

DEEP LEARNING BASED PERSON BIOMETRIC IDENTIFICATION

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Abstract: The article is about the biometric person identification using Deep Learning methods. The issues related to the preprocessing of the signal, the extracting of biometric features and classification are considered. The implementation of the LSTM Deep Learning model, which is a kind of Recurrent neural network, is discussed. Factors affecting the accuracy of biometric identification are being studied

1. Introduction

Modern authentication technologies are subject to hacking. It is considered that biometric identification is more reliable. Biometric authentication includes some tools to identify individuals by using their unique, measurable physiological and behavioural characteristics for example face recognition, iris, retina, voice, and fingerprint. However, biometric authentication systems are increasingly facing the risk of being tricked by biometric tools such as anti-surveillance masks, contact lenses, vocoders, or fingerprint films [1]. There are a few ways for increasing of biometric authentication reliability. First one is intended to improve an existing technology. For example, Tan and Schuckers from Clarkson University reported about vulnerability of fingerprint scanners because hackers are used artificial fingers made from Play-Doh, gelatine and silicone molds [2]. Authors proposed an anti-spoofing detection method based on ridge signal and valley noise analysis, to quantify perspiration patterns along ridges in live subjects and noise patterns along valleys in spoofs. Based on these features, separation (live/spoof) is performed using standard machine learning tools including decision trees and artificial neural networks. Authors show that the performance can reach 99.1% correct classification overall [2].

Bogdanov et al. investigated factors affecting the accuracy of biometric identification based on the using of electrocardiograms [3], [4]. PTB (290 subjects) [5] and ECG-ID (90 subjects) [6] digitized ECG databases were used under researching. Authors compared the accuracy of electrocardiogram recognition by various methods of machine learning (table 1) [4].

Table 1.

Accuracy of electrocardiograms recognition by various methods of machine learning

Database	Gaussian Mixture Models	Random Forests	Support Vector Machines	Logistic Regression
PTB	0.80	1.00	0.95	0.83
ECG-ID	0.66	0.98	0.93	0.79

Table 1 show, on the one hand, that the random forests method is more precise and on the other hand, we can see that the accuracy of recognition also depends on the registration hardware used. To increase the accuracy, you can tune the model hyperparameters. So, when using the default parameters in the SVM method, we have an accuracy of 0.93 (in the case of the ECG-ID database), however, by tuning the parameters on grid we found the best values for 'kernel' parameter is 'rbf', for 'C' parameter is 10, for 'gamma' parameter is 0.99. Using parameters found we can increase the accuracy to 0.99. The same is true for other methods [3].

Interesting results were obtained when studying the effect of sample size on the accuracy of recognition (table 2) [4].

Table 2: The effect of sample size on recognition accuracy (PTB database)

Sample size	Gaussian Mixture Models	Random Forests
10	0.96	1.00
30	0.82	1.00
50	0.80	1.00
70	0.82	1.00
90	0.77	1.00
290	0.80	1.00

Table 2 shows that the accuracy of recognition by the method of Gaussian Mixture Models increases with an increase in sample size on the plateau (0.80), while the accuracy of recognition by the method of random forests does not depend on the sample size.

Bogdanov et al. showed that the recognition accuracy is practically independent of the recording time [4].

2. Related work

The next approach involves the use of new biometric identification technologies. Recently there have been published papers on biometric identification using electroencephalograms [1].

Another way for improving of accuracy of recognition is using of multimodal biometric systems. The main objective of multimodal biometrics is to reduce one or more false accept rate, false reject rate and failure to enrol rate [7]. Bumbarov et al. proposed a face and ECG based multimodal system [7]. Under face recognition the challenge is face detection in scenes with complex background, different lightning conditions, changes in pose, human expressions etc. [7]. To overcome these problems author proposed a framework including Face Detection, Subspace Projection and Classification. Face Detection is intended to locate a human face in a scene and extract it as a single image. For performing of Face Detection authors used a combination of two classifiers (Haar-like features' cascade of weak classifiers, intended for fast detection of face-like objects. The second classifier is a Convolutional Neural Network (CNN) used for filtration of falsely detected faces). Subspace Projection based on Principal Component Analysis (PCA) and Spectral Regression (SR) algorithms was used for dimensionality reduction of the detected facial images, when represented as vectors in high-dimensional Euclidean space. Support Vector Machines algorithm was used for classification of detected faces [7]. The Framework was tested on image database from the Computational Vision at the California Institute of Technology. Best accuracy was 95.26%.

