Welch-GAN: Generating realistic photoplethysmography signal from frequency-domain for atrial fibrillation detection

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Abstract

Training machine learning algorithms from a small and imbalanced dataset is often a daunting challenge in medical research. However, it has been shown that the synthetic data generated by data augmentation techniques can enlarge the dataset and contribute to alleviating the imbalance situation. In this study, we propose a novel generative adversarial network (GAN) architecture — Welch-GAN and focused on examining how its influence on classifier performance is related to signal quality and class imbalance within the context of photoplethysmography (PPG)-based atrial fibrillation (AF) detection. Pulse oximetry data were collected from 126 adult patients and augmented using the permutation technique to build a large training set for training an AF detection model based on a one-dimensional residual neural network. To test the model, PPG data were collected from 13 stroke patients and utilized. Four data augmentation methods, including both traditional and GANs, are leveraged as baseline in this study. Three different experiments are designed to investigate each data augmentation methods from the aspect of performance gain, robustness to motion artifact and training sample size, respectively. Compared to the un-augmented data, by training the same AF classification algorithm using augmented data, the AF detection accuracy was significantly improved from 80.36% to over 90% with no compromise on sensitivity nor on negative predicted value. Within each data augmentation techniques, Welch-GAN has shown around 3% superiority in terms of AF detection accuracy compared to the baseline methods, which suggests the state-of-the-art of our proposed Welch-GAN.

Introduction

It is reported that the general adult population has atrial fibrillation (AF) at a rate of 1.5% - 2% approximately [1], and the prevalence of AF in the general population is expected to increase over years due to an aging population. Furthermore, AF is associated with a 5-fold increased risk of ischemic stroke, 3-fold increased risk of heart failure, and 2-fold increased risk of heart disease-related death. Because of the potentially large numbers of patients who may benefit from continuous AF screening, an affordable, continuous, and wearable monitoring system is key to large-scale identification and timely treatment of AF. Photoplethysmography (PPG) - an emerging low-cost technology – is a potential alternative to ECG (electrocardiogram) for AF detection. PPG-based AF detection devices can potentially be advantageous over ECG-based devices, because they are generally more cost-effective and less invasive, and portable [2,3]. For PPG based AF detection, it has been shown that deep learning algorithms achieved better results than traditional statistical algorithms [4-7]. Recent studies used balanced real-world PPG datasets collected in ambulatory environment to train deep learning (DL) algorithms [5-10]. However, since most AF cases are paroxysmal, collecting a large number of signals associated with AF to train a deep learning algorithm is arguably a daunting task [4]. In addition, although datasets from general hospital settings or from free-living subjects can be abundant and accessible, AF samples are seldomly present in these datasets owing to the low prevalence of AF in general population. Therefore, more imbalanced datasets were collected than balanced ones.

Data augmentation has become a standard regularization technique to handle imbalance situation in machine learning, particularly in image classification tasks. It can help not only reduce overfitting when training supervised learning models [11,12,13], but also leverage a limited dataset to train machine learning models by transforming existing samples to new ones. However, augmentation on photoplethysmography data has only been experimented in a few studies. Gotlibovych et al. [14] randomly selected segments within one raw PPG signal, and applied scaling and additive shifts on the segments with random amplitudes, then added the generated samples into the training set for AF detection. However, a major part of the data in this experiment were recorded during sleep, which did not contain relevant factors such as motion artifact and hence made the trained model unsuitable for processing PPG signals from ambulatory settings. Also, the investigation of the effect on data augmentation was only explored during training procedure to show augmented data can help smooth the training loss, the influence of data augmentation on the testing performance was not well explored. Another study, PlethAugment [15], investigated a generative adversarial network (GAN) for PPG data augmentation. Three different conditional GANs were tested on various public datasets for different tasks, showing that GAN can help generate realistic PPG signals and improve the performance of PPG based tasks. This study has also investigated the effect of generated synthetic data on class imbalance and the influence of
different ratios of real-world to artificial training data on the classification performance. However, the authors failed to compare GANs with traditional augmentation techniques, such as shifting and cropping. Furthermore, AF detection was not evaluated in the experiments. Additionally, they only compared GAN to limited baseline methods. Whether GAN is the best augmentation technique remain to be adequately demonstrated.

