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COMPARISON OF METHODS FOR CORRECTING OUTLIERS IN ECG-BASED BIOMETRIC IDENTIFICATION

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Abstract

The aim of this paper is to compare the efficiency of various outlier correction methods for ECG signal processing in biometric applications. The main idea is to correct anomalies in various segments of ECG waveform rather than skipping a corrupted ECG heartbeat in order to achieve better statistics. Experiments were performed using a self-collected Lviv Biometric Dataset. This database contains over 1400 records for 95 unique persons. The baseline identification accuracy without any correction is around 86%. After applying the outlier correction the results were improved up to 98% for autoencoder based algorithms and up to 97.1% for sliding Euclidean window. Adding outlier correction stage in the biometric identification process results in increased processing time (up to 20%), however, it is not critical in the most use-cases.

Keywords: Euclidean distance, autoencoders, outlier correction, ECG signal, human identification, biometrics.

1. Introduction

The measurement science is essential for the progress in the such conventional areas as: science and technologies [1–3], ecology [4], medicine [5–7], but recently also finds application in economy [8] forensics [9], cybersecurity [10]. A new trend in metrology is the use of robust approaches and machine learning technologies to improve metrological characteristics of measuring tools, including increased accuracy of measurements [11, 12]. This results in noticeable progress in the development of new metrological procedures [13], including in situ procedures [14], in the characterization of new materials or processes when there is no reference source, for example, in the use of such a new marker as an *electrocardiogram* (ECG) in biometry [15].

Biometrics is a field of study focused on human identification using some unique biological properties of a person. These properties are typically grouped into classes: physiological (fingerprint, iris, voice, face), and behavioral (signature, keyboard typing manner). Typically, biometric markers should fulfill the following requirements [16]:
– unique for each person;
– universal (present for all individuals);
– stability over time;
– easy to measure;
– low sensitivity to other physiological factors (stress, fatigue, *etc*).

There are also additional requirements which are not mandatory but their availability is considered a big advantage:
– fraud resistance (difficult to mimic);
– continuous nature (always available to measure);
– liveness indication (proper only to live humans).

Classical biometric approaches operate under the assumption that various physiological or behavioral patterns are individual and unique and with minimal or no variability over time. Recent progress in the field of information technologies and consumer electronics, the last breakthrough in the artificial intelligence domain, wearable devices and the Internet of things makes a lot of sense in the investigation of new alternative biometric techniques. The aim is to develop more reliable, flexible, user-friendly and highly fraud-resistant systems.

Biosignals might be one of the best choices as alternative biometric markers, as they carry important information about the psychophysiological state of the separate organs and the entire human being. Such information is important not only in medical practice for diagnosing possible diseases but is also widely used in other areas such as: affective informatics (monitoring of psycho-emotional assimilation of drivers and operators in critical infrastructure objects, lie detectors), rehabilitation engineering (exoskeletons), human-machine interaction (brain-computer interfaces) [17, 18]. As shown in [19, 20], biosignals can also be used in construction of access control systems applying the procedure of human identification based on their physiological parameters.

An ECG signal is one of the most promising for this type of biometric applications. This is due to a number of factors, such as a relatively high signal level (compared to Electroencephalogram), regular nature, easy to measure (does not require stimulating equipment in contrast to Photoplethysmography or Bioimpedance Analysis), available on any part of the body (chest, neck, extremities, fingers). These factors allow one to build hardware which is relatively simple, cheap and easy to use in everyday life [21–23].

The common feature of almost all types of biosignals is high variability over time, due to biological processes inside the body. There appear problems caused by inaccurate input parameter selection of the signal processing method. Typical example is spectrum leakage in the DFT algorithm where changes of fundamental frequency cause misadjustment to the length of the measuring window. In such cases, spectrum interpolation methods are used [24–27]. This variability of biosignals complicates the selection of informative parameters unique to a particular person and it also provides higher fraud resistance since biosignal is more difficult to fake. A typical phenomenon in biosignals processing is outliers. The term "outlier" refers to the part of the signal that abnormally deviates from adjacent segments.

