Arrhythmia Classification using Deep Learning and Machine Learning with Features Extracted from Waveform-based Signal Processing

Po-Ya Hsu[1]* and Chung-Kuan Cheng[1]

Abstract— **Arrhythmia is a serious cardiovascular disease, and early diagnosis of arrhythmia is critical. In this study, we present a waveform-based signal processing (WBSP) method to produce state-of-the-art performance in arrhythmia classification. When performing WBSP, we first filtered ECG signals, searched local minima, and removed baseline wandering. Subsequently, we fit the processed ECG signals with Gaussians and extracted the parameters. Afterwards, we exploited the products of WBSP to accomplish arrhythmia classification with our proposed machine learning-based and deep learning-based classifiers. We utilized MIT-BIH Arrhythmia Database to validate WBSP. Our best classifier achieved 98.8% accuracy. Moreover, it reached 96.3% sensitivity in class V and 98.6% sensitivity in class Q, which both share one of the best among the related works. In addition, our machine learning-based classifier accomplished identifying four waveform components essential for automated arrhythmia classification: the similarity of QRS complex to a Gaussian curve, the sharpness of the QRS complex, the duration of and the area enclosed by P-wave.**

Clinical relevance— **Early diagnosis and automated classification of arrhythmia is clinically essential.**

I. INTRODUCTION

Arrhythmia is a serious cardiovascular disease due to its high prevalence and associated high mortality [1]. Given its severity, real time monitoring and early diagnosis of arrhythmia are critical in clinical practice. In this end, electrocardiogram (ECG) has become a popular arrhythmia diagnostic tool, as ECG is non-invasive and easily accessible. According to the Association for the Advancement of Medical Instrumentation (AAMI), ECG signal of arrhythmia is classified into five types: non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q). Each class requires different treatment [2], and therefore, correctly identifying the arrhythmia types is essentially important before any treatment administered.

Numerous arrhythmia computer-aided diagnosis (CAD) algorithms have been proposed. Most of these CAD tools rely on hand-crafted morphological features extraction such as identification of P-wave, QRS complex, T-wave or frequency analysis [3], [4], [5]. Such approach reveals to be error-prone on separate datasets where ECG fiducial points are difficult to recognize [6].

Unlike morphological feature extraction CAD, deep learning-based approach has become popular recently owing to its self-learning ability. Explicit features are not required to train a deep neural network (DNN) [6], [7], [8]. However, interpretability and imbalanced labels still remain to be challenges in deep learning-based CAD for arrhythmia [9].

In this paper, we present a waveform-based signal processing (WBSP) technique. WBSP is inspired by Gaussian-modeled ECG proposed by McSharry *et al.* [10]; in [10], an ECG beat is constructed with Gaussian mixtures and limit cycle. We demonstrate that WBSP can contribute to achieving:

1) Extracting features for machine learning-based classifiers without explicitly identifying P, Q, R, S, T waves of an ECG beat
2) Allowing balanced arrhythmia labels trained in deep learning-based classifiers and still reaching satisfying results
3) Incorporating limit cycle concept into DNN
4) Providing intrinsic data-oriented interpretation for clinical diagnosis

We organize the structure as follows. In section II, we first introduce the database used and then elaborate on WBSP. Next, we demonstrate the procedure of training machine learning-based and deep learning-based classifiers. In the end of section II, we describe how the performance of the classifiers are evaluated. Then in section III, we present our results and compare them with other reported works. Last, we conclude our work in section IV.

II. METHODS

A. Database

We selected MIT–BIH arrhythmia database [11] from publicly available PhysioNet [12] to validate our waveform-based arrhythmia classifiers. The data includes a total of 48 records sampled at 360 Hz, and all 48 records contain ECG data of 30 minutes duration. For all the records, we chose lead II signal for analysis if available; otherwise, we selected the signal from the first channel for experiments.

B. Waveform-based Signal Processing

There were four steps in WBSP procedure as demonstrated in Figure 1: low-pass filtering, local minima search, removal of drift, and curve fitting. First, we passed the raw ECG signal into a low-pass filter with 35 Hz cutoff frequency. Next, we found the local minima of the filtered ECG signal. To be more precise, the start and the end of the signal were both considered as local minima. Subsequently, we used cubic spline to connect the local minima found in the previous step and subtracted the piece-wise cubic spline curve from the filtered ECG signal so as to remove the

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drift. Every local minima data-point became zero after the drift removal, and we refer these zero valued local minima as *knots* in the rest of the paper. Last, we fit each curve between every two neighboring knots with a Gaussian model as expressed in (1).

$$G(t) = a \cdot e^{-((t-b)/c)^2} \tag{1}$$

We recorded the area and the ratio of the curve as defined in (2) and (3) for R-peak detection.

$$area := \sqrt{|a|} \cdot |c| \tag{2}$$

$$ratio := |\frac{a}{c}| \tag{3}$$

According to McSharry et al. [10], Gaussian curves are suitable to model the P, QRS, and T waves of ECG signals; therefore, we chose Gaussian curves to parameterize the curve between each two neighboring knots.

