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Research on Estimation of Blood Glucose Based on PPG and Deep Neural Networks

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Abstract. Diabetes is one of the three major chronic diseases in the world. At present, the number of diabetic patients in the world is increasing year by year, which has become one of the main threats to us. Therefore, it is very important to monitor blood glucose level. Clinically, blood glucose is measured by collecting fingertip blood, but this method has many disadvantages. In this paper, PPG signals are used to estimate BGL using deep neural networks (DNN). Finally, we found that the success rate of our DNN blood glucose estimation model reached 90.25%, and achieved good results. It provides a choice for the commercialization of noninvasive blood glucose detection technology.

1. Introduction

Diabetes is one of the world’s three major chronic diseases. According to data from the World Health Organization (WHO), International Diabetes Federation (IDF), and the Chinese Health and Family Planning Commission’s "China Diabetes Prevention and Control" data, an estimated 422 million adults worldwide suffer from diabetes. It has become the country with the most diabetes patients, accounting for more than a quarter of the total number of diabetes patients in the world [1]-[2]. Diabetes is a chronic disease. Because the body cannot adjust the blood glucose concentration to the normal range, it may cause a series of problems in the body, such as cardiovascular disease, kidney failure, blindness, etc. [3]. There are two types of diabetes. Type I diabetes is congenital, and the exact cause of it is currently unknown [4]-[5]. Type II diabetes is caused by the body's inability to use insulin effectively. For diabetic patients, it is necessary to accurately understand their blood sugar and conduct real-time treatment. For people who are on the verge of high-risk diabetes, blood glucose monitoring plays a vital role in preventing diabetes, and real-time blood glucose monitoring is very important for both patients and high-risk groups. In the current clinical field, the minimally invasive blood glucose detection method uses blood glucose test strips to take blood from the fingertips, and obtains blood glucose by analyzing the color changes of the test strips. This method is widely used because of its high accuracy, but this method has many disadvantages. Obviously, for example, patients suffer physical and mental pain, high risk of infection, and high cost. Therefore, non-invasive blood glucose testing methods have become a research hotspot. This paper proposes a non-invasive blood glucose detection method based on deep neural network and PPG, which provides a choice for the commercialization of non-invasive blood glucose detection technology.

2. Related Work

Non-invasive blood glucose monitoring is a diabetes management method that can perform continuous blood glucose monitoring in the body while providing patients with a convenient and non-invasive measurement technology. Based on different measurement methods, such as reverse iontophoresis, combined reverse iontophoresis and enzyme-based gas detection biosensors, Raman spectroscopy and near infrared spectroscopy (NIRs), several non-invasive biosensors have been proposed. Most spectroscopic techniques cannot be applied to clinically developed portable blood glucose monitors. In terms of spectroscopy, infrared (IR) is less affected by these substances and physical conditions, so the most representative method for non-invasive blood glucose detection is near-infrared spectroscopy [6]. The PPG signal is a reflection of the blood flow in the blood vessel and is generally recorded from the fingertips of the subject, where infrared light is measured through the tissue and backscattered light [7]. PPG signal can not only be used for the assessment of cardiovascular disease [8], but also can be used to predict blood pressure and blood sugar [9]. Linear correlation analysis and nonlinear correlation analysis are widely used in near infrared spectroscopy analysis. Because the linear relationship of Lambert Beer's law is interfered by individual differences, human complexity and noise interference, including multiple linear regression analysis (MLR), principal component regression analysis (PCR), partial least squares (PLS) [10] The linear correlation analysis is not ideal in non-invasive blood glucose detection, however, using deep neural network (DNN) for nonlinear correlation analysis can achieve better results.

3. PPG Signal Processing

In the process of PPG signal acquisition, external interference and weak body movement will cause the signal quality to deteriorate. Therefore, in dynamic spectrum analysis, it is a very important step to process the signal, remove or suppress interference, and obtain the true signal as much as possible. The possible noise interference of PPG signal during the acquisition process mainly includes:

(1) Power frequency interference

Power frequency interference is electromagnetic interference generated by AC power supply or surrounding electrical appliances. It is composed of 50Hz and its integer multiples of frequency harmonics, with a small amplitude. Power frequency interference will cause burrs to appear on the waveform of the PPG signal, making the entire waveform less smooth.

