



**NON-LINEAR FEATURES AND FEATURE
SELECTION ALGORITHMS FOR SPEECH BASED
PREDICTION OF BODY MASS INDEX (BMI)**

by

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DECLARATION OF THESIS

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LIST OF ABBREVIATIONS

| | |
|---------|--|
| ANOVA | Analysis of Variance |
| ApEn | Approximate entropy |
| AUC | Area under the receiver operating characteristic curve |
| BMI | Body Mass Index |
| CORR | Correlation coefficient between F_0 and intensity |
| CSFS | Combine Sequential Feature Selection Algorithms |
| ELM | Extreme Learning Machine |
| F_0 | Fundamental frequency |
| FE | Fuzzy Entropy |
| FS | Feature Selection |
| GSA | Gravitational Search Algorithm |
| HPSOGSA | Hybrid PSO and GSA |
| HOSA | Higher Order Spectral Analysis |
| KNN | K-Nearest Neighbor |
| LPC | Linear Prediction Coefficients |
| LPCC | Linear Predictive Cepstral Coefficients |
| MFCC | Mel Frequency Cepstral Coefficients |

| | |
|--------|------------------------------|
| MW | Mother Wavelet |
| PNN | Probabilistic Neural Network |
| PSO | Particle Swarm Optimization |
| RE | Rényi Entropy |
| SampEn | Sample entropy |
| ShEn | Shannon entropy |
| SD | Subject Dependent |
| TE | Tsallis Entropy |
| WPT | Wavelet Packet Transform |

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LIST OF SYMBOLS

| | |
|-----|------------------------------|
| e | The prediction error |
| m | length of pattern |
| P | Population |
| q | Wavelet sub-band coefficient |
| r | coefficient of similarity |
| V | Velocity of the Particle |

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Ciri Bukan Linear dan Pemilihan Ciri Algoritma bagi Ramalan Berasaskan Ucapan untuk Index Jisim Badan (BMI)

ABSTRAK

Obesiti dan berat badan berlebihan telah menjadi kebimbangan yang semakin meningkat disebabkan oleh kesan negatif ke atas kesihatan manusia. Obesiti dianggap sebagai punca utama beberapa penyakit serius seperti kencing manis, penyakit kardiovaskular, dan sindrom metabolik, dan ia telah menjadi wabak. Hari ini, indeks jisim badan (BMI) digunakan secara meluas sebagai alat untuk mengelaskan berat badan normal, berat badan berlebihan, kurang berat badan dan obesiti. Ukuran ini kadang-kadang tidak sesuai untuk penjagaan kesihatan jauh atau penjagaan kesihatan u yang menyokong rawatan umum dan perkhidmatan perubatan kecemasan dalam masa nyata di lokasi terpencil. Para penyelidik telah meneroka hubungan antara pengecaman pertuturan dan BMI. Isyarat ucapan mempunyai hubungan yang rapat dengan status BMI, yang diramalkan oleh gabungan ciri-ciri utama. Tujuan kerja penyelidikan ini adalah untuk meramalkan status BMI (normal, berat badan berlebihan dan gemuk) menggunakan isyarat pertuturan tanpa pengukuran berat dan ketinggian. Dalam kerjakerja penyelidikan ini, paket 'wavelet' berdasarkan ciri-ciri entropi tak linear dan algoritma pemilihan ciri telah dicadangkan untuk meramalkan status BMI melalui isyarat ucapan daripada normal, gemuk dan berat badan berlebihan subjek. Isyarat ucapan yang direkodkan (bunyi /ah/) diurai hingga tahap lima menggunakan pengubah paket 'wavelet' (WPT). Beberapa ciri-ciri ini diekstrak daripada pekali paket 'wavelet' dan juga ujian Analisis Varians (ANOVA). Dalam kajian ini, dua jangka-pendek cepstral berdasarkan kaedah ciri pengestrakan (MFCC, LPCC), WP tenaga dan enam ciri-ciri entropi tak linear, iaitu entropi Contoh, Tsallis, Kabur, Anggaran, Renyi dan Shannon (berjumlah 492 ciri-ciri) diekstrak daripada isyarat bunyi /ah/ menggunakan WPT dan dimasukkan ke pelbagai pengelas seperti Mesin Pembelajaran Extreme (ELM), k-jiran terdekat (KNN) dan Kebarangkalian 'Neural Network' (PNN) untuk klasifikasi. Penilaian prestasi protokol dalam tesis ini menggunakan 75 subjek. Keputusan menunjukkan bahawa kematraan ciri-ciri set adalah lebih tinggi (492 ciri-ciri), yang meningkatkan kadar pengiraan dan juga membawa kepada pemasangan lebih objektif, yang menurunkan prestasi klasifikasi BMI. Pemilihan ciri boleh menyelesaikan masalah dengan kematraan dalam beberapa aplikasi. Untuk menyelesaikan masalah itu, tesis ini cuba untuk mencadangkan dua algoritma pemilihan ciri, iaitu gabungan algoritma pemilihan ciri berurutan (CSFs) (ke belakang, ke hadapan, individu, dan Plus-l-bawa pulang-r) dan Hybrid algoritma pengoptimuman PSOGSA (HPSOGSA) dengan gabungan pengoptimuman zarah berpaya (PSO) dan Algoritma Graviti Cari (GSA) untuk mengurangkan lagi dimensi ruang ciri dan mengenal pasti subset ciri yang paling relevan, yang mempunyai keupayaan diskriminasi yang lebih tinggi untuk membezakan status BMI yang berbeza. Paket 'wavelet' berdasarkan ciri entropi tak linear menunjukkan prestasi yang lebih baik daripada Tenaga dan Cepstral jangka pendek berdasarkan kaedah ciri pengestrakan (MFCC, LPCC). Ciri-ciri set yang dicadangkan dinilai dengan eksperimen subjek bersandar (SD). Pengelasan ketepatan diperolehi dalam lingkungan 95,64% - 98,11% (CSFS), dan 97,65% - 98,62% (HPSOGSA) menggunakan ELM untuk meramalkan status BMI.

