Biometric Identification from Raw ECG Signal Using Deep Learning Techniques

Lukasz Wieclaw[1], Yuriy Khoma[2], Pawel Falat[3], Dmytro Sabodashko [4], Veronika Herasymenko [5]

[1,3] University of Bielsko-Biala, 2 Willowa St., 43-309 Bielsko-Biala, Poland, lwieclaw@ath.bielsko.pl, http://www.eng.ath.bielsko.pl/

[2,4,5] Lviv Polytechnic National University, 12 Bandera St., 79013 Lviv, Ukraine, khoma.yuriy@gmail.com, http://www.lp.edu.ua/en/lp

***Abstract* — The paper presents and discusses a novel method of biometric identification based on ECG data. The main idea of the study is to apply Deep Neural Networks (DNN) for human identification based on the raw ECG signal. To improve overall system accuracy various signal pre-processing and outlier detection techniques have been applied. Also, to make ECG identification approach more user friendly, three-finger measurement scheme has been proposed. All experiments have been made using self-collected Lviv Biometric Data Set.**

Keywords* — *deep learning; neural networks; biometrics; human identification; electrocardiogram; ECG dataset.

I. Introduction

Biometrics is the science that uses statistical methods to recognize the human identity based on the physiological and behavioural attributes of the individual, such as fingerprints, face and voice. The term "biometrics" is composed of two Greek words: "bio" indicating life and "metric" indicating to measure.

In the modern society, there is an obvious need for reliable and robust human recognition techniques in critical secure access control, international border crossing and law enforcement applications. Biometric systems operate under the premise that numerous physiological or behavioural human characteristics are individual and unique. These characteristics can be reliably acquired and represented as numeric data which enables automatic decision-making for identification purposes.

There are two basic operating modes in biometrics. The first is the verification (or authentication) mode. In this mode system performs one-to-one comparison of captured features with a specific template stored in a biometric database in order to verify if the individual is a person he/she claims to be. The second is the identification mode where system performs one-to-many comparison against a biometric database attempting to establish the identity of an unknown individual. If the comparison of the biometric sample with a database template falls within a previously set threshold the system will succeed in identifying the individual. [1].

Human identification based on ECG is a relative new and fast developing approach [12]. The ECG signal is created by electrical impulses coming from the brain to the heart. Each of these pulses is stimulating various parts of the heart to make a complete beat. There is a number of factors creating ECG variants among normal persons, e.g. anatomy, position and size of the heart, chest geometry, age, sex, weight.

Comparing to common commercial biometric systems, such as fingerprints, hand geometry and face recognition, ECG identification has a several advantages [1,2,3]:

1. It is more fraud resistant, because of its internal biometric nature, which makes imitation more complicated than in case of external biometrics systems.
2. Possibility to provide fresh biometric reading continuously.
3. Good accuracy even in abnormal cases, low sensitivity to noise.
4. It is relatively easy to acquire: ECG signals acquisition can be made with the fingers and hand palms using one lead sensor or textile electrodes.

The process of ECG identification consists of the following phases: data acquisition, pre-processing, feature extraction, feature reduction and classification [3,4,5].

Data acquisition is required to register individual's ECG signals. Due to recent advances in biomedical instrumentation, besides conventional means of ECG signal reading, ECG signals can be acquired through the chest, using a shirt with textile embedded electronics, through the neck, using a necklace with a pendant, through the fingers and hand palms with a lead sensor or textile electrodes. In this case sensor does not need to be allocated at the body of a person as required previously [6,7].

Phase of ***pre-processing*** is intended to remove various distortion effects and to keep useful information in the ECG input signal. Digital band-pass filters or wavelet transform can be used for noise reduction, power-line suppression, baseline-wandering removal etc. In addition, at this stage segmentation and normalization of ECG signals is performed. Thus, the single heart beat signal is sent to further processing [8,9].

The next stage of ECG identification process is ***extracting of features***. Features are the representative ECG attributes allowing to recognize the specific person using inter-subject variability. Feature selection is a critical step for pattern recognition. Today, there are many approaches to performing feature selection which can be divided into two categories: fiducial or non-fiducial. Both approaches have advantages and disadvantages.

