Abstract — We present a novel approach to denoise electrocardiographic signals (ECG), utilizing deep recurrent neural network built of Long-Short Term Memory (LSTM) units. The network is pretrained using synthetic data, generated by dynamic model ECG and fine-tuned with a real data from Physionet PDB database of ECG signals. The results show that a 10-layer DRNN has a mean squared error as low as 0.179 for denoising real signals with white noise of amplitude 0.2 mV, making it a viable alternative for other commonly used methods. We also investigate the impact of synthetic data on the network performance on real signals. Our results show that networks pretrained with synthetic data have better results than network trained with real data only, regardless of the training set size. We propose to explain this by means of the transfer learning framework and the analogy to human cognitive process.

Index Terms — ECG signal denoising, deep learning, recurrent neural networks.

1. INTRODUCTION

Electrocardiography (ECG) is a diagnostic process that records the electrical activity of the heart over time. The measurement is done by electrodes attached to the patient’s body and a medical device called electrocardiograph. Nowadays there are typically 10 electrodes used, placed on the chest and limbs.

A result of the procedure is the electrocardiogram - a graphical visualization (waveform) of changes in electrical potential of heart. For a 10-electrode measurement, electrocardiogram contains 12 waveforms, one for each angle of measurement, called "leads". Each ECG waveform is a quasi-cyclical time series. Its values represent electrical potential measured for specific lead for some period of time, usually ~10 seconds. Each quasi-cycle on the waveform represents one cardiac cycle, therefore it has typical frequency between 60 - 100 bpm. The cycle itself has characteristic components named P, Q, R, S, T corresponding to specific events during the cardiac cycle. Three of them: Q, R and S create so-called QRS complex - the main "spike" in the cycle, corresponding to sudden depolarization of ventricles. Visual analysis of properties of QRS complex and other points is usually performed manually by diagnostician and allows to identify abnormalities and diseases causing them.
• Power line interference - results in random component at 60 or 50 Hz, depending power supply frequency
• Electrode contact noise - caused by improper contact of between the body and electrodes.
• Motion artifacts - produced by patient’s movements which affect electrode-skin impedance, resulting in 100-500 ms long distortions.
• Muscle contractions - muscle activity produces noise with 10% of regular peak-to-peak ECG amplitude and frequency up to 10 kHz. The duration is typically around 50 ms.
• Base line wander - caused by respiratory activity. Amplitude this noise is ~15% of ECG amplitude.

This paper introduces a new way to denoise the ECG signal, utilizing deep recurrent neural networks (DRNN). The network is trained using two datasets synthetic one and a real data. We also study how using synthetic dataset affect the network performance.

The structure of this paper is as follows: in section 2 we review existing approaches to denoising ECG signal and related applications utilizing neural networks. In section 3 we discuss a dynamic model for generation of synthetic ECG signals. In section 4 an idea of deep recurrent denoising network for ECG processing is presented. Section 5 contains test results. In section 6 we present conclusions.

2. RELATED WORKS

Denoising ECG data is a known problem; a number of techniques therefore exists. Common approaches are listed in [2]. They are:

• Filtering techniques:
  o IIR Notch filter [3] [4]
  o FIR filtering [5]
  o Adaptive filters [6] [7] [8]
• Discrete Wavelet Transform (DWT) [9] [10]
• Bionic Wavelet Transform (BWT) [11]
• Filtered Residue (FR) Method [12]
• Empirical Mode Decomposition (EMD) [13] [14] [15]

In recent years, one can observe appearance of new attempts to signal filtering, utilizing machine learning methods and neural networks. They can be placed in above taxonomy as a specific kind of adaptive methods. Moein [16] investigated multi-layer perceptron networks for ECG noise removal. For training, a relatively small dataset of 100 signal samples was used. The expected outputs were produced by denoising input signals using Kalman filter. The test set consisted of 20 samples. The network was able to achieve error rate less than 0.5 for all of them. However, it is worth noting that due to the nature of the dataset, the network learned to simulate the Kalman filtering. Therefore, by training the network this way, one cannot achieve better performance than the Kalman filtering itself.

An interesting approach to neural network-based noise reduction is described in [17]. It utilizes both neural networks and wavelet transform, in a form of Wavelet Neural Networks (WNN). Such networks are a special kind of three-layer feedforward neural networks, employing a set of wavelets as activation functions. The network training is a two-phase process; first, using 400 iterations of specialized algorithm – Adaptive Diversity Learning Particle Swarm Optimization (ALDPSO) – that performs global search in the population of 20 candidate networks. The second phase are 1600 iterations of gradient descent of the best-performing network from previous phase. The training and test data are real signals from PhysioBank database; however, there is no information about amount of the data used. The network input is then noised using with a white noise of signal-to-noise ratio (SNR) 17.7 dB, and expecting output is a clean, unprocessed signal. The trained network is able to filter a signal to have approximately 21.1 dB SNR, which is 4.1 dB of improvement.

