocking actions.	136
B.0.2	Raw feature validation using one-way ANOVA for throwing actions.	137
B.0.3	Raw feature validation using one-way ANOVA for lifting actions.	138
B.0.4	Raw feature validation using one-way ANOVA for walking actions.	139
D.0.5	Feature selection and reduction validation using one-way ANOVA for knocking action.	150
D.0.6	Feature selection and reduction validation using one-way ANOVA for throwing action.	151

D.0.7 Feature selection and reduction validation using one-way ANOVA for lifting action. 152

D.0.8 Feature selection and reduction validation using one-way ANOVA for walking action. 153

F.0.9 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using feature selection and reduction methods across different classifiers and actions through subject dependent. 156

F.0.10 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using feature selection and reduction methods across different classifiers and actions through subject independent. 158

F.0.11 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using feature selection and reduction methods across different classifiers and actions through gender dependent (Male). 160

F.0.12 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using feature selection and reduction methods across different classifiers and actions through gender dependent (Female). 162

F.0.13 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using feature selection and reduction methods across different classifiers and actions through gender independent (Testing set: Male). 164

F.0.14 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using feature selection and reduction methods across different classifiers and actions through gender independent (Testing set: Female). 166

G.0.15 Feature weighting method validation using one-way ANOVA of knocking action. 168

G.0.16 Feature weighting method validation using one-way ANOVA of throwing action. 169

G.0.17 Feature weighting method validation using one-way ANOVA of lifting action. 170

G.0.18 Feature weighting method validation using one-way ANOVA of walking action. 171

H.0.19 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using different classifiers for feature weighting methods through subject dependent. 173

H.0.20 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using different classifiers for feature weighting methods through subject independent. 175

H.0.21 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using different classifiers for feature weighting methods through gender dependent (male). 177

H.0.22 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using different classifiers for feature weighting methods through gender dependent (female). 179

H.0.23 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using different classifiers for feature weighting methods through gender independent (Testing set: Male). 181

H.0.24 Classification result of emotion (angry, happy, neutral, sad) (% ± std. dev), overall accuracy (% ± std. dev) and g-mean (% ± std. dev) using different classifiers for feature weighting methods through gender independent (Testing set: Female). 183

LIST OF FIGURES

NO.		PAGE
2.1	Ekman's basic emotions as expressed by the facial and body posture:	10
2.2	Dimensional models, where, (a): Two dimensional model (Russell et al., 1989; Yik et al., 1999) and (b) Three dimensional model (Chen et al., 2012).	11
2.3	Number of publications standards published by IEEE (provided by an IEEExplorer search with the 'keywords' AND 'Emotion' AND 'Affective Computing' AND 'Affective State' in Abstract, 1.4.2015): a) in conference proceedings, b) in Journals and Magazine.	12
2.4	Classical process for the emotion recognition system.	18
3.1	The flow of the research activities.	35
3.2	Markers positions.	37
3.3	a) World coordinate system of right wrist; b) Body coordinate system of right wrist; c) Body-local system origin located on the pelvis of the skeleton, on which the coordinates are written as horizontal, medio-lateral and vertical or x, y, z, respectively.	38
3.4	Segmentation process of the human walking action.	39
3.5	Using PCA to identify the informative joints for the walking action signal. (a) The intensity colour value of all joints in the walking action signal, (b) The PCA transformation of the walking action signal.	40
3.6	Evaluation based on red lines for (a) Full body; (b) Upper body; (c) Head and right hand; (d) Right and left hand; (e) Right hand; (f) Lower body.	46
3.7	Selected features with weighting above 0.04 (red lines) for actions (a) Knocking; (b) Throwing; (c) Lifting; (d) Walking.	50
3.8	PCA Transformation Process.	52
3.9	Principal Components vs. Total Residual Power plot.	54
3.10	LDA Transformation Process.	54
3.11	Implementation of a feature weighting method using the FCM algorithm.	60

