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A novel method based on convolutional neural networks for deriving standard 12-lead ECG from serial 3-lead ECG*

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Abstract: Reconstruction of a 12-lead electrocardiogram (ECG) from a serial 3-lead ECG has been researched in the past to satisfy the need for more wearing comfort and ambulatory situations. The accuracy and real-time performance of traditional methods need to be improved. In this study, we present a novel method based on convolutional neural networks (CNNs) for the synthesis of missing precordial leads. The results show that the proposed method receives better similarity and consumes less time using the PTB database. Particularly, the presented method shows outstanding performance in reconstructing the pathological ECG signal, which is crucial for cardiac diagnosis. Our CNN-based method is shown to be more accurate and time-saving for deployment in non-hospital situations to synthesize a standard 12-lead ECG from a reduced lead-set ECG recording. This is promising for real cardiac care.

Key words: Convolutional neural networks (CNNs); Electrocardiogram (ECG) synthesis; E-health
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1 Introduction

Electrocardiogram (ECG) is one of the most important noninvasive diagnostic tools for heart disease and one of the most commonly performed cardiology tests. In the traditional conventional 12-lead ECG, 10 electrodes are placed on limbs and on the surface of the chest (Tomašić and Trobec, 2014). However, with intelligent hardware, it is common that the number of measurement sites is smaller than eight (Nelwan and Meij, 2006), so the diagnostic utility of a conventional ECG system is often poor and impractical in homecare, self-care, ambulatory, and emergency recording conditions. With the rapidly increasing incidence of heart disease worldwide, more convenient and accurate ECG monitoring for pre-hospital care is required. As a result, it is of great value to design a simple, easy-to-use lead set system for accurate reconstruction of the 12-lead ECG (Kors and van Herpen, 2010). In addition, the development of intelligent hardware motivates the development of other new measuring systems (Drew et al., 1999).

In the 1940s, systems which derive 12-lead ECG from reduced numbers of electrodes were developed (Kors and van Herpen, 2010). When the first system synthesized the 12-lead ECG from the orthogonal lead system introduced by Frank (1956), such derived

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12-lead ECG made progress. Since then, many ECG reconstruction systems have been introduced and quality has been significantly improved.

Multiple-regression techniques are the most common methods used to derive the reconstruction transforms. Scherer et al. (1990) investigated the synthesis from the subsets of 12-lead ECG I, II, and V2 by measurements on 12 patients. Nelwan (2005) proposed that the one precordial lead can be synthesized from the others. The result showed that the personalized approach was more effective than a universal approach. They also used other lead methods for experiments (Nelwan et al., 2004) and showed that the subsets of 12-lead ECG were better than the EASI system for synthesizing the 12-lead ECG.

Even though some lead theories (Horáček et al., 2002) described the linear relationship between each lead, nonlinear methods have been considered to further enhance the reconstruction accuracy, and make up for the weakness of the traditional linear method, which may lead to noise and uncertainty of electrode placement (Duin, 2000). However, it is not certain that the relationship of each lead is definitely linear (Gulrajani, 1998; Modre et al., 2006). Atoui et al. (2004, 2010) applied artificial neural networks (ANNs) for analysis. In their work, they extracted a 1 s duration representative cycle from every 10 s interval original signal, and determined the P, QRS, and T onsets and offsets of the representative cycle. As a result, the representative cycle signal in the interval [P-onset−18 ms, T-offset+38 ms] was used for further experiments. Then they used leads I, II, and V2 and a set of 50 ANNs for the synthesis and obtained better results than the method based on multiple linear regression.

However, the training process of the ANN-committees-based method is time-consuming and unable to perform a real-time transform, because of the large sample size (1000 samples per second). In addition, part of the diagnostic information is lost in the process of extracting a representative cycle, which in turn causes a decline in accuracy. The drawbacks of the ANN-committees-based method prompt us to find a new way to save time and keep details.

