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MOBILE SYSTEM FOR ECG SIGNALS COLLECTION AND PROCESSING IN REAL-TIME

Abstract. *The article considers a system for collecting and processing electrocardiogram signals using wearable electrocardiographs. Measurement of electrocardiogram signals from such devices imposes additional requirements for signal processing, as the measurement takes place without the participation of doctors. Accordingly, control over the quality of measurement is entrusted to patients. A pipeline for real-time processing of electrocardiogram signals was built. The system architecture and each stage of signal processing are described. The FIR filter is used to filter the signal to remove low and high frequencies that contain signal noise. To test the system, the cardiograms of various people were collected from a wearable electrocardiograph. For validation of the electrocardiogram signals, a convolutional neural network (CNN) approach was selected. Resulting CNN was trained on the collected dataset. Additionally, an algorithm for validating the entire record based on the decision rules was created empirically. Testing of algorithms prediction accuracy and performance was performed. Results of this testing led to the conclusion that the system can work with high accuracy in real-time.*
Key words: *ECG, CNN, validation, RPM*

Introduction. Various wearable devices allow to measure human biosignals outside of the hospital and provide analysis of these biosignals or share measurements with doctors for expert analysis. This process is called Remote Patient Monitoring (RPM)[1]. This approach brings a lot of benefits to the healthcare system, but at the same time, it brings challenges for automated data analysis. Even with highly accurate devices, there is no guarantee that data will be measured correctly by the patient. Measurements are done outside the hospital, and as a result, without control of measurement correctness from the doctor's side.

Nowadays wearable devices for Lead I ECG measurement [2] have become widespread for Remote Patient Monitoring. Lead I ECG means the measurement of the signal between two electrodes located one the hands of the patient. These devices are designed to make short recordings of ECG signal for a heart health assessment, which can be done automatically or by manual doctor analysis. However, such an approach brings some challenges[3]:

- **Muscle noise** - appears if the patient is moving their hands or making too much pressure on the device during measurement.
- **Baseline wandering** - noise generated during the breathing process.
- **Signal inversion** - happens if a patient has swapped the hand location (put left hand on the electrode for the right hand and vice versa). In this case, the signal will be inverted which may lead to incorrect automatic analysis.
- **Other measurement issues.** Devices may be placed incorrectly(low contact with skin, too dry skin), so the recorded signal will be non-distinguishable from random noise.

Each measurement might be reviewed by a doctor, even after automatic analysis. In practice, doctors are interested in reviewing only measurements marked as "bad" - signals which were classified by automated analysis as signals with the potential presence of illnesses. The presence of problems described above may lead to misclassification, and as result to the unjustified expenses for the patients and the unwanted load of the doctors.

Various approaches for the ECG signal validation exist, but most of them were designed for validation of the signals from the holter devices (ECG recording under doctor's control, or using other leads)[4-5], or are not suitable for the use on the smartphones for the real-time ECG signal validation due to computational complexity, or low resulting accuracy[6-7]. Based on described challenges, a method for the real-time ECG signal validation on the smartphone will be proposed in this paper.

This paper is organized as follows: first, full system architecture will be described in detail, with emphasis on how system components interact. Next, a data pipeline and various methods for ECG data processing inside this pipeline will be described. After this, a CNN-based architecture for ECG signal validation will be proposed. The final section contains the evaluation of the results and a discussion of the future work on the system.

System architecture

The proposed system architecture consists of 3 main parts(pic. 1):

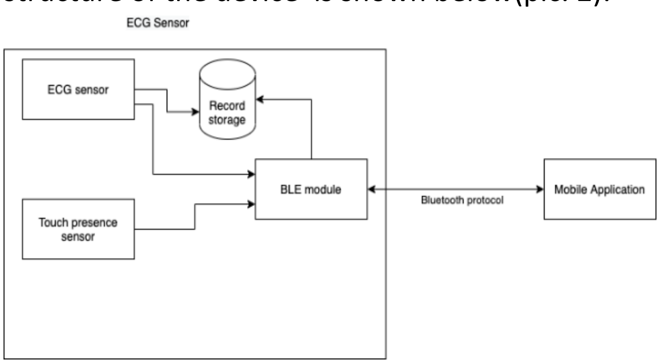
- hardware device
- mobile application
- backend application

Pic. 1. System overview

This paper focuses on the mobile application part.