To address the discrepancy between the need of specific GAN for PPG based AF detection and the available solution, we propose Welch-GAN, a generative adversarial network which takes a random signal as input and output AF PPG signal. The Welch-GAN is built based on the same architecture of DCGAN [16]. Different from DCGAN, Welch-GAN considers frequency-domain distance into the loss function in addition to the classic cross-entropy loss. In the results, we show that the augmented AF signals from Welch-GAN have the nearest distribution to the real AF signal and the improved AF detection accuracy benefits the most from Welch-GAN compared to other augmentation techniques. Main contributions of this paper are summarized:

- To our knowledge, we are the first work which incorporates the Welch method into the loss function for PPG signal generation. Also, we are the first work which consider using GAN to generate synthetic PPG data for AF detection.
- Instead of manually setting the weights λ between welch-loss and cross entropy loss, we propose a quantitative method to find the best λ to balance the two loss functions. For different λ, we first calculate the auto-correlation of each signal and use Maximum Mean Discrepancy (MMD) to measure the distance between generated signal and real AF signal. Optimal λ will be selected based on minimal MMD distance.
- Beside tested on internal dataset, we evaluate different trained model from each augmentation method on a public PPG dataset, which proves the generalizability of our proposed GAN to the PPG signal for AF detection.

The rest of this paper is organized as follows. Section 2 discusses the prior related work on signal generation. Next, the details of our experiments, including datasets and training procedures, as well as our proposed method is discussed in Section 3. Finally, the results and analyses are presented in Section 4, followed by a discussion and summary of our work in Section 5.

Related work

Our previous work has reviewed most of the studies focusing on AF detection from PPG signal in recent years [4]. Consequently, the deep learning trend has been more and more popular and achieves state-of-the-art performance for PPG based AF detection. Aliamiri and Shen [6] proposed a hybrid architecture leveraging both convolution and recurrent into the model for the purpose of AF detection. An additional signal quality assessment model is also adopted to discard signals with poor quality. In their later work [5], they proposed a Resnet based model to detect AF on PPG signals from ambulatory situations. Although results show it is robust to motion artifacts, signal quality in their data remains to be better than real world setting in which major part of the signals are in poor quality. Torres et al [17] collected and released a public-available PPG dataset with annotation for both signal quality and AF. They also proposed a multi-task framework which trains the quality assessment and AF detection simultaneously. However, since a major part of the quality labels are machine-generated, these label noise could influence the optimization process for AF detection through back propagation. Sarkar et al. [18] Proposed BayesBeat, which leverages the Bayesian neural network into the area of AF detection, showing significant increased performance compared to the other state-of-the-art methods. However, the influence of data imbalance on BayesBeat in not well investigated, since the distribution of real world PPG can be significantly different from training data.

Deep learning algorithms are data hungry. The acquired data is not always sufficient for training. Different augmentation methods are also leveraged in order to solve the data shortage problem. Soonil et al. [8] enables 20 seconds overlap between consecutive PPG segments when splitting the continuous PPG recording, which can be considered as a basic data augmentation method. Although it indeed enlarges the training sample size, additional information will not be introduced into the training data. Similar to the work [14], Cheng et al. [19] adopted three traditional data augmentation methods: Scaling, Adding Gaussian noise and randomly changing the amplitude. Random combinations of these three methods are applied to the PPG signal to enlarge the training sample size. However, those augmentation methods can accidently change the PPG signal from normal sinus rhythm to other arrhythmias, which will introduce additional label noise into the training set at the same time. Andrius et al. [20] developed a model to simulate PPG signal from ECG during AF. The model takes the RR intervals calculated from ECG as the input. Each PPG signal can be considered as a linear combination of log-normal and two Gaussian functions, which can characterize the pulse width, amplitude and scale separately. Therefore, the model is capable of simulate PPG signal during AF or with premature beats. Although results demonstrate that the generated PPG is close to the real PPG morphologically, it remains doubts that those generated PPG is helpful for the downstream classification task.