3.12 Weighting process for the *i* dimensions of a dataset using a binary encoded output based on data weighting (*i* is the dimensional feature *1,2,3…n*). 63

3.13 Implementation of feature weighting method using binary encoded output. 64

4.1 Proportion of significant features (p-value <0.05) using the one-way ANOVA. 75

4.2 Proportion of significant features $p < 0.05$ using the one-way ANOVA. 77

4.3 Comparison performance of all the selected features among different actions by considering the overall accuracy (%) and g-mean (%): (a) evaluation of subject dependent, (b) evaluation of gender dependent (Male), (c) evaluation of gender dependent (Female), (d) evaluation of subject independent, (e) evaluation of gender independent (Testing Set: Male), (f) evaluation of gender independent (Testing Set: Female). 79

4.4 Proportion of the features selected using different feature selection methods in the statistical measures category. 85

4.5 Proportion of the features selected using different feature selection methods in the joint category. 87

4.6 Proportion of the features selected using different feature selection methods in the dynamic parameter category. 89

4.7 Proportion of significant features (p-value < 0.05) for the feature selection and reduction methods. 90

4.8 Class distribution plot of the selected features using the feature selection and reduction methods for different actions: 92

4.9 Comparison of the performance of feature selection and reduction method among of different actions by considering of overall accuracy (%) and g-mean (%): (a) evaluation for subject dependent, (b) evaluation for gender dependent (Male), (c) evaluation for gender dependent (Female), (d) evaluation for subject independent, (e) evaluation for gender independent (Testing Set: Male), (f) evaluation for gender independent (Testing Set: Female). 95

4.9 (continued): Comparison of the performance of feature selection and reduction method among of different actions by considering of overall accuracy (%) and g-mean (%): (a) evaluation for subject dependent, (b) evaluation for gender dependent (Male), (c) evaluation for gender dependent (Female), (d) evaluation for subject independent, (e) evaluation for gender independent (Testing Set: Male), (f) evaluation for gender independent (Testing Set: Female). 96

4.10 Comparison of the performance of emotional states in case of subject dependent, gender dependent (Male), gender dependent (Female), subject independent, gender independent (testing set: Male) and gender independent (testing set: Female) for the knocking, throwing, lifting and walking actions. 100

4.11 Class distribution plot of feature extracted from CFS and LDA across different actions. 106

4.12 Class distribution plot of the features selected through CFS + FWFCM and LDA + FWFCM for different actions. 108

4.13 Class distribution plot of the features selected through CFS + FWBEO and LDA + FWBEO for different actions. 109

4.14 Comparison of the performance of the feature weighting method for different actions by considering the overall accuracy (%) and g-mean (%): (a) evaluation for subject dependent, (b) evaluation for gender dependent (Male), (c) evaluation for gender dependent (Female), (d) evaluation for subject independent, (e) evaluation for gender independent (Testing Set: Male), (f) evaluation for gender independent (Testing Set: Female). 110

A.0.1 Kinematic signal for each emotion in distance, speed, acceleration and jerk of knocking action. 131

A.0.2 Kinematic signal for each emotion in distance, speed, acceleration and jerk of throwing action. 132

A.0.3 Kinematic signal for each emotion in distance, speed, acceleration and jerk of lifting action. 133

A.0.4 Kinematic signal for each emotion in distance, speed, acceleration and jerk of walking action. 134