The reasons might be both external (parasitic electromagnetic radiation, transient processes in electronic circuits) or internal origin (overlap with other types of signals, *e.g.* Electromyogram or respiration). Elimination of the outliers' impact is one of the most important transformations in the signal processing channel of ECG based biometric systems [28]. Therefore, the purpose of this work is to compare the effectiveness of outlier correction methods for ECG signals in combination with various classification algorithms in biometric applications.

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2. ECG signal outliers

As mentioned in the section above the ECG signal might be seriously affected by various factors such as muscle noise, respiration movements, displacement of the electrodes, *etc*. Despite the use of various noise suppression methods, such as filtration, in many cases the shape of the ECG signal remains severely distorted. If the waveform of some ECG heartbeats are seriously distorted compared to the other adjacent beats, such segments can be referred to as anomalies or outliers. Since the ECG signal is of a regular nature, a good way for understanding the specific of ECG outliers is visual estimation using heartbeat alignment. It assumes that raw denoised signal waveform should be split into separate heartbeats followed by R peak alignment. An example of an ECG outlier is shown in Fig. 1.

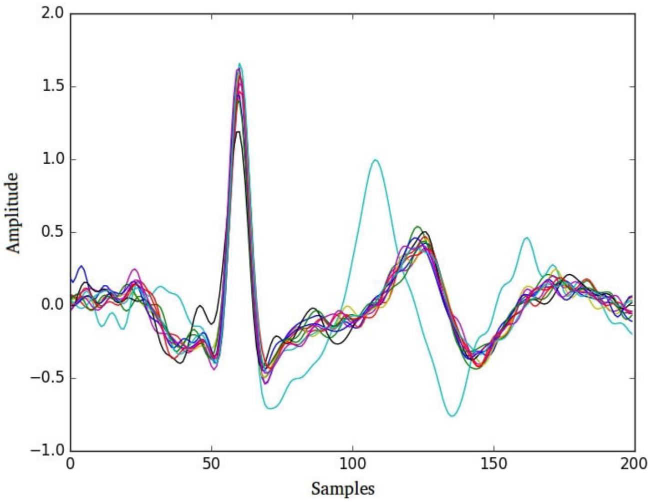

Fig. 1. Abnormal ECG heartbeats (outliers): small (black curve) and big (blue curve).

As it follows from Fig. 1, outliers can be split into two groups: big and small. In practice, big outliers make it more difficult for the classifier to generalize (the model tries to learn abnormal variations instead of focusing on minor informative details). Small outliers can be treated as some kind of adversarial examples, they are not very notable but can significantly confuse classifier and results in poorer system performance.

Traditionally, outlier processing methods have been focused on detecting and removing abnormal segments. Currently, there are several approaches to detect outliers, which use mathematical statistics, correlation analysis and machine learning tools. One group of methods (supervised classification) is based on the model of "normal" data and on the calculation of deviations of the data analyzed from this model [28–33]. The "normal" data model can be formed by averaging all the heartbeats in a given session. By another paradigm (unsupervised clustering), algorithms detect outliers based on the density of feature space. Instances that are localized in a dense region are considered normal, while instances in sparse regions are considered abnormal [28, 34–36].

In all known studies, the heartbeats with detected outliers are eliminated from further analysis. The main difference of the authors' approach is to correct distorted samples in segments, not to reject them. This makes it possible to maximize the amount of data used for training of the biometric system's classifier and provide more accurate results. In addition, the advantage of the proposed method is its effectiveness for the detection of both small and big anomalies.

3. Detecting and Correcting Outliers

In this paper the authors correct abnormal segments and keep them for model fitting and validation. The basic idea is presented in [30] and [37]. This approach increases the statistical base which is very important for small and medium size datasets. In addition, the system will have higher accuracy in real-world applications because of better generalization and processing of abnormal samples. The biggest disadvantage of this approach is increased processing time. A brief explanation of the outlier correction concepts developed in the previous works is provided. General block diagrams for the methods are presented in Fig. 2.