Besides traditional augmentation techniques mentioned above, several studies have conducted GANs to generate synthetic PPG signal. Since PPG signals are more vulnerable to human movement compared to ECG. Heen et al. [21] introduce a GAN to generate high quality PPG signal from the simultaneous ECG. The architecture contains a Bi-LSTM based generator and 1DCNN based discriminator. However, the proposed GAN can only deal with 1-second ECG and generate 1-second PPG. One has to stick consecutive one-second of PPG in order to get a longer duration signal, by which 29 abrupted connecting point will be introduced if we want a 30-second PPG. In SynSigGAN [22], a GAN model is proposed to generate four kinds of physiological signals (ECG, EEG, EMG, PPG). In the preprocess stage, each signal will be transformed to wavelet, after specific thresholding for the purpose of denoising, inverted wavelet transformation is adopted here to convert the signal back. As the last part of preprocessing, one automatic segmentation is leveraged here to determine the length of each kind of physiological signal from GAN. However, no downstream classification task is conducted here to practically exam the effect of the SynSigGAN. Seyed et al. [23] proposed a cycle GAN [24] based approach to generate PPG signal for RR (respiratory rate) estimation. In addition, a novel loss function is invented to take the RR of generated signal into account. Results show that, by adding the augmented PPG signal, the accuracy of RR estimation outperforms other state-of-the-art methods on an identical experiment setting and dataset. Although authors admits that lack of noisy PPG is one of their limitation, this study suggests that introducing novel and task-related loss function is a promising solution to many GAN based tasks.
Methods

**PPG Data**

**Training data:** Continuous fingertip PPG (fPPG) recordings were collected from pulse oximeters in 126 in-hospital patients aged between 18 and 95 years (median 63) who admitted to UCLA medical Center between April 2010 and March 2013. A board-certified cardiologist marked the start and end of AF episodes based on co-registered ECG recordings. 104 of 126 patients (83%) had recordings with Non-AF rhythms, 14 of 126 patients (11%) had recordings with persistent AF rhythms, and 8 of 126 (6%) patients had recordings with mixed (AF and non-AF) rhythms. Continuous PPG recordings were divided into consecutive non-overlapping 30-second records. Each 30s record was labeled “AF” or “non-AF” depending on if it was extracted within or outside an AF marked episode, respectively. The retrospective use of this dataset for this study was approved by UCSF IRB with a waiver of patient consent (IRB approval number: 16-18764).

**Testing data:** A set of continuous wrist PPG data (wPPG) were collected from wearable devices (Empatica E4) worn by 13 acute stroke patients admitted into the Neurological intensive care unit of UCSF Medical Center between October 2016 and January 2018. Patients were aged between 19 to 91 (median = 73.5). 8 of 13 (61%) patients had recordings with AF episodes. The collected PPG recordings lasted between 3h and 22h (median = 10.5h). With the same method used in the training data, the continuous signal in the test set were segmented into consecutive non-overlapping 30s segments (5831 in total). A subset of the testing set was built using 2683 of 5831 (46%) segments for which high inter-rater agreement could be obtained between three annotators who labeled the records with respect to signal quality (good vs. bad). The details on signal quality annotation can be found in [17]. Table 1 shows the distribution of AF and Non-AF segments in the training and testing sets. The protocols approved by UCSF’s Institutional Review Board were informed to all the enrolled patients, and written consent was provided by the patients before this study was conducted.
Table 1. Number of records in the training and testing sets.

| Center                  | Training set | Testing set |
|-------------------------|--------------|-------------|
| UCLA medical center     | 126          | 13          |
| UCSF Neuro ICU          |              |             |
| Number of patients      |              |             |
| Age                     | 18 to 95 years (median 63) | 19 to 91 (median = 73.5) |
| Number of records       | AF 36855     | AF 1216     |
|                         | Non-AF 249278 | Non-AF 1467 |
| Total                   | 176133       | 2683        |
| Percentage              | 15.24%       | 84.75%      |
|                         | 45.32%       | 43.68%      |

Artifact proportion

Each 30-second record from the testing set was annotated with respect to the proportion of artifact following the protocol described in our previous publication[16]. The artifact proportion was calculated by selecting all segments in a PPG record that were considered corrupted then dividing their combined length by the total length (30 seconds) of the signal. Artifacts within two 30-sec PPG signals were highlighted in examples shown in Figure 1.

Figure 2. PPG segments with motion artifacts marked in yellow.

AF Annotation

The testing set was annotated with respect to AF presence by 7 clinicians as described in a previous study[17]. Guided by 7-lead ECG recordings, simultaneously recorded PPG signals were labeled “AF”, “Not AF”, or “Not Sure” if they were respectively identified to contain AF rhythm, other rhythms than AF, or ambiguous/unidentifiable rhythms. Figure 2 shows the distributions of the number of records with respect to artifact proportions for AF and Non-AF conditions.