To the best of our knowledge, there are not recorded attempts usage of DRNNs for the specific purpose of denoising of ECG signal. In general, recurrent neural networks are used quite often for signal processing, including denoising. Google Scholar website yields 1820 results for the query ”deep RNN for denoising”. Known applications of these networks include acoustic signals [18] or videos [19]. A relatively popular approach recently is to combine LSTM-based RNNs with autoencoder-like training, resulting in deep recurrent denoising networks [20] [21] [22]. The recurrent network with this architecture is trained to recreate the noised input signal.

3. NEURAL NETWORK ARCHITECTURE

We propose to use deep recurrent denoising neural networks (DRDNN) for denoising of ECG signal. They are a kind of deep recurrent neural networks (DRNN), and, as such, have two distinct features. The first one is that they consist of multiple (> 2) layers stacked together - this approach is also known as a deep learning. Such deep architectures, while requiring more computational power than typical "shallow" neural networks, were
proven to be highly effective in various application, due to their ability to learn hierarchical representation of the data - initial layers learn "simple" features, while next layers learn more complicated concepts. Interestingly enough, it is still not known in general why deep neural networks are more effective than shallow ones. Several hypotheses were proposed [23] [24] [25], but the research is still ongoing.

The second distinct feature of DRNNs (and all recurrent neural networks in general) is their ability to preserve its internal state over time. It is usually obtained by introducing recurrent connections in the network, that return the previous output of the neuron to itself and/or other units in the same layer. This makes them a common choice for machine learning tasks involving processing or prediction of sequences and time series [26].

A popular architecture of deep RNN involves specific kind of building blocks called Long-Short Term Memory (LSTM) units [27]. As the name suggests, they remember its internal state for either long or short period of time. A typical LSTM is composed of four components: a memory cell, and three gates: input, output and forget. Each gate is connected with other through its input and output; several connections are recurrent. Processing of the LSTM unit updates its internal state $c_t$ (memory cell) and, simultaneously, produces the output vector $h_t$:

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$
$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$
$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$
$$c_t = \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \circ i_t + f_t \circ c_{t-1}$$
$$h_t = o_t \circ \sigma_h(c_t)$$

$x_t$ is the input vector, while $f_t, i_t$ and $o_t$ are activation vectors of input, forget and output gates, respectively. $W$ denotes weight matrices of respective gates. The operator $\circ$ denotes the Hadamard product. $\sigma_g, \sigma_c$ and $\sigma_h$ are activation functions. In a typical implementation, $\sigma_g$ is the sigmoid function while $\sigma_c, \sigma_h$ are hyperbolic tangent functions.

LSTM units can be connected into a larger structure in two ways. The first one is connecting output of cell memory and hidden gate of one cell to the input and output of the forget gate, resulting in a single LSTM layer. Such layer can be then stacked by connecting inputs of one layer to output of the next layer. This allows to build multilayer, deep LSTM network.

The input signal to LSTM network is applied one sample at a time. It is then propagated through each layer and result a single output in each iteration. Therefore, the output signal of N length can be obtained by applying the input of the same length. This is perfectly fine for denoising purposes such as ours, however it is worth nothing that for classification of prediction tasks, the signal needs to be "flattened". Therefore, many DRNN-based architectures contain also some number of feedforward layers.

LSTM networks can be trained using backpropagation through time (BPPT) and its variants [28]. This algorithm works similar to classical backpropagation but operates on the unfolded structure of the recurrent network. This works because every recurrent network can be "unfolded" into equivalent feedforward network. The loss function is calculated as an average cost for all time steps in the sequence.

In this paper, we use the deep recurrent denoising neural network, which is a specific hybrid of DRNN and a denoising autoencoder. The denoising autoencoder is a neural network trained to recreate noised input data, with input layer of the same width as the output layer. DRDNN are therefore DRNN with input layer of the same shape as the output layer, trained by applying noised signal to the input and expected to produce its denoised equivalent at the output.

General architecture of DDRNNs for ECG denoising proposed in this paper is presented in Figure 2. The ECG signal can be represented as a one-dimensional vector $x$. It is applied to the network and outputted by it, element-by-element at each time step $t$, resulting in the output vector $y$. Therefore, the network has both input and output of width 1. The signal is then processed by a dense feedforward layer (with 64 rectified linear units) and a certain number (0-10) of LSTM layers, 64 units each. To prevent overfitting, a dropout layer is used, which randomly switches off neurons during training with probability 0.5. The dropout is used only during the pre-training and fine-tuning; it is switched off during validation and testing. The last two layers are dense layers again, with 64 and 1 ReLUs, respectively.