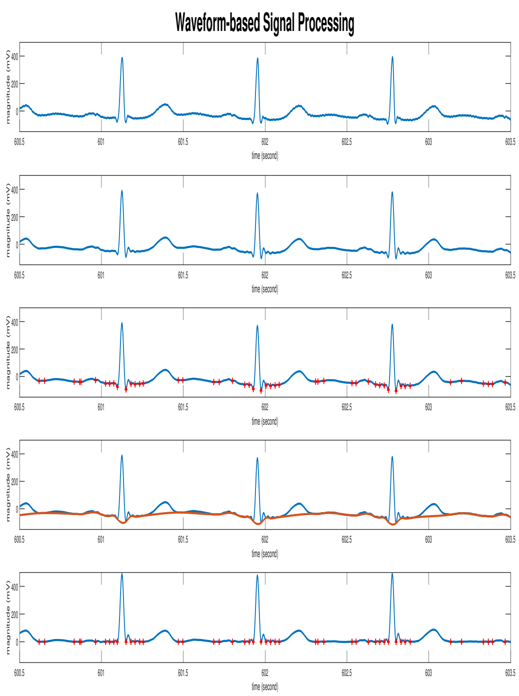

Fig. 1. Demonstration of Waveform-based Signal Processing Method. Top row shows the raw ECG signal. The second row displays the low-pass filtered signal. The middle row plots searched local minima in red cross. The fourth row illustrates the cubic spline-connected drift to remove in orange. The last row displays the processed signal for Gaussian fitting, in which the knots are shown in red cross.

C. *WBSP for Arrhythmia Classification*

We leverage the WBSP processed ECG data to accomplish both machine learning-based and deep learning-based arrhythmia classification tasks.

1) Machine Learning Classification: We elaborate on the feature extraction and classifiers selection for machine learning-based approach.

Extract Features for Machine Learning: We selected two types of features based on the WBSP method: Gaussian and cubic spline. Gaussian features are the parameters (a, b, c) defined in Eq. (1), *area* and *ratio* expressed in Eqs. (2) and (3), and *coefficient of determination* R^2, which interprets how well the Gaussian model fits the curve. Cubic spline features contain *Values of the two knots*, *integral of the cubic spline*, *the peak value of the cubic spline*, and *the time intervals between the two knots and the centered peak*. In WBSP, the filtered signal is decomposed into Gaussian parameterized curves and cubic spline drifts. For this reason, we selected the features from these two types of waveform.

Figure 2 displays one ECG beat sample to have features extracted from. For each labeled ECG beat, we empirically chose the features from the curves enclosed by twenty knots with the annotated R-peak positioning as the centered curve. That is, each ECG beat has nine curves preceding the R-peak, nine curves succeeding the R-peak, and one center curve, which generates a total of $(6+5) \times (9+1+9)+1 = 210$ features for one ECG beat.

Select the Training Classifiers: The experimented classifiers were optimizable ensemble (ENS), random forests (RF), linear and quadratic kernel support vector machines (SVM), k-nearest neighbors (k-NN), and boosting classifiers.

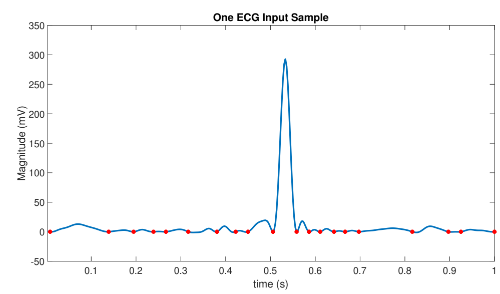

Fig. 2. Demonstration of one ECG input sample. The blue line is the ECG signal, and the red dots are the knots. QRS complex stands in the center, and each side has nine curves enclosed by ten knots.

2) Deep Learning Classification: We demonstrate how we construct the input image and neural network architecture for the deep learning-based technique.

Prepare Data for 2D-CNN: As shown in Figure 3, we transform 1D ECG data into 2D images for deep learning to incorporate limit cycle and continuity concepts. The scheme is to employ the *knots* generated by WBSP. We also selected each ECG beat with 20 *knots* enclosed as we did in the machine learning approach. Afterwards, we projected the ECG data onto a circle with the two endpoints neighboring each other. That is, we view the ECG beat as a limit cycle, which is also a technique adopted by McSharry et al. [10]. For each ECG beat, we generated two circled images: one for WBSP processed curve, and the other for cubic spline drift.