Figure 3. Distribution of the proportion of artifact in the testing record set.
Residual model for AF detection

The model in this study is one variant of 1D Resnet model adapted from the original design[19], which has 34 layers in total as reported in Table 2. The first layer is made of 48 one-dimensional convolutional filters. The kernel size of each filter was set to 80 in order to capture a longer range of contextual signal information. Four stages of residual layers with different number of residual blocks are connected to the first layer. One fully connected layer is appended as the last prediction layer with two neuron units as a binary classification. ReLU is used as the activation function for all convolutional layers. Sigmoid is used as the active function for the output layer. In the training process, categorical cross-entropy is set as the loss function and Adam is used as the optimizer. The training process is conducted with 50 epochs and the learning rate is set at 1e-4 with a decay factor at 1e-6. The best epoch is selected based on the minimal loss value on the validation set.

Baselines

Data-copying: As a straightforward data augmentation method, data-copying simply duplicates the signal and then adds them into the training set.

Permutation: Each 30-sec PPG signal is divided into five equal-length sub-segments which are rearranged by randomly permuting their order and concatenated to form a new 30-sec signal.

Deep convolutional generative adversarial network (DCGAN) and DCGAN with Wasserstein distance (W-DCGAN):

GAN has two components: generator network G and discriminator network D, as shown in Fig. 1(b). G receives random noise z and generates ‘fake’ PPG signal. D is a binary classifier and fed with both real and fake PPG signal, then determine whether the input signal is real or fake. The training process of GAN is a zero-sum game, which generator and discriminator trying to achieve the minimal value of the object function:

\[
\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)} [\log D(x)] + E_{z \sim p_{z}(z)} [\log (1 - D(G(z)))]
\]

Convolutional neural network (CNN) based models are capable of learning good feature representations, leading to achieve state-of-the-art performance in many classification tasks. Compared to vanilla GAN, DCGAN can be considered as an extension to the field of CNN, which adopts the structure of deep CNN to improve the quality of generated signal and accelerate the converge process.

The Wasserstein deep convolutional generative adversarial network (W-DCGAN) is a further extension of DCGAN. In DCGAN, we only change the model structure and keep the same cost function as vanilla GAN. By introducing the Wasserstein distance, we can not only improve the training stability but also enable a cost function which is related to the quality of generated signal. The new cost function is

\[
\min_G \max_D L_{WGAN}(D, G) = -E_{x \sim p_{data}(x)} [D(x)] + E_{z \sim p_{z}(z)} [D(G(z))]
\]

Welch-GAN

Adding additional loss into the cost function of the generator has been proved to be helpful. For PPG signal, only focusing on time-domain information can have two problems, as shown in Fig. 5. First, PPG segments are split from continuous recordings at random points, which makes signals are not
time-aligned and also hard to align (Fig. 5 (a)). Second, under-fitted signal could be closer to real signal than well-fitted signal in only time-domain (Fig. 5 (b)). To address these two problems, we introduce signal’s frequency domain information to the design of the loss function. First, even two similar signals are not time-aligned, they still can have similar distribution in the frequency domain. Second, although under-fitted signal can be more near to the real signal than generated signal from well-fitted GAN in time-domain, the difference is huge when transformed to the frequency domain.

Welch’s method [26] for estimating power spectra is carried out by dividing the time signal into successive blocks, forming the periodogram for each block, and averaging.

Denote the m-th windowed, zero-padded frame from the signal x by,

\[ x_m(n) \triangleq w(n)x(n + mR), n = 0, 1, \ldots, M - 1, m = 0, 1, \ldots, K - 1 \]  

\[ P_{x_m, M}(\omega_k) = \frac{1}{M} |FFT_N[k, x_m]|^2 \triangleq \frac{1}{M} \sum_{n=0}^{N-1} x_m(n)e^{-j2\pi\beta_k/N} \]  

\[ \text{Premature iteration L1 distance } = 0.043 \quad \text{Well-train iteration L1 distance } = 0.052 \]

Figure 5. Examples for two problems existing if only consider time-domain information

where R is defined as the window hop size and let K denote the number of available frames. Then the periodogram of the m-th block is given by

as before, and the Welch estimate of the power spectral density is given by.
\[ \tilde{P}_{\Delta x}^{W}(w_k) \triangleq \frac{1}{K} \sum_{m=0}^{K-1} P_{x_m, M}(w_k) \]  

(5)

In other words, it's an average of periodograms across time. When \( w(n) \) is the rectangular window, the periodograms are formed from non-overlapping successive blocks of data.