Bumbarov et al. when working with electrocardiograms used ECG signals collected from 28 individuals using own ECG registration hardware. The sampling rate is 512Hz and the resolution is 12bit. Authors trained the system using subsets from these signals. The testing was done two weeks later in order to be sure the time invariance of the features [7].

Authors extracted morphological features from electrocardiograms which present simultaneously amplitude and temporal characteristics of the ECG waves as well as their shape based on linear projections in subspaces [7]. Authors used Principle Component Analysis (PCA) and Linear Discriminant Analysis

(LDA) [7]. All experiments with kernel versions of PCA and LDA were made using the Gaussian kernel function. The best accuracy was 95.7% [7].

When combining of Face Recognition and ECG based Personal Identification authors used the output probabilities of Radial Basis Neural Network classifier (for ECG recognition) and LIBSVM library for calculating the output probabilities of SVM classifier (for Face Recognition) [7]. Bumbarov et al. show that combining probabilities output of ECG identification and Face Recognition framework give accuracy of 99.5% [7].

Zhang et al. proposed a multimodal biometric authentication system including three parts: an Invalid ID Filter Model to block invalid subjects, a Gait Identification Model and an EEG Identification Model [1]. The first two models realize a one-class SVM algorithm and a Recurrent Neural Network based deep learning model, respectively. The third model combines autoregressive coefficients, an RNN structure, and an SVM classifier. The system is trained with a gait dataset of 160,000 samples and an EEG dataset of 108,000 samples. Experimental results show an overall accuracy of 0.983 along with an overall false acceptance rate (FAR) of 0.0 and a false rejection rate (FRR) of 0.019.

Another approach of multimodal biometric authentication proposed Manjunathswamy et al. [8]. Authors used ECG and fingerprints as sources of biometric features. Authors extracted 12 morphological features from electrocardiograms and 2 features (bifurcations and terminations) from fingerprints. Manjunathswamy et al. reported on 82.40% accuracy score for ECG recognition, 92.60% accuracy score for fingerprint recognition and 97.50% accuracy score after fusion of two modalities [8].

3. Motivation and aim

The goal of the researches presented is develop a method of biometric identification using ECG based on Long Short-Term Memory (LSTM) network. The project includes data acquisition, signal preprocessing, feature extraction and classification.

4. Using of artificial neural networks for biometric recognition

Very interesting results may be obtained when using of Deep Learning technologies for Biometric Recognition and classification of cardiac arrhythmia [9]. Usually authors use a Multilayer Perceptron (MLP) neural networks or Recurrent Neural Networks (RNN) for biometric classification. Gawande et al. described a biometric system based on MLP intended for ECG recognition [9]. Authors used lead II for analysis. ECG samples from 8 healthy individuals are recorded regularly during 36 months. Authors extracted 7 statistical and 3 morphological features. Each electrocardiogram contains at least 5 ECG cycles. Seven statistical features have been extracted after decomposing the ECG signal by using wavelet transform. Three morphological feature using Pan Tompkins algorithm are calculated [9]. Multilayer Perceptron Neural Network with single hidden layer is trained with 3 runs and 1000 epochs. The testing results show that the MLP has accuracy of 99.76 during experimentation [9].

