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# The Fusion of HRV and EMG Signals for Automatic Gender Recognition during Stepping Exercise

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***Abstract***

*In this paper, a new gender recognition approach in accordance with the fusion of features extracted from electromyogram (EMG) and heart rate variability (HRV) during stepping activity using a stair stepper device is proposed. The fusion of EMG and HRV is investigated based on feature fusion approach. The feature fusion is carried out by chaining the feature vector extracted from the EMG and HRV signals. A proposed approach comprises of a sequence of processing steps which are preprocessing, feature extraction, feature selection and the feature fusion. The results demonstrated that the fusion approach had enhanced the performance of gender recognition compared to solely on EMG or HRV for the gender recognition.*

***Keywords***: *gender recognition, feature fusion, heart rate variability (HRV), electromyography (EMG), Sstepper*



## 1. Introduction

Automatic gender recognition plays an essential role in recognition of an individual. Gender recognition can help adequately to reduce the search time by constraining the further seeking stage to either a male or female database. Any appropriate biosignal trait can be utilized for further classification once a person is recognized as male or female. Automatic recognition of gender can also give an imperative sign in various security, surveillance and rehabilitation based applications.

Gender is known to have an effect on HRV [1, 2] and EMG [3, 4]. A few studies have examined gender differences in autonomic control during exercise [5], [6]. Ahamed *et al.*, examined gender-related changes in the biceps brachii muscle by EMG signal analysis [4]. They found that the male subjects produced a higher and steadier signal than the female subjects. More recently, our previous work had explored the HRV response during short-term exercise by stair stepper machine [2]. The paper also makes a comparison of the finding significant HRV features between young healthy male and female and showed that there exist a significant gender difference in HRV features during short-term stepping exercise.

Furthermore, there are various techniques for tackling the issue of gender recognition, for example, based on fusion of face and gait information [7], fusion of facial strips [8], color information [9], sift features [10], fusion of different spatial scale features elected by mutual information from the hyhistogram of LBP (local binary patterns), intensity, and shape [11]. Plus, there are also techniques based on gabor filters combined with binary features [12], using a hybrid of gabor filters and local binary patterns to draw out face features and use self-organized map (SOM) for classification [13]. Next, there are methods based on extraction of the hip joint data that was computed from the Biovision Hierarchical data [14] and from gait sequences with arbitrary walking directions [15]. Moreover, it is true that physiological signals are also able to be implemented in gender classification. Thus, the physiological signals which are EMG and HRV signals collected during stepping activity are utilized in this research. But, there is not strong enough classification results to identify gender if using only one physiological signal. Hence, the information from both EMG and HRV is combined together to get better classification result.

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This paper considers the fusion of EMG and HRV signals from the same stepping sequence to carry out gender recognition and the feature fusion is used in order to compare the performance of the combination of EMG and HRV at this level. To the best of our knowledge this is the first method to combine EMG with the HRV for automatic gender recognition during short-term stepping exercise using a stepper. After that, the ongoing work can be used to support the interface system of the controllable current-induced stair stepper in rehab application. This paper is a further research on [2] and part of an attempt to use data take out from the distinct physiological signals in order to design a robust and reliable automatic system. So, gender could be assessed and less monitoring lower limb could be developed in rehabilitation system [16], which may assist to isolate male and female subjects to undergo rehabilitation process. It seems that the gender factor motivates people differently, in performing consistent exercise for rehab.

## 2. Research Method

The proposed young gender recognitions are composed of processing steps as described in the following sections.

### 2.1. Data Acquisition

. The research was accomplished in the Faculty of Biomedical and Health Science Engineering, Universiti Teknologi Malaysia, Johor Bahru. This study was done on 10 healthy, untrained young volunteers (mean 23.9 years, range 25 to 30), 5 were male and 5 were female participants. All participants were free from any disease and clarified about the procedures and their informed consent was obtained.

The TMSi DAQ was applied to record the EMG and ECG signals synchronously for gender recognition during exercise using stair stepper. The TMSi DAQ was utilized with three pairs of active surface electrodes and a single reference surface electrode to determine the electrical signals from the muscle and cardio. These surface electrodes are circular in shape (diameter=11.4 mm) and are composed of silver/silver chloride (Ag/AgCl) material. The stair stepper was applied to perform a stepping activity in order to produce the electrical activity of the muscle and heart as shown in Figure. 1. Metronome (45 beat per minute) was utilized to set the stepping rate. A metronome is a instrument used by musicians that indicates time at a chosen rate by giving a fixed tick.