(2) EMG interference

In the process of collecting PPG signals, friction caused by the contact between the human finger and the sensor, and slight shaking of the human body or the finger will cause EMG interference. Its frequency characteristic is closer to white noise, distributed in 5~2000Hz. Generally, EMG interference is treated as Gaussian white noise.

(3) Baseline drift

Baseline drift is a kind of low frequency interference, which is distributed between 0.05 Hz and 1 Hz, mainly concentrated around 0.1 Hz. As long as it is an active signal from the human body, there will be baseline drift, which is unavoidable, because the cause is due to human breathing and weak body movement.

PPG signal processing includes the removal of baseline drift and denoising. This article uses wavelet transform to remove noise and baseline drift. Wavelet transform (WT) is a new transform analysis method. It inherits and develops the localized idea of short-time Fourier transform, and can provide a "time-frequency" window that changes synchronously with frequency. It is an ideal tool for signal time-frequency analysis and processing. Multi-scale decomposition of PPG signal is performed by wavelet transform, and the baseline trend of PPG signal can be observed in the decomposed low-frequency coefficients. The baseline drift can be eliminated by subtracting the baseline from the original signal. The original PPG signal and the processed PPG signal are shown in Figure 1.

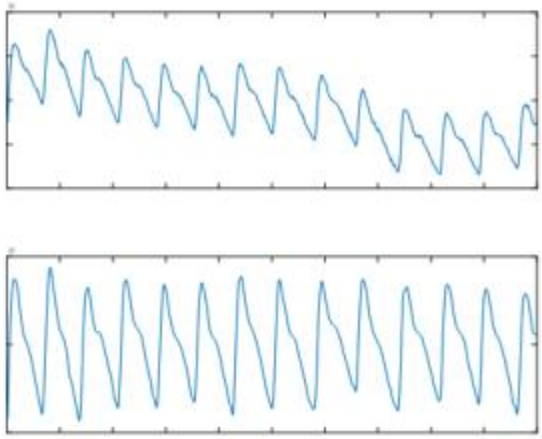

Figure 1. Original PPG signal and PPG signal after Processing

4. Feature Extraction

4.1. Kaiser-Teager Energy Feature

The Kaiser-Teager energy (KTE) energy operator can be used to track the instantaneous energy of the signal. It is a standard tool for calculating the energy distribution of periodic signals. The calculation formula for KTE energy characteristics is:

$$KTE(t) = x(t)^2 - x(t+1)x(t-1) \tag{1}$$

If you want to calculate the KTE energy value of a window, you need to calculate the real-time energy characteristics of each segment first, which can be obtained according to the above formula:

$$KTE_n(t) = S_{frame}(t,n)^2 - S_{frame}(t+1,n)S_{frame}(t-1,n) \tag{2}$$

Among them, t=1, 2, ... $L_{frame} - 1$

Then you can find the mean value of KTE energy value for each window KTE^{μ}, variance KTE^{σ}, quarter distance KTE^{iqr}, slope KTE^{skew}

4.2. Spectral Energy Logarithmic Feature

According to research, the breathing rate can affect blood pressure, and blood pressure and blood sugar in diabetic patients are closely related. We can estimate the respiratory frequency by the logarithm of the spectral energy, so the logarithm of the spectral energy can be used as one of the feature vectors:

$$logE_n = \left(\sum_{\tau=1}^{L_{frame}} S^2{}_{frame}(\tau,n)\right) \tag{3}$$

Then calculate the variance $logE_n^{\sigma}$ and the interquartile difference $logE_n^{iqr}$ of the logarithm of the spectral energy of the entire window according to each slice.

4.3. Spectral Entropy Feature

Spectral entropy is the entropy value of pure matter calculated based on thermodynamic principles and spectral data. When using spectroscopy for quantitative analysis, spectral entropy is one of the commonly used characteristic values, which can be calculated by the following formula.

First, perform fast Fourier transform on slice $S_{frame}(\tau,n)$:

$$FFT\left(S_{frame}(\tau,n), L_{FFT}\right) \rightarrow X_n,\ L_{FFT} = 512 \tag{4}$$

Then regularize X_n to get:

$$\frac{|X_n[k]|^2}{\sum_{j=1}^{L_{FFT}} |X_n[j]|^2} \rightarrow P_X^n[k] \qquad\qquad k = 1,2, \ldots L_{FFT} \tag{5}$$

Then the spectral entropy is calculated according to $P_X^n[k]$,

Finally, calculate the mean value H^{μ}, variance H^{σ}, quarter distance H^{iqr} and slope H^{skew} of the spectral entropy.

