2016 International Conference on System Science and Engineering (ICSSE)
National Chi Nan University, Taiwan, July 7-9, 2016

A Two-Stage Intelligent Model to Extract Features from PPG for Drowsiness Detection

Nila Novita Sari and Yo-Ping Huang
Department of Electrical Engineering
National Taipei University of Technology
Taipei 10608, Taiwan

***Abstract*—This paper presented a two-stage intelligent model that combined the wavelet packet transform (WPT) and functional-link-based fuzzy neural network (FLFNN) to access drowsy level. Early detection of drowsiness can help prevent drivers from involving in car accidents. According to the report of U.S. National Highway Traffic Safety Administration, drivers falling asleep while driving were responsible for at least 100,000 automobile crashes annually that resulted in an annual average of 40,000 non-fatal injuries and 1,550 fatalities [3]. Furthermore, the National Sleep Foundation had reported that 60% of adult drivers drove with drowsy and 37% of them had eventually fallen asleep during driving [4]. The fact behind those reports indicated that there is a dire need to develop a sensor device that detects drowsy status at an early stage.**

***Keywords*—Photoplethysmograph (PPG), wavelet packet transform (WPT), drowsiness, functional link-based fuzzy neural networks (FLFNN).**

I. INTRODUCTION

Most research today aimed to develop new technology that can measure the drowsiness level by using biomedical signal to extract crucial features related to the heart rates [1,2]. Analysis of heart rate variability (HRV) provides useful information about drowsiness level to predict the driver's concentration on the road. Traditionally, biomedical signals from Electrocardiograph (ECG) were used to monitor the activity of heart in clinical trials. However, this technique is inconvenient in practical usage because multiple sensors were attached to the user's chest that made them feel uncomfortable.

To resolve the problem this study devised a photoplethysmograph (PPG) sensor device, a pulse-sensor (open source hardware), to measure the bio-signals for detecting the driver's drowsy level. There are two kinds of wearable PPG, including the sensor transmission and reflectance modes, and this study uses the reflectance mode. Installation of the proposed biomedical sensor to detect the drowsiness level of the driver is shown in Fig. 1. The data collected from pulse-sensor contained the information about the heart (cardiac) activities. PPG device was used as a portable heart activity module. By using the transmission mode of PPG signal measurement, the sensor must be attached to a site on the body where the transmitted light can be readily detected. Index finger and earlobe are the preferred monitoring position.

The open source hardware had the specifications of diameter, overall thickness and voltage which were 0.625" (~16mm), 0.125" (~3mm) and 3V to 5V, respectively. This pulse sensor used green super bright reverse mount LED from Kingbright (AM2520ZGC09). The measurement recorded the PPG signals from fingertip of index finger for 10 minutes due to the need to calculate the heart rate variability from PPG signal required at least 5 minutes data measurement.

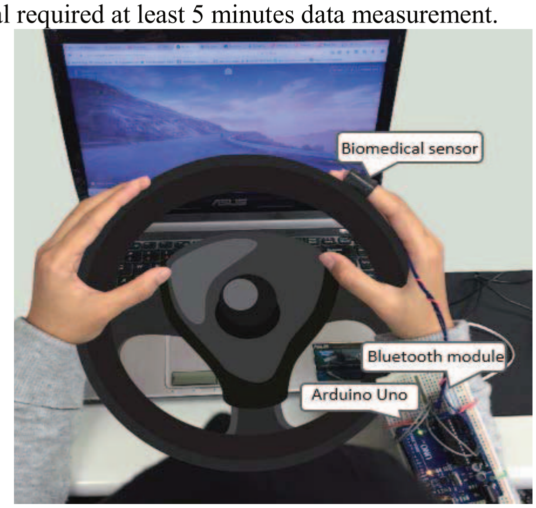

Fig. 1. Installation of biomedical sensor to detect the drowsiness level of the driver.

II. TWO-STAGE MODEL

The proposed method is a two-stage model that used wavelet packet transform (WPT) as a feature extractor followed by a functional-link-based neural fuzzy network (FLFNN) for classification [5,6]. In order to accurately identify the inflection points from the raw data of PPG signals, finding the first derivatives of raw data is necessary. Then, it was required to find the maximal peak in an interval and ignore the neighboring signals. The purpose of finding the peak was for the calculation of the heart rate. The wavelet packet transform for n-level decomposition is shown in Fig. 2.

A 6-level wavelet packet transform with 5Hz sampling rate was used in this study. The 6-level wavelet packet transform decomposition gave the nodes $N(6,i)$, with i=0-63 [6]. Those signals were processed by the wavelet packet transform to find heart rate variability (HRV) spectral, which included LF/HF, HF, and LF for further analysis. Frequency band of 0.15-0.4Hz was known as the high frequency (HF) while the fluctuation in the spectral band of 0.04-0.15Hz was termed as the low frequency (LF). LF band was located at the nodes of N(6,1), N(6,2) and N(6,3) while HF band was at the nodes of N(6,4), N(6,5), N(6,6), N(6,7), N(6,8), N(6,9) and N(6,10). The corresponding frequency band in each node was obtained from the root mean square (RMS) measurement as shown in Table I. The energy level in each node from those two band ranges (LF and HF) was used to calculate the ratio of LF/HF that was reported to have strong relationship to the drowsiness level in the literature.

The underlying analysis was performed in MATLAB 2012a. Using wavelet transform packet, the first stage feature parameters, including LF, HF and ratio of LF/HF, were calculated. All these extracted features were fed into the functional-link-based fuzzy neural network classifier as shown in Fig. 3.

