ECG Classification Based on Unfixed-Length Segmentation of Heartbeat

Bin Chen, Yuchun Guo, Yishuai Chen, Hongyun Zheng
School of Electronics and Information Engineering
Beijing Jiaotong University, Beijing, China 100044
Email: {16120044, ychguo, yschen,hyzheng}@bjtu.edu.cn

Tong Liu
BCCKTA Key Laboratory, Beijing Computing Center
Beijing, China 100094
Email: liutong@bcc.ac.cn

***Abstract*—An automatic ECG classification system is of great significance. Deep learning (DL) methods, e.g. convolutional neural network (CNN), are proved very useful for ECG classification. Due to that DL methods require the input data with fixed length, current work segments beat with fixed length. But obviously, the length of beat is varying with the changing temporal, personal, or contextual conditions. We solve the contradiction by segmenting beat with unfixed length and then reshape the beat to that with fixed length. Based on this, we extract inner-beat, beat and inter-beat representation. We validate our method on MIT-BIH dataset and the accuracy reaches 95.45%, better than related work.**

***Index Terms*—ECG classification, beat segmentation**

I. Introduction

With the help of wearable or portable ECG monitoring devices, together with ECG classification systems, cardiovascular patients can be informed of ECG abnormalities in time. Though the existing classification systems have reached a high accuracy [1]–[3], there is still space for optimization.

Current work focuses on classifier choice and feature expression. For classifier choice, CNN is widely used. For feature expression, beat feature is widely used. Besides, inner-beat feature, i.e. P wave, QRS waves and T wave, is introduced [4]. Beat segmentation is necessary for both classifier choice and feature expression. On the one hand, DL methods require beat with fixed length. On the other hand, the length of beat or wave varies. However, the existing work segments beat or wave with fixed length, ignoring the dynamic character. It is a problem to meet DL methods requirements and precisely segment beat at the same time.

To solve this problem, we redefine the length of beat and segment beat with unfixed length. Then we reshape the beat to that with fixed length, without changing the waveform which is vital for feature extraction and classification. Based on the proposed beat segmentation, we obtain inner-beat and inter-beat representation. The latter means the correlation between beats. We use 1-D CNN to extract features and classify beats. Finally, we evaluate our method on the MIT-BIH dataset.

II. Method

A. Obtaining Beats

Even for a doctor, it is nontrivial to determine the start and the end point of a beat, while the R peak can be identified quickly and accurately with Pan et al. [5] method. We define the length of RR interval as the length between the current R peak and the next R peak. Moreover, the length of RR interval is close to the real length of the beat. So we define the real length of the beat as the length of RR interval. For beat i,

$$l_i = R_{i+1} - R_i \tag{1}$$

where R_i and l_i denote the R peak and the real length of beat i, respectively. The RR interval includes the P wave of the next beat but excludes the P wave of the current beat. To obtain a complete beat, we shift l_i leftward by l_f, and l_f is the same for all beats. Then the real lengths of obtained beats vary.

To meet 1-D CNN requirement, which means the input data should have a fixed length, we need to reshape the beat to that with fixed length. One of the solutions is scaling. But scaling causes different beats having different frequencies, changing the waveforms to different extent. However, the waveforms are critical for ECG classification. Therefore we use padding & truncating method. We pad zeros to the end of the beat when l_i is smaller than L_s, where we call L_s valid length. Otherwise, we truncate the beat at the end. The choice of L_s should be made carefully and reasonably, because the beat is incomplete if L_s is too small or padding excessively at the end. More details will be discussed in Section III. Using the proposed method, the obtained beat is of a fixed length L_s and its real length varies. The subgraphs (a) and (b) in Fig. 1 show the results of different beat segmentation methods.

B. Obtaining Other Beats Representations

Similar to the problem existing in beat detection, the boundaries of waves are also not clear enough to detect automatically, but each wave occupies a relatively fixed proportion. Based on the new beat, we can extract PQRST waves precisely. Considering the dynamic character of wave, instead of dividing the beat into three non-overlapping parts [4], we extract wave by overlapping sampling. The length of wave is as follows,

$$\begin{cases} L_P = (n_P + n_o) * L & \text{(2a)} \\ L_R = (n_R + 2 * n_o) * L & \text{(2b)} \\ L_T = (n_T + n_o) * L & \text{(2c)} \\ n_P + n_R + n_T + 2 * n_o = 1 & \text{(2d)} \end{cases}$$

where L_P, L_R, L_T mean the length of P wave, QRS waves and T wave respectively. n_P, n_R, n_T are the parameters that represent the proportion of each wave in a beat. n_o is an