Figure 1. Experimental setup during stepping activity for EMG and ECG data acquisition [2]

**2.2. Preprocessing**

**ECG:** The ECG pre-processing and HRV quantification is implemented by using the Kubios HRV software [17]. Kubios HRV is progressive and convenient to utilize the software for HRV interpretation. Moreover, the software supports a few information for ECG and RR interval (RRi) data. It contains the algorithm to detect an adaptive QRS peaks and mechanisms to correct the artifacts, remove the trend and analysed the sample.

The R-wave is automatically recognized by applying an assembled QRS detection algorithm in ECG data processing using Kubios. Basically, the Pan-Tompkins algorithm is utilized for the QRS detection algorithm in the Kubios software [18]. The preprocessing part contains bandpass filtering of the ECG, squaring of sample data and moving average filtering. The function of the bandpass filtering is to reduce the powerline interference, baseline wander and any other noises. Highlight peaks and smooth, close by peaks is the function of the squaring and moving average filtering respectively.

There are about three minutes of ECG signal recording is required for HRV signal analysis under normal physical and mental circumstances. Essentially, the HRV signal obtained from the Kubios was used in this research.

**EMG:** The EMG was filtered using a lowpass filter and highpass filter with a cutoff frequency of 20Hz and 300Hz respectively. The synchronization of EMG and HRV as shown in Figure 2, are required to achieve the combination between two modalities as explained later.

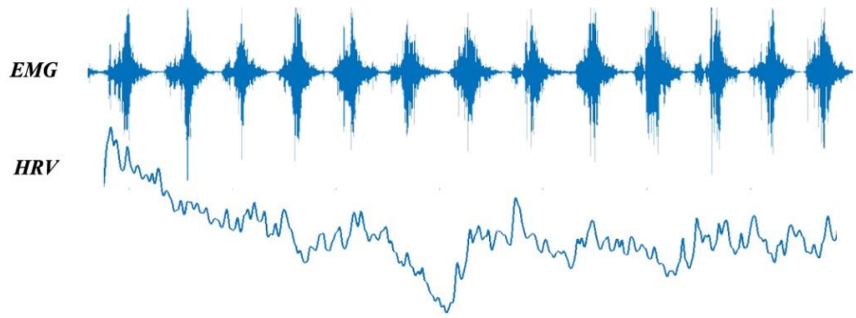


Figure 2. The synchronization of EMG and HRV

**2.3. Feature Extraction**

This section explains in brief the analysis parameters comprised in the Kubios software for HRV and analysis parameters for EMG.

**2.3.1. HRV Features**

The measurements and the indications operated are basically in accordance with the guidelines given in [19]. HRV features were extracted from time domain, frequency domain and non-linear generated from the Kubios Software as shown in the Figure 3.

**Time domain features:** The mean of RR interval (ms), standard deviation of RR (SDNN (ms)) , mean of heart rate (HR (1/min)), SD of HR (1/min), RMSSD (ms), NN50 (count), pNN50 (%), HRV Triangular Index and TINN (ms).

**Frequency Domain - Fast Fourier Transform (FFT) spectrum:** The very low frequency (VLF (Hz)) peak, low frequency (LF (Hz)) peak, high frequency (HF (Hz)) peak, VLF power (ms$^2$), VLF power (%), LF power (ms$^2$), LF power (%), LF power (n.u.), HF power (ms$^2$), HF power (%), HF power (n.u.), ratio of LF and HF (ms$^2$) and total power (ms$^2$).

**Frequency Domain - Autoregressive (AR) spectrum:** The VLF peak (Hz), LF peak (Hz), HF peak (Hz), VLF power (ms$^2$), VLF power (%), LF power (ms$^2$), LF power (%), LF power (n.u.), HF power (ms$^2$), HF power (%), HF power (n.u.), ratio of LF and HF (ms$^2$) and total power (ms$^2$).