Fiducial techniques can be divided in morphological, amplitude and temporal. These methods are based on location of the specific anchor points on the ECG recordings, namely fiducials, such as wave's peaks, boundaries, slopes and other. Detecting fiducial points is a challenging process due to the high variability of the signal. Further the fiducials are used for generating the feature set. These features can be extracted with adaptive thresholds, wavelet transform and other means [10,11,12].

Non-fiducial methods do not use the characteristic points. Instead of this they are extracting features directly from the ECG signal or its fragments using this trait of the ECG signal as a quasi-periodicity. Non-fiducial approaches deal with a large amount of redundant feature sets that need to be reduced. In this case the challenge is to remove this information in a way that the intra-subject variability is minimized and the inter-subject is maximized. Literature overview has shown that non-fiducial methods may be subdivided in three main categories: autocorrelation based, phase space based and frequency based analyses [2,10,19].

The last stage of ECG recognition process is ***classification***. On this stage selected feature subsets of ECG signals are applied as classifier inputs. Depending on how accurately and appropriately these features have been chosen classifier will make correct or wrong decision.

Classification methods which have been proposed during the last years include Bayesian Networks, Kalman Filtering, Hidden Markov Models, Linear Discriminant Analysis, Genetic Algorithm, Decision Trees, k-Nearest-Neighbour, Self-Organizing Map, Fuzzy Logic Algorithm, Support Vector Machine, Artificial Neural Network [2,14,15,20]. Each approach contains its own advantages and disadvantages.

The aim of this study is the attempt to use Deep Neural Networks (DNN) for the identification of an individual based on raw ECG signal. Unlike existing approaches, the proposed method joins function of two stages – feature extraction and classification.

II. Data Acquisition

Arduino Uno and e-Health Sensor Platform V2.0. Arduino Uno is a microcontroller board based on the ATmega328P, with 16 MHz quartz crystal and USB port for programming, debugging and data transfer [13]. The e-Health Sensor Platform V2.0 extends Arduino Uno and allows to implement biometric and medical applications. The body monitoring can be conducted using 10 different sensors: pulse, oxygen in blood, airflow (breathing), body temperature, electrocardiogram, glucometer, galvanic skin response (sweating), blood pressure, patient position (accelerometer) and muscle/electromyography sensor [14].

Data acquisition was made using differential OpAmp schema followed by 8-bit ADC operating at 277 Hz sampling rate. ADC data was transferred to PC via COM-port using PySerial library. Each measurement lasted approximately 10 seconds, which means that user records typically contains approximately 10 or more heart beats.

It was decided to use modified Lead I schema for to place electrodes on the body surface and record the ECG tracing. Modified schema requires user to touch the electrodes with two fingers of his left hand and one finger of the right as shown at the picture below. This method is very convenient and can be applied for user authorization in everyday life. In our experiments in order to minimize preprocessing efforts user was in a sitting position and neutral emotional state during the measurement with minimal or no body and hand movements. Each record additionally has passed manual visual quality analysis.

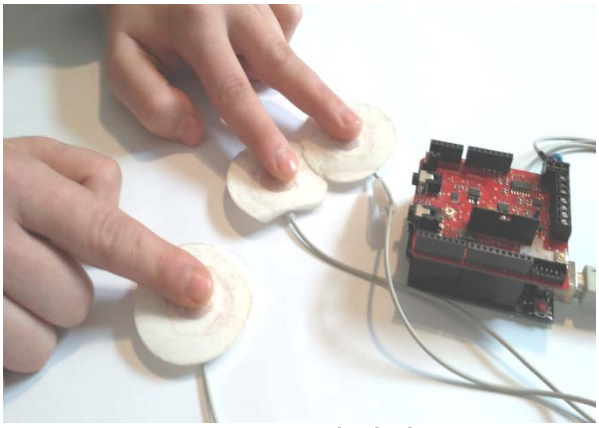


Figure 1. ECG recording hardware

III. Signal Preprocessing

The measured signal should be a subject of preprocessing which includes filtering, segmentation and normalization. The preprocessing stage prepares input signal to classification.

ECG signal is influenced by multiple factors. The recording is made through electrodes, which capture more than just the electrical activity of the heart.

Common noise/distortion sources in ECG signal measurements are:

1. Baseline wander (low frequency noise caused by perspiration that affects electrode impedance, respiration, body movements, for example finger movements on the electrode);

2. Electromagnetic fields from power lines can cause 50 Hz sinusoidal interference and its harmonics;

3. Muscle artifacts including respirations movements;

4. Noise generated by electronic devices used in signal acquisition circuits.

The informative part of ECG signal locates between 5 and 35 Hz. In order to remove all of the distortions mentioned above a bandpass IIR-filter was applied. Filter parameters were taken as follows: polynomial type - Butterworth, filter order - 7, sampling rate - 277 Hz, stopband - below 1 Hz and above 50 Hz, passband - between 4 and 35 Hz, stopband gain - 20 dB, passband gain - 1 dB. Filter was designed using SciPy library.

Filtered signal was normalized from the raw ADC digits to the range from -1 to +1. The next step was to split signal into separate heat beats. In order to detect R-peaks, Hamilton algorithm from BioSPPy library was used [15]. Afterwards, the signal is split up into individual heart beats, using an assumption that informative part of common heart beat doesn't exceed 270 samples (80 samples to the left of R-peak and 170 samples to the right). For shorter beats signal was accomplished with zeros at the end.

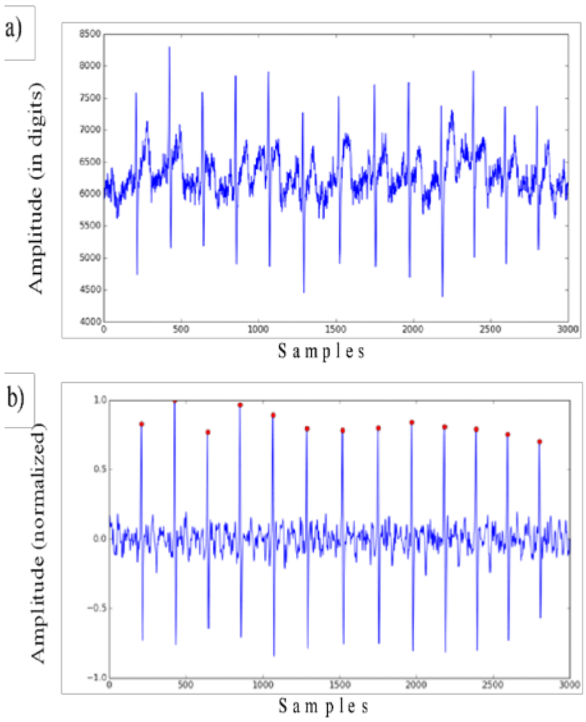
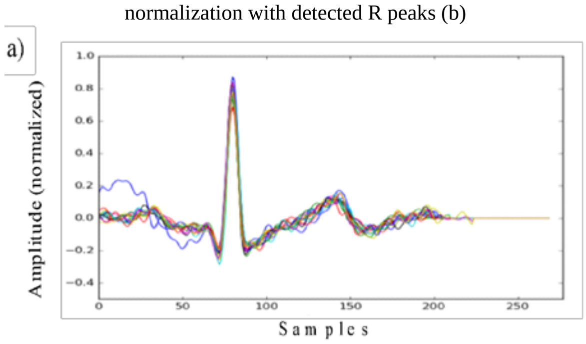


Figure 2. Raw ECG signal (a) and ECG signal after filtering and normalization with detected R peaks (b)