4.4. Other Features

Other characteristics include gender, age, height, weight and BMI, which are mainly derived from the subject's basic information and physiological parameters.

5. DNN

Deep learning networks have some similarities with traditional neural networks. Both have a similar hierarchical structure, including input layer, hidden layer and output layer. Only two adjacent layers are connected, and the same layer and cross-layer There is no connection between them. The difference between the two is that traditional neural networks usually have only two to three layers of neural networks, with limited parameters and computational neurons, limited ability to approximate complex functions, and limited learning capabilities, while deep learning networks have more layers, and introduced more effective algorithms.

This article extracts a variety of features, including the characteristics of the PPG signal and the individual characteristics of the subject. We fuse these features as the input of the network, and use these features to train the blood glucose estimation model based on the deep neural network to obtain blood glucose level. The estimated value of the blood glucose estimation model is shown in the following figure 2.

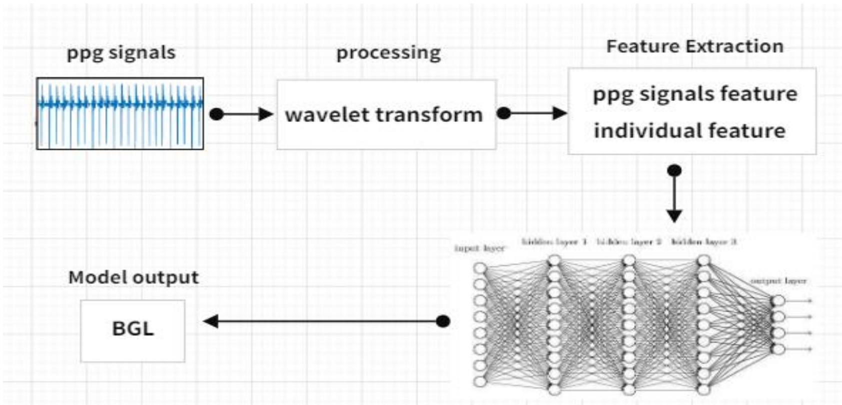

Figure 2. Blood glucose estimation model

6. Experiment and Results

6.1. Data Set

The data set comes from the public database of Guilin People's Hospital [11] and the public data set of GitHub. The data of Guilin People's Hospital includes 219 subjects. The data set covers the age range of 20-89 years old. The collected data includes the examinee's height, weight, age, BMI, PPG signal, etc. When the PPG signal is collected, the sampling accuracy of the waveform data is set to a sampling rate of 1khz, and the AD conversion accuracy is 12 bits. Each subject recorded and saved three fragments. Each fragment included 2100 sampling points with a duration of 2.1 seconds. During the 3-minute data collection phase, each PPG segment of a particular subject has a skew SQI value. Values greater than 0 are saved. If the value is less than 0, the application will prompt the user to reacquire the PPG signal. The data set on GitHub records both blood glucose level and PPG data, as well as the height, weight, age, and BMI of the subject. In the end, we use 80% of the selected data set as the training data set and 20% as the test data set.

6.2. Result

Because the subjects are all PPG signals tested in a routine state, we took the blood glucose range between 3.9-6.1mmol/L as the criterion for normal value, and used DNN to perform non-invasive blood glucose estimation on the selected data. The results showed that our test success rate reached 90.25%, which shows that the model trained by the selected features has good performance in blood glucose prediction.

7. Conclusions and Future Works

In this paper, we propose a non-invasive blood glucose method. We extract features from the subjects' PPG data in the public database, and then combine the individual characteristics of the subjects and use these features as the input for the blood glucose model estimation. Obtain the estimated value of blood glucose. We took the range of blood glucose value between 3.9-6.1mmol/L as the criterion of normal value, and found that our DNN blood glucose estimation model has a detection success rate of 90.25%, which has achieved good results. In future research, we will strive to extract more effective PPG features to achieve better accuracy, at the same time, the amount of data in this experiment is not much, and we will collect more PPG data in the future for further research, strive to provide more choices for the commercialization of non-invasive blood glucose detection technology.

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