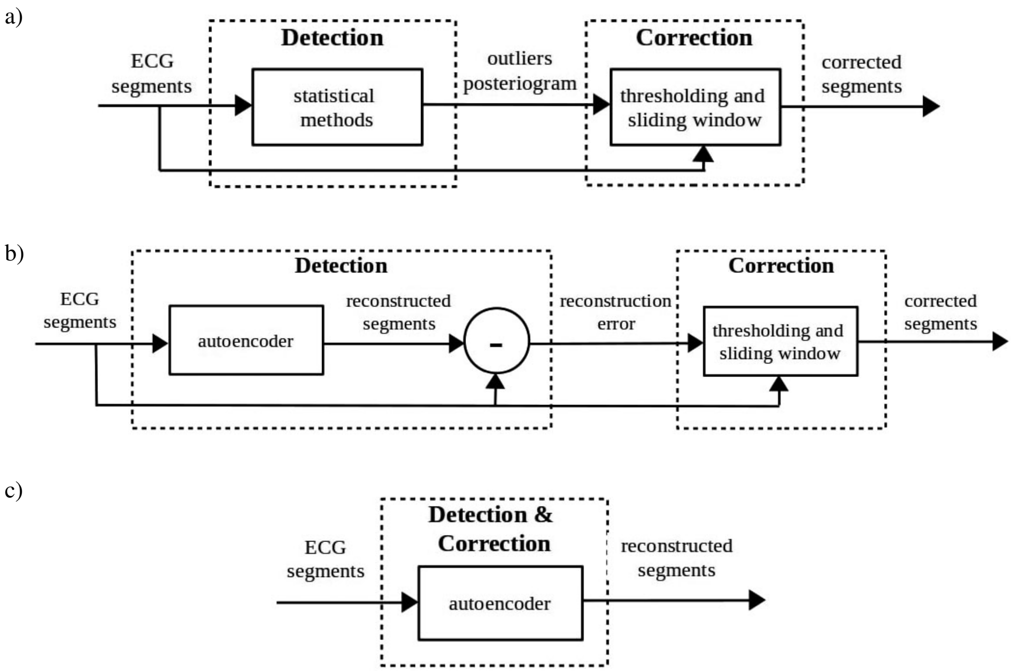

Fig. 2. Block diagram for outliers detection and correction flows based on various approaches: a) correction window with statistical reference, b) correction window with autoencoder reference, c) autoencoder-based correction.

The first method is based on a sliding window that calculates Euclidean distance between the samples within the window and some statistical reference (mean values for a given experiment). The idea behind this method [30] is based on the assumption that analysis of the samples distribution within each window allows to indicate and localize short-time abnormal perturbations of the ECG signal. For this purpose the distance between current samples (within a window) and some statistical reference (mean values) are calculated. If it turns out that distance exceeds some threshold all samples for current window are treated as outliers and should be corrected by replacement with the reference (mean) values. The procedure should be run recursively until no outlier are left for a given window.

Thus, method with statistical reference can be split into two major stages:

1. Finding outliers sections (windows) in each heartbeat, within which the deviation of even one sample exceeds a defined threshold.
2. Replacing those outliers sections with equivalent sections acquired as a result of averaging of all heartbeats.

In the first stage, namely outlier detection, a vector of average values for each sample is defined:

$$\overline{x}(n) = \frac{1}{K}\sum_{k=1}^{K} x(k,n) \tag{1}$$

where $x(k,n)$ – element of the ECG record data matrix $X(K, N)$; $k = 1, \ldots, K$ – rows representing number of heartbeats; $n = 1, \ldots, N$ – columns representing number of samples per beat.

Also, the vector of standard deviations is calculated using formula (2)

$$std(n) = \frac{1}{K-1}\sqrt{\sum_{i=1}^{K} x(k,n) - \bar{x}(n)}\,. \tag{2}$$

Further, average value of standard deviation for matrix $X(K, N)$ can be calculated as

$$\overline{std} = \frac{1}{N}\sum_{n=1}^{N} std(n). \tag{3}$$

At last, the original matrix $X(K, N)$ of samples of the ECG record can be replaced with a binary matrix $O(K, N)$ the same dimension

$$o(k,n) = \frac{|x(k,n) - x(n)|}{\overline{std}} > threshold \tag{4}$$

where $o(k, n)$ – element of the binary matrix $\mathrm{O}(K, N)$, where each non-zero value represents the detected outlier (for a given index of sample and record).

