The Use of Neural Network Methods and Atomic Functions in the Problem of Biometric Authentication by ECG

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Abstract

The most widespread methods of biometric authentication are not resistant to falsification today. So other more secure individualized features are sought for the biometric authentication problem. One alternative is the heartbeat signal and the electrocardiogram (ECG) signal, in particular. It is individual-specific in the sense of amplitude, peak and other characteristics, and thus difficult to be faked. This article discusses an algorithm for biometric ECG authentication system based on convolutional neural networks. The use of the atomic activation function will also be considered in comparison with the ReLU, which is often used in this type of neural networks. To evaluate the results obtained, metrics are introduced, a numerical experiment is set up using the developed software, within the framework in which the convolutional neural networks have been implemented. To compare the efficiency of classifiers, the estimates of Accuracy, Recall, Specificity, Precision, F_1-measure are given. Loss functions and ROC curves have been plotted for each algorithm and dataset.

Keywords

Neural network, Convolutional neural network, Activation function, atomic function

1. Introduction

Nowadays password-based authentication is the main identification tool, but it is insecure for a number of reasons [1, 2]. The main reason is insufficiently complex passwords, despite the emergence of password storage services. Therefore, biometric authentication is now increasingly used, which utilizes distinctive characteristics that can be used to recognize and verify the legitimacy of users. The ECG signal has great potential to become a powerful authentication tool due to its properties. Moreover, recently, heart rate variability has been deeply studied and it has been proven that due to the characteristics of human anatomy, the ECG cannot be faked [3]. It is also worth noting that this characteristic cannot be removed without special sensors, which prevents information leakage. Its further use as biometrics, in addition to diagnostics in medicine, is due to the factors described in [4].

In general, two types of errors are considered in biometric systems: false positive (type I error), which leads to denial of access to a legitimate user, and omission of events (type II error), which leads to access to the system by an illegitimate user. These errors are inversely related and are regulated by the decision threshold by the classifier in favor of convenience (reduction of type I errors), or in favor of safety (minimization of type II errors).

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2. Materials and Methods

For the experiment, the international PhysioBank ATM database of measurements of normal heart rate MIT-BIH nsrdb was used[2]. This database includes 18 long term ECG records of subjects. The subjects included in this database did not have significant deviations from the norm; these include 5 men between the ages of 26 and 45 and 13 women between the ages of 20 and 50. For a randomly selected legitimate user, 18 signals of 10 seconds each were collected from the total recording, for the rest, 2-3 segments were selected, also 10 seconds each.

2.1. Preprocessing of ECG signals

The original data requires preliminary processing, as it contains noise and various distortions. The signal was filtered using a Butterworth bandpass filter (BFB) of 0.5–45 Hz [5, 18], which allows one to reduce the frequency and remove signal distortions while retaining significant components.

After filtering, it is necessary to highlight the signs of the ECG signal, mainly the *QRS* complex, *P* and *T* waves [6]. The features were extracted according to the following algorithm:

1. Detect *R* waves in the general ECG signal.
2. Divide into ECG cycles between adjacent *R* waves.
3. Interpolate ECG cycles (since templates can have different lengths and frequencies, it is necessary to interpolate each cycle before normalization; in this work, interpolation was carried out using the cubic spline algorithm [7]).
4. Normalize ECG cycles using the algorithm [7].
5. Next, you need to select a single template, for this the average value at each point is calculated, i.e. for each $X_i \in [0 : 0{,}01 : 1]$ calculate the mean value $M(X_i) = Medium\left(C_j(X_i)\right)$, where $X_i \in [0 : 0{,}01 : 1]$ and $j \in [0 : 1 : 10]$; display the ECG cycle $M = M(X_i)$, where $X_i \in [0 : 0{,}01 : 1]$.