Non-Linear Features and Feature Selection Algorithms for Speech Based Prediction of Body Mass Index (BMI)

ABSTRACT

Obesity and overweight have been a growing concern due to their negative impacts on human's health. Obesity is considered as a major cause of some serious diseases such as diabetes, cardiovascular diseases, and metabolic syndrome, and it has become epidemic. Today, body mass index (BMI) is widely used as a tool to classify normal weight, overweight, underweight and obesity. These measurements are sometimes not suitable for remote healthcare or u-healthcare supporting general treatment and emergency medical service in real time at remote locations. The researchers have explored the association between speech recognition and BMI. Speech signals have a close relation with BMI status, which is predicted by a combination of key features. The purpose of this research work is to predict BMI status (normal, overweight and obese) using speech signal without weight and height measurements. In this research work, wavelet packet based nonlinear entropy features and feature selection algorithms were proposed to predict BMI status via speech signal of normal, obese and overweight subjects. The recorded speech signal (/ah/ sounds) were decomposed up to level five using wavelet packet transform (WPT). Several features were extracted from the wavelet packet coefficients and an Analysis of Variance (ANOVA) test. In this research, two short-term cepstral based feature extraction methods (MFCC, LPCC), WP based energy and six nonlinear entropy features, namely Sample entropy, Tsallis, fuzzy, Approximate, Rényi and Shannon (totally 492 features) were extracted from the /ah/ sound signals using WPT and fed to various classifiers such as Extreme Learning Machine (ELM), k-Nearest Neighbour (KNN) and Probabilistic Neural Network (PNN) for classification. The performance evaluation protocol in this thesis used 75 subjects. The results indicated that the dimensionality of the feature set is higher (492 features), which increases the computational cost and also leads to over-fitting of the objective, which degrades the performance of BMI classification. Feature selection can solve problems with dimensionality in a few applications. To solve such problems, this thesis attempted to propose two feature selection algorithms, namely combination of sequential feature selection algorithms (CSFS) (Backward, Forward, Individual, and Plus-*l*-takeaway-*r*) and Hybrid PSOGSA optimization algorithm (HPSOGSA) with the combination of Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) to further minimize the dimension of feature space and identify the most relevant feature subset, which has higher discrimination ability to distinguish different BMI status. Wavelet packet based nonlinear entropy features performed better than Energy and short-term cepstral based feature extraction methods (MFCC, LPCC). The proposed feature set was evaluated with subject dependent (SD) experiment. The classification accuracy was obtained in the range of 95.64% - 98.11% (CSFS), and 97.65% - 98.62% (HPSOGSA) using ELM to predict BMI status.

CHAPTER 1

INTRODUCTION

1.1 Research Background

Obesity is currently a growing concern in field of health. Thus, today, this issue becomes a global phenomenon (Deckelbaum & Williams, 2001; Hasler et al., 2004). Indeed, obesity problem has received much attention of individuals from health sectors, and then this issue has dominated other hot topics like malnutrition all over the world. The reliable sources of data reveal that almost 600 million people around the globe must suffer from obesity while people from grownups who are overweight are approximately 1.9 billion (Organization, 2015; Poobalan & Aucott, 2016). This problem of obesity has negatively affected their health and daily life, and even some side effects reduce their lifespan as compared to the past (Organization, 2015; Stewart & Wild, 2015). Obesity refers to the disequilibrium in medical condition, and it occurs when the body mass considerably increases, and the level of body fat is triggered. If the fat level in the body increases and reaches to a particular level, it leads to serious diseases such as cardiovascular disease and cancer (Javed et al., 2015). There are a variety of economic, cultural and social determinants of obesity that varies from country to country, individual to individual and time to time (Goryakin, Lobstein, James, & Suhrcke, 2015). Good medical treatment has been recommended to the people suffering from obesity; otherwise they will face even severe side effects of such obesity. Previous studies were conducted examine if the Body Mass Index (BMI) is related to the instigated diseases. It was found that there are different ways to measure obesity including BMI, waist circumference and waist to hip ratio, skin fold thickness-biceps, and body composition.

