# ECG Classification Based on Unfixed-Length Segmentation of Heartbeat


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**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.


## Introduction

Current ECG classification systems [1, 2, 3] segment beat with fixed length, ingoring that the length of beat is varying with the changing temporal, personal, or contextual conditions. On the one hand, DL methods require beat with fixed length. On the other hand, the length of beat or wave varies. It is a problem to meet DL methods requirements and precisely segment beat at the same time.

To solve this problem, first, 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.

## Method

### Obtaining Beats

In Fig. 1, 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.[4] method. As the length of RR interval is close to the real length of the beat. So we define the real length of beat as the length of RR interval, called $l_i$. As shown by the solid red line in Fig. 1, we shift $l_i$ leftward and get a varying length of beat, which is varying.

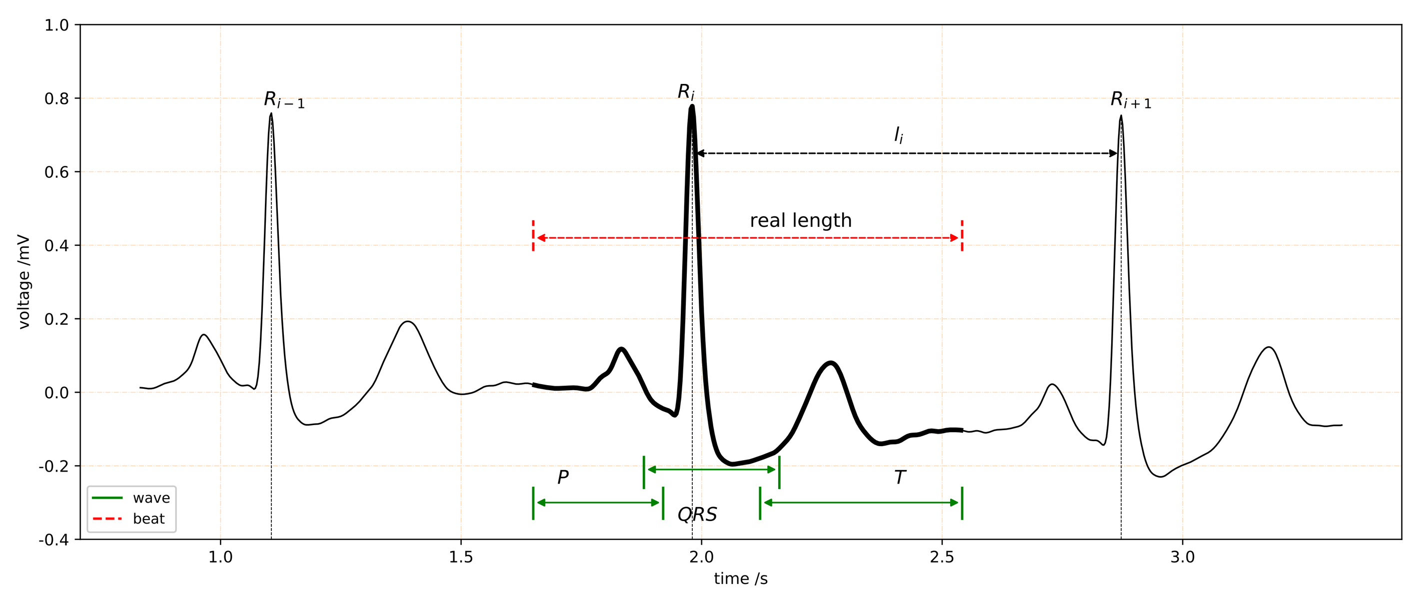


**Figure 1:** Proposed segmentation method.

To meet 1-D CNN requirement, which is the input data should have a fixed length, we need to reshape the beat to that with fixed length. We use padding & truncating method. We pad zeros to the end of the beat when $l_i$ is smaller than $L_s$, and we call $L_s$ valid length. Otherwise, we truncate the beat at the end. Then the obtained beat is of a fixed length $L_s$ and its real length varies. 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. Fig. 2 show the results of beat segmented with different $L_s$. The subgraphs (a) and (b) in Fig. 3 show the results of different beat segmentation methods.