2.2. Overview of Neuron Network Architecture

In deep learning, a convolutional neural network (CNN or ConvNet) is a class of deep neural networks most commonly used to analyze visual images [8]. The essence of convolution is to create another set of values, which is called a kernel or filter. Today, there are other layers in the traditional convolutional neural network that are interspersed with convolutional layers. Activation layer is a layer that is a kind of non-linear function (usually ReLU and its modifications), often logically combined with a convolution layer. The pooling layer is a layer that is a non-linear compaction of the feature map. The maximum function (or Softmax) is usually used. The last layer of the network is the fully connected layer. Each neuron in this layer is a perceptron with a nonlinear activation function.

A schematic diagram of the convolutional neural network used in this study is shown in Fig. 1.

The unique approximation properties of artificial neural networks are largely achieved due to activation functions that determine the dependence of the output signal on the weighted sum of signals at the input of the neuron. Thus, the artificial neuron is characterized by its activation function. Non-linear activation functions allow neural networks to solve non-trivial problems with a small number of nodes. Let's consider the used activation functions.

ReLU is a rectified activation function, its idea is that the excitation of biological neurons cannot be expressed with a negative value (1). Neurons introduce nonlinearity at zero that can be used to make decisions.

$$f(x) = \max\{0, x\}. \quad (1)$$

[2] Open access databases on PhysioNet, 2021. URL: https://physionet.org/about/database/.

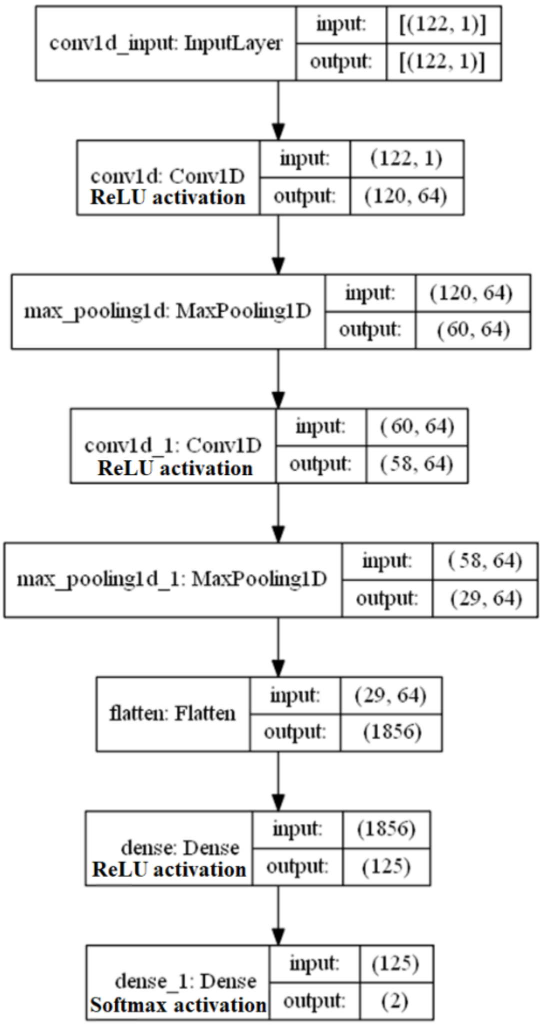

Figure 1: Convolutional neural network scheme

Sigmoidal functions based on finite infinitely smooth solutions of functional differential equations with deviating argument are often called atomic functions (AF); they were first introduced in the works of V.L. Rvachev and V.A. Rvachev [9, 10]. Atomic functions are a convenient tool for numerical analysis, approximation theory, digital signal processing [11-13]. Despite the fact that AF $up(x)$ is not an entire function and has an infinite spectrum, expansion (2) provides a satisfactory quality of approximation in the interval [-1,1]. The appearance of the function, as well as its derivative, is shown in Fig. 2.

$$up(x) = \sum_{k=-2^n+1}^{2^n-1} up\left(\frac{k}{2^n}\right) sinc[\pi(2^n x - k)], \qquad (-1 \le x \le 1). \tag{2}$$

Let's consider the capabilities of AF for the presentation of activation functions. We will choose the simplest AF $up(x)$ as the basic one.