The BMI is very popular among well-being experts and in the field of medicine. It is considered as a valuable tool which is used to determine whether a person is obese, overweight or underweight. It can be calculated by dividing the body weight measure in kilograms by the height measured in meters and taking square (Javed et al., 2015; Sperrin, Marshall, Higgins, Renehan, & Buchan, 2015) as shown in Equation (1.1).

$$BMI = \frac{weight(kg)}{height(m)^2} \quad (1.1)$$

Table 1.1 below shows the BMI categories as defined by the World Health Organization (WHO).

Table 1.1: BMI categories as defined by the WHO

| Weight status | BMI kg/m² |
|-----------------------------|-----------------------------|
| Underweight | <18.5 |
| Normal weight | 18.5-24.9 |
| Pre-obese/overweight | 25-29.9 |
| Obese class I | 30-34.9 |
| Obese class II | 35-39.9 |
| Obese class III | ≥ 40 |

An adult BMI of between 25-29.9 kg/m² shows the status of overweight of an individual. BMI of 30kg/m² or above indicates obese status (Organization, 2000).

BMI has been considered as the most valuable tool to determine if the individual is facing any type of obesity, and it has several advantages such as efficiency, swiftness and accuracy. Moreover, BMI can be used in all age brackets and for all genders. However, BMI has its limitations in the estimation of obesity degree (Kragelund & Omland, 2005; Prentice & Jebb, 2001). First, BMI does not discriminate between mass due to lean mass and mass due to fat mass. Therefore, a person with a high amount of lean muscle tissue could be classified as obese when this individual may have a low percentage of adipose tissue. Secondly, there is a relatively large standard error (+5%)

on estimating the percentage of fat from BMI (Lobman, Houtkooper, & Going, 1997). Therefore, BMI is not a recommended method of body composition for fitness evaluation. Thirdly, the relationship between BMI and adiposity may differ among the ethnic groups (Anuurad et al., 2003; Bozkirli, Ertorer, Bakiner, Tutuncu, & Demirag, 2007; Deurenberg, 2001) due to the different tissue density and varying amount of lean body mass. For example, people of African American and Polynesian descent tend to have a higher BMI but lower relative percentage of body fat while people of Ethiopian and Thai descent tend to have a lower BMI and a higher relative percentage of body fat (Deurenberg, Yap, & Van Staveren, 1998).

BMI has similar limitations in children; for example, there is a significant increase in height and weight of people in the 5-18 age range which results in dramatic changes in BMI (Freedman & Sherry, 2009). Additionally, BMI is not suitable for measuring body mass of pregnant women and for people with short height.

A number of researchers have examined whether a listener can judge physical characteristics of the speakers from speech. Previous research focused on identifying sex of the speakers (Lass, Hughes, Bowyer, Waters, & Bourne, 1976; Schwartz, 1968), age (Hartman & Danhauer, 1976; Neiman & Applegate, 1990), race (Lass, Mertz, & Kimmel, 1978; Walton & Orlikoff, 1994), and body size, i.e., weight and height (Bricker & Pruzansky, 1976; Gonzalez, 2003; Kreiman, 1997). Identifying weight and height of the speakers still remains debatable. Previous researchers (Lass, Beverly, Nicosia, & Simpson, 1978; Lass & Davis, 1976) reported that the listener has the ability to estimate weight and height of the speaker directly from the recorded speech samples in different conditions.

Furthermore, researchers investigated the association between speech signals and the status of BMI as an emerging area of research. A variety of methods have been

used to forecast BMI classes such as obese, overweight, and normal classes which depend on a blend of voice characteristics related to BMI level (Lee, Kim, Ku, Jang, & Kim, 2013; Lee, Ku, Jang, & Kim, 2013). After rigorous testing, researcher came to the conclusion that obese people have numerous distinguished modifications in speech features as compared to normal individuals, such as vocal instability, hoarseness, murmuring, shimmer, altered jitter and reduced maximum times of phonation times along voice suffocation at the time of emission. These problems might be caused by the stocks of abnormal fats accumulated in various acoustic tract structures like on uvula, soft palate, posterior and lateral walls of the walls of nasopharyngeal and on the tongue's posterior area (Da Cunha, Passerotti, Weber, Zilberstein, & Cecconello, 2011).