In our studies, we then combine the Welch estimate with cross-entropy as the final loss function of the generator. As shown in Fig.1, the loss function is defined as:

\[ L_{\text{welch-GAN}} = L_{\text{adv}}(Real, Fake) + \lambda \times L_{\text{MSE}}[Welch(Real), Welch(Fake)] \]  

(6)

**Hyperparameter tuning**

As shown in Fig.1, the Loss function of the generator in Welch-GAN has two parts: Cross entropy loss and welch loss with the weight of \( \lambda \). Different from many other studies which set the weights \( \lambda \) manually, we select the \( \lambda \) by optimizing a quantitively grid search process. First, we choose a large range of \( \lambda [0, 3] \) with a step of 0.1. Second, 300 real PPG signals are selected and 300 randomly PPG signal will be generated from each \( \lambda \) separately, then all the signals will be represented to autocorrelation coefficients. Last, the best \( \lambda \) will be chosen based on the least MMD distance between generated signals and real signals.

**Table 2. The architecture of one-dimensional Resnet**

| Layer Name          | Output Size | 1D Resnet-34 |
|---------------------|-------------|--------------|
| conv1               | 1801×48     | 1×80 kernel, 48, stride 4 |
|                     |             | BatchNorm    |
|                     |             | Max pool with size 4 |
| residual blocks_1   | 112×48      | \( \begin{align*} 1×3, 48 \\ 1×3, 48 \end{align*} \times 3 \) |
|                     |             | Max pool with size 4 |
| residual blocks_2   | 28×96       | \( \begin{align*} 1×3, 96 \\ 1×3, 96 \end{align*} \times 4 \) |
|                     |             | Max pool with size 4 |
| residual blocks_3   | 7×192       | \( \begin{align*} 1×3, 192 \\ 1×3, 192 \end{align*} \times 6 \) |
|                     |             | Max pool with size 4 |
| residual blocks_4   | 7×384       | \( \begin{align*} 1×3, 384 \\ 1×3, 384 \end{align*} \times 3 \) |
| Average pooling     | 1×384       |               |
| Fully connected     | 1×2         | 384×2 fully connections |
| Sigmoid             | 1×2         |               |

**Experiment design**

Three experiments are designed to investigate the welch-GAN and baseline methods in three different aspects.

**Experiment 1**: Since there is an imbalance problem in the original training data, in which AF is the minority class and Non-AF is the majority class. And the ratio of samples between AF and Non-AF is around 1:7. To investigate whether a more balanced training data would help the final classification accuracy. In the first experiment, we augmented only the AF cases to 1 fold, 3 fold and 6 fold increase compared to the original number of AF training samples, respectively. To generate those augmented AF cases, the proposed welch-GAN and four baseline models are all conducted. Different metrics, such as accuracy, sensitivity, etc., are used to compare the effect of each augmentation method.

**Experiment 2**: The factor of signal quality cannot be neglected when conducting experiments on PPG signals. Besides performance gain, we also want to investigate the relationship between the increased accuracy and the proportion of artifact within the PPG signals. In the second experiment, we split
this testing subset into four groups based on the percentage of artifacts: clean (0% - 20%), [21%-60%) and [61%-100%). Then we pick models with the best accuracy from experiment 1 for each augmentation method and test the picked model on those four groups separately.

Experiment 3: From the results of experiment 1, we observe that an accurate AF detector benefits the most from a balanced training set. However, another factor, the total number of training samples, has not been investigated. To test the effect of training sample size, we constitute a series of balanced training set with an increasing sample size from 30,000 to 450,000. For each training set, the Non-AF cases are all randomly selected from the original data. At the same time, if the number of required AF cases (e.g., 15,000 AF cases are need for the sample size of 30,000) is less than original AF cases, then they are randomly selected. When the required AF cases exceeds original size, additional AF samples will be generated by each augmentation methods.