$$f(x) = \int_{-1}^{x} up(t)dt = \begin{cases} up\left(\frac{1}{2}x - \frac{1}{2}\right), & \text{при } x \le 1 \\ 1, & \text{при } x \le 1 \end{cases}. \tag{3}$$

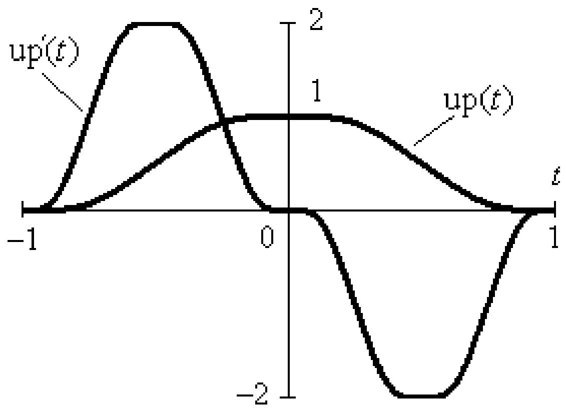

Figure 2: Atomic function up(x) and its first derivative

Then, by virtue of the main functional differential equation for the AF $up(x)$, we obtain a simple expression for the derivative:

$$f(x) = up(x) = f(2x + 1) - f(2x - 1). \tag{4}$$

Based on the properties described above, it can be assumed that using these functions, the result of neural network classification can be expected at least no worse than using the rectified activation function ReLU [17]. To test this hypothesis, a numerical experiment was carried out, described below.

3. Numerical experiment

After preliminary preprocessing of the ECG signal and the stage of feature extraction, a vector of 122 coefficients representing the signal template was obtained for each signal. Figure 3 shows a view of several templates from the general sample, superimposed for clarity of data variability.

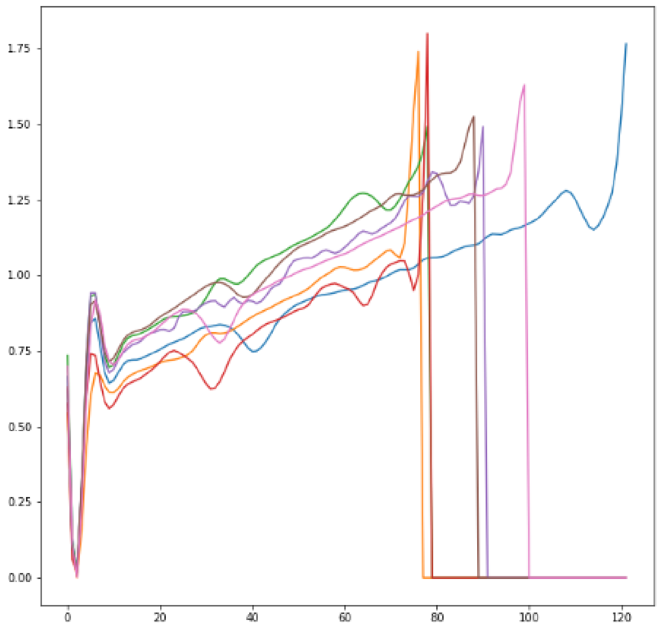

Figure 3: Superimposed ECG signal templates

3.1. Performance evaluation strategies

The neural network parameters were selected empirically. CNN consists of two convolutional layers, between which are pooling layers and two fully connected layers of 125 neurons each, with FA ReLU, or atomic FA; there are two neurons with Softmax FA on the output layer. During training, the cross-validation coefficient was zero, since in biometrics tasks it is necessary to achieve overfitting of the neural network for better recognition of a legitimate user.

In the NN model, a binary classification is used to recognize ECG signals: class "1" defines a legitimate user, and class "0" is an illegitimate user. To assess the effectiveness of the binary classifier, the following assessment metrics are calculated: the proportion of correct answers (accuracy); precision; recall; sensitivity; specificity, *F*-measure [14, 15] and ROC-curve [16].

4. Results

Table 1 shows the metrics of the effectiveness of the compared activation functions in training process of the constructed neural network.