E.0.5 Adjust optimal k-value for KNN classifier. 154

E.0.6 Adjust optimal k-value for FKNN classifier. 154

E.0.7 Adjust optimal spread factor (σ) for PNN classifier. 155

LIST OF ABBREVIATIONS

ANOVA	-	Analysis of Variance
ANN	-	Artificial Neutral Network
APL	-	Action Perception Laboratory
BML	-	Biological Motion Library
CFS	-	Correlation Feature Selection
CMU	-	Carnegie Mellon University
DT	-	Decision Tree
ECG	-	Electrocardiogram
EI	-	Emotional Intelligence
EMG	-	Electromyogram
FABO	-	Bi-modal Face and Body Gesture
FACS	-	Facial Action Coding System
FCBF	-	Fast Correlation Based Filter
FCM	-	Fuzzy C-mean
FFDA	-	Functional Fisher Discriminant Analysis
FFT	-	Fast Fourier Transform
FKNN	-	Fuzzy K- Nearest Neighbor
FPCA	-	Functional Principal Component Analysis
FWBEO	-	Feature Weighting Binary Encoded Output
FWFCM	-	Feature Weighting Fuzzy C-mean
GDA	-	Generalized Discriminant Analysis
GEMEP	-	Geneva Multimodal Emotion Portrayals
GSR	-	Galvanic Skin Response

HMM	-	Hidden Markov Model
IEMOCAP	-	Interactive Emotional Dyadic Motion Capture
IQ	-	Intelligence Quotient
KNN	-	K- Nearest Neighbor
KPCA	-	Kernal Principle Component Analysis
LDA	-	Linear Discriminant Analysis
LR	-	Logistic Regression
MANOVA	-	Multivariate analysis of variance
NB	-	Naïve Bayes
PC1	-	Principle Component 1
PCA	-	Principle Component Analysis
PNN	-	Probabilistic Neural Network
PTSD	-	Post-Traumatic Stress Disorder
RMS	-	Root Mean Square
SPCA	-	Supervised Principal Component Analysis
SOG	-	Shape of Gaussian
SVM	-	Support Vector Machine
UCLIC	-	University College London Interaction Centre
WEKA	-	Waikato Environment for Knowledge Analysis

LIST OF SYMBOLS

$d_k(t)$	-	Distance
$p_k(t)$	-	Position of joint motion
$v_k(t)$	-	Speed
$a_k(t)$	-	Acceleration
$j_k(t)$	-	Jerk
μ	-	Mean
Max	-	Maximum
Min	-	Minimum
σ	-	Standard deviation
Med	-	Median
LogE	-	Log energy
En	-	Entropy
F-value	-	Critical value for the F-distribution
p-value	-	Probability of obtaining test statistical result
z	-	z-score

Pelaksanaan Kaedah Ciri Pemilihan dan Pertimbangan untuk Pengenalan Emosi daripada Tindakan Manusia

ABSTRAK

Emosi ialah keadaan semulajadi, naluri fikiran yang berasal dari keadaan, perasaan atau hubungan dengan orang lain. Emosi boleh dikategorikan terutamanya oleh ungkapan psiko-fisiologi, tindak balas biologi, interaksi badan dan keadaan mental. Dalam interaksi sosial, komponen emosi merupakan elemen penting dalam komunikasi, maklum balas dan menyampaikan maklumat. Setiap hari, tubuh manusia telah berkembang untuk melaksanakan tugas-tugas yang canggih untuk membawa maklumat tentang emosi. Kebelakangan ini telah melihat peningkatan yang ketara dalam penyelidikan model pengkomputeran untuk proses emosi manusia terutamanya dalam interaksi badan. Walau bagaimanapun, kebanyakan penyelidik kurang untuk menangani masalah dalam pra pemprosesan teknologi dan banyak bergantung pada kaedah tradisional untuk mentafsir emosi. Oleh itu, projek ini bertujuan untuk membangunkan kaedah pengenalan emosi yang lebih baik daripada tindakan manusia yang merangkumi pengekstrakan deskriptor dinamik (jarak, kelajuan, magnitud pecutan dan magnitud jerk) dan sifat-sifat statistik (min, maksimum, minimum, sisihan piawai, median, log-energy, RMS dan entropi) daripada data posisi sendi, ciri pemilihan / pengurangan (Relief-F, cepat berdasarkan korelasi penapis (FCBF), korelasi ciri pemilihan (CFS), linear analisis diskriminan (LDA) dan prinsip analisis komponen (PCA)), kaedah ciri pemberat (ciri pemberat berdasarkan ‘Fuzzy’ C-min (FWFCM) dan ciri pemberat berdasarkan binari dikodkan output (FWBEO)) dan pengenalan daripada emosi yang menggunakan pengelasan berbeza (K-jiran terdekat (KNN), ‘Fuzzy’ K- jiran terdekat (FKNN) dan rangkaian kebarangkalian neural (PNN)). Selepas pengekstrakan ciri, ciri-ciri yang relevan/berlebihan telah dikeluarkan menggunakan Relief-F, FCBF, CFS, LDA dan PCA. Selanjutnya, untuk mengurangkan tahap pertindihan yang besar antara ciri yang berkaitan / tidak berlebihan, tesis ini mencadangkan ciri kaedah pemberat berdasarkan FWFCM dan FWBEO untuk meningkatkan keupayaan diskriminasi ciri-ciri dan juga untuk mengurangkan tahap pertindihan di antara ciri-ciri. Eksperimen pengelasan emosi berbeza seperti subjek bergantung, subjek yang bebas, jantina bergantung dan jantina yang bebas telah dijalankan. Langkah-langkah prestasi seperti ketepatan dan g-min keseluruhan dipertimbangkan untuk penilaian pengelasan itu. Keputusan eksperimen menunjukkan bahawa kaedah pemberat ciri-ciri yang dicadangkan (FWFCM dan FWBEO) berkesan untuk mengklasifikasikan emosi dalam tindakan manusia dengan ketepatan maximum adalah 100%.