Page et al. presented a low-power wearable ECG based biometric authentication system [10]. The approach uses 1-lead ECG data at sample rate of 500 Hz. The main processing block consists of three major stages: 1. Preprocessing, 2. QRS Identification, and 3. User Identification. To achieve the goal of biometric authentication, the system used neural networks for both detecting QRS complex segments and performing user identification. When preprocessing it is filtering and normalization of signal was performed. To QRS complex identification a neural network model consisting of a single 307-node hidden layer with 60% dropout and a tanh activation function was built. Authors reported on 99.54% accuracy. According to Page et al. the model required 2 hidden layers with sizes 577 and 380, dropout rates 76% and 78% and a tanh activation function [10].

Tantawi et al. described ECG based Biometric Recognition system. PTB, MIT_BIH and Fantasia electrocardiogram datasets were used under researching [11]. Authors used as biometric features a RR intervals extracted and decomposed using discrete Daubechies wavelet in wavelet coefficient structures which was reduced by excluding the uninformative coefficients and they are fed into a Radial Basis Functions (RBF) neural network for classification [11]. The best accuracy achieved was 95.89% [11].

Kim et al. decided to use weighted fuzzy membership functions (NEWFM) for biometric authentication using ECG [12]. They extracted biometric features from 73 subjects in the Physionet Database using Haar-wavelet transformation coefficients a4, d3, and d4. Extracted features then were entered into the neural network with weighted fuzzy membership functions for use in order to categorize ECG waveforms in the proposed biometric authentication model [12]. Authors have reached accuracy of 98.32% using proposed method [12].

5. Data

We used a digitized ECG database Physikalisch-Technische Bundesanstalt (PTB) presented by prof. Michael Oeff to physionet.org project [13]. The warehouse includes 549 ECG samples from 290 subjects. Each ECG record included 12 standard leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6) and three Frank leads (vx, vy, vz). The sampling rate was 1 kHz, the bit depth was 16 bits in the voltage range ± 16.384 mV. Most subjects suffered from various cardiovascular disorders, the control group included 51 healthy subjects [13].

6. Preprocessing

The preprocessing we started with extracting of lead 1 (Fig. 1).

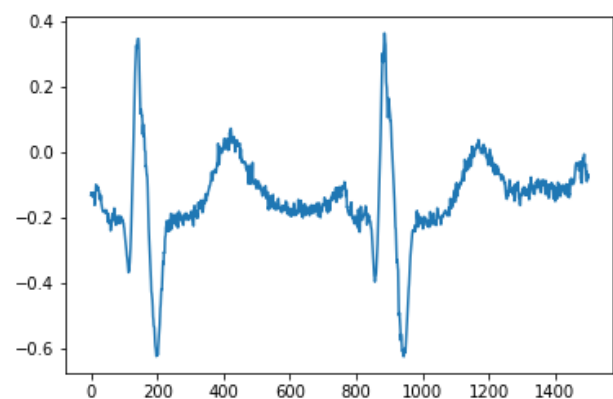


Fig 1. The first lead of ECG

As we can see from Figure 1, the original signal is redundant and contains artefacts. To eliminate the redundancy, we applied a low-pass filter with a cutoff frequency of 50 Hz (Fig. 2).

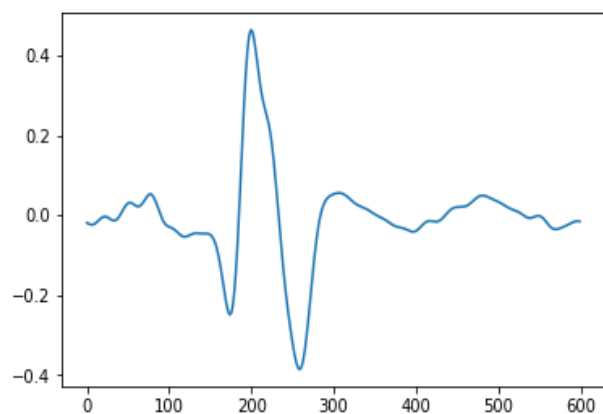


Fig 2. The signal after low-pass filter

Further, the signal was cut into fragments of 600 values. The fragments thus obtained were synchronized over the R peaks of the QRS complex (Fig. 3).