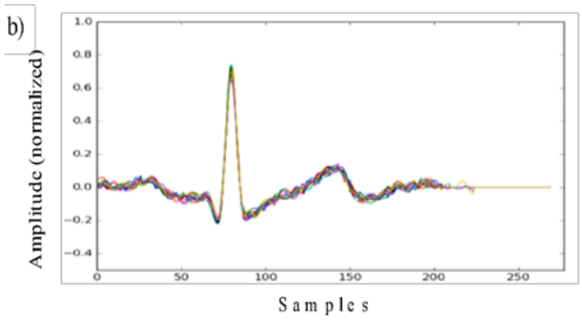


Figure 3. ECG segments (heart beats) aligned to R peak before (a) and after outlier correction (b)

Also, ECG preprocessing included selection of appropriate beats and remove various artifacts. Sliding window approach was used for uniformity and outliers' detection. This works as follows: ECG beats are split into fixed-length windows (windows may overlap). And, if standard deviation of at least one sample exceeds certain selected threshold, then all samples within the window are recognized as outliers. Samples outliers are replaced by the mean values obtained by averaging corresponding samples from other segments. This procedure is done iteratively until no more outliers can be detected. Afterwards, samples have been averaged across all heart beats for each record. Details of ECG signal preprocessing are shown on the Fig. 2 and Fig. 3.

IV. Classification

Supervised machine learning uses pre-existing records for its learning. Neural network infers a set of rules from collection of provided samples during learning (training set). Once the best model weights are selected, it can be used to predict results for previously unseen instances (testing set). Depending on database characteristics, nature of the problem and model usage peculiarities, the classification algorithm can be chosen from a variety range of possible options.

A deep feedforward neural network (also known as multi-layer perceptron or MLP) was chosen as basic architecture for this study. The details are the following: 270 neurons in input layer (corresponding to 270 preprocessed features), three hidden layers with 70, 50, 30 neurons and 19 neurons in output layer (corresponding to number of classes). Rectified Linear Unit was selected as activation function for hidden layers and softmax as activation function for output layer. Training algorithm - Adagrad, number of training epochs - 3000, learning rate - 0.05, L1 regularization rate - 0.001.

After training stage is finished the system performance should be evaluated. Accuracy was used for the classification performance metric. The data set was randomly split into train set (70%) and test set (30%). To prevent skewed classes problems, this split was done for each class separately, thus each class is proportionally represented in both train and test data.

V. EXPERIMENTS AND RESULTS

For current research 147 ECG records of 18 unique persons have been selected from Lviv Biometric Data Set. Minimal number of records per person is 3. Train set consists of 88 records, test set - 49 [16].

Experiments were made in Python 2.7. Following frameworks and libraries were used skflow, scipy, numpy, matplotlib, sci-kit learn. All deep learning algorithms were implemented on the top of Tensorflow framework. The source code of the project can be found here [17, 18].

Experiments have been performed using parameters and configurations from section 3. Training stage long for around 10 minutes on the machine with following parameters: CPU - Intel Core i7-5500, operating system - Ubuntu 14.04, 8 GB RAM.

The aim of the first experiment is to check how stable classification results are. The reason for that is that DNN weights are randomly initialized. Consequently, models will end up with different results even if they were trained under same conditions (data and hyperparameters). For this purpose, different (selected) DNN architectures were trained iteratively for 100 times. The results are shown in the table below. As follows from the results the deviation is significant for all architectures. Thus, the most reasonable approach is to run same model multiple times and pick-up the best one. Classification accuracy does not vary strongly from architecture to architecture. For further experiments in this research three hidden layers with 70, 50, 30 neurons were chosen.

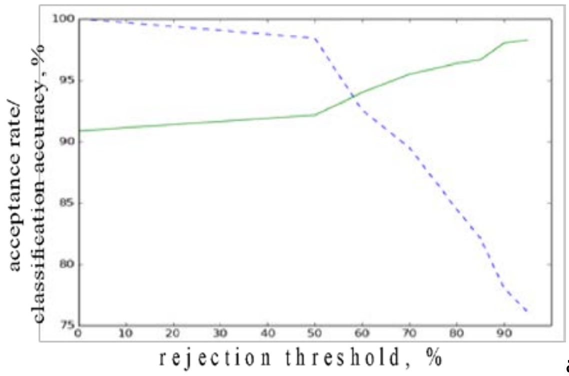
TABLE I. ACCURACY DISPERSION FOR DIFFERENT DNN ARCHITECTURES

Neurons in hidden layers	Mean accuracy, %	Accuracy standard deviation, %
[100 70 50 30]	88.50	3.35
[70 50 30]	88.97	2.81
[50 50 20]	84.14	5.28
[70 20]	88.84	4.23

Second experiment was conducted to investigate how number of classes impacts the overall classification accuracy. The results are shown in the table below. As we can see, additional classes do not impact system's significantly.