Implementation of Feature Selection and Weighting Methods for Emotion Recognition from Human Actions

ABSTRACT

Emotion is a natural, instinctive state of mind emanating from one's circumstances, mood or relationships with others. Emotion can be characterized primarily by the psycho-physiological expressions, biological reactions, body interaction and mental states. In social interaction, emotional component serves as an important element in communication, response and conveying information. Every day, the human body has evolved to perform sophisticated tasks to carry information about emotions. Recent years have seen a significant expansion in research on computational models of human emotional processes primarily in body interaction. However, most researchers fail to address the problem in preprocessing technologies and mainly rely on traditional methods to interpret emotion. Thus, this thesis aims to develop improved emotion recognition methods from human actions which includes the extraction of dynamic descriptors (distance, speed, magnitude of acceleration and magnitude of jerk) and statistical features (mean, maximum, minimum, standard deviation, median, log-energy, RMS and entropy) from joint position data, feature selection/reduction (Relief-F, fast correlation-based filter (FCBF), correlation feature selection (CFS), linear discriminant analysis (LDA) and principle component analysis (PCA), feature weighting methods (feature weighting based on fuzzy C-mean (FWFCM) and feature weighting based on binary encoded output (FWBEO)) and recognition of emotions using different classifiers (K-nearest neighbor (KNN), fuzzy K-nearest neighbor (FKNN) and probabilistic neural network (PNN)). After feature extraction, irrelevant/redundant features were removed using Relief-F, FCBF, CFS, LDA and PCA. Further, to reduce the higher degree of overlap among the relevant/non-redundant features, this thesis proposes FWFCM and FWBEO based feature weighting methods to enhance the discrimination ability of the features and also to minimize the degree of overlap among the features. Different emotion recognition experiments such as subject dependent, subject independent, gender dependent and gender independent were carried out. The performance measures such as overall accuracy and g-mean were considered for the evaluation of the classifiers. The experimental results demonstrate that the proposed feature weighting methods (FWFCM and FWBEO) are effective to classify emotion in human action with a maximum accuracy of 100%.

