ECG Biometrics using RNN and CNN

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Abstract

Background: Biometric Systems (BS) are based on a pattern recognition problem where the individual traits of a person are coded and compared. The Electrocardiogram (ECG) as a biometric emerged, as it fulfills the requirements of a BS.

Methods: Inspired by the high performance shown by Deep Neural Networks(DNN), this work proposes two architectures to improve current results in both identification and authentication: Temporal Convolutional Neural Network (TCNN) and Recurrent Neural Network (RNN). The last two results were submitted to a simple classifier, which exploits the error of prediction of the former and the scores given by the last.

Results: The robustness and applicability of these architectures were tested on Fantasia, MIT-BIH and CYBHI databases. The TCNN outperforms the RNN achieving 100%, 96% and 90% of accuracy, respectively, for identification and 0.0%, 0.1% and 2.2% equal error rate for authentication.

Conclusions: When comparing to previous work, both architectures reached results beyond the state-of-the-art. Even though this experience was a success, the inclusion of these techniques may provide a system that could reduce the validation acquisition time.

Full Text

Due to technical limitations, full-text HTML conversion of this manuscript could not be completed.

However, the manuscript can be downloaded and accessed as a PDF.

Figures

(a) Recurrent Neural Network Approach

(b) Temporal CNN Approach

Figure 1

Proposed architectures. (1a) depicts the whereRNN approach each input (x_n) is fed into to a embedded matrix (E) where the result vector enters into a se- quence of three Gated Recurrent Units (GRU) (G) cells. The output of this sequence is transformed through a fully connected network and a softmax function resulting in o_n . (1b) depicts the Temporal Convolutional Neural Network (TCNN) approach, where a time window (TW) and the first complete cycle are input to two different sequences of CNN blocks (CN) each comprised by a one dimensional convolutional layer with N dilation factor, a batch normalization and a ReLU activation function. One of the networks has N number of blocks while the other $N - 2$, they both end in a fully connected network and then the last vector is summed giving the output for classification.

(a) Recurrent Neural Network Approach

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Figure 2

Pre-processing phase for the RNN model.

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Figure 3

Distribution of the score of the RNN network for the predictor ECG 8 for each of the ECG signals of the Fantasia Dataset. While (3a) refers to a single window of 512 samples, (3b) is using the evaluation for a batch size of 20 windows. δ_1 , δ_2 and δ_3 are three examples of increasing threshold values.

Figure 3

Distribution of the score of the RNN network for the predictor ECG 8 for each of the ECG signals of the Fantasia Dataset. While (3a) refers to a single window of 512 samples, (3b) is using the evaluation for a batch size of 20 windows. δ_1 , δ_2 and δ_3 are three examples of increasing threshold values.

Figure 4

Results for the Fantasia dataset. 4a is the identification results with the increase of batch sizes. 4b and 4c are the confusion matrix for the best results for RNN and TCNN approaches, respectively, and respective metrics of accuracy (acc) specificity (sp) and sensitivity (st). 4d

and 4e are the evolution of the EER values over time for both approaches.

(a)

(b) RNN.

acc - 100%; sc - 100%; st - 100%

(c) TCNN.

acc - 99.1%; sc - 100%; st - 99.1%

(d) RNN

(e) TCNN

Figure 4

Results for the Fantasia dataset. 4a is the identification results with the increase of batch sizes. 4b and 4c are the confusion matrix for the best results for RNN and TCNN approaches, respectively, and respective metrics of accuracy (acc) specificity (sp) and sensitivity (st). 4d and 4e are the evolution of the EER values over time for both approaches.

(a)

(b) RNN:

acc - 96.4%; sp - 99.9%; st - 96.4%

(c) TCNN:

acc - 91.3%; sp - 99.9%; st - 91.3%

Figure 5

Results for the MIT-BIH dataset. 5a is the identification results with the increase of batch sizes. 5b and 5c are the confusion matrix for the best results for RNN and TCNN approaches, respectively, and respective metrics of accuracy (acc) specificity (sp) and sensitivity (st). 5d and 5e are the evolution of the EER values over time for both approaches.

Figure 5

Results for the MIT-BIH dataset. 5a is the identification results with the increase of batch sizes. 5b and 5c are the confusion matrix for the best results for RNN and TCNN approaches, respectively, and respective metrics of accuracy (acc) specificity (sp) and sensitivity (st). 5d and 5e are the evolution of the EER values over time for both approaches.

(a)

(b) EER values through time.

Figure 6

Results for the CYBHi dataset for each approach. M1 represents the first moment and M2 represents the second moment.

(a)

(b) EER values through time.

Figure 6

Results for the CYBHi dataset for each approach. M1 represents the first moment and M2 represents the second moment.