Hardware device

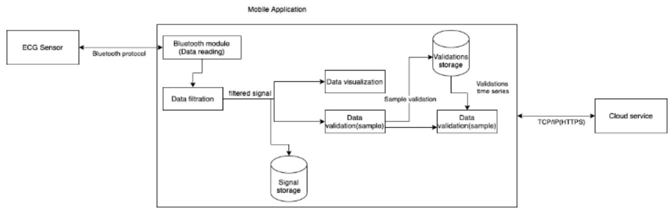
Lead I device for recording ECG with a sampling rate of 512 Hz. Device recording data to the buffer and streaming data over Bluetooth. Data bufferization is required to avoid packet loss, so the mobile application might be able to re-read missings packets. An algorithm for data integrity will be described in Section 3.2. Touch presence sensor tracks touch presence, to finish measurement if touch is absent. The high-level structure of the device is shown below(pic. 2):



Pic. 2. High-level device architecture

Mobile application

A mobile application designed for the data reading, processing, and transmission to the cloud service for further data analysis and sharing with the doctor for establishing a diagnosis. The mobile application structure is shown below(pic. 3):



Pic. 3. Mobile application structure

The purposes of each module shown above are following:

- **Bluetooth module**: Communication with the hardware device(data reading)
- **Data filtration:** Initial data pre-processing for further operations
- **Data visualization:** visualization of collected signal to the patient in real-time with validations results.
- **Data validation(sample)**: Validation of each new sample with the convolutional neural network.
- **Data validation(full record)**: Rule-based algorithm for validation of recorded signal for the final decision about the validity of the full record.

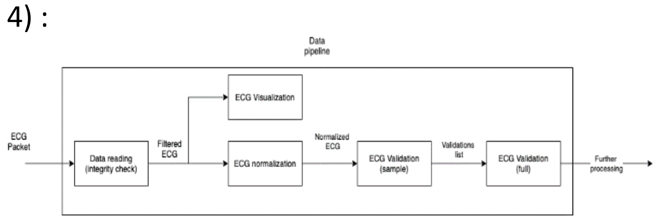
Cloud service

Cloud service is responsible for data storage, deep data analysis, and sharing measurements with doctors for making a diagnosis based on doctor's expertise and results of automated analysis.

Data processing pipeline

Pipeline overview

A pipeline that triggers each time as new points are packed is received from the sensor. From a data perspective process organized as follows(pic. 4) :



Pic. 4. Data pipeline structure

Data reading

Communication with the device built on the "pub/sub" model. Mobile application subscribes to data recording from the device. Each received packet has an index number. If a new packet has index n+2 while the previous has index n - it means that packet with index n+1 was last. The application will retry to receive a packet with a given index. If failed - the whole record will be marked as corrupted and measurement will be canceled. The record length used for this paper experiment was 90 seconds. Due to the algorithm of data integrity, data visualization and processing may lag behind the process of data reading(Algorithm 1).

Algorithm 1. Data reading integrity verification algorithm

Input. packet_index

Output. None

if packet_index -1 == last_received_index:

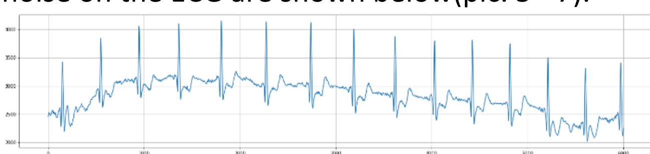
return

else:

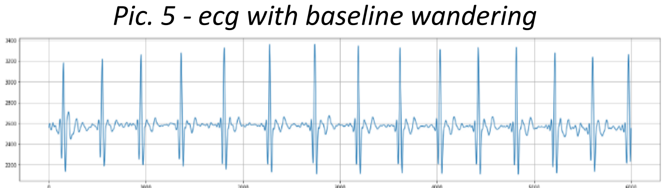
request_packet_by_index(packet_index - 1)