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CHAPTER 1

INTRODUCTION

1.1 Towards the Emotional Intelligence Machines

The ubiquitous use of computer technology in human life has become a trend and it seems endless. Over the years, many new technologies have been developed to make our lives more enjoyable and manageable. This development has led to the production of computers that are much faster, efficient and can do better jobs than humans. However, one of the biggest issues that provide a barrier, which prevents man and machine from melding together, is that humans can understand and express emotion, whereas computers cannot. This leads to questions such as "Why would machines need emotional intelligence?" It is easy to think of emotion as something not required for basic intelligent functioning and thus it is hard to encode in a computer programme. Therefore, "why do you need to bother giving emotional abilities to machines?" The development of technologies is not about giving more 'emotional' to the intelligence of machines. It is about how emotional intelligence could solve many problems that exist presently, while enabling good technologies for the future. This is a chance to give machines more human-like abilities to communicate with users.

Most of the people already know that too much or too little emotion can impair rational thinking and behaviour. Body reaction such as facial expression, tones of voice, gestures, postures, eye contact, touch and expressive movement are forms of nonverbal communication that can contribute in the emotional development. People find it easy to express their feelings during walking, sitting, talking, jumping, running or while doing other physical activities. For instance, a person may walk slowly while dropping his head when he is gloomy, stretch his body when nervous or sit idly when he is feeling lazy. Neuroscience research studies state that people who essentially have emotional problems are more prone to have strong damages in their daily functioning. An article from Pacer Centre has explicated that emotional experiences during childhood can result in difficulties while growing up (Pacer Center, 2006). In addition to the Diagnostic and Statistical Manual of Mental Disorders Fourth Edition Revised (DSM-IVR) criteria, several types of emotional disorder affect children and youth. Some of these include, Post Traumatic Stress Disorder (PTSD), adjustment disorders, major depressive disorder, Attention Deficit/ Hyperactivity Disorder (ADHD), autistic disorder, anxiety disorders and many more (Pacer Center, 2006). Scientists have collected evidence that shows that the emotional skills are a basic element of intelligence, especially useful for learning preferences and adjusting to what is crucial. Thus, there are many reasons for the development of emotional intelligence machines and involve teaching the machine to understand human emotions and thus enlisting their help for the facilitation of human work in several applications such as:

a) *Monitoring system*: A Monitoring system provides new computational challenges and has wide applications in hospitals, security systems, factory environments and many more. For example, out stationed doctors or nurses can assist the patients in the hospital by monitoring the emotional state such as depression and autism in the patient behaviour on their cell phones using the visual inspection systems. In a different scenario, if the patient is wearing a heart monitor, for either general fitness tracking or health monitoring, then the technology can also potentially be tested to measure the changes of heart rate variability associated with the emotional stress and cognitive. In a work environment, the emotional fatigue is of special interest to improve the safety and anxiety of workers. In addition, the video system security can be used to detect emotional outbursts in day-to-day communication and detect suspicious behaviour such as criminal activity (e.g. fighting and attacking) as a security function.

b) *Entertainment*: Robotic entertainment is an interesting topic to explore. In fiction, the robot has formed its sense of emotions and their own identity. This theme has been already adopted in forms of art and film industry like the interactive robot theatre. The transfer of the design rules for the believable characters from character animation and storytelling brings to more software agents and entertaining robots. A first feeling robot designed in 2010 by European researchers known as Nao, which understands emotional state as well possesses the ability to imitate and learn them. Nao is programmed with emotional responses for feelings as sadness, fear, excitement and it can interact with humans. It can develop personality and learn to remember faces and essential behaviour involving certain people. Another application is the selection of music according to the emotional state of the listener (automatic music selector). Sophisticated computer-aided learning software interacts emotionally to avoid boredom and keep the user interested.

The ability to feel and react appropriately to user emotive feedback is of importance for increasing the consumption of adaptive computer systems (e.g., software agents, video retrieval systems and many more). Emotional intelligence contains the ability to recognize, express, have emotions, matched with the ability to control these emotions, utilize them for constructive purposes and skilfully handle the emotions of others.

Emotional intelligence skills have been shown to be a better predictor of IQ to measure success in life.