In the second stage, namely outlier correction, following transformation is performed:

$$x\,(k,n\colon n+L) = \begin{cases} \bar{x}\,(n\colon n+L), & \text{if any in } \ o\,(k,n\colon n+L) = 1, \\ x\,(k\colon n+L), & \text{if any in } \ o\,(k,n\colon n+L) = 0, \end{cases} \tag{5}$$

where $\overline{x}(n\colon n+L)$ – all averaged samples within window of length L,
$x(k,n\colon n+L)$ – all samples of record k, within window of length L,
$o(k,n\colon n+L)$ – all outliers indexes of record within window of length L.

In fact the threshold and window length are hyperparameters of the algorithm which values are selected empirically. As shown in [37] outlier correction, it is not a straightforward task to find optimal values of hyperparameters that will satisfy all the cases. The process is not easy to automate and it requires lots of human intuition. This is one of the main disadvantages of the described method.

An alternative approach is to use machine learning algorithms for outlier detection instead of analytical expressions [37]. There are multiple techniques for this task, but the most promising is the use of autoencoders [38, 39].

An autoencoder are neural networks that aims to copy their inputs to their outputs (Fig. 3). They work by compressing the input into a latent-space representation and then reconstructing the output from this representation. Commonly autoencoders are applied to feature selection and extraction. This kind of network is composed of two parts:

1. **Encoder:** This is the part of the network that compresses the input into a latent-space representation. It can be represented by an encoding function $h = f(x)$.

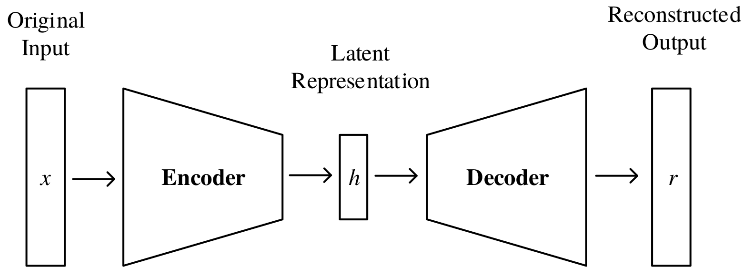

Fig. 3. Architecture of an autoencoder.

2. **Decoder:** This part aims to reconstruct the input from the latent space representation. It can be represented by a decoding function $r = g(h)$.

Nowadays, autoencoders are a very popular family of neural networks in many applications. They are widely used for advanced non-linear data filtering and denoising, dimensionality reduction and learning embeddings representation, *etc*.

The proposed algorithm for outlier correction works as follows:

1. An autoencoder model is trained on each heartbeat waveform. While training it learns weights that will be able to minimize total reconstruction error on the entire dataset.
2. Passing data through trained model and comparing the difference between original and reconstructed samples values will indicate potential abnormal samples.
3. If abnormal samples follow each other sequentially the segment is treated as outlier.
4. All the outlier segments are replaced with mean values of the rest of the segments using the same procedure as in the previous version of the outliers correction algorithm [37].

In fact, this method is also based on the correction window, but the reconstruction error of autoencoder is used instead of a statistical reference.

The third approach is also based on an autoencoder and is for the first time proposed in this article.

This approach works as follows:

– autoencoder model is trained on the set of all heartbeats for each ECG record;
– after model being trained, each separate heartbeat is fed into the autoencoder and turned into compressed representations and, then, into a reconstructed signal. The reconstructed ECG heartbeats represent anomaly-free waveform and are used for further classification.

The process of fitting an autoencoder model to the encoder and decoder with only one hidden layer is described below. Autoencoder converts input vector x into a latent-space representation h:

$$h = f(x) = \sigma(Wx + b). \tag{6}$$

Here, σ is an element-wise activation function such as a rectified linear unit.