**Nonlinear:** The poincare plot (SD1 (ms) & SD2 (ms)) where SD1 and SD2 is the standard descriptors, approximate entropy (Apen), sample entropy (Sampen), correlation dimension, Detrended Fluctuation Analysis (DFA (alpha 1 & alpha 2)), recurrence plot (Lmean (beats), Lmax (beats) where Lmax is the length of the longest line of recurrence point in a continuous row within the recurrence plot and Lmean is a mean line length , recurrence rate (REC (%)), determinism (DET (%)) and shannon entropy (Shanen).

Figure 3. Kubios software for HRV

#### 2.3.2. EMG Features

EMG features were extracted from time domain and frequency domain as follows: **Time domain features:** The mean, standard deviation (SD), root mean square (RMS), variance, skewness and kurtosis. **Frequency domain features:** The mean frequency and mid frequency.

#### 2.3.3. Feature Selection

The accuracy of the classification process may adversely affect if some of redundant irrelevant features of the features extracted are not appropriately eliminating [20, 21]. Hence, the feature selection method is applied, which is the wrapper method developed in [20, 21] using Weka in order to pick out an ideal feature subset of EMG and HRV with least redundancy and greatest class discriminability. If the dimensionality of the feature set is decreased while the precision of the classification is either enhanced or stay natural, the feature selection is viewed as successful.

#### 2.3.4. Feature Fusion of EMG and HRV during Short-Term Stepping Activity by Stepper

The proposed structure for feature fusion of EMG and HRV is depicted in Figure 4. The EMG and HRV windows were preprocessed before implementing feature extraction processes. From the huge set of features extracted, a feature subset was picked using the wrapper-based feature selection method [20]. Then, The resulting feature vector $F_{\overline{EMG}}$ and $F_{\overline{HRV}}$ were chained to build a single composite feature vector, $F_C$, presented by

$$\mathrm{F_C} = [\mathrm{F}_{\overline{\mathrm{EMG}}}|\mathrm{F}_{\overline{\mathrm{HRV}}}] \quad (1)$$

After that, the composite feature vector was applied to several statistical classifiers for the feature fusion process. The explored classifiers were: Decision Tree (J48), NB (Naïve Bayes) and *k*-NN (*k*-Nearest Neighbors) with *k*=1, 3 and 5. The results are demonstrated in section 3.

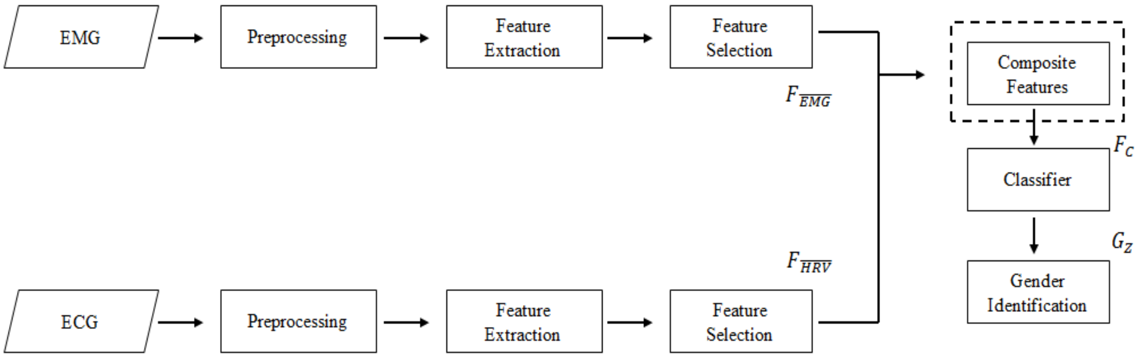


Figure 4. Automatic gender *recognition* process based on EMG-HRV feature fusion

## 3. Performance Analysis and Discussion

The performance of the EMG-HRV feature fusion process, as specified by the classification outcomes, is shown in Figure 5. The figure demonstrates that the 1-NN and 5-NN yields the optimal overall performance for gender recognition during short term stepping exercise by stepper machine. Both 1-NN and 5-NN classifiers achieved 80% sensitivity and almost 100% specificity.