Data filtering

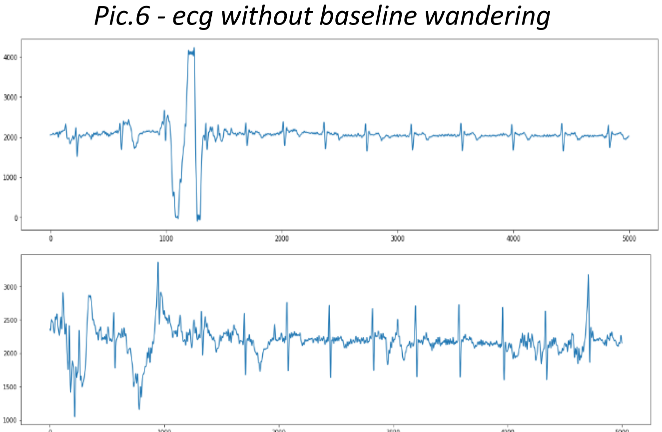
ECG is an electrical signal, and so it can be influenced by various types of noise. The most well-defined and easiest to counter type is power line interference. It happens when external alternating current influences ECG. Other types of noise include muscle noise which is caused by muscular electrical activity or noise caused by the movement of the person that conducts measurement. Influences of different types of noise on the ECG are shown below(pic. 5 - 7).



Pic. 5 - ecg with baseline wandering



Pic.6 - ecg without baseline wandering

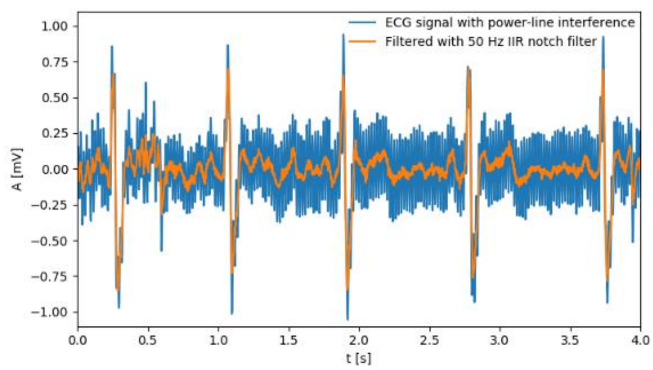


Pic. 7. Ecg noise caused by movement of the person

ECG analysis is not a new technique, and so a lot of ECG filtering approaches were developed. Most popular are FIR[8] and IIR[9] filtering. They are used to remove the noise of specific frequencies from the signal, and so the use of them is associated with some challenges. Often noise frequencies may overlap with frequencies of P waves and T waves of ECG. In this case filtering of these frequencies would affect the morphology of these waves, which is inacceptable for most cases of ECG analysis. Hence, there are two options:

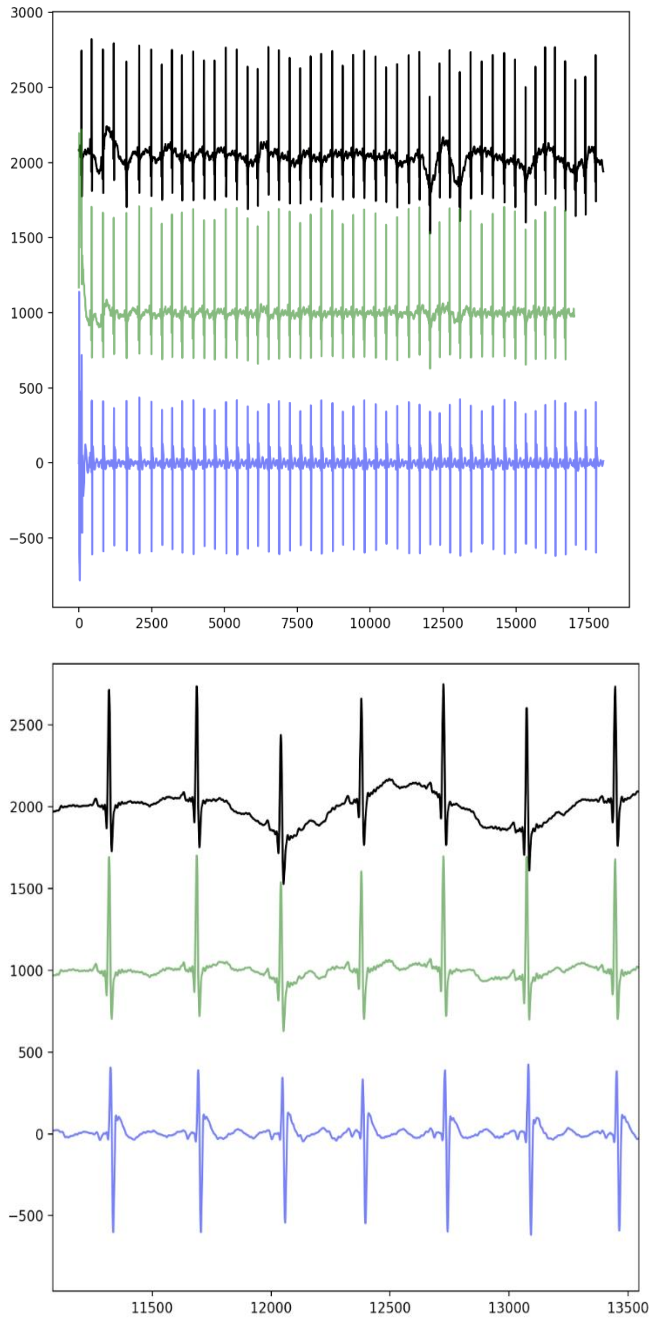
- Remove the frequency band that includes all the noise and alter the ECG morphology making the signal irrelevant for analysis in most cases. This approach may be applicable in some of the cases, such as Heart Rate Variability (HRV) analysis - when it's important to only accurately detect R waves.
- Use a frequency band that doesn't include P-wave and T-wave data and leave some noise in it.