Table 1
Comparison of the AF effectiveness

AF / Metrics	ReLU		Atomic	
	Train	Test	Train	Test
Accuracy	0.9753	1.0000	0.9877	1.0000
Recall	0.9753	1.0000	0.9877	1.0000
Precision	0.9753	1.0000	0.9877	1.0000
ROC-AUC	0.9476	1.0000	0.9877	1.0000
FN	0.0322	0.0000	0.0163	0.0000
FP	0.0322	0.0000	0.0163	0.0000
Loss	0.2948	0.2353	0.0957	0.0190
Specificity	0.9545	1.0000	0.9772	1.0000
F-мера	0.9505	1.0000	0.9681	1.0000

Further in Fig. 4 there are shown the ROC curves for assessing the quality of binary classification, graphs of recognition accuracy, graphs of loss functions, and a graph of changes in the number of type II errors (FP) during training.

For testing, samples were selected that did not participate in training the neural network model. In total, 20 samples were used for testing, 10 of which belong to a legitimate user.

When using a ReLU activation function, the probability of a legitimate user's samples belonging to class "1" is on average 0.9979, and of samples of other users to class "0" - ~ 1.0000. This indicates both that the model is well trained and type II errors are minimized, and that the probability of false positives is small.

When using Atomic AF, the probability of a legitimate user's samples belonging to class "1" is on average 0.9667, and of samples of other users to class "0" - 0.9758. Slightly worse than using ReLU.