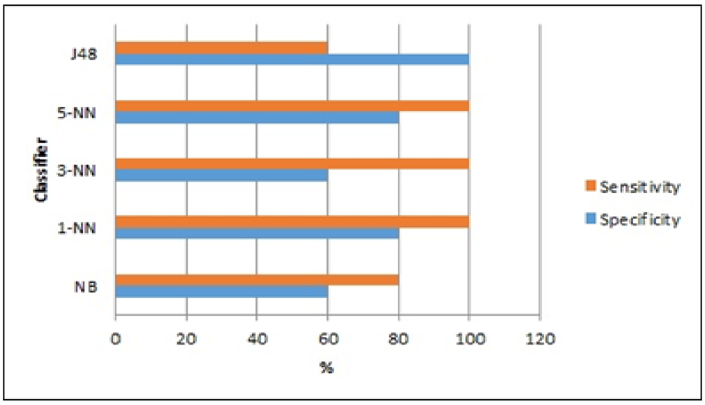


Figure 5. Performance of different classifier for gender assessment during short-term stepping exercise based on EMG and HRV features fusion

To evaluate the additional estimation of the proposed classification approach for gender recognition, their performances are compared to those based on EMG or HRV. Table 1 demonstrates the performances of 1-NN classifiers in terms of sensitivity (SEN) and specificity (SPE). The feature-based combination classifier achieved 80% SEN and almost 100% SPE compared to 60% SEN and 60% SPE using the EMG features alone and 80% SEN and 60% SPE using the HRV features only. Table 2 shows the performances of 5-NN classifier in terms of SEN and SPE too. The feature-based combination classifier reached 80% SEN and almost 100% SPE compared to 40% SEN and 80% SPE using the EMG features and 80% SEN and 80% SPE using the HRV features only.

This indicates that the fused features for 1-NN have significantly enhanced the SPE (+40%) of gender recognition during short-term stepping exercise by stair stepper machine compared to SPE achieved using either EMG or HRV features. The improvement of SEN through feature fusion was remarkable (+20% using EMG alone and +0% using HRV alone). Meanwhile, the combined features for 5-NN have significantly improved the SPE (+20%) of gender recognition during short-term stepping exercise by stepper machine compared to SPE achieved using either EMG or HRV features. Also, the improvement of SEN through feature fusion was remarkable (+40% using EMG alone and +0% using HRV alone). Thus, from the discussion above, the 1-NN classifier is better performance compared to 5-NN classifier.

Furthermore, this paper also improves the gender recognition results compared to latest previous research. Das D obtained 76.79% gender recognition rate based on human gait using Support Vector Machine (SVM) [22], Archana GS [23] obtained 80% gender classification of speech performance using SVM and Hossain S [24] found 85% of male and 74% accurate decision based on the fingerprint based gender identification. This paper achieved 80% SEN and almost 100% SPE which is 90% gender correct rate using 1-NN classifier based on the fusion of HRV and EMG physiological signals.

Table 1. Performance Comparison Of Gender Recognition During Short-Term Stepping Exercise Using A Stepper Machine From Single Signal Classification (EMG/HRV) and The Proposed Fusion System for 1-NN Classifier

| EMG | | HRV | | Feature Fusion | |
|---|---|---|---|---|---|
| SEN (%) | SPE (%) | SEN (%) | SPE (%) | SEN (%) | SPE (%) |
| 60 | 60 | 80 | 60 | 80 | ~ 100 |

Table 2. Performance Comparison Of Gender Recognition During Short-Term Stepping Exercise Using A Stepper Machine From Single Signal Classification (EMG/HRV) and the Proposed Fusion System for 5-NN Classifier

| EMG | | HRV | | Feature Fusion | |
|---|---|---|---|---|---|
| SEN (%) | SPE (%) | SEN (%) | SPE (%) | SEN (%) | SPE (%) |
| 40 | 80 | 80 | 80 | 80 | ~ 100 |

## 4. Conclusion

An approach for the fusion of EMG and HRV signals acquired during short-term stepping activity by stepper machine were proposed in this study. The fusion of the features extracted from EMG and HRV signals has prompted a better performing automatic gender recognition compared to solely on EMG and HRV signals. The outcomes affirmed that information from EMG and HRV complement each other and their combination provides better gender recognition performance compared to solely on EMG and HRV. Gender factor encourages people contrastingly in committing consistent exercise in rehab application. Therefore, this effort may support to isolate male and female subjects to experience rehabilitation process.

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