Results

Experiment 1

A. Performance of augmentation methods

In the first experiment, we quantify the performance of all the augmentation methods via different metrics. Table 3 summarizes the performance of AF detection for different combinations of original and augmented data sets. A cutoff class probability threshold of 0.5 was used.

| Augmented AF fold | Original | Data-copying | Permutation | DCGAN | W-DCGAN | Welch-GAN |
|-------------------|----------|--------------|-------------|--------|----------|-----------|
|                   | 1        | 3            | 6           | 1      | 3        | 6         | 1         | 3         | 6         | 1         | 3         | 6         | 1         | 3         | 6         |
| Accuracy          | 0.8036   | 0.8446       | 0.9161      | 0.9154 | 0.8995   | 0.9214    | 0.9383    | 0.8874   | 0.9165   | 0.9269    | 0.8569   | 0.9196    | 0.9322    | 0.9935    | 0.9260    | 0.9609    |
| Specificity       | 0.9609   | 0.9905       | 0.9850      | 0.9822 | 0.9927   | 0.9921    | 0.9927    | 0.9918   | 0.9959   | 0.9952    | 0.9856   | 0.9907    | 0.9945    | 0.9973    | 0.9938    | 0.9938    |
| PPV               | 0.6915   | 0.7828       | 0.8768      | 0.9264 | 0.8161   | 0.8546    | 0.8808    | 0.8338   | 0.8701   | 0.8854    | 0.7993   | 0.8922    | 0.9280    | 0.8516    | 0.8653    | 0.9382    |
| NPV               | 0.9894   | 0.9831       | 0.9787      | 0.9024 | 0.9933   | 0.9938    | 0.9941    | 0.9872   | 0.9940   | 0.9932    | 0.9760   | 0.9604    | 0.9374    | 0.9959    | 0.9910    | 0.9920    |

Within each augmentation methods, we can observe an increasing accuracy following a more balanced training set. From 1-fold to 3-fold, there is an averagely 3% improvement in accuracy and PPV. At the same time, 6-fold (balanced training set) would have the best performance compared to 1-fold, 3-fold and original.

Comparing to training only on the original imbalance data, simply double the AF cases would bring in 4% of accuracy boost and 9% improvement in PPV. Furthermore, a balance training set with duplicating all the AF cases 6 times would help increase the 11% accuracy and 23% of PPV. Permutation, DCGAN and W-DCGAN have the similar performance, while the proposed welch-GAN would help increase the performance dramatically, with a 26% more in accuracy and 23% in PPV without compromising other metrics in the same time.

Since data-copying just duplicates the AF cases to balance the training set, which will not introduce additional information to data. Comparing to the data-copying, we can have around 4% of improvement in terms of accuracy from permutation, DCGAN and W-DCGAN. At the same time, our proposed welch-GAN would improve the accuracy at around 6% and 7% improvement in terms of PPV.

B. test on public PPG dataset

Most public PPG dataset are designed for the purpose of heart rate estimation or motion detection. In 2020, the study [deepbeat] has been published in the NPJ digital medicine and released their data with both signal quality and AF annotation. There are three difference between our data and deepbeat data. First, the deepbeat data is collected from wrist type watch in the ambulatory setting, while our data is collected from fingertip in the ICU setting. Second, the signal length of one segment is 25 seconds with a sample rate 32, ours is 30 seconds with sample rate 240. Third, the preprocessing details were not reported clearly in their paper and may differ from ours. Based on above, before testing our model on the deepbeat test set, we first upsample their signal length to the same as ours and then adopted the min-max normalization on their data. Our models are selected based on best results from experiment 1A for each methods and Table 4 summarizes the performance.

Among our models, the proposed welch-GAN still shows a leading performance in terms of F1 score (0.91) and sensitivity (0.88), which is improved around 15% F1 score compared to the data-copying and 26% in terms of sensitivity. Compared to deepbeat models, our methods are not able to achieve a sensitivity over 90%, indicating that our models fail to detect as many AF segment as they do.
Table 4. Performance on external data provided by deepbeat[17]

| Model       | Sensitivity | Specificity | False positive rate | False negative rate | F1 score |
|-------------|-------------|-------------|---------------------|---------------------|----------|
| Original    | 0.47        | 0.99        | 0.005               | 0.53                | 0.62     |
| Data-copying| 0.62        | 0.99        | 0.003               | 0.38                | 0.76     |
| Permutation | 0.82        | 0.99        | 0.006               | 0.18                | 0.88     |
| DC-GAN      | 0.70        | 0.99        | 0.002               | 0.30                | 0.82     |
| W-DCGAN     | 0.70        | 0.99        | 0.003               | 0.30                | 0.82     |
| Welch-GAN   | 0.88        | 0.99        | 0.009               | 0.12                | 0.91     |

Experiment2: Robustness to artifacts

In addition to performance gain, experiment 2 is designed to investigate the relationship between signal quality and different augmentation methods. Fig. 6 compares each method’s performance gain within different proportion of artifacts.