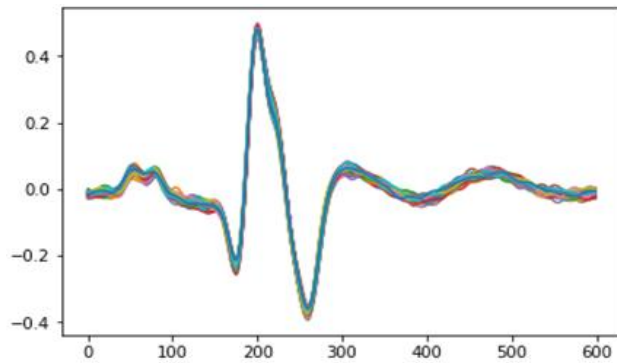


Fig 3. The ECG signal after preprocessing

7. Feature extraction

Under the researching we used a two types of biometric features: 1) temporal and amplitude values of Q, R and S-regions of lead 1 and amplitude values of Q,R and S-regions of lead 3 (9 features in total), 2) entire cardio cycle from lead 1 (600 values). Temporal and amplitude features were extracted according to Bogdanov et. al [4].

8. Classification

8.1. Recurrent Neural Networks

Recurrent neural networks (RNN) are a powerful and reliable type of neural networks and currently belong to the most promising algorithms, since they are the only ones that have internal memory.

Because of their internal memory, RNN is able to remember important things about what they got, which allows them to be very accurate in predicting what will happen next. It is for this reason that they are the preferred algorithm for sequential data such as time series, speech, text, financial data, audio, video, weather and much more, as they can form a much deeper understanding of the sequence and its context compared to other algorithms.

In the RNN, the information cycles through the loop. When it makes a decision, it takes into account the current input, as well as what it learned from its previously received inputs (Fig. 4).

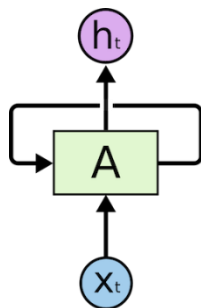


Fig 4. This loop structure allows the neural network to take the sequence of input [14]

The image below (Fig. 5) shows the deployed RNN. On the left you can see RNN, which unfolds after the equal sign. It should also be noted that there is no cycle after the equal sign, since different time stamps are rendered and the information is transferred from one time sign to the next. This illustration also shows why RNN can be viewed as a sequence of neural networks.

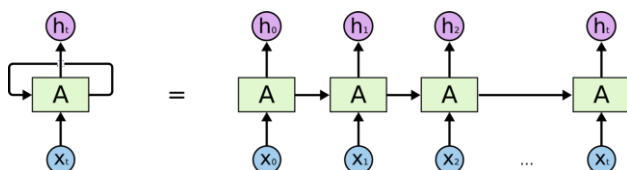


Fig 5. Unrolled version of the net. First, it takes the $x_{(0)}$ from the sequence of input and then it outputs $h_{(0)}$ which together with $x_{(1)}$ value is the input for the next step. Thus, the $h_{(0)}$ value and $x_{(1)}$ value is the input for the next step. Analogous, $h_{(1)}$ value from the next is the input with $x_{(2)}$ value for the next step and so on. This way, it keeps remembering the context while training [14].

There are two obstacles that RNN faces. One of the modifications of recurrent networks, which we will consider below, solves these problems.

One of the problems is the problem of "exploding" gradients. The essence of the problem lies in the fact that the algorithm can assign a large value to the scales without any particular reason. Another problem is the disappearing gradients. When gradient values become too small, the model stops learning or studies too slowly. This was a serious problem in the 1990s and it is much more difficult to solve than the first one. Fortunately, it was solved with the concept of a network of long short-term memory (LSTM).

Long long-term memory networks (LSTMs) are a modification of recurrent neural networks, which basically expand their memory. Therefore, it is well suited for studying important experiments that have a very long period of time between them.