The purpose of this study is to present a novel synthesis system based on CNNs. The CNNs are inspired by the cells in the primary visual cortex, and are hierarchical neural networks with alternation of convolutional layers and a subsampling layer (Hubel and Wiesel, 1959). The difference of each CNN is based on the realization of convolutional and subsampling layers and the training method. Since CNN learns the feature from the training data directly, it can avoid loss of effective features and enhance accuracy. The weights are identical on the same feature map, so the CNNs can learn in parallel. Thus, compared to other neural networks, CNNs are easier to train since they have much fewer connections and parameters (Krizhevsky et al., 2012). With the above-mentioned advantages, CNNs are used in this study to reduce the time consumption and improve the accuracy. While better results are achieved, the elapsed time of the proposed method is only 7% of that of the ANN-committees-based method.

2 ECG database

2.1 PTB diagnostic ECG database

The data used in this study are obtained from the PTB diagnostic ECG database (Bousseljot et al., 1995; Goldberger et al., 2000). The database contains 549 records from 290 subjects (aged 17–87 years, mean 57.2 years; 209 men, mean age 55.5 years, and 81 women, mean age 61.6 years; ages were not recorded for 1 female and 14 male subjects). Each subject is represented by one to five records. Each record includes 15 simultaneously measured signals: the conventional 12 leads (I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6) together with the three Frank lead ECGs (Vx, Vy, Vz). Each signal is digitized at 1000 samples per second, with 16-bit resolution over a range of ±16.384 mV. Fig. 1 shows a set of 10 s ECG signal of record patient001.

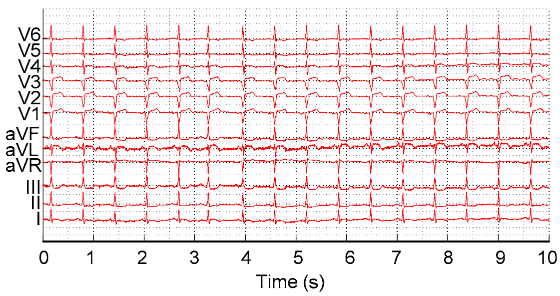

Fig. 1 A 10 s set of record patient001

Most of these ECG records offer a detailed clinical summary, including age, gender, diagnosis, and, where applicable, data on medical history, medication, and interventions. The clinical summary is not available for 22 subjects. Table 1 shows the diagnostic classes of the remaining 268 subjects.

Table 1 The diagnostic classes in the PTB diagnostic ECG database

Diagnostic class	Number of subjects
Myocardial infarction	148
Cardiomyopathy/Heart failure	18
Bundle branch block	15
Dysrhythmia	14
Myocardial hypertrophy	7
Valvular heart disease	6
Myocarditis	4
Miscellaneous diseases	4
Healthy controls	52

2.2 Study population

Unlike Atoui et al. (2010) who used 10 s ECGs of the Cardiology Hospital of Lyon, we use all the heartbeat interval data of the PTB diagnostic ECG database, and each patient has two pairs of ECGs, each consisting of the following:

1. A 3-lead ECG based on I, II, and V2 as the input database.

2. Other 9-lead ECG of standard lead ECG as the target database.

To evaluate the results, we divide the study population into two subsets, DS1 and DS2. Dataset DS1 consists of the 161 patients (116 male, 45 female; mean age±SD=58.55±14.25). Dataset DS2 consists of the remaining 129 patients (93 male, 36 female; mean age±SD=55.51±15.19).

3 Data preprocessing

3.1 Denoising of ECG signals

We use the method based on discrete wavelet transform (DWT) and soft thresholding to denoise the ECG signal (Addison, 2005). For DWT, the Daubechies6 wavelet is used to decompose the ECG stream to eight levels, and only 3rd/4th/5th detail coefficients are used to reconstruct the new signal for removing motion artifacts (Zhang et al., 2016; 2017a). To calibrate the baseline shift of ECG signals, we use the normalized least mean square (NLMS) algorithm to conduct adaptive noise filtering. The results show that this method can effectively correct the baseline shift and noise while maintaining the geometric characteristics of the ECG signal. Fig. 2 shows the comparison of the original signal and the denoised signal.