We first can notice that, all the methods fail to detect AF accurately in the poor quality group (more than 60% of artifacts). At the same time, both methods can achieve over 90% accuracy for the good quality group (0% of artifacts). While in both poor quality and good quality group, the proposed welch-GAN has outperformed the rest of the methods, achieving approximately 6.5% percent accuracy improvement in good quality group and 11% in poor quality group, respectively.

The boost in accuracy by data augmentation shown in Table 3 mainly attributes to the accuracy boost in the moderate quality group (less than 60% of artifacts), achieving 13% accuracy improvement on average. With artifacts introduced to the signal, the performance of the model trained on original imbalance set suffer greatly, dropping from 91% to 75% in terms of accuracy. Although, data-copying shows certain durability to the increasing artifacts (dropping from 90% to 83%), the rest of augmentation methods still show capability of being robust to the artifacts. Among all the methods, the accuracy of permutation as well as welch-GAN only drop 7% when 60% of artifacts are in one PPG signal. At the same time, welch-GAN always leads the accuracy in all four groups.

Experiment3: Data augmentation at different sample size

To evaluate the effect of training sample size, experiment 3 is conducted. A series of training set with an increasing sample size from 30,000 to 450,000 is constituted, same residual network is trained based on each training set separately and tested on the same test data. Then this process is repeated for all the augmentation methods. Fig. 7 compares the accuracy for different training set from different methods. When the sample size is less 50,000, since no artificial data is introduced into the training set, the accuracy remains at a range of 66% to 70% for all the methods.

We can observe a clearly increasing trend with larger size of training samples for all the methods. In the same time, when the sample size increases from 100,000 to 300,000, all five methods has the steepest slope, indicating fastest increase in terms of accuracy. Among all the methods, the proposed welch-GAN (purple line) keeps approximately 4% lead in terms of accuracy when the sample size is from 150,000 to 300,000. Although there is a plateau for all the methods from 300,000 to 400,000, the welch-GAN still keeps the lead when sample size exceeds 400,000.
To study the difference between GANs, we conduct an additional experiment, trying to visualize the distribution of the synthetic data generated by different GANs. We first randomly select 300 real AF signal and generated 300 synthetic AF signal from each GAN, then use UMAP to visualize the distinction of real signal versus synthetic signal. Fig. 8(a) reports the distribution of real and synthetic signals. Compared to the distribution of real AF signal (green dots), DCGAN (red dots) and W-DCGAN (purple dots) only capture part of the characteristic of real AF signal, and they do not share much overlap, while the proposed welch-GAN (orange dots) is more capable of representing the distribution of real AF signal. Same phenomenon can also be observed in Fig. 8 (c), the autocorrelation of signals from Welch-GAN is also spread out and have similar distribution to real AF signals. Signal from DCGAN and W-DCGAN only capture parts of the distribution of real AF signal.

In Fig.8 (b), although major part of PSD plot is overlapped with four colors, signals from welch-GAN are still able to capture the distribution of real signal in the left tail. Fig.9 brings us more aspect to observe the results. In Fig.8, we random select one sample from each GAN method as well as the real NSR and AF signal. We can see that the PSD for three GANs are similar to real AF signal, which is the main reason for the major overlapping in Fig.8 (b).
The present study proposes a novel design of generative adversarial network-welchGAN, as one approach to conduct data augmentation for PPG signal to further improve the accuracy of AF detection. In the same time, four different baseline data augmentation methods are also considered, including two traditional approach: data-copying and permutation; and two GAN approach: DCGAN and W-DCGAN. Three experiments are designed to investigate the effect of each augmentation methods from different aspect, including a direct comparison with one previous published work in NPJ digital medicine.