W is a weight matrix and b is a bias vector. Weights and biases are usually initialized randomly, and then updated iteratively during training.

The decoder then displays the latent-space representation in the reconstructed signal r of the same dimension as the input signal x:

$$r = g(h) = \sigma' \left(W'x + b'\right) \tag{7}$$

where σ', x', W' for the decoder can be unrelated to the corresponding σ, x, W for the encoder.

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During the autoencoder model training, the value of the reconstruction error, also called the loss function, needs to be minimized:

$$L(x, r) = \|x - r\|^2 = \|x - \sigma' \left(W' \left(\sigma(Wx + b)\right) + b'\right)\| . \tag{8}$$

Similarly to other artificial neural networks, autoencoders are trained using the back propagation algorithm.

The dimensionality of latent-space representation is smaller than the dimensionality of the input signal so the encoder learns the basic features shared among the whole set of the ECG heartbeats. Thus trained autoencoder is able to extract outliers from the ECG signal while preserving natural variability among neighboring ECG segments which results in more accurate and robust classification models.

The main difference from the previous implementation is the use of the reconstructed signal for further classification instead of analyzing and processing the reconstruction error. In this way, the outlier detection phase is not presented as a separate transformation as all outliers will be corrected at the autoencoder reconstruction stage immediately. Unlike the two previous approached, this algorithm does not require the correction window and is purely machine learning based.

4. Biometric system description

The general structure of the designed biometric system is presented in Fig. 4 and is similar to the one described in [40]. The biometric system consists of ECG measurement instrumentation (electrodes with appropriate electronic devices) and an ADC. Data points at the ends of each heartbeat are dropped because they represent non-informative sections such as isolines. Central data points will be used to run outlier correction and classification algorithms.

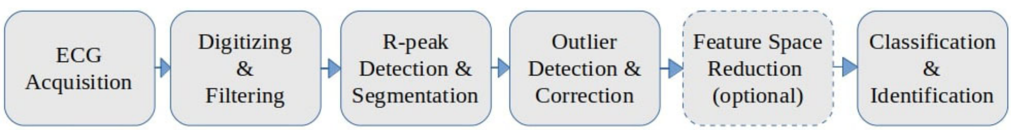

Fig. 4. Block diagram of ECG biometric system.

We also proposed two-alternative data processing pipelines: with and without dimensionality reduction. The first approach is the same as described in the paragraph above and includes filtering, segmentation and normalization followed by one of the outlier correction algorithms. Another approach proposes the use of feature space reduction on the top as in [30]. This technique is commonly used in machine learning and can help to improve classification performance. In our case, it was decided to use the *Principal Component Analysis* (PCA) as one of the simplest, commonly used and efficient compression algorithms [41].

The classification is the final transformation in the data processing channel of the biometric system. In previous works [30, 37], we used *Linear Discriminant Analysis* (LDA) as the top-level classifier. In this paper, we propose to extend the list of classifiers by adding *Support Vector Machines* (SVM) and *K-Nearest Neighbours* (KNN) [42, 43].

5. Experiments and results

The experiments were performed for different configuration without correction at all and with three different correction methods. Classifier and autoencoder are initialized with random weights so each experiment was run multiple times and average values are presented. Splitting into the train and test subsets was performed randomly with the ratio of 0.7 and 0.3 respectively. The results are presented in the table below.

In previous works, tests were performed on a Physionet ECG-ID dataset [44]. In this paper, we used a self-collected Lviv Biometric Dataset [45]. All the records were acquired using an eHealth Arduino extension board [46, 47]. Details on the measurement and data preparation procedures are presented below.

Data acquisition was made with an 8-bit ADC operating at the sampling rate of 277 Hz. The average record duration is about 10 seconds. Time intervals between records (for one user) vary from a few seconds (sequential measurements) up to several months. An updated version of the Lviv Biometric Dataset contains over 1400 recorded cardiograms of 95 persons. This dataset is 4.5 times larger than the ECG-ID dataset (about 300 records for 90 persons) which was used in previous works.