LSTM is designed to solve the problems of long-term dependence. Remembering information for long periods of time is practically their default behavior, not what they are trying to learn. LSTMs also have the same chain as RNN, but the repeating module has a different structure. Instead of having a single layer of a neural network, there are four interacting in a specific way.

8.2. Architecture of Deep Learning Model

Architecture of Deep Learning Model is shown in Fig 6.

Depending on the extracted features, the form of the input and output data changes from the ECG. Then the data goes to the first LSTM layer. All outputs of this layer are fed to the next LSTM layer with 256 blocks. After the treatment with this layer goes a fully connected layer. This layer outputs a vector whose length depends on the number of objects to be classified in the database.

Table 3

Results of the experiment

Description of the features submitted to the model	The Model of Deep Learning (all subjects)	The Model of Deep Learning (healthy subjects)
9 features from lead 1 and 3	0.97	0.92
Entire cardio cycle (600 points)	0.99	0.98

As we can see the method using entire cardiocycle as feature table is more precise.

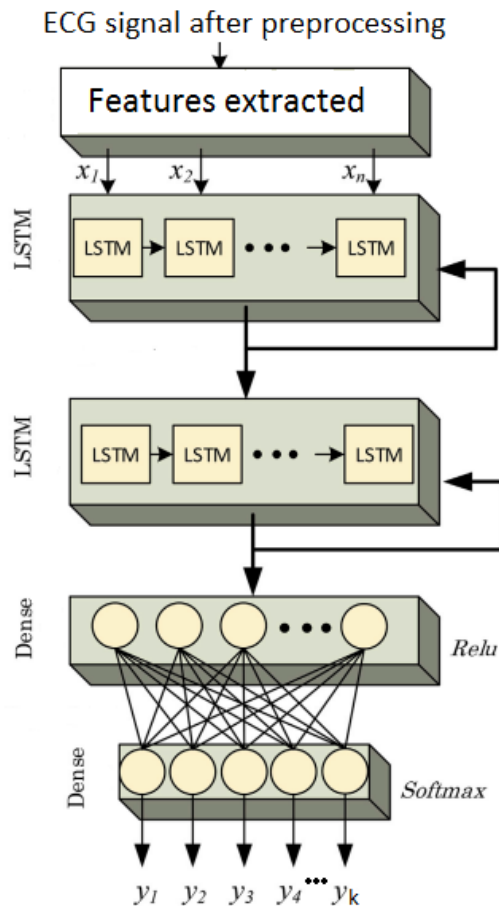


Fig 6. Architecture of Deep Learning Model

8.3. Experiment

For the final experiment, two methods of extracting features were chosen. The first way is to give our model the entire cardiocycle. The second way is to use the main points of the QRS complex of the first and third leads.

Regardless of the way in which features were extracted, the accuracy of the model was calculated using the cross-validation method. For this purpose, the data was divided into 10 parts. In total, the model goes through 10 complete training cycles. At each iteration of the cycle, the network is trained in 9 parts and tested on one. Thus, each part will be used as a test set. For the value of the final accuracy, the arithmetic mean was taken.

Also, regardless of how we extract the features, we need to encode the class labels. Since the output layer of our model is a vector whose length is equal to the number of classes, we should apply the following method: we code our class labels with a unique length vector equal to the number of classes in such a way that only one component is equal to one and the others to zero.

Since there were subjects in our database with different numbers of measurements, it was interesting to see how many records at different time intervals affect the accuracy of the model. It is also worthwhile to conduct the experiment by sampling only healthy individuals. The results of all the experiments are shown in Table 3.

9. Conclusion

The results of the work show that deep learning methods with a larger training sample allow us to find hidden patterns in data that allow us to better classify an object than using features that have been selected manually. Since a high recognition accuracy was obtained and the cardiograms were recorded at different time intervals, this leads to the conclusion that the cardiogram contains invariant features.