Fortunately, the frequency of the alternating current is 50 Hz or 60 Hz depending on the country, and this frequency may be excluded from the signal without any risk(Pic. 8).



Pic. 8. Example of Power-line interference removal on ECG using IIR filtering

On the picture below(Pic. 9), you may see an example of filtering of ECG signal with FIR and IIR filters. Raw signal is displayed on the top, bandpass FIR filter with all the valuable frequencies inside the band in the middle and IIR filter that totally removes low-frequency noise (baseline wandering) but alters the morphology. Bandpass FIR filter with cutoff frequencies of 0.5 Hz and 40 Hz was selected for this implementation.



Pic. 9. Example of performance of FIR (green) and IIR (blue) filtering for noise removal on raw ECG signal (black)

Data preparation

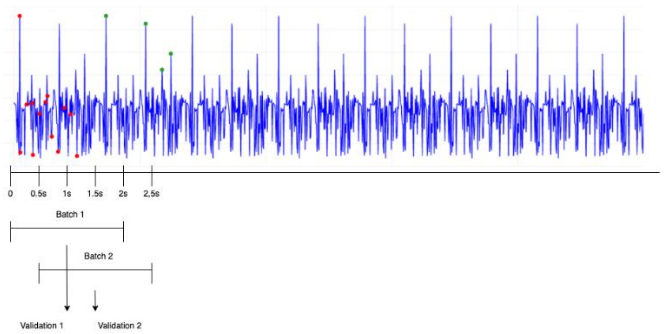
For the data preparation was used normalization algorithm, to remove differences between records of different people related to the angle of the heart axis, which leads to the different projection of the signal:

$$X_{normalized} = \frac{X - mean(X)}{std(X)},$$

where X - ECG points to an array of length 1000.

Data validation(sample)

Data validation performs using CNN for ECG signal validation(described in Section 4). Validation performs on 1000 consecutive ECG points(2 seconds) with step 250 points(0.5 second). Validation results is a probability of Interference results are stored as time series used for full record data validation(Section 3.6). Validation process and validation array forming for the full record validation shown on the picture below(pic. 10)



Pic. 10. Data validation process

Data validation(full record)

Full record validation performs every time, new validations adds to the validations list, using the following algorithm(Algorithm 2):