![Figure 2. Architecture of deep recurrent neural network for denoising](image)

4. SYNTHETIC ECG SIGNAL GENERATION

For generation of synthetic training data, we used a dynamic model described in [29]. It allows to generate a realistic ECG signal basing on statistical properties of the signal, like mean and deviation of heart rate or low/high
frequency power ratio. Additionally, the model incorporates a set of morphological parameters of P, Q, R, S and T events that can be specified. Finally, it is possible to define measurement parameters of generated signal, like signal sampling frequency and measurement noise.

The model is described by a set of three differential equations:

\[
\begin{align*}
\dot{x} &= ax - \omega y \\
\dot{y} &= \omega x + ay \\
\dot{z} &= -\sum_{i \in \{P, Q, R, S, T\}} a_i \Delta \theta_i \exp\left( -\frac{\Delta \theta_i^2}{\Delta b_i^2} \right) - (z - z_0)
\end{align*}
\]

where

\[
\begin{align*}
\alpha &= 1 - \sqrt{x^2 + y^2} \\
\Delta \theta_i &= (\theta - \theta_i) \mod 2\pi \\
\theta &= \text{atan2}(y, x)
\end{align*}
\]

Above equations describe a trajectory of a point in 3D space with coordinates \((x, y, z)\). The trajectory is cyclical, revolving around a limiting circle of unit length. This reflects the quasi-periodicity of the signal.

The baseline wander of the ECG incorporated into a model by defining \(z_0\) as a periodic function of time:

\[
z_0(t) = A \sin(2\pi f_2 t)
\]

where \(A\) is the signal amplitude (in mV) and \(f_2\) is the respiratory frequency.

The model defines also a power spectrum \(S(f)\) of the signal. It is a sum of two Gaussian distributions:

\[
S(f) = \frac{\sigma_1^2}{\sqrt{2\pi c_1}} \exp\left( \frac{(f - f_1)^2}{2c_1^2} \right) + \frac{\sigma_2^2}{\sqrt{2\pi c_2^2}} \exp\left( \frac{(f - f_2)^2}{2c_2^2} \right)
\]

where \(f_1, f_2\) are means, \(c_1, c_2\) are standard deviations and \(\sigma_1^2, \sigma_2^2\) are powers in low- and high-frequency bands, respectively.

To use a model in practice, several parameters need to be specified. The main goal here is to obtain a signal as similar to the real data as possible. Morphological parameters \((a_i, b_i, \theta_i)\) were set for each of P, Q, R, S and T events, with the same values as in [29]. Frequency and spectral parameters were also mostly the same, with the exception of heart rate standard deviation - value of 5 was used. Moreover, the sampling rate used was 512. The signal had additive uniform (white) noise with amplitude 0.01. It was treated as a “base” noise level – a different from the one being added later for denoising task. A sample of generated synthetic signal can be seen in figure below.

5. Reference Model

As a reference model of denoising method, used an approach based on Undecimated Wavelet Transform (UWT), described by Hernández and Olvera [9]. The main principle of the method is signal decomposition using stationary wavelet transform:

\[
\omega_v(t) = \frac{1}{\sqrt{v}} \int_{-\infty}^{+\infty} s(t) \psi^* \left( \frac{t - \tau}{v} \right) dt
\]

where \(\omega_v\) are the UWT coefficients, \(v\) is the scale coefficient, \(\tau\) is the shift coefficient and \(\psi^*\) is the complex conjugation of the mother wavelet. As a mother wavelet, Daubechies D6 wavelet was used, due to its similarity to the ECG signal.

Signal decomposition is an iterative process, with each iteration producing the approximation of the signal and detail coefficients for given level \(k\) of decomposition (see Figure 4).

After the decomposition, the signal is filtered by removing coefficients below the threshold \(T\). The signal is then reconstructed from coefficients by performing inverse wavelet transform.

In our implementation, two customizations of the original method were used in order to adjust the method to our needs. First, a five-level decomposition was used, as it was empirically determined to yield the best results. Second, the universal threshold proposed by Donoho and Johnson [30] was used, defined as:

\[
T = \sigma \sqrt{2 \log N}
\]

where \(\sigma\) is the median absolute deviation of coefficients and \(N\) is the number of data points.

6. Results

The tests were conducted to answer two questions: what is the effectiveness of DRNN for denoising of ECG
data and whether (and how) pre-training with a synthetic data affects network performance.