In the presence of a huge array of data, deep training methods should be used to detect hidden patterns, rather than using manual selection of features.

References

1. Zhang X., Yao L., Chen K., Wang X., Sheng Q.Z., Gu T. DeepKey: An EEG and Gait Based Dual-Authentication System. ACM J. Comput. Cult. Herit., Vol. 9, No. 4, Article 39. Publication date: March 2017.
2. Tan B., Schuckers S. Spoofing Protection for Fingerprint Scanner by Fusing Ridge Signal and Valley Noise. <https://www.clarkson.edu/sites/default/files/2017-11/spoofingprotection.pdf>
3. Bogdanov M.R., Dumchikov A.A., Kartak V.M., Fabarisova A.I. Optimizing Factors Influencing on Accuracy of Biometrical Cardiomtry. OPTA-SCL 2018, Omsk, Russia, published at <http://ceur-ws.org>.
4. Bogdanov M.R., Kartak V.M., Dumchikov A.A., Fabarisova A.I. Factors Influencing Accuracy of Biometrical Personal Identification Based on Cardiograms. DOI: 10.1134/S1054661818030033. ISSN 1054-6618, Pattern Recognition and Image Analysis, 2018, Vol. 28, No. 3, pp. 421–426. © Pleiades Publishing, Ltd., 2018.
5. Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. Circulation 101(23):e215-e220 [Circulation Electronic Pages; <http://circ.ahajournals.org/content/101/23/e215.full>]; 2000 (June 13).
6. Nemirko A.P., Lugovaya T.S. Biometric human identification based on electrocardiogram. Proc. XII-th Russian Conference on Mathematical Methods of Pattern Recognition, Moscow, MAKS Press, 2005, pp. 387-390. ISBN 5-317-01445-X.
7. Ognian Boumbarov, Yuliyen Velchev, Krasimir Tonchev and Igor Paliy (2011). Face and ECG Based Multi-Modal Biometric Authentication, Advanced Biometric Technologies, Dr. Girija Chetty (Ed.), ISBN: 978-953-307-487-0, InTech, Available from: <http://www.intechopen.com/books/advanced-biometric-technologies/face-and-ecg-based-multi-modal-biometric-authentication>
8. Manjunathswamy B.E., Abhishek A.M., Thriveni J, Venugopal K R, Patnaik L.M. Multimodal Biometric Authentication using ECG and Fingerprint. International Journal of Computer Applications (0975 – 8887). Volume 111 – No 13, February 2015.
9. Gawande P.S., Ladhake S.A. Artificial Neural Network based Electrocardiogram Classification for Biometric Authentication. International Journal of Computer Applications (0975 – 8887). Volume 109 – No. 2, January 2015.
10. Page A., Kulkarni A., Mohsenin T. Utilizing Deep Neural Nets for an Embedded ECG-based Biometric Authentication System. 978-1-4799-7234-0/15/\$31.00 ©2015 IEEE.
11. Tantawi M., Revett K., Salem Abd-B., Tolba M. ECG based Biometric Recognition using Wavelets and RBF Neural Network. Recent Advances in Information Science. ISBN: 978-960-474-304-9.
12. Kim Ho J., Lim J.S. Study on a Biometric Authentication Model based on ECG using a Fuzzy Neural Network. 4th International Conference on Advanced Engineering and Technology (4th ICAET). IOP Conf. Series: Materials Science and Engineering 317 (2018) 012030 doi:10.1088/1757-899X/317/1/012030
13. Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. Circulation 101(23):e215-e220 [Circulation Electronic Pages; <http://circ.ahajournals.org/content/101/23/e215.full>]; 2000 (June 13).
14. Amit Shekhar. Understanding the Recurrent Neural Network. <https://medium.com/mindorks/understanding-the-recurrent-neural-network-44d593f112a2>
15. Nikolenko S. Deep learning. <https://logic.pdmi.ras.ru/~sergey/teaching/mlhse17/35-dl2-backprop.pdf>