Build the Deep Neural Network: Our DNN architecture is shown in Fig. 4. The infrastructure of the proposed DNN is based on AlexNet [13]. AlexNet stacks layers of convolutional neural network (CNN) to enable recognizing patterns of different scales in an image; furthermore, layers of operations such as pooling and normalization are often inserted in between two CNNs.

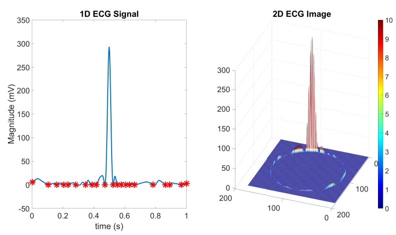

Fig. 3. Illustration of transforming a 1D ECG signal to a 2D image to train a deep neural network arrhythmia classifier; left subplot displays one ECG beat and marks the knots as red stars; right subplot demonstrates the 2D ECG image as an input sample to the deep neural network

In our design, we have a DNN of 30 layers. The first layer is an input layer of size $73 \times 73 \times 2$, and the last layer is the classification output. As shown in Fig 4, the dimensionality of the input changes at the 2^{nd}, 10^{th}, 15^{th}, 22^{nd}, 25^{th}, and 28^{th} layers, at which the former are CNN and the latter are fully connected (FC) layers. Following the input is a CNN layer with 32 filters of size 3×3. From the 2^{nd} to the 10^{th} layers, the operations include ReLU, normalization, max pooling, grouped convolution (GC) of 32 filters, and another repeated procedure exclusive of the GC. The 10^{th} layer is a CNN layer with 48 filters of size 5×5. Subsequently, the operation layers contain ReLU, GC of 48 filters, and another repeated procedure. At the 15^{th} layer, it is a CNN with 48 filters of size 7×7. Starting from the 16^{th} to the 21^{st} layer, it includes a series of operations without changing the activation dimensions: ReLU, GC of 48 filters, ReLU, GC of 48 filters, ReLU, and max pooling. From the 22^{nd} to the 29^{th} layers, they consist of typical classification structures. We design the numbers of activation units of FC at the 22^{nd}, 25^{th}, and 28^{th} layers as 512, 128, and 5. In between each FC layers are ReLU and dropout at 0.6. At the 29^{th} layer, softmax is used to compute the classification result and generate the output at the 30^{th} layer.

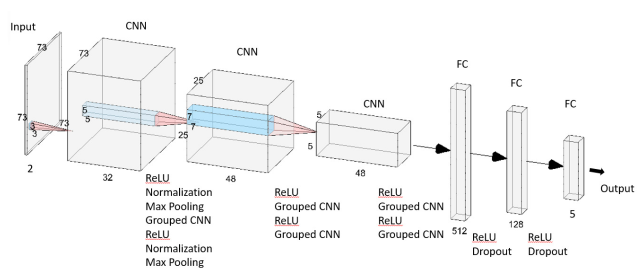

Fig. 4. Diagram of the architecture of the deep neural network. The numbers represent the dimensions of the data in the network.

We trained the DNN with stacks of transformed ECG images as input and their corresponding classification labels as output. For the input, we set the image size as 73×73. The whole training required twenty epochs and a mini-batch size of 100 in each epoch. Random shuffling was included. The DNN training was run with a single GeForce GTX 1050 graphics card on MATLAB 2019B.

D. Data Partition and Performance Evaluation

TABLE I
SUMMARY OF CLASSIFIED HEARTBEAT TYPES

Hearbeat Type	AAMI	Total #	Training (%)
Normal	N	74625	10%
Left bundle branch block	N	8037	40%
Right bundle branch block	N	7217	40%
Atrial premature	S	2529	40%
Aberrated atrial premature	S	149	40%
Nodal (junctional) premature	S	83	40%
Premature ventricular contraction	V	7099	40%
Fusion of ventricular and normal	F	800	40%
Ventricular flutter wave	V	472	40%
Atrial escape	N	16	40%
Nodal (junctional) escape	N	229	40%
Ventricular escape	V	106	40%
Paced	Q	6984	40%
Fusion of paced and normal	Q	977	40%
Unclassifiable	Q	33	40%

We conducted experiments by using the proposed machine learning-based and deep learning-based classifiers to classify the 15 ECG beat types into 5 categories N, S, V, F, Q according to ANSI/AAMI EC57 of arrhythmia classification [14]. Table I lists the 15 beat types and their corresponding categories. Class *N* includes normal, left bundle branch block, right bundle branch block, atrial escape, and nodal (junctional) escape beats; class *S* contains atrial premature, aberrated atrial premature, and nodal (junctional) premature; class *V* consists of premature ventricular contraction, ventricular flutter wave and ventricular escape; class *F* is composed of fusion of ventricular; class *Q* includes paced, fusion of paced and normal, and unclassifiable.