The literature on direct relationship between BMI status (normal, obese and overweight) and speech signal and the accuracy is limited. Hence, the current research attempted to propose a novel way of predicting BMI status through a combination of nonlinear entropy features, feature selection and classification algorithms.

1.2 Problem Statement

Weight and height (kg/m^2) are used to measure BMI values. Today, BMI is widely used and has many advantages such as accuracy, swiftness and efficiency. Furthermore, it can be used for both genders and all age categories. For this reason, there is a measurement of weight and height on the spot to gain patients' BMI value. Yet, it is inappropriate to use such measurements for emergency medical service or for remote healthcare locations (Hall, Larkin, Trujillo, Hinds, & Delaney, 2004).

However, most of people are unclear about their exact weight when BMI is diagnosed due to a slowly or rapidly change in patients' weight over time. Recently, researchers have investigated the association between speech signal and the BMI status

as an emerging area of research. Very few studies focus on the literature on direct relationship between BMI status and speech signal.

The prediction of BMI status using speech signal is still challenging. It's challenging because (a) the researchers collected the speech data of subjects only from Korea (Lee, Ku, et al., 2013). This problem is caused by the criteria of BMI classification proposed by WHO. Noticeably, this criteria varies within the race regions. For this reason, race region is one of the characteristics that should be considered to predict BMI status for use in different conditions, (b) a few feature extraction algorithms have been used to predict BMI status (Lee, Ku, et al., 2013), and many feature extraction algorithms have not been applied in this application such as nonlinear entropy features. Additionally, very few feature selection algorithms have been implemented in this application (prediction of BMI status using speech signal), (c) the researchers have obtained less than 74% of accuracy when predicting BMI status (normal, overweight and obese).

1.3 Research Objectives

The purpose of this research is to predict BMI status (normal, overweight and obese) using speech signal without weight and height measurements. This work mainly focuses on wavelet packet based nonlinear entropy features, feature selection and machine learning algorithms that can represent the hidden and minute information for the prediction of BMI status (Normal, obese and overweight) from speech signals.

The primary objectives are:

- 1) To extract wavelet packet based nonlinear entropy features from the recorded /ah/ sounds;
- 2) To develop two feature selection algorithms (CSFS and OFS) and select a suitable feature selection techniques.
- 3) To evaluate the proposed methods for the prediction of BMI status.

1.4 Contributions

The contributions of this work are:

- Developing a speech signal database with different countries of origin (multiplicity of the races) for the prediction of BMI status;
- A new set of features based on wavelet packet and nonlinear entropy from speech signal for prediction of BMI status;
- CSFS and HPSOGSA feature selection algorithms were validated using speech signal (/ah/ sounds);
- Subject dependent (SD) experiment was conducted using utterances of collected data set (/ah/ sound), and the classification accuracies are obtained in the range of 95.64 % - 98.11 % (CSFS), and 97.65 % - 98.62 % (HPSOGSA) using ELM for prediction of BMI status. The results are significantly better than those reported in the previous works.

1.5 Scope

The current research explores the topic on prediction of BMI status (normal, overweight and obese) using speech signal (/ah/ sound). In this research work, the speech samples were collected only from volunteers (age varies from Twenty years to Forty years) and wavelet packet based nonlinear entropy features (totally 372 features) were extracted. To test the efficiency of the proposed feature set, the combination of standard features was used, and several experiments were conducted. The results indicated that the proposed features were more efficient in predicting BMI status. Two feature selection algorithms namely, the combination of sequential feature selection algorithms (CSFS) (Backward, Forward, Individual, and Plus- l -takeaway- r) and Hybrid PSO-GSA optimization algorithm (HPSO-GSA) with the combination of Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) were proposed in this research work. To reduce the feature size dimensionality, the cost of classification/learning algorithm and to identify the most useful feature subset. The limitation of proposed method is that a small database was used and the number of females is less.

1.6 Organization of the Thesis

This thesis is organized into five chapters.

Chapter 1 introduces the research background, the problem statement, research objectives, contributions, scope and organization of the thesis.

Chapter 2 reviews previous studies on the relationship between speech signal and BMI status (normal, overweight and obese). The different features extracted from

speech signals and different machine learning algorithms employed to predict BMI status were also elaborated.

Chapter 3 describes the details of the data collection procedure, features extracted, feature selection and classification algorithms used in this work.

Chapter 4 presents the recognition rates achieved from different features sets for the recorded speech signals (/ah/ sounds). It also represents visualization of the proposed nonlinear entropy features and the statistical analysis of the feature set.

Chapter 5 presents the conclusions and the suggestions for further studies.

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