1.2 Research Problem and Challenges

Due to the potential wide-ranging applications and technical challenges across many fields, automatic emotion recognition has been a hot topic in pattern recognition and computer vision over the past three decades. Previously, most of the efforts have focused on different modalities, targeting facial expressions, voice expressions and physiological signals. However, less research regarding the association between body movements with basic human emotions has been conducted. In addition, there are many weaknesses in the quality of statistical features and the feature reduction techniques proposed previously, especially in the subject independent recognition and gender independent recognition (Hauskrecht et al., 2007). For example, data components group such as interclass and intra-class variation which obviously depends on the choice of the features. These results can lead to the low accuracy of emotion recognition in most of the emotion recognition applications. Regarding this issue, this work aims to enhance the emotion recognition rate. This is expected to pave the way for the use of the bodily expressions to their full potential. The following are the problems that can pose significant challenges in body movement:

a) The relationship between emotions and body movements is regarded as weak and is less understood as compared to other modalities such as facial and voice expressions. This poses a challenge for the development of a computational model of body expressions where how to define emotions that increase and grow over a range of eliciting situations, from physical stimuli to complex situations, keeping with the roles in social interaction and individual behaviour.

b) In some scenarios, most of the motion signal is dominated by the action performed and the emotional variations are very subtle. The motions for analysis are also likely to be subjected to greater statistical noise as the recording procedures are less controlled than for the more archetypal expressions. Additionally, body motion contains a higher degree of flexibility that makes it difficult to measure.

c) Unlike modalities such as voice and facial expression, communication of emotions by the body movement and expressions require further research in order to obtain a better view regarding how various emotional states can contribute to the perception and recognition.

1.3 Research Aims and Objective

The aim of this research is to develop a recognition system for detecting emotions from the general body motions. The objectives are as follows:

a) To extract different statistical features and to select the best features using the chosen feature selection and reduction techniques.

b) To enhance and classify the best-selected features by using the feature weighting method and machine learning classifier.

c) To evaluate and validate the proposed methods in recognising emotion from knocking, throwing, lifting and walking actions.

1.4 Scope of the Research

This thesis presents a systematic approach to investigate emotion in human actions. The research work concentrates on the implementation of the feature enhancement techniques for improving the recognition rate of emotion in human actions. Biological motion library database was used in this study. Four different emotions namely angry, happy, neutral and sad and four actions namely knocking, throwing, lifting and walking were considered. Statistical features were extracted from the kinematics (distance, speed, acceleration and jerk) of human movement. To make sure the features used are relevant and useful, the feature selection and reduction techniques were implemented. These techniques are very important in reducing features while maximising the classification rate. The empirical studies into feature selection and reduction techniques mostly have been confined to the identification of the number or percentage of features to be maintained in order to maximise the effectiveness of the classification. However, in this case, we assume that the quality of the features has a great influence on the performance of a learning algorithm with respect to the classification rate. Therefore, we proposed the feature weighting methods as enhancement techniques to increase variation between the features. Three classifiers were employed for the classification of emotion in human actions such as KNN, FKNN and PNN classifier.

1.5 Thesis Outline

This thesis is organized for the development of a recognition system for detecting emotions from general body motions. There are five chapters.

Chapter 1 is an introduction of this research. This chapter gives brief information about the overview background of emotional intelligence machines, research problems and challenges, research aim and objectives, scope of the research fields.

Chapter 2 reviews the research background of this research. This chapter covers models of emotion from psychological experiments and the potential view of emotional intelligence machines from different modalities (e.g. physiological studies, facial, and speech and body expression). The chapter also surveys the fundamental process of the development of human body expression systems and includes the explanation of different existing methods such as a database, feature extraction, dimensional feature reduction and classification. At the end, the research contribution is presented.

Chapter 3 discusses the research methodology. This chapter explains the description of the data collection, segmentation, feature extraction, feature selection and reduction techniques, along with proposing the feature enhancement techniques and classification methodologies.

Chapter 4 combines the results from the motion analysis and the emotional features developed in Chapter 3 to build an emotion classification system in human actions.

Chapter 5 summarizes the finding and limitation for this research and suggest directions for future recommendation.