Performance improvement

Data augmentation that improves inter-class balances does provide performance gain, and improved balance correlates to improved performance. The accuracy of machine learning algorithms, for example Resnet we adopted in this study, would benefit more from a balance training set. Since an imbalanced data set will make the learned model biased or skewed, which makes it perform terrible on the test set. From Table 3, comparing to the original, all the other groups have better inter-class balance situation and thus show better AF detection accuracy. Further, we also conclude that there is a positive relationship between the improved balance and performance gain. In Table 3, within each augmentation method, increasing augmented AF cases will bring more accurate AF detection result. To tease out the influence of balance, we applied data-copying as one of the baseline methods. From Table 3, comparing to data-copying, various augmentation techniques arrived at performance gain of different extends, indicating additional information must be brought into the training set by those techniques. However, two basic GANs do not outperform the traditional approach, permutation. For DCGAN and W-DCGAN, since only model output probability will be considered as part of the cost function for both generator and discriminator, they will not pay attention to the distance between real and fake PPG signal. Although mean square error (MSE) can be the cost function for the generator to measure the distance for two signals, the PPG segments are split from continues recordings at random points, leading the PPG signals are not time aligned (potential shift between two signals), and MSE is not capable to capture the time wrapping distance. At the same time, proposed Welch-GAN taking consideration of additional PPG spectral information offers best overall performance. This is an adequate proof that using frequency-domain distance as the generator loss function is better than using time-domain. In frequency-domain, firstly two signals can be measured even they are not time-aligned. Secondly, since fake PPG signals are generated from random noise, which both low-frequency noise and high frequency noise are present. DCGAN and WGAN will not take care of those noise randomly. However, from frequency-domain aspect, those noise can be easily eliminated during the training process.

Performance improvement of proposed Welch-GAN can be generalized to other dataset, and better performance can be overserved than other DA techniques.

Deep learning models appreciate increase sample numbers when inter-class balance has been controlled for all DA techniques investigated. Among them, proposed Welch-GAN stays on top of the performance majority of times. Since the number of AF cases in original training set is limited, when the required AF sample size exceeds the original number, those exceeded AF cases will be generated by augmentation methods. In Fig. 5, results show that keeping adding synthetic data would not degrade the performance, on the contrary, the AF detection accuracy keeps increase rapidly.

Robustness to noise

Welch-GAN demonstrates great tolerance to signal noise and provides consistency performance improvement compared with other methods. It is obvious that the performance on poor quality signals is degraded as compared to the clean quality signals. Out of the four testing groups with different artifact levels, two groups with artifact levels at (0% - 20%) and (20%-60%) benefited the most from the augmentation methods. Compared to these two testing groups, the rest two groups, i.e., -clean and with artifact level at (60%-100%), -still got improved in terms of detection accuracy, but not as
significantly. For the clean group, since the pattern of AF episodes in perfect quality PPG signals is already clear, even the model trained on the original imbalanced training set is capable of detecting AF with a high accuracy on those perfect quality signals, as shown in Fig.6. At the same time, applying augmentation techniques helps the accuracy the least when tested on the group with artifact level at (60%-100%), in which even the accuracy of the augmented model is under 50%. To understand why Welch-GAN performs better than other GANs, exemplar samples are randomly selected and visualized. From Fig.8A, it demonstrates Welch-GAN covers better on the sample distribution of real AF signals compared with other GANS, which show only partial coverage in the UMAP scatter plot. And its quantitively revealed by the MMD value.

Limitations and future works

By the novel integration of spectral information in ECG in the loss function, AF samples from Welch-GAN capture more comprehensive information in the ECG waveform than others and help improve the performance of downstream AF classification task. Other features that might help further captures a more complete characteristics will be our next steps to include in the DA process.

The present study focuses on comparison of different DA techniques, so the same DL architecture, i.e. Resnet-34, is adopted to achieve fair comparison. The goal prevents us from exploring various DL models and customizations that can further improve the classification performance. It will be another future direction for our study.

Conclusion

In the medical data analysis area, it remains difficult to obtain both large and well-annotated datasets. Data shortage and imbalance are challenges to properly train high-performing machine learning algorithms. In this study, we proposed Welch-GAN, a novel GAN architecture which takes the frequency-domain knowledge into consideration for loss function, to augment PPG signals for AF detection. One-dimension Resnