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# Heart rate prediction model based on neural network

Minmin Luo<sup>1,\*</sup> and Kaibin Wu<sup>2</sup>

<sup>1</sup>School of Biomedical Engineering, Southern Medical University, Guangzhou 510515, China

<sup>2</sup>Class of 2016<sup>th</sup> Biomedical Engineering (Imaging Engineering), School of Biomedical Engineering, Southern Medical University, Guangzhou 510515, China

\*E-mail: 22809017@qq.com

**Abstract.** Heart is an essential organ of human body and heart rate (HR) is the most obvious heart activity in daily life. In order to predict heart rate, a heart rate prediction model based on LSTM (Long Short-Term Memory) neural network is proposed in this paper. This model combines five physiological parameters as input to ensure the validity of heart rate prediction. The results show that Adam-LSTM is a good method for heart rate prediction and reflects the tendency of heart rate change in daily life. At the same time, the experimental results show that the root mean square error of prediction value is small and the validity is high.

## 1. Introduction

In daily life, the most common change of physiological parameters perceived by us is the heart rate. Heart rate (HR) refers to the number of times the heart beats in one minute, which can be affected by many factors [1], mainly including physical activities, mental state, gender, age, physical health, heart diseases and so on. Therefore, the study of the heart rate and its influencing factors is of great importance.

So far, there have been a lot of researches on heart rate and the influencing factors[2], such as the heart rate prediction based on physical activities [3], the assessment of autonomic nervous system, and the measurement of energy consumption. Although these researches have been applied in many fields, they are performed on the basis of the relationship between a single factor and the heart rate and focus on exploring the direct relationship between the two, but few studies related to the heart rate and multiple influencing factors have been made. Internationally, Paver[4] et. al, established a human activity monitoring model based on ECG signals, rather than HR; Meijer[5] et al. set up the relationship between heart rate and human activities in some special experimental scenarios. However, there were limited activities and singular variables in the experiment, which cannot fully reflect the actual heart rate changes. Heart rate prediction is to estimate the heart rate at the next moment based on now and other influencing factors. Reliable and effective heart rate prediction has great significance for the prevention and control of some cardiovascular diseases. Yet most of the current studies only considers estimating the heart rate at the next moment by the previous heart rate, without considering other physiological factors such as gender, age, physical activities, mental state and so on.

In this paper, LSTM[6] neural network is employed to establish a heart rate prediction model based on multiple influencing factors, so as to obtain effective heart rate prediction values and provide ideas for the subsequent heart rate anomaly detection system.



## 2. Method

### 2.1. Method overview

This paper uses Long Short-Term Memory (LSTM) to avoid gradient explosions in the circulating neural network. Three “gate” structural designs are used by LSTM to control the transmission of information in the neural network, to train the input compression depth data and compression force data, and to predict the change of CPP. The model can generally be divided into the following three steps: data preprocessing, model training, model prediction, as shown in figure 1.

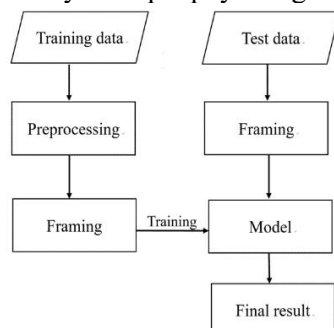
### 2.2. Data preprocessing

The collected heart rate data is often unequal in length, and improper handling may increase the difficulty of training. To this end, this paper intercepts the fixed length of each set of data and performs five-point secondary smoothing on the data.

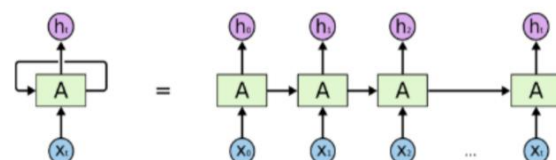
### 2.3. Model

#### 2.3.1. Model structure

In the traditional feedforward neural network, each step of each parameter is independent and is in lack of correlation with the time. But in the heart rate predication, changes in physiological signals are closely related to time. The heart rate at the present moment depends on the changes of various physiological parameters before the moment  $t$ , so the time related cyclic recurrent neural network (RNN) is introduced in this paper( RNN[7]). Unlike feedforward neural network, RNN is a time series-based network model. The parameters in the network are not only related to the current input but also linked to the past, which can establish the time correlation between the previous information and the current environment. However, due to the role of activation function, the ordinary RNN will have the problem that the parameters in the neural network are not updated, which is known as gradient disappearance. Like all RNNs, LSTM can make any calculation that can be done by the traditional computer as long as there are enough network elements. Compared with the traditional RNN network, the LSTM neural network has an effective mechanism, that is, the forget gate, which avoids the problem of gradient explosion and gradient disappearance in the standard RNN network. In LSTM, a memory unit dedicated to saving historical information is added.. The historical information in the network will pass through three gates: the input gate, the forget gate, and the control of the output gate, solving the problem of the gradient explosion that occurs in the RNN. Nowadays, LSTM is mainly used in natural language translation, physiological signal prediction, image and subtitle and other fields that are in linear relationship with the time, and can perfectly simulate the problem of multiple input variables. Moreover, it has unique advantages to changes of heart rate signal prediction caused by multiple physiological parameter inputs.



**Figure 1.** Algorithm flowchart.



**Figure 2.** LSTM topology diagram.

The LSTM-based heart rate predication model in this paper consists of the input layer, hidden layer and output layer, as shown in figure 2. Relying on the long-term memory characteristic of LSTM and combined with the multivariate input, it is transformed into the supervised learning, which completes

the inputs according to five physiological characteristics of the testees, namely, heart rate signal, gender, age, physical activities and mental state. At the same time, the model retains seven blank inputs, where more targeted physiological parameters can be designed for different testees. For example, hypertension patients may add the parameter of blood pressure, whereas the hyperglycemia suffers may choose blood glucose as the variable. In addition to the mental state, the input signals used must be recorded synchronously to further improve the accuracy. A portable active signal monitor is applied for the physical activity state to record the current activity signal of the testee (acceleration in three directions, x, y, z).

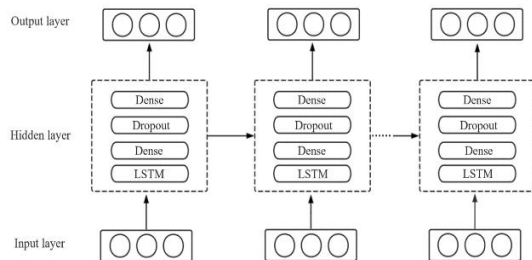
The preprocessed data is used as the input layer and the input data has 5 characteristics. The first layer of the neural network is the LSTM layer, which contains 50 neurons. Dropout[8] regularization process is performed by inputting the pooling layer to prevent overfitting. Besides, the dropout is connected to a fully connected layer, and the output is the heart rate predicted value. Through the operation of forward transmission, the neural network continues to transmit the information of the previous moment in the form of the memory stream, affecting the processing of each newly input data as well as the output of each phase. Adaptive moment estimation (ADAM)[9] is employed by the LSTM network in this paper to update the LSTM network parameters, and the results of heart rate prediction is obtained synchronously.

### 2.3.2. Model building

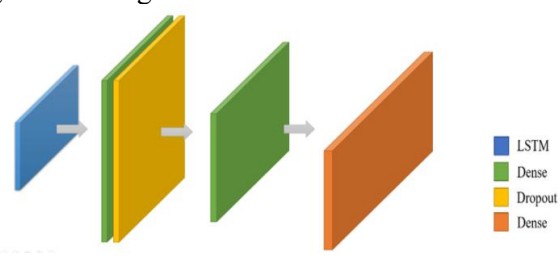
In this paper, the sequential model in the in-depth learning framework keras is introduced to linearly stack multiple network layers with the add function. The specific process is as follows:

- (1) 1 layer LSTM network model is added, input data dimension is 50, with the activation function of tanh;
- (2) A fully connected Dense layer is added, with the activation function of linear.
- (3) Each layer is configured with the dropout rejection rate of 0.2 to prevent overfitting.
- (4) A fully connected layer is added, the activation function of ReLU to connect the hidden layer and output.

The network structure of the model is shown in figure 3 and figure 4.



**Figure 3.** LSTM-based CPP prediction model structure.



**Figure 4.** Heart rate prediction network.

### 2.3.3. Model training and testing

#### 1. Model Parameter Setting

Before training, it is necessary to configure the model optimizer, loss function and indicator list. The mean absolute difference MAE is chosen in this paper as the loss function for the acquisition of the model output error.

As SGD[10] algorithm has a slower convergence speed, it is prone to oscillate at the same time of result prediction, so Adam is selected as the optimizer in this paper. The optimized Adam algorithm has a faster convergence speed, which also improves the accuracy.

#### 2. Model Training

The number of samples batch size in each training is set as 128, with the training rounds epoch of 100; also, the test data set is specified for the model to output the record of each training.

#### 3. Model Predication

The trained model needs to be verified on the test set, where the root mean square error (RMSE) is used to verify the accuracy of model prediction.

### 3. Result

The data of this paper was collected by the laboratory, a total of 48 samples, with the sampling rate of 50Hz, and the data length ranging from 90s to 580s. The testee is a healthy young man without any history of heart disease, who maintains a good mental state and the physical activity is slow walking. The recorded data is divided into two parts. The signal data in the first part is used as the data set for neural network training; and the remaining data (20%) is used as the test data set. There are 5 labels, including heart rate signal, gender, age, physical activity, mental state. Each label is standardized, and the label subordinates are free of mutual exclusion.