To fulfill the classification task, we split the data by following similar procedure recommended by [15] to sample the ECG beats due to the imbalance of the data. We randomly sampled 10% of normal beats and 40% of other types of heart beats to train our classifiers. To be more specific, we trained our models with 19.5% of data and run the testing on 80.5% of data.

We evaluated the performance of the proposed waveform-based arrhythmia classification method with accuracy and sensitivity, which are both commonly adopted metrics in classification tasks. For each arrhythmia type, sensitivity is defined as the ratio of the number of the correctly labeled class (true positives) over the total of the specified class (true positives + false negatives). Accuracy is expressed as the number of correctly labeled classes divided by the summation of the evaluated ECG beat number. In addition to the conventional performance evaluation, we observed the feature importance to leverage the application of WBSP.

III. RESULTS

A. Performance of the Classifiers

We summarize the classification results of ours and other reported research work evaluating on the same dataset (in-

TABLE II
ACCURACY AND SENSITIVITY OF ARRHYTHMIA CLASSIFICATION

work	Acc	S_N	S_S	S_V	S_F	S_Q
Acharya et al.[6] 1D-CNN	94.0%	91.6%	**89.0%**	94.1%	**95.2%**	97.4%
Yang et al.[7] PCAnet	97.9%	**99.6%**	71.3%	87.5%	75.0%	98.4%
Our ML	**98.8%**	99.3%	86.6%	**96.3%**	75.2%	**98.6%**
Our DL	97.8%	98.6%	76.2%	**95.3%**	70.5%	97.7%

cluding paced beats) in Table (II). Our best machine learning-based classifier is the optimizable ensemble classifier, which reaches an overall accuracy of 98.8%. Other experimented machine learning-based classifiers arrive at an accuracy of 97.6% for RF, 96.5% for quadratic SVM, 95.2% for boosting, and 94.2% for kNN. Referring to the deep learning-based method, our classifier achieves an overall accuracy of 97.8%.

Both of our proposed classifiers are competitive with other published works as displayed in Table II. Regarding the overall accuracy, our ensemble classifier has the best performance. As to the sensitivity, both classifiers outperform Yang et al. [7] and Acharya et al. [6] in class V, and the ensemble classifier even reaches the best sensitivity in class Q. Moreover, both classifiers present fair sensitivities in the other three classes. By fair, we mean the sensitivities achieved surpass (class N, S, and F) one of the two published works.

B. Important Features in Arrhythmia Diagnosis

Figure 5 demonstrates the feature importance of Gaussians computed from our trained ENS classifier, and the resulting features can further support the clinicians in arrhythmia identification. We are able to visualize four features that play significant roles in arrhythmia classification. Two of them originate from QRS curve: goodness-of-fit R^2 and ratio; and the other two features derive from QRS left neighboring curve: the width and area parameterized by a Gaussian. The observations imply that the shapes of possible P-wave (or the wave preceding QRS complex) and QRS complex significantly affect the arrhythmia classification results.

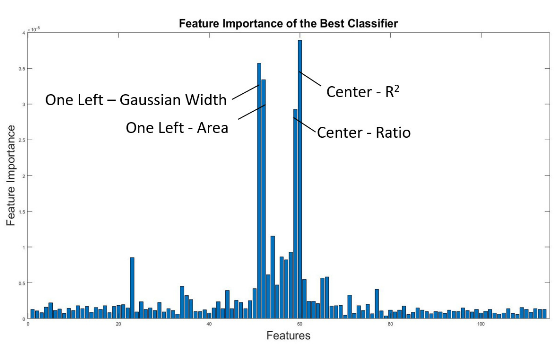

Fig. 5. Illustration of the feature importances of the best classifier

IV. CONCLUSIONS

We propose a waveform-based signal processing method for electrocardiogram. More importantly, we demonstrate how WBSP can be applied to devise machine learning-based and deep learning-based arrhythmia classifiers. In arrhythmia classification tasks, we achieved one of the state-of-the-art performances with an accuracy of 98.8%, sensitivity of 96.3% in class V, and sensitivity of 98.6% in class Q. In addition, we found the key waveform parameters that contribute to arrhythmia classification with the proposed WBSP method. We intend to explore WBSP on different biosignals in the future.

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