In order to remove noise and artifacts from the signal a bandpass Butterworth filter with bandwidth between 5 to 35 Hz was applied. The filtered signal was normalized from raw ADC digits to the range from -1 to $+1$. The next step was to split the signal into separate heart beats. In order to detect R-peaks, a Hamilton algorithm from the BioSPPy library was used [48].

Each correction algorithm has a few hyperparameters to be tuned such as window length, threshold for correction window and the number of layers and neurons for the autoencoder. The optimal values were chosen according to the results presented in [30, 37]. Thus, the window length is 5 samples with the gain of 0.5 for statistical reference and the threshold of 0.9 for an autoencoder reference. The autoencoder consists of four layers with 100 neurons per layer and a ReLU activation function for each neuron.

It is proposed to use the accuracy and processing time as the metrics for algorithm comparison. Accuracy was calculated as the ratio of correctly classified records to all records in the test set [43]. Table 1 presents the results obtained using different outlier detection and correction models on both the train and test sets.

Table 1. Performance of outlier correction algorithm.

Correction algorithm		**No correction**	**Correction window with statistical reference**	**Correction window with autoencoder**	**Autoencoder-based correction**
processing time, ms		0	6	830	800
accuracy, %	LDA	86.1	95.6	92.5	91.1
	SVM	74.2	93.8	91.1	94.6
	KNN	77.6	97.0	95.0	97.5
	PCA + LDA	83.1	96.2	95.0	98.0
	PCA + SVM	69.8	94.0	91.7	94.8
	PCA + KNN	78.7	97.1	95.7	97.7

As it follows from the experimental results, the best accuracy was achieved after applying the LDA classifier in combination with the PCA (98%) or the KNN classifier without the PCA

(97.5%). In both cases the autoencoder-based outlier correction algorithm was applied. The biggest trade-off of this correction algorithm is relatively low processing speed (almost 1 second in comparison with a few milliseconds for the correction window with the statistical reference). The most time-consuming stage of the identification process is ECG signal acquisition, as a heartbeat recording takes from 0.5 to 1 second. In order to perform reliable identification in real-world applications at least 5-7 beats are required which results in 5 seconds of operating time. Thus, adding autoencoder-based outlier correction stage will increase identification time only up to 20% which should not be critical in most of the applications.

However, it is important to notice that autoencoder-based algorithms are relatively consuming in terms of computations and memory consumption and thus non-trivial to implement which makes the correction window with the statistical reference more attractive for real-time embedded implementation.

6. Conclusions

Biometrics is a field of study focused on the human identity recognition using some physiological and behavioral parameters (biomarkers). The most common biomarkers are fingerprint, voice, iris, hand geometry *etc*. However, widespread use of IoT and wearable devices enables to extend the set of existing systems with new channels. One of the most promising examples is the ECG signal.

One of the biggest issues in biosignal processing and analysis are so called “outliers”, segments of the signal that differ significantly from the nearby segments. Attenuation of their impact is a critical for reliable development of the ECG-based biometric system [28].

In previous papers [30, 37], the authors proposed several methods for outlier correction based on the correction window with the statistical reference and the correction window with autoencoder reference. In this article a novel algorithm is proposed which is based on the reconstructed signal of the autoencoder and does not require the correction window. The purpose of the current work is to compare the efficiency of the mentioned outlier correction algorithms using two metrics *i.e.* identification accuracy and processing time.

As follows from the results presented in Section 5, even though that autoencoder-based algorithm is much more time consuming than the correction window with the statistical reference, the entire identification time will be increased only by 20% which should not be critical in most cases. On the other hand, autoencoders allows reducing the identification error up to 2% (98% accuracy) while the correction window provides 2.9% (97.1% accuracy). The baseline error is about 14% (the accuracy without any correction is around 86%) so in any case the outlier correction algorithms tend to decrease identification error in 4.8-7 times which makes it reasonable to include the correction stage in the ECG-based identification channel.

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