The predictions obtained by LSTM neural network heart rate predictor from the training dataset and test dataset are shown in the figure 5. The predicted heart rate is represented by a solid blue line and the actual heart rate is indicated as a yellow dotted curve. The results show that after the completion of predictor training, the predicted heart rate value can be well in line with the actual heart rate value.

In order to compare the superiority of the ADAM algorithm in the prediction of heart rate in the ADAM-LSTM model, the ADAM and SGD gradient descent algorithms is predicted respectively under the same condition. The comparison of the LSTM predication evaluation optimized by the two algorithms is shown in table 1, where Root Mean Square Error (RMSE) and (Mean Absolute Percentage Error MAPE) are used to compare the validity of the algorithms. The result shows that ADAM is significantly better than SGD.

In the meantime, the LSTM heart rate predictor based on multivariate input works quite well, with a root mean square error less than 0.5, indicating high validity.

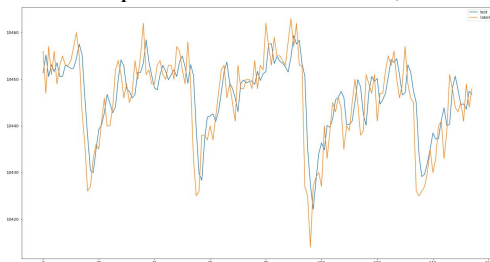


Figure 5. Heart rate prediction.

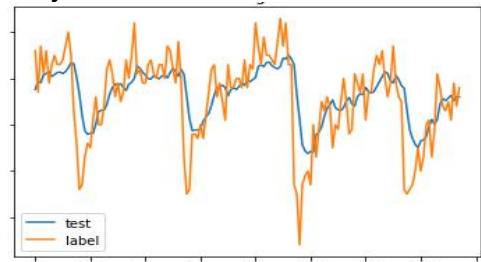


Figure 6. General heart rate prediction and training convergence curve.

### 4. Discussion

Table 1. Comparison of the effects of Adam and SGD optimization algorithms

Model	RMSE	MAPE/%
Sgd-LSTM	0.458	11.93
Adam-LSTM	0.208	6.592

Note:  $RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y_i^*)^2}$ ,  $MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|y_i^* - y_i| \times 100}{y_i}$

n is the size of the sample, y is the actual value of HR, y\* is the predicted value of HR

When other parameters are the same, the effect of prediction by solely relying on the heart rate before the t moment is shown in the figure 6. Under the same training conditions, not only the prediction result is undesirable, but also the training convergence curve declines slower.

From the comparison between the actual data and the predicted data, we can see that although the mean absolute error of the prediction is in a small range, no complicated environment is introduced in the process of data collection. In more complicated cases, such as the testee's more intense physical

activities, more unstable mental state, and even the emergence of other diseases, the neural network prediction proposed in this paper has a great application prospect and potential. It can be seen that the stability of neural network prediction is still in need of improvement in different situations, which is also one of the priorities in the future work.

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### References

- [1] Malik, M., Heart rate variability. Standards of measurement, physiological interpretation, and clinical use. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. *Circulation*, 1996. 93(5): p. 1043-65
- [2] La Rovere, M.T., et al., Baroreflex sensitivity and heart-rate variability in prediction of total cardiac mortality after myocardial infarction. ATRAMI (Autonomic Tone and Reflexes After Myocardial Infarction) Investigators. *Lancet*, 1998. 351(9101): p. 478-84
- [3] Zhu Bing, Xiao Feng and Yan Chimin. Neural Network Heart Rate Predictor. *Computer and Digital Engineering*, 2009. 37(7): 169-71
- [4] Pawar, T., S. Chaudhuri and S.P. Duttagupta, Body Movement Activity Recognition for Ambulatory Cardiac Monitoring. *IEEE Transactions on Biomedical Engineering*, 2007. 54(5): p. 874-82
- [5] Jéquier, E., K. Acheson and Y. Schutz, Assessment of energy expenditure and fuel utilization in man. *Annual Review of Nutrition*, 1987. 7(7): p. 187-208.
- [6] Graves, A., Long Short-Term Memory. *Neural Computation*, 1997. 9(8): p. 1735-80
- [7] Williams, R.J. and D. Zipser, A learning algorithm for continually running fully recurrent neural networks. 1989
- [8] Srivastava, N., et al., Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of Machine Learning Research*, 2014. 15(1): p. 1929-58
- [9] Kingma, D. and J. Ba, Adam: A Method for Stochastic Optimization. *Computer Science*, 2014.
- [10] Bottou, L., Large-Scale Machine Learning with Stochastic Gradient Descent. 2010.