Algorithm 2. Full record validation

Input. validations_list

Output. is_valid

if len(longest_sequence_unvalid) > unvalid_sequence_treshold:

return False

if count(unvalid_validations) > unvalid_validations_treshold:

return False

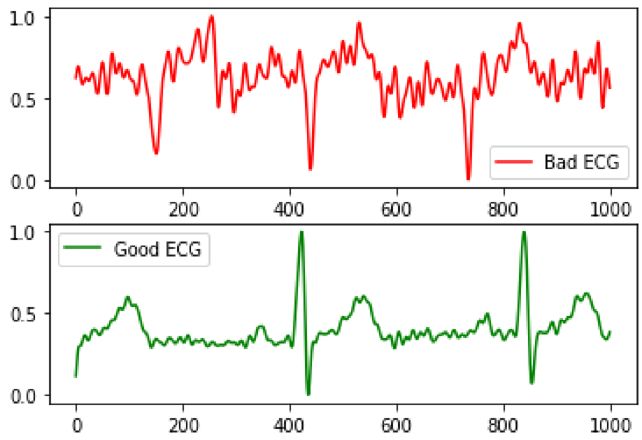
return True

For record length 90 seconds (or 177 validations for window 1000 and step 250), were defined next parameters:

- longest_sequence_unvalid = 17 (which represents 10 consecutive seconds of signal which wasn't recognized as ECG signal)
- unvalid_validations_treshold = 88 (which represents value that equal to 50% of all validations performed for the record)

CNN for ECG signal validation

Deep convolutional neural networks (CNN) are known for their ability to learn complex visual patterns[11]. Therefore, the given technique was chosen for automatic ECG signal validation, since there is a visual difference between clear and corrupted signals as shown in the picture (pic .11).



Pic.11. Examples of bad (red) and good (green) ECG signals.

Approach description

Autoencoders (AE) are neural network architectures that in an unsupervised manner learn data representation by compressing and reconstructing it as close as possible to the input [12].

Given network is trained with a regular backpropagation algorithm, where loss function measures the difference between the actual object that was passed as the input and reconstruction at the output. In the case of ECG samples, the suitable loss is a mean squared error between input ECG and then reconstructed signal.

How to use the described approach for ECG validation, or for anomaly detection in particular? In this case, the task is to separate a set of "good" ECG signals from any other type of signal with significantly different morphology, which is called anomalies, or outliers. Such samples can occur because of muscle noise, movements, electrical inference, other noises, or even some inputs that did not contain any ECG signs. The most straightforward way to tackle this problem is to build a supervised learning model that solves binary classification for "noise"/"clear ECG". However, in this case, the algorithm will not be robust for new unseen anomalies that weren't in the labeled dataset, so the model has to be retrained on an updated dataset that includes new anomalies. This approach is inconvenient for production use, thus a more stable approach will be described further.

To solve a given problem with AEs, the reconstruction error is used as the criteria of the anomaly. The given hypothesis is valid because if AE is trained only on ECG data and has not seen any other type of signal, it will learn to reconstruct them quite accurately (with low mean squared error) [10]. In case of passing some noisy ECG or other non-ECG signals to the trained AE, it won't be able to reconstruct it (reconstruction error will be high compared to clear ECG samples).

In general, the algorithm of using AEs for anomaly detection contained the following steps:

1. Gather data of only correct ECGs
2. Train an AE to compress and reconstruct them
3. Calculate the average MSE (mean squared error) between ECGs and their reconstructions
4. Based on some samples of anomalies find a threshold alpha, where decision logic will be:
   a. if error > alpha: this is an anomaly
   b. else: it is good ECG

The above-described approach seems to work pretty well, but the major drawback is that there is no control on what exactly models take into account while deciding which ECG is good or bad. From the human expert perspective for current applications, such as ECG where the R peaks can be clearly seen (or probably not 100% clearly, but distinguishable by human experts). But the current model can't assure that it takes into account exactly present and visible R peaks, and detailed empirical analysis proves this point. We have seen samples, where reconstruction error was low, below the threshold, but there were no R peaks present and the opposite - an ECG sample with clearly seen R peaks could have had high reconstruction error.