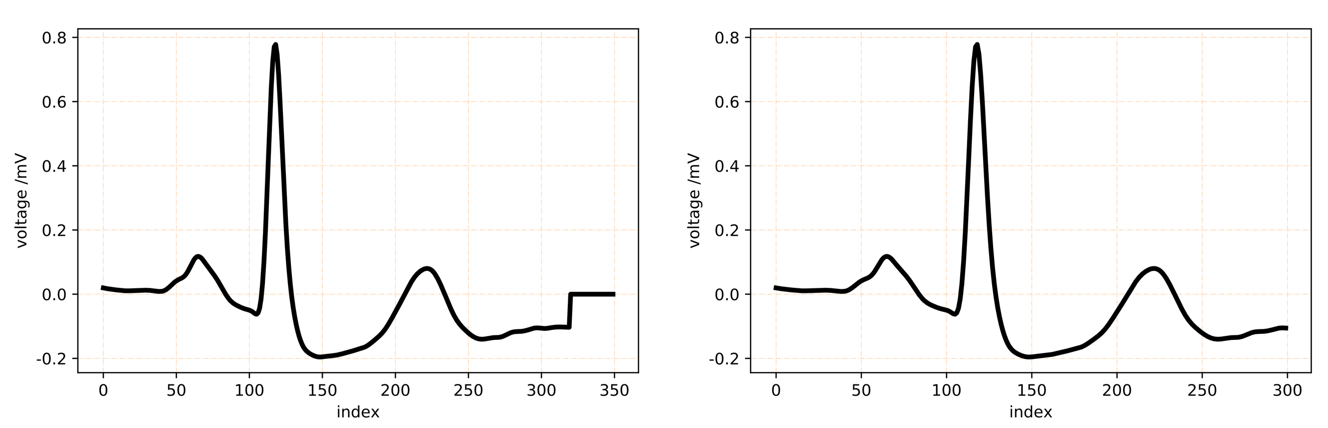


**Figure 2:** Results of beat segmented with different $L_s$.

### 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. As shown by the solid green lines in Fig. 1, considering the dynamic character of wave, instead of dividing the beat into three non-overlapping parts [5], we extract wave by overlapping sampling. The subgraphs (c) and (d) in Fig. 3 show the results of different wave segmentation methods.

And the real length ratio of two adjacent beats can be used to express the correlation between beats, which is called inter-beat representation. Besides, the real length, $l_i$, is also used as a feature.