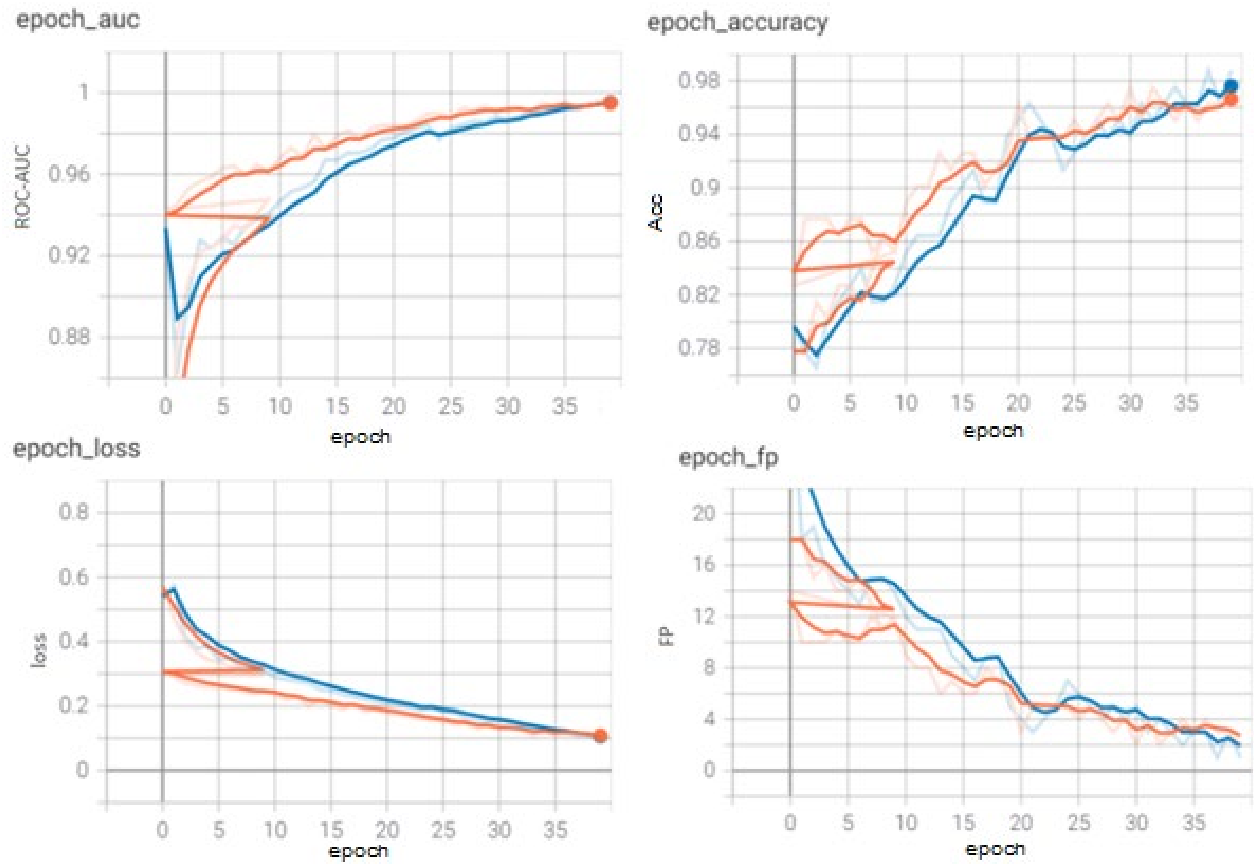

Figure 4: Superimposed ECG signal templates

5. Conclusions

This paper describes the results of using a convolutional neural network in combination with the use of an atomic activation function in the task of biometric authentication.

When comparing the two activation functions, we notice that for the submitted model of the neural network, ReLU and atomic AF, which is often used in similar architectures, the atomic AF showed itself better during training (1% of skipping events during training, F-measure equal to 0.9681). But in testing, ReLU performed better, which shows its suitability for the authentication task. However, taking into account the specifics of the operation of neural networks in authentication systems, the indicator of efficiency during training is of decisive importance, since when a new user is added to the system, the template of this user of the neural network will be presented. And in the future, during the operation of the network, it deals with those objects of marked data that have already been presented to it. Since within the framework of the authentication procedure, only the verification of the data presented by the user is carried out for the possibility of issuing rights to access limited resources.

As we can see, convolutional neural networks show high results in training and testing in biometric authentication tasks, which indicates that they can be effectively used to implement these information security systems, including to check the user's access rights by heart rate. Research shows that such authentication methods are quite promising [19]. A number of products are already on the market and are becoming widespread (e.g. Nymi Workplace Wearables[3] and ECG/EKG algorithms[4]), and many more will appear in the near future. Questions of practical implementation and directions for improving the software and mathematical part of such systems will be relevant for quite a long time.

[3] Nymi Workplace Wearables, 2021. URL: https://www.nymi.com/nymi-band.

[4] A suite of powerful ECG/EKG algorithms and analytics for user identification, 2021. URL: https://www.b-secur.com/heartkey/.

References

[1] Ivanov A., Sulavko A. Draft of the Third National Standard of Russia for Fast Automatic Learning of Large Correlation Neural Networks on Small Training Samples Of Biometric Data. Voprosy kiberbezopasnosti. 2021. No 3(43), pp. 84-93. DOI: 10.21681/2311-3456-2021-3-84-93. (in Russ.).

[2] K. Sidek, F. Sufi, I. Khalil and D. Al-Shammary, "An efficient method of biometric matching using interpolated ECG data," 2010 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES), 2010, pp. 330-335, doi: 10.1109/IECBES.2010.5742255.

[3] Wang, Y., Agrafioti, F., Hatzinakos, D. and Plataniotis, K.N., "Analysis of Human Electrocardiogram for Biometric Recognition". EURASIP J. Adv. Signal Process. 2008, 148658 (2007), doi: 10.1155/2008/148658.

[4] Plácido da Silva, Hugo, Fred, Ana, Lourenco, Andre and Jain, Anil, "Finger ECG signal for user authentication: Usability and performance." IEEE 6th International Conference on Biometrics: Theory, Applications and Systems, BTAS 2013, (2013), pp. 1-8, doi: 10.1109/BTAS.2013.6712689.

[5] S. Butterworth, "On the Theory of Filter Amplifiers," Experimental Wireless and the Wireless Engineer, Vol. 7, 1930, pp. 536-541.