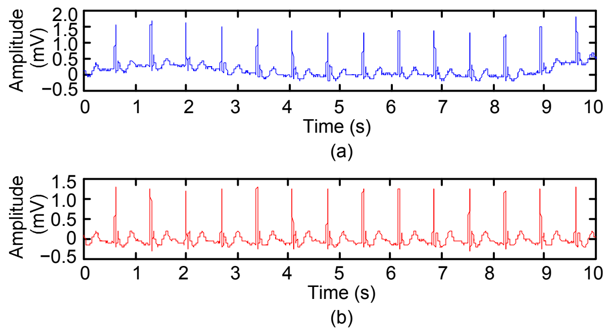

Fig. 2 Comparison of the original ECG signal (a) and the denoised ECG signal based on DWT (b)

3.2 Segmentation

Many different algorithms have been investigated for R-peak detection. Pan and Tompkins (1985) used filters and window integration to detect the R-wave. Zhang et al. (2016) proposed an auto-segmentation approach using an adaptive threshold. Since the V4-lead signal of this lead has the best geometric characteristics of the R wave, we use Pan and Tompkins' method to detect the location of R waves in the V4-lead signal in the study, and the effect is shown in Fig. 3. Then we segment the other leads ECG signal by the $[R_i-(R_i-R_{i-1})/2, R_i+(R_{i+1}-R_i)/2]$ interval. Figs. 4 and 5 present the segment of the input 3-lead ECG and the target 12-lead ECG record used in the experiment, respectively.

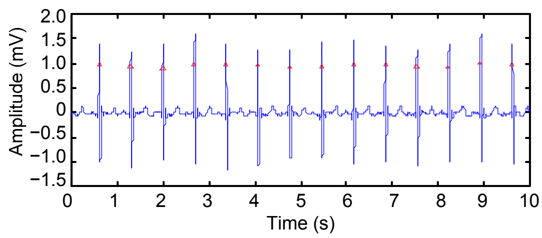

Fig. 3 The detection effect of R-wave position

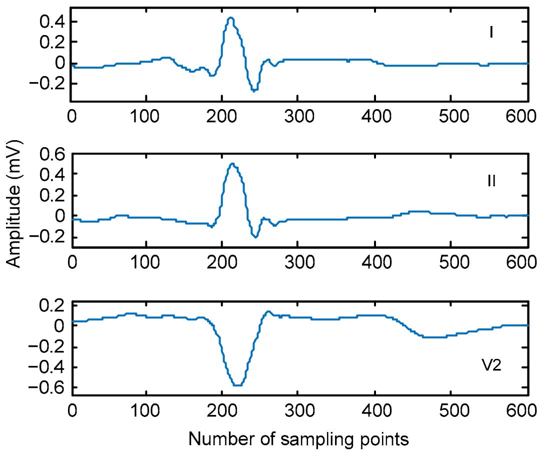

Fig. 4 The input ECG signal interval

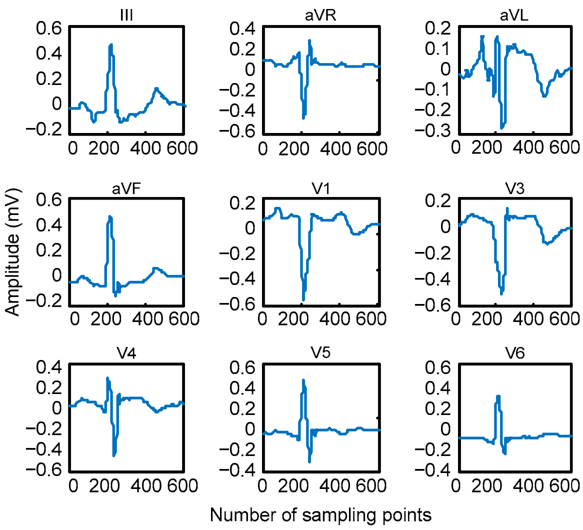

Fig. 5 The target ECG signal interval

4 Synthesis based on convolutional neural networks

4.1 Background and motivation

A neural network is inspired by brain structures where layer-wise neurons are organized in a way that can represent high-level abstraction (Zhang et al., 2017b) and considered as a powerful recognition method (Srivastava et al., 2014). The convolutional neural network, first introduced by LeCun et al. (1990), has maintained the most advanced performance (Ciregan et al., 2012) and inspired recent research (Serre et al., 2007; Lee et al., 2009). CNN consists of convolution layers and sub-sampling/pooling layers, and finally uses a constant factor for computation (Palm, 2012).

