A Deep Bidirectional GRU Network Model for Biometric Electrocardiogram Classification Based on Recurrent Neural Networks

Introduction

In this paper, a deep Recurrent Neural Networks (RNNs) based on Gated Recurrent Unit (GRU) in a bidirectional manner (BGRU) was proposed for human identification from electrocardiogram (ECG) based biometrics, a classification task which aims to identify a subject from a given time-series sequential data. Despite having a major issue in traditional RNN networks which they learn representations from previous time sequences, bidirectional is designed to learn the representations from future time steps which enables for better understanding of context, and eliminate ambiguity. Moreover, GRU cell in RNNs deploys an update gate and a reset gate in a hidden state layer which is computationally efficient than a usual LSTM network due to the reduction of gates. The experimental results suggest that the BGRU model, the combination of RNN with GRU cell unit in bidirectional manner, achieved a high classification accuracy of 98.55%. The proposed models were evaluated with two publicly available datasets: ECG-ID Database (ECGID) and MIT-BIH Arrhythmia Database (MITDB). This paper demonstrates the feasibility and effectiveness of applying various deep learning approaches to biometric identification and also evaluate the effect of network performance on classification accuracy according to the changes in percentage of training dataset.

Proposed Architecture

Bidirectional RNN with gru cell (BGRU)

In this model, the cell unit at the hidden layers are substituted by where gated recurrent units (GRUs). Moreover, to address one of the most important challenges, overfitting, in deep neural networks, the dropout layer is also applied in each cell. However, as the outputs at the last layer resulting from both forward and backward streams, the late-fusion for bidirectional networks is concatenated into a single vector and, it is followed by a softmax activation function to obtain N-dimensional output. The forward track traces the input segment from left to right, whereas the backward track traces back the input from right to left can be defined as follows:

$$o_t^f, h_t^f, c_t^f = GRU^f(c_{t-1}^f, h_{t-1}^f, x_t; W^f).$$
$$o_t^b, h_t^b, c_t^b = GRU^b(c_{t-1}^b, h_{t-1}^b, x_t; W^b).$$

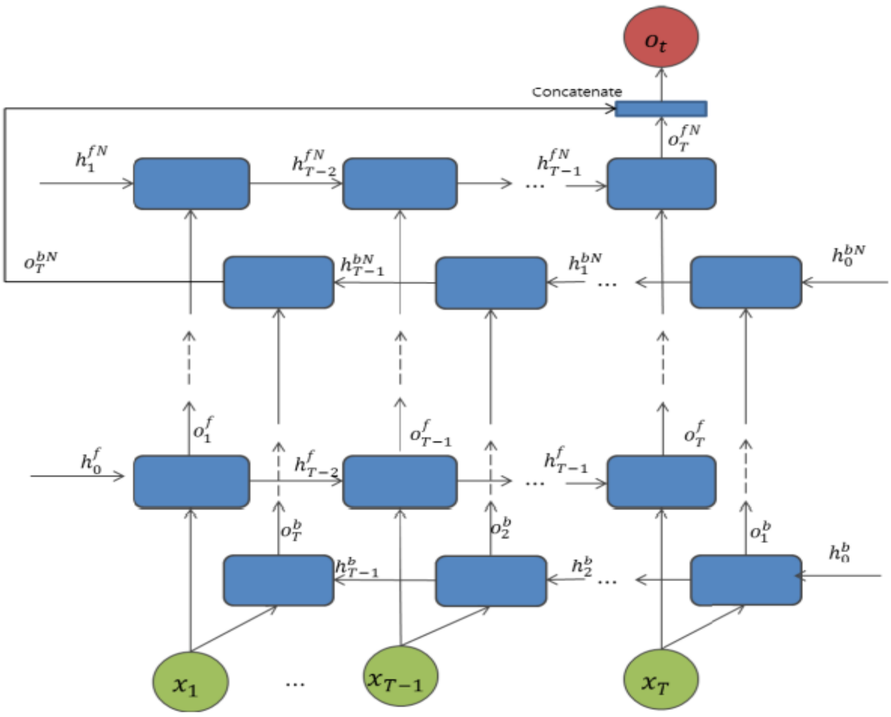

FIGURE 6. **Proposed bidirectional RNN based models where the hidden blocks can be used as either LSTM or GRU cells.**

Conclusion

Here, the task of ECG based biometrics human identification was carried out based on deep RNN networks in bidirectional training manner with LSTM and GRU cell unit, which recently have performed a significant performance in the field of machine learning. Although being held a major issue in traditional RNN networks which they learn representations from previous time sequences, bidirectional networks are designed to learn the representations from future time steps which allows for better understanding of context, and eliminate ambiguity. In addition, GRU cell in RNNs deploys an update gate and a reset gate in a hidden state layer which is computationally efficient than a usual LSTM network due to the reduction of gates but still can perform as much as LSTM network does.

However, the disadvantage of this method is the time cost of the training phase, which is a general problem of most deep networks, and the variation of the length of a segmented window for respective datasets should perform to investigate the optimal length of a window which capture a signle heartbeat of a signal for corresponding dataset. On the other hand, limitations of our proposal can be considered as data dependent acquistion where only ECG-I type data are suitable for pre-processing phase before training.