TABLE II. CLASSIFICATION ACCURACY VS NUMBER OF USERS

Number of users	3	5	7	10
Accuracy, %	97.03	94.69	93.26	88.97
Number of users	12	14	16	18
Accuracy, %	88.97	92.78	88.43	88.97



a

Figure 4. Classification accuracy (solid line) and identification rate (dotted line)

By default, DNN classifier will assign the records of unknown user to one of the existing classes, which is completely wrong for identification purposes. However, the reliability of such decision will be low. To handle this issues rejection option is required, which allows to skip identification if DNN's predicted probability is lower than certain threshold, On the other hand this can lead to a problem when some records of known user will also be rejected (e.g. because of the poor signal quality). The aim of the third experiment was to select the best rejection threshold to get optimal relation between classification accuracy and identification rate. The results are shown at the figure below. As follows from the presented chart, the optimal threshold is around 70%. For this threshold classification accuracy achieves ~96%, while acceptance rate still remains ~90%, which relatively high.

VI. CONCLUSIONS

Biometric identification is a key to solving many problems related to such areas as information security and access control, authorization, digital and online transactions, etc. Using biosignals in addition to common biometric techniques such as fingerprints, iris and face recognition for multi-factor identification is quite promising approach. Current study was focused on human identification using ECG data.

In the recent years, deep learning has shown tremendous results in solving commercial and scientific problems. The aim of the study was to combine deep learning techniques with ECG signal for human identification. This approach was promising because of two reasons. Firstly, deeply learning typically overperform most of the other classification techniques in terms of accuracy, which can lead to more reliable and robust identification results. Secondly, deep learning allows to perform identification using raw ECG data, without feature preparation step, which is required for most of the other techniques, and is quite challenging to implement from both algorithmic and computational points of view.

In current study embedded MCU device with Differential Amplifier circuit was used for ECG recording purposes. All signal preprocessing and classification was done on the PC side. To make data recording procedure more user-friendly Lead I was modified and data was collected not from human chest, but from fingers of both hands (two left hand fingers and one right hand finger). This approach shows that ECG biometric systems can be miniaturized and integrated with existing biometric systems or other consumer electronics gadgets.

Recorded data was used to create Lviv Biometric Data Set which currently contains 137 ECG records of 18 unique persons and is publicly available on the Internet.

Main results of the study are following:

- Number of users identified, as well as number of neurons and hidden layers have significant impact on identification accuracy comparing to other factors;
- Identification accuracy can vary strongly for same model structure and training hyperparameters, probably because of random weights initialization and non-convex cost function. To achieve higher accuracy same experiment should be run multiple times and model with the best results should be selected for further usage;
- To prevent wrong identification in case of unknown user rejection threshold was proposed to ignore identification results which has low confidence level. Optimal threshold value at 70% was selected to maximize ratio between classification accuracy and acceptance rate.

The results achieved are not as encouraging as expected. Possible reason of this is ECG distortions that remain after filtering and relatively small number of records per class. Identification accuracy can be potentially improved by using another solution, for example other DNN architectures, more advanced outlier correction algorithms, data augmentation which uses generative models (generative adversarial networks, variational autoencoders) or other techniques. These hypotheses require further research and investigations.

ACKNOWLEDGMENT

This research received no specific funding from any organization in the public, commercial, or not-for-profit sectors.