A convolution network has the following advantages in signal processing compared with a general neural network: (1) The input image and network topology can be well matched; (2) Feature extraction and pattern classification are carried out simultaneously in training; (3) Sharing weights can reduce the training parameters of the network, making the neural network structure easier and more adaptable.

Recently, CNNs have been used in medical imaging (Gacsádi and Szolgay, 2010; Shin et al., 2016). This led us to synthesize the 12-lead ECG based on the CNNs method. We try to evaluate the influence of our method on the improvement of similarity through experimental results.

4.2 Proposed approach

Since the ECG signal is a 1D data vector and the reconstruction process is time-independent, the first problem we face is turning the signal into a 2D matrix of data points. Considering 1D-ECG to 2D-ECG conversion, we refer to the gradient-based method on image/shape reconstruction (Ettl et al., 2008) and the traditional matrix reconstruction method based on slipping insertion (Lu et al., 2017). In this study, we compute the gradient of the input signal, and then repeat and arrange them as Fig. 6 (1 represents the #1 original signal and 1' represents the gradient of the #1 signal). Overall, a total of 150 000 images are obtained. We use 120 000 images as a training set to train the CNNs, and for validation, 30 000 images as a testing set to evaluate the proposed method. The aim of this transformation is not only to satisfy the input requirements, but also to obtain more details of the input signal.

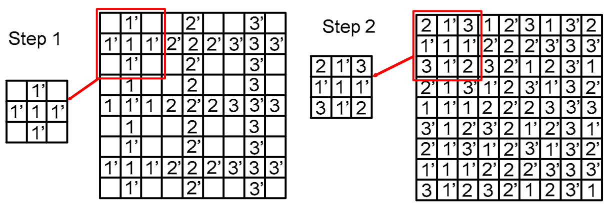

Fig. 6 The structure of the input signal

Fig. 7 is the structure schematic of the proposed method and the details of the CNNs are given in Fig. 8.

The convolutional and pooling layers compose each CNN stage. The aim of the convolutional layer is to represent more information from the previous layer, and the pooling layer is used to merge similar features in each stage (Zhang et al., 2017c). In this study, we use the back-propagation method (Bojarski et al., 2016) to train the multi-layer CNN, which applies the chain rule for derivatives to compute the gradient of a predefined objective function relative to all the neuron parameters (Zhang et al., 2017d). We set the learning rate as 0.1, the batch size as 100, and the number of training epochs as 1.

As shown in Fig. 8a, our convolution has the first convolution layer C1 consisting of six feature maps, which are computed using overlapping 4×4 kernels on the input 9×9 signal data. The convolution operation can enhance the original signal feature and reduce the noise. At layer S2 (first subsampling layer) (Fig. 8b), there are six feature maps, each of size 3×3 obtained by subsampling based on max-pooling using a 2×2 kernel on the output of the Cl layer. According to the principle of image local correlation, subsampling of the image can reduce the amount of data processing while retaining useful information. Each unit in the feature map in layer S2 is connected to the 2×2 neighborhood of the corresponding feature map in layer C1. A sigmoid function is used to compute the final output. So, the mapping from a layer to the next layer can be seen as a convolution operation. The S-layer can be seen as a fuzzy filter, playing a secondary feature extraction role. The spatial resolution between the hidden layers decreases, and the number of planes contained in each layer increases. This can be used to detect more feature information.

Similarly, at layer C3 (2nd convolution layer) (Fig. 8c), there are 12 feature maps which are computed using overlapping 3×3 kernels on the output of layer S2. Then, we obtain 12 features at layer F computed from these 12 kernels of size 1×1 (Fig. 8d). Finally, we use a sigmoid function as the networks' output instead of the traditional one.

When training, the feature maps of C3 are concatenated into a feature vector, feeding into the fifth layer and the final layer, which consists of N output neurons corresponding to the point number of the ECG sample. We train the CNNs with stochastic gradient descent (SGD) on the full subset DS1. The batch size is set as 100 and the fixed learning rate is set as 1. We also initialize the weight using the stochastic weight method and choose the one with the best similarity performance.