The solution is in adding the second output to the model that predicts R peaks on the ECG sample making the model multiheaded. Now, the described model will not just reconstruct the ECG signal, but also predict R peaks on it. If both R peaks will not be found and reconstruction error is low, the ECG sample is accepted if the good one, if any of the conditions fails - a sample will be rejected as an anomaly. Thus, the algorithm changes to the following:

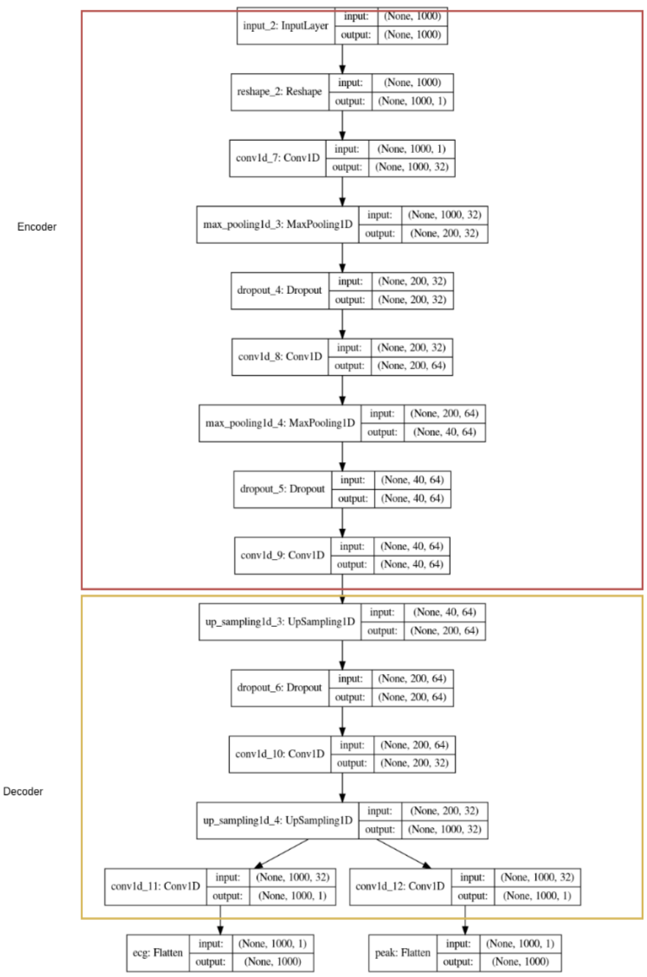
1. Gather data of only correct ECGs
2. Label R peaks on the ECGs
3. Train an AE to solve 2 tasks simultaneously:
   a. compress and reconstruct ECG signal (MSE error)
   b. find R peaks on the ECG (categorical cross-entropy error)

4. Calculate the average MSE (mean squared error) between ECGs and their reconstructions and save it as THRESH
5. Based on some samples of anomalies find a threshold alpha, where decision logic will be:

- if error <= alpha AND at least one R peak found on ECG: it's good ECG
- else: it's an anomaly

Model architecture

The resulting architecture of CNN autoencoder with two heads for ECG signal validation, is shown below(pic. 12):



Pic. 12 Architecture of CNN for ECG signal validation

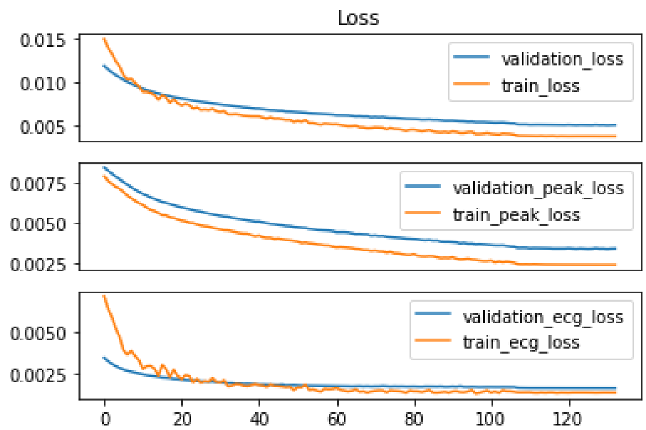
The network accepts 1000 points array as input, and has 2 outputs:

- ECG: reconstructed ECG sample
- peak: sparse vector with ones on points that correspond R-peaks on ECG signal

Dataset and model training

The training dataset contained 9392 pairs (raw signals, sparse vector with R-peaks). The validation set contained 3131 corresponding pairs. To adjust thresholds 6029 samples with corrupted signal were used.

The network was trained with a regular backpropagation algorithm using Adam optimizer [13-14] with a learning rate of 0.001 during 150 epochs. Learning curves for total and separate losses (MSE and binary cross-entropy) change are shown on plots (pic). According to the plots, the learning stage performed well and validation all validation losses are low but slightly higher than training, reflecting the absence of overfitting(Pic. 13).



Pic.13. Losses during training

Results evaluation

Prediction performance

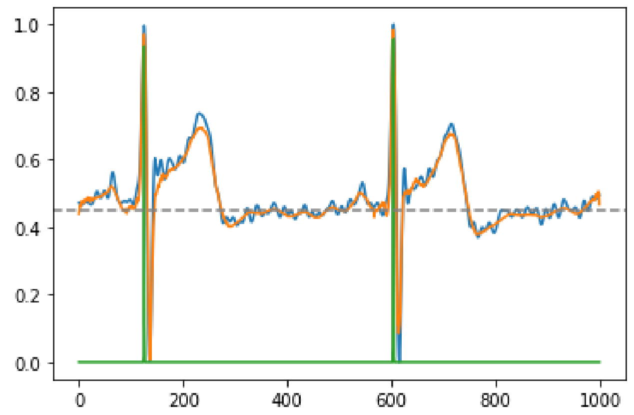
After training, a model was evaluated on a validation set and a set of corrupted samples. The resulting mean average error and maximal probability for each set can be seen in the table below(Table 1).

Table 1

Resulting mean average error and maximal probability

	Validation	Corrupted samples
MAE	0.0278201	0.02929014132
Mean max proba (MMP)	0.8442083	0.7556953

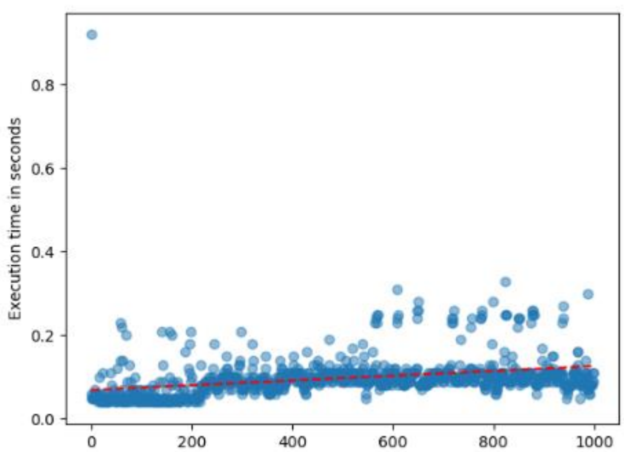
Based on obtaining results, decision thresholds were set to 0.075 for MAE and 0.45 for mean max probability. Given values provide quite an accurate separation between valid and noisy signals. An example of algorithm performance (MAE= 0.01609, MMP=0.9563) is shown on pic. with performance(Pic. 14).



Pic. 14. Model output (blue - original signal, yellow – reconstructed signal, green R-peak position prediction, dashed grey - MMP threshold)

Application performance

Results of data validation for samples of length 1000 points are shown below(Pic.15)



Pic. 15. Model interference speed performance

Received results display that's average model interference lasts for 0.2 seconds, which allows validating data in real-time with a window of 2 seconds(1000 points) and step of validation 0.5 seconds(250 points). Statically speaking validation ends earlier than the new batch for the validation becomes available. Which allows us to provide near real-time sample validation.

Conclusions

This article was dedicated to the processing of the ECG signals collected from wearable devices. Such devices have become very popular in healthcare for remote patient monitoring. However, since measurements with wearable devices are taken by patients without doctors' control, it may lead to incorrect measurements and as result to improper diagnosis with automated algorithms for disease detection, or by doctor manual review.

Typical problems related to measurements from wearable devices were described, and the architecture of the system for ECG signal collection and processing was developed. The architecture of the system includes algorithms for the data integrity check, algorithm for the noises removal, and data normalization for the ECG signal quality validation as the last stage.

For ECG signal quality validation were trained a convolutional neural network on the dataset collected from the wearable ECG monitor. This dataset was spilled on a dataset with a valid signal for training, and a corrupted signal for the test. All algorithms were deployed to the mobile application and works in near real-time mode, which allows giving fast feedback to the users about how properly they are measuring ECG signals.

In the future, might be suitable to design a more intelligent algorithm for the full record validation, since the current implementation was designed empirically. Also might be suitable to optimize algorithms for the lower analysis window size for faster feedback about measurement quality.

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