[6] Meixue Yang, Bin Liu, Miaomiao Zhao, Fan Li, Guoqing Wang, Fengfeng Zhou, "Normalizing electrocardiograms of both healthy persons and cardiovascular disease patients for biometric authentication." PLoS One. 2013 Aug 20; 8(8): e71523, pp. 1-7, doi: 10.1371/journal.pone.0071523.

[7] Felipe Gustavo Silva Teodoro, Sarajane M. Peres, and Clodoaldo A. M. Lima, "Feature selection for biometric recognition based on electrocardiogram signals," 2017 International Joint Conference on Neural Networks (IJCNN), 2017, pp. 2911-2920, doi: 10.1109/IJCNN.2017.7966216.

[8] Valueva, M.V.; Nagornov, N.N.; Lyakhov, P.A.; Valuev, G.V.; Chervyakov, N., "Application of the residual number system to reduce equipment costs for the implementation of a convolutional neural network." Matematika i komp'yutery v modelirovanii, Elsevier BV (2020), Vol. 177, pp. 232–243, doi: 10.1016/j.matcom.2020.04.031. (in Russ.)

[9] V. L. Rvachev and V. A. Rvachev, "A certain finite function," Dokl. Akad. Nauk UkrSSR, Ser. A, No. 8, 1971, pp. 705–707. (in Russ.)

[10] V. L. Rvachev and V. A. Rvachev, "Nonclassical Methods of Approximation Theory in Boundary-Value Problems", Naukova Dumka, Kiev, 1979. (in Russ.)

[11] Basarab M.A., Zelkin E.G., Kravchenko V.F., Yakovlev V.P., "Digital signal processing based on the Whittaker – Kotelnikov – Shannon theorem", M.: Radiotekhnika, 2004, ISBN: 5-93108-064-3. (in Russ.)

[12] Kravchenko V.F., Rvachev V.L., "Algebra of logic, atomic functions and wavelets in physical applications", M.: Fizmatlit, 2006, ISBN 5-9221-0752-6. (in Russ.)

[13] Soldatenkov V.A., Achildiev V.M., Gruzevich Yu.K., et al., "Human internal organs diagnostics based on heart biophysical signals", XXVII St. Petersburg International Conference on Integrated Navigation Systems Collection of materials, 2021, in press.

[14] Konnova N.S., Khaperskaya V.Yu., "Application of machine learning algorithms and neural networks for SCG signal classification", Biomeditsinskaya radioelektronika, 2020, Vol. 23, Issue 1, pp. 5-20, doi: 10.18127/j15604136-202001-01. (in Russ.)

[15] Konnova N.S., Basarab M.A., Khaperskaya V.Yu., "Application of machine learning algorithms for SCG signal classification", Proc. of 3rd International conference on Image, Video Processing and Artificial Intelligence (IVPAI-2020), Shanghai, China, 2020, 115841L, doi: 10.1117/12.2579578.

[16] Kohavi R, "A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection", 14th International Joint Conference on Artificial Intelligence, Palais de Congres Montreal, Quebec, Canada, 1995, pp. 1137-1145.

[17] Andres Hernandez-Matamoros, Hamido Fujita, Enrique Escamilla-Hernandez, Hector Perez-Meana, Mariko Nakano-Miyatake, “Recognition of ECG signals using wavelet based on atomic functions”, Biocybernetics and Biomedical Engineering, Vol. 40, Issue 2, 2020, pp. 803-814, doi: 10.1016/j.bbe.2020.02.007.

[18] K.M. Gaikwad and M.S. Chavan, “Removal of high frequency noise from ECG signal using digital IIR butterworth filter”, IEEE Global Conference on Wireless Computing & Networking (GCWCN), 2014, pp. 121-124, doi: 10.1109/GCWCN.2014.7030861.

[19] Nastaran Maus Esafahani and Parinaz Saadat, “Human Authentication based on Bioelectrical Signals”, International Journal of Computer Science and Information Security (IJCSIS), Vol. 14, No. 2, February 2016, pp. 39-45.