Two datasets of ECG signals were used, the first one containing 4000 synthetic sequences and the second one containing 4000 real sequences. Real dataset came from Physionet PTB diagnostic database [31]. Signal in database are available for 15 leads - we decided to use aVL lead only, since it is considered the most one in terms of diagnosis [32]. Synthetic dataset was generated using dynamic model described in previous section. The signals in both datasets were split into 300 samples-long sequences, therefore 2,4 million data samples were used in total.

The signals were preprocessed by normalizing them to have a zero mean. Such preprocessed datasets were used as expected outputs during training and testing of networks. The inputs signals for networks were produced by adding a white noise with amplitude 0.2 mV to reference signal.

In the first test, 11 RNNs were trained using synthetic data, with 75% used as a training set, and 25% as a validation set. The networks consisted of various number of hidden LSTM layers – from 0 to 10. Training algorithm was Adaptive Momentum method (Adam) over time, with batch size 256. Training was 20 epochs long. Loss function for both training and validation sets was mean squared error.

The best validation losses obtained during training by each network are presented in Figure 5. Deeper networks generally performed better than shallow ones, especially compared to the network without any LSTM layers (the leftmost bar). The best performing network was the deepest one, consisting of 10 LSTM layers, which obtained the smallest training and validation losses, both equal to 0.0033. Quite interestingly, even without further fine-tuning, the networks were able to denoise the real data as well. For example, the deepest network obtained 0.190 MSE on a test dataset of real signals. For comparison, the wavelet-based denoiser obtained 0.181 MSE for the same dataset.

In the second test, we analyzed how the duration of pre-training affects the performance of fine-tuned networks. A set of 20 DRNNs with 10 LSTM layers each was prepared. Each network was pre-trained using artificial dataset and the same methodology as the first test, with number of epochs ranging from 1 to 25. Afterwards, they were fine-tuned with 2727 sequences and validated on 274 sequences from real dataset. To minimize the potential effect of overfitting, only minimal losses achieved during fine-tuning were considered.

Results (Figure 6) support the thesis that pre-training on synthetic data allows to achieve better results after fine-tuning even after a single epoch. The best result was obtained with 10 epochs of pretraining. Increasing pre-training duration more than this does not seem to improve the quality of the network.

Effectiveness of pre-training can be also verified by comparison of training progress of pretrained and non-pretrained networks, as seen in Figure 7. Pretrained network had a lower validation loss from the beginning and achieved better overall result.
Compared to the wavelet-based method, fine-tuned DRNN achieved 0.179 MSE on filtering the test dataset, meaning that it performed better than the reference method (0.181). Visual results of denoising can be seen in Figure 8. It seems that although wavelet denoiser resulted in a smoother signal, it lacked high-frequency details that were recovered by DRNN.

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7. CONCLUSIONS

Obtained results show that DRDNN can be used for effective denoising of ECG signals, having mean squared error as low as 0.179. It is therefore yet another area where deep networks show their superiority over shallow architectures. However, increasing number of layers causes a risk of network overfitting. It could be overcome using regularization techniques for deep learning such as L1/L2 penalties, drop-out or drop-connect. It is possible that tuning up hyperparameters would result in even better performance than obtained in this paper.

Another important conclusion comes from the analysis of influence of synthetic training data on network performance. The outcome suggests that networks trained with artificial data have better performance than networks trained with real signals only. This can be partially explained by the interpreting the training process by means of “transfer learning” framework [33]. It is a popular deep learning technique that allows to train the network using training data with different domain, distribution and task than the target data. The network can be then applied to the target task with relatively small amount of fine-tuning. Transfer learning is explained by the analogy of human learning process: people can use previously gained knowledge to solve problems faster, even if such knowledge was acquired for different domain. This explains that network trained with synthetic ECG data were able to denoise real signal as well.

Still, the transfer learning hypothesis in its original form does not explain why pretraining with artificial data was more beneficial than using real data only, even though lack of pretraining was compensated by fine-tuning batches. We propose to explain this by using another analogy to the human cognitive process. It is natural for people to learn by observing simpler examples first and more complicated ones later. This allows to gain knowledge incrementally, by grasping the “essence” of the knowledge first and then fine-tuning it with more complex examples. Learning from the complex examples usually yields rather mediocre results. In terms of network training, synthetic ECG data was based on some mathematical model. Models are, by definition, a simpler view of something more complicated. In our case, ECG signal model was a rather simple one, not including many bio- & electro- physical phenomena. Moreover, it assumed a very naive model of noise. However, it was easier to learn than real data. Therefore, network trained on synthetic data was able to faster learn the “essence” of the ECG signal and utilize this knowledge for learning from real data. This implies that using artificial training data is a promising approach not only in situations of data shortage (which is often the case in a medical field) but also to improve the quality of the network with the a priori knowledge included in the mathematical model of the data.
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