4.3 Algorithms for comparison

As mentioned in Section 1, we use two other methods for synthesis comparison. We introduce the two other techniques in turn.

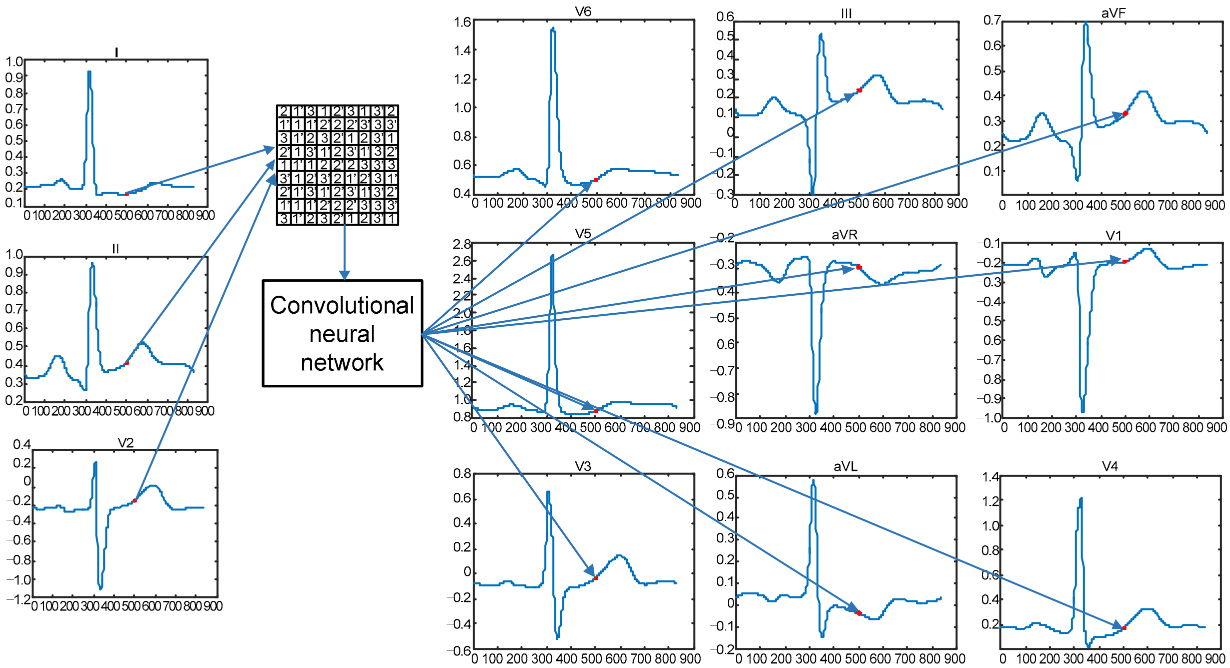

Fig. 7 The structure schematic of the proposed method

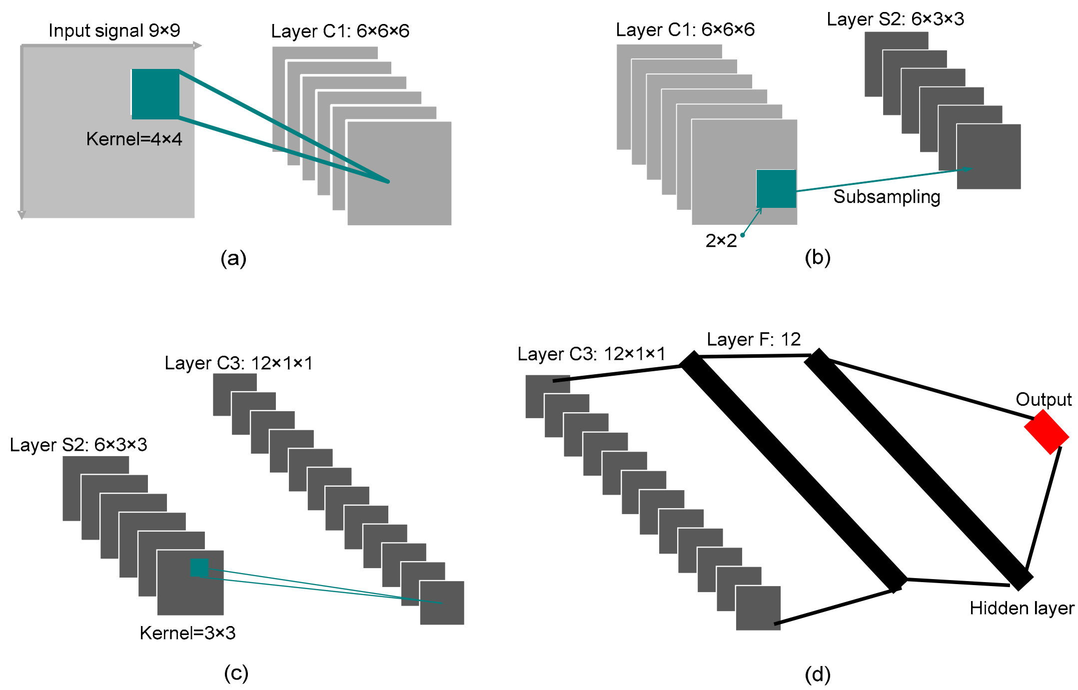

Fig. 8 Actions at different layers of the CNN: (a) computation from the input signal to layer C1; (b) computation from layer C1 to layer S1; (c) computation from layer S1 to layer C2; (d) computation from layer C2 to output

4.3.1 Multiple-regression-based method

The aim of the multiple-regression-based method is to compute a global transformation matrix that synthesizes the missing leads of the ECG signal by

$$V_i = a_{i0} + a_{i1}\mathrm{I} + a_{i2}\mathrm{II} + a_{i3}\mathrm{V2}.$$

We consider the standard 12-lead ECG of dataset DS1 to calculate the generic multiple-regression transform matrix. For testing, we use dataset DS2 to calculate the similarity between the synthesized signal and the original signal.

4.3.2 ANN-committees-based method

We use the ANN-committees-based method proposed by Atoui et al. (2010) to synthesize the missing (III, aVR, aVL, aVF, V1, V3, V4, V5, V6) from the recorded (I, II, V2) ECG subset. This method uses an ensemble of 50 multi-layer feedforward ANNs to build up ANN committees for synthesis. These ANNs have 1 hidden layer and 15 neurons per hidden layer and are trained by means of a supervised back-propagation algorithm. A linear activation function is used for the output neurons, and a sigmoid transfer function is used for the hidden layer. The final outputs of ANN committees are obtained by summing up the output of every single ANN and dividing them by 50.

We use dataset DS1 for network training and adapt the cross-validation strategy (LeCun et al., 1990) to train each of the 50 ANNs of the committee. Then we use dataset DS2 to test the ANN committees and also to calculate the similarity between the synthesized signal and the original signal.

5 Results

We apply the above methods to synthesize the missing (III, aVR, aVL, aVF, V1, V3, V4, V5, V6) from the recorded (I, II, V2) ECG subset. No matter which method is used, the correlation coefficient of leads III, aVR, aVL, aVF is 100% because of the linear relationship of limb leads (I, II, III, aVR, aVL, aVF). Following this, we conduct a correlation analysis between the output and the original ECG signal. We then calculate the lead-by-lead signal differences to assess the quality of the reconstruction of our method and the compared methods. The experiments were performed in the environment of macOS Sierra, Intel Core i5 2.9 GHz, and 16 GB memory. As shown in Table 2, the CNN-based method has better reconstruction results than the ANN-committees-based method and multiple-regression-based method. Fig. 9 is the line chart of the results.