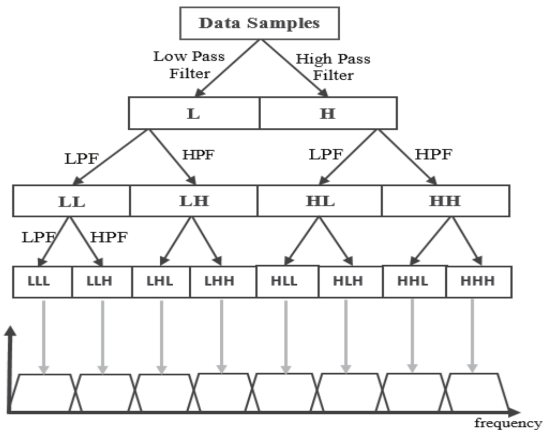

Fig. 2. Wavelet packet transform for n-level decomposition (resulting nodes) [6].

TABLE I. THE FREQUENCY BANDS CORRESPONDING TO THE 6TH WP DECOMPOSITION

HRV frequency bands	WPT Nodes	Corresponding frequency band
	N(6,0)	0-0.0390625 Hz
LF (0.04-0.15 Hz)	N(6,1)	0.0390625-0.078125 Hz
	N(6,2)	0.078125-0.1171875 Hz
	N(6,3)	0.1171875-0.15625 Hz
HF (0.15-0.4 Hz)	N(6,4)	0.15625-0.1953125 Hz
	N(6,5)	0.1953125-0.234375 Hz
	N(6,6)	0.234375-0.2734375 Hz
	N(6,7)	0.2734375-0.3125 Hz
	N(6,8)	0.3125-0.3515625 Hz
	N(6,9)	0.3515625-0.390625 Hz
	…	…
	N(6,63)	2.4609375-2.5 Hz

TABLE II. THE EXPERIMENT RESULTS OF WPT FEATURE EXTRACTION

Experiment	LF/HF	HF	LF	Condition
1	0.8058	2.3848	1.9217	Normal
2	0.7711	2.2943	1.7692	Normal
3	0.4267	2.3355	0.9965	Drowsiness
4	0.715	2.6959	1.9275	Normal
5	0.7629	2.7876	2.1265	Normal
6	0.5086	2.6566	1.3512	Drowsiness
7	0.5482	2.1953	1.2034	Drowsiness

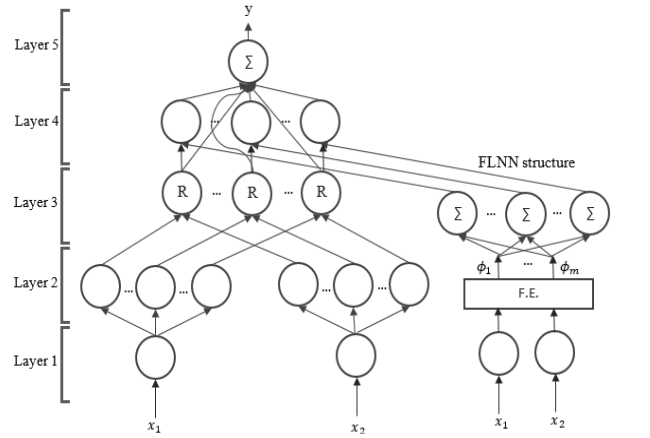

Fig. 3. A structure functional-link-based fuzzy neural network (FLFNN) [5].

III. CONCLUSIONS

Feature extraction results from WPT as shown in Table II provided several parameters of HRV for further usage in FLFNN classifier. The significant difference of energy levels from LF and LF/HF between two different statuses (normal and drowsiness) verified that the proposed model is effective in detecting the drowsiness level.

The current model can be further improved by extending the duration of experiments such as to one hour so that more driver's signals can be measured for analyzing the drowsy and fatigue levels during driving.

ACKNOWLEDGMENT

This work was supported in part by the Ministry of Science and Technology, Taiwan under Grants MOST103-2221-E-027-122-MY2 and by a joint project between the National Taipei University of Technology and Mackay Memorial Hospital under Grants NTUT-MMH-105-04 and NTUT-MMH-104-03.

REFERENCES

[1] B.G. Lee, B.L. Lee and W.Y. Chung, "Wristband-type driver vigilance monitoring system using smartwatch," *IEEE Sensors J.*, vol. 15, no. 10, pp. 5624-5633, Oct. 2015.

[2] B.G. Lee and W.Y. Chung, "Driver alertness monitoring using fusion of facial features and bio-signals," *IEEE Sensors J.,* vol. 12, no. 7, pp. 2416-2422, July 2012.

[3] D. Royal, *National survey on distracted and driving attitude behavior: 2002*, The Gallup Organization, Washington D.C., March 2003.

[4] M.R. Rosekind, "Underestimating the social cost of impaired alertness; safety, health and productivity risks," *Sleep Medicine,* California, USA, no. 6, pp.S21-S25, Sep. 2005.

[5] Y.T. Liu and C.H. Chuang, "EEG-based driving fatigue prediction system using functional-link-based fuzzy neural network," in *Proc. of Int. Conf. on Neural Network (IJCNN),* Beijing, China, pp.4109-4113, July 2014.

[6] Z.G. Sallo, "Wavelet transform based HRV analysis," in *Proc. of Int. Conf. in Engineering,* Roma, Romania, no. 12, pp.105-111, Dec. 2014.