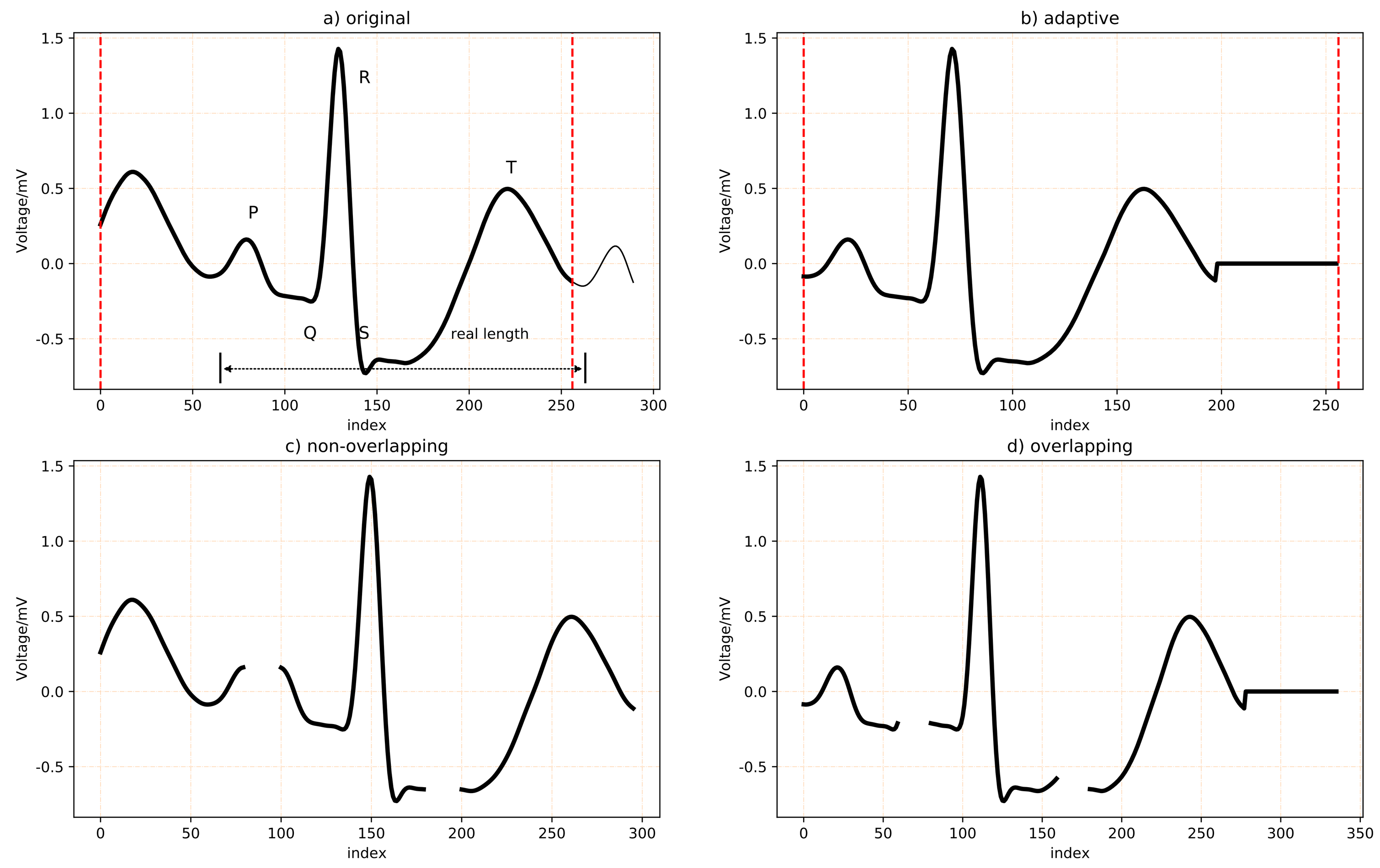


**Figure 3:** Examples of different segmentation methods. (a): fixed-length beat segmentation method [2]; (b): proposed unfixed-length beat segmentation method; (c): non-overlapping wave segmentation method [5] based on (a); (d): proposed overlapping wave segmentation method based on (b).

## Experiments

The ECG dataset from MIT-BIH arrhythmia database is used and the dataset partitioning method is same to Zubair et al.[2]. 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. In Fig. 4 we find that most of the real lengths range from 300 to 350, therefore we set $L_s$ to 300.

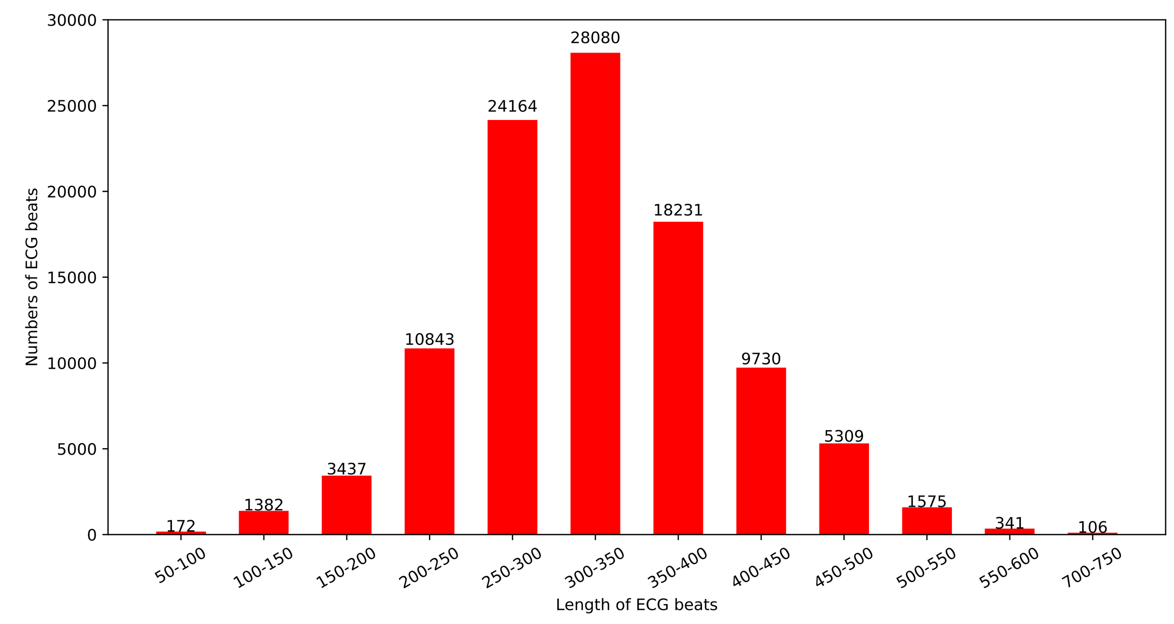


**Figure 4:** Distribution of beat real length.

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. 1.

**Table 1:** The comparison of related work.

| Methods | [1] | [2] | [5] | Proposed |
|---|---|---|---|---|
| Year | 2014 | 2016 | 2017 | - |
| Accuracy | 91.7% | 92.7% | 93.47% | **95.45%** |

## Conclusions

In this paper, we have proposed an ECG classification system. 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 [5], 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.

## References


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