Table 2 Correlation coefficient *r* between the original ECG signal and the reconstructed ECG signal obtained using the three methods

Lead	r (%)		
	CNN	ANN-committees	Multiple-regression
III, aVR, aVL, aVF	100.00	100.00	100.00
V1	94.40	91.40	91.42
V3	94.48	95.66	96.51
V4	93.80	89.74	89.20
V5	94.65	94.54	93.01
V6	97.44	97.15	96.58

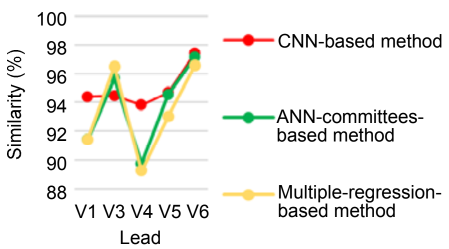

Fig. 9 Line chart of similarity obtained using three methods

The results show that the proposed method performs better in the reconstruction of leads V1, V4, V5, and V6. Note that the proposed method increases the similarity between the reconstructed signal and the original signal of the V4 lead by over 4%. As can be seen, the ANN-committees-method has worse performance when the ECG is for patients with pathological changes. Fig. 10 presents a comparison of the reconstructed signal of the V4-lead signal using the ANN-committees-based method and based on the original pathological changes. It is clear that the reconstructed signal does not displace such meaningful pathological changes (The direction of R-wave in the reconstructed signal is contrary to that of the real signal, which may lead to misdiagnosis). Fig. 11 shows that the signal reconstructed using the proposed CNN-based method displaces an invert R wave as the original signal. The correlation coefficient is 35.63% for the ANN-committees-based method and 91.04% for the CNN-based method. Therefore, the proposed method has better performance in the reconstruction.

We compare the time consumption of our method with that of ANN. As shown in Fig. 12, the elapsed time of our method is only 7% of that of the ANN-committees-based method, because the weight-sharing method can reduce the number of parameters.

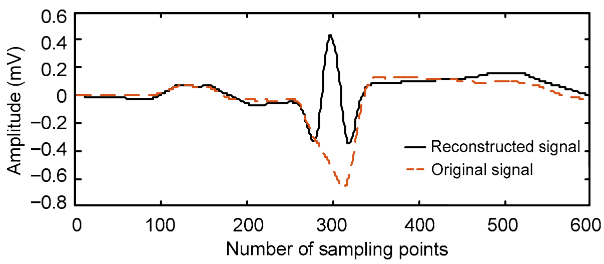

Fig. 10 Comparison of the original V4-lead signal and the reconstruction signal using the ANN-committees-based method

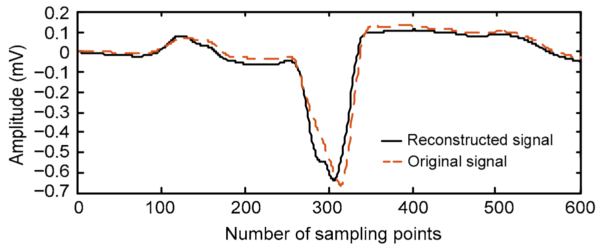

Fig. 11 Comparison of the original V4-lead signal and the reconstruction signal using the CNN-based method

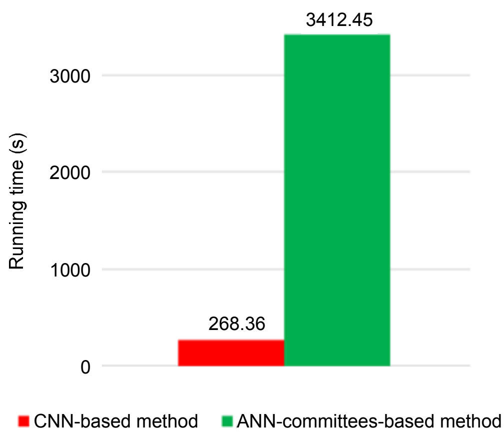

Fig. 12 Running time of the proposed CNN-based method and the ANN-committees-based method

6 Conclusions and future work

Twelve-lead ECG is one of the most important cardiac diagnostic tools. The need for synthesis of 12-lead ECG from fewer leads increases dramatically as portable devices often provide limited electrodes. The reduction of running time during synthesis is important, considering the large amount of signal and the real time requests. In this paper, we investigate the convolutional neural networks method in detail, and apply it to the reconstruction of an ECG signal. Compared to linear regression and ANN, our method has not only better similarity between the reconstructed and original ECGs, but also less time consumption. We also believe that the generic synthesis method can be further modified using a higher-volume training database.

In the future we will consider how to optimize the initial weight more efficiently and improve the topology of the network. We will continue to improve the effectiveness of the generic approach and provide better support for more patient types.

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