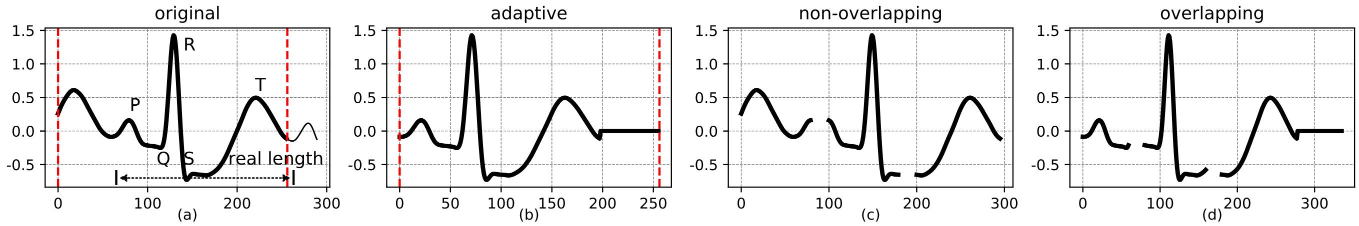

Fig. 1: Examples of different segmentation methods. (a): fixed-length beat segmentation method [2]; (b): proposed unfixed-length beat segmentation method; (c): non-overlapping wave segmentation method [4] based on (a); (d): proposed overlapping wave segmentation method based on (b).

overlapping parameter. The subgraphs (c) and (d) in Fig. 1 show the results of different wave segmentation methods.

The real length of beat is proved a useful feature. And the real length ratio of two adjacent beats can be used to express the correlation between beats, which is called inter-beat representation. In our method, for beat i, the real length ratio of two adjacent beats is defined as,

$$r_i = \frac{l_{i-1}}{l_i} \tag{3}$$

where r_i notes the real length ratio ofbeat i-1 and its adjacent beat i. Besides, the real length, l_i, is also used as a feature.

III. EXPERIMENTS

A. Dataset

The ECG dataset from MIT-BIH arrhythmia database is used, excluding 4 paced beat record(102, 104, 107 and 217). The labels recommended by Association for Advancement of Medical Instrumentation (AAMI) are adopted, including the following five types: N (normal beat), S (supraventricular ectopic beat), V (ventricular ectopic beat), F (fusion beat), and Q (unclassifiable beat). For all records, modified-lead II signals are used. Similar to Zubair et al. [2], for the first 20 record (100-124) from the MIT-BIH database, 75 beats are randomly selected from each type-N, type-S and type-V beats, and all beats of type-F and type-Q are selected. A set of these 245 beats and the beats from the first 5 minutes of the second 24 record (200-232) are used for training. All the other beats are used as test dataset. 5000 samples are randomly selected from the test dataset as validation dataset. In all experiments, the aforementioned dataset partitioning method is adopted.

B. Setup and Results

For the choice of L_s, we calculate the real length of beat for the entire database, and then count the number of beat in each interval with a length of 50. We find that most of the real lengths range from 300 to 350, therefore we set L_s to 300. For the choice of l_f, we delineate a range based on medical knowledge and select values with a certain interval, i.e. [50, 75, 100, 125, 150]. We obtain the highest classification accuracy among all experiments when setting l_f to 125. Other parameters are obtained in the similar way, we set n_P to $\frac{1}{4}$, n_R to $\frac{1}{6}$, n_T to $\frac{5}{12}$ and n_o to $\frac{1}{12}$. We stack three convolutional layers when the input is beat and two layers when the input is wave. Two fully connected layers and an output layer follow.

Though CNN is widely used, the number of classifiers can be different. Some studies use one classifier for all patients while the others use one classifier for one patient. Clearly, using one classifier for all patients has a better generalization ability and practicality. Forasmuch, we adopt the former method in our work. To reduce the randomness of the network, we repeat experiments for ten times. The final result is the mean of the ten experiments. The classification accuracy of our system is up to 95.45%, higher than other related work. The comparison of related work is given in Tab. I.

TABLE I: The comparison of related work.

Methods	Tang et al. [1] (2014)	Zubair et al. [2] (2016)	Acharya et al. [4] (2017)	Proposed
Accuracy	91.7%	92.7%	93.47%	**95.45%**

IV. CONCLUSION

In this paper, we have proposed an ECG classification system and verified its performance with extensive experiments. Our contributions include: 1) beat segmentation with unfixed length, helps to segment beat more precisely than other related work, then we reshape the beat to that with fixed length to meet the requirement of DL methods; 2) compared to [4], the wave segmentation method is improved based on the obtained beat; 3) the introduction of multi-scale representation, i.e. inner-beat, beat and inter-beat representation, is proved very useful. The accuracy of our method is higher than other related work.

Acknowledgment

This work was supported in part by the National Science Foundation of China under Grant No. 61572071 and 61872031.

References

[1] Tang, X., and L. Shu. "Classification of electrocardiogram signals with RS and quantum neural networks." International Journal of Multimedia and Ubiquitous Engineering 9.2 (2014): 363-372.

[2] Zubair, Muhammad, Jinsul Kim, and Changwoo Yoon. "An automated ECG beat classification system using convolutional neural networks." IT Convergence and Security (ICITCS), 2016 6th International Conference on. IEEE, 2016.

[3] Acharya, U Rajendra , et al. "A Deep Convolutional Neural Network Model to Classify Heartbeats." Computers in Biology and Medicine 89(2017).

[4] Xiang, Yande, et al. "ECG-Based Heartbeat Classification Using Two-Level Convolutional Neural Network and RR Interval Difference." IEICE Transactions on Information and Systems 101.4 (2018): 1189-1198.

[5] Pan, Jiapu, and Willis J. Tompkins. "A real-time QRS detection algorithm." IEEE Trans. Biomed. Eng 32.3 (1985): 230-236.