REFERENCES

[1] Handbook of Biometrics. Jain A., Flynn P., Ross A.A. (Eds.). *Springer, 2008, 564 p.*

[2] Fratini A., Sansone M., Bifulco P., Cesarel M. Individual identification via electrocardiogram analysis. *BioMed Eng OnLine. 2015, pp. 1-23.*

[3] M. Bassiouni, W.Khalefa, El-Sayed A. El-Dahshan, Abdel-Badeeh. M. Salem. A study on the Intelligent Techniques of the ECG-based *Biometric Systems. Recent Advances in Electrical Engineering, pp.26-31.*

[4] Kaur G., Singh D., Kaur S. Electrocardiogram (ECG) as a Biometric Characteristic: A Review. *International Journal of Emerging Research in Management &Technology, 2015, (Volume-4, Issue-5), pp. 202-206.*

[5] Matos A.C., Lourenc A., Nascimento J. Embedded system for individual recognition based on ECG Biometrics. *In: Proceedings Conference on Electronics, Telecommunications and Computers – CETC 2013, pp. 265 – 272.*

[6] AlMahamdy M., Bryan Riley H. Performance Study of Different Denoising Methods for ECG Signals. *In: Proceedings The 4th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH-2014), 2014, pp. 325 – 332.*

[7] Lourenco A., Silva H., Santos D.P., Fred A. Towards a Finger Based ECG Biometric System. *In: Proceedings - The International Conference on Bio-inspired Systems and Signal Processing (BIOSIGNALS 2011), Rome, Italy, 26-29 January, 2011.*

[8] Khandait P.D., Bawane N.G., Limaye S.S. Features Extraction of ECG signal for Detection of Cardiac Arrhythmias. *In: Proceedings - National Conference on Innovative Paradigms in Engineering & Technology (NCIPET-2012), pp. 6-10.*

[9] Karpagachelvi S., Arthanari M., Sivakumar M.. ECG Feature Extraction Techniques - A Survey Approach. *In: Proceedings - International Journal of Computer Science and Information Security, Vol. 8, No. 1, (IJCSIS), April 2010, pp. 76-80.*

[10] Varshney M., Chandrakar C., Sharma M. A Survey on Feature Extraction and Classification of ECG Signal. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 3, Issue 1, January 2014, pp. 6572-6576.*

[11] Soorma N., Tiwari M., Singh J. Feature Extraction of ECG Signal Using HHT Algorithm. *International Journal of Engineering Trends and Technology (IJETT) – Volume 8 Number 8- Feb 2014, pp. 454-460.*

[12] Meet BioLock: Smart Biometrics for Tomorrow [Electronic resource]. – 2016. – Access mode: https://united.softserveinc.com/blogs/biolock-smart-identity-authentication/ (last access: 21.03.17). – Title from the screen.

[13] Arduino UNO & Genuino UNO [Electronic resource]. – Access mode: https://www.arduino.cc/en/Main/arduinoBoardUno (last access: 21.03.17). – Title from the screen.

[14] e-Health Sensor Platform V2.0 for Arduino and Raspberry Pi [Electronic resource]. – Access mode: https://www.cooking-hacks.com/documentation/tutorials/ehealth-biometric-sensor-platform-arduino-raspberry-pi-medical (last access: 21.03.17). – Title from the screen.

[15] BioSPPy - Biosignal Processing in Python [Electronic resource]. – Access mode: https://github.com/PIA-Group/BioSPPy (last access: 21.03.17).

[16] Lviv Biometric Data Set [Electronic resource]. - 2017 – Access mode: https://github.com/YuriyKhoma/Lviv-Biometric-Data-Set (last access: 21.03.17).

[17] The source code of the project [Electronic resource]. - 2017 – Access mode: https://github.com/YuriyKhoma/ecg-identification (last access: 21.03.17).

[18] TensorFlow [Electronic resource]. – Access mode: https://www.tensorflow.org/ (last access: 21.03.17).

[19] Bernaś M., Płaczek B. Period-aware local modelling and data selection for time series prediction. *Expert Systems With Applications, Vol. 59, Oct 2016, pp. 60-77.*

[20] Bernas M., Orczyk T., Musialik J. Justified granulation aided noninvasive liver fibrosis classification system. *BCM Medical Informatics and Decision Making, Vol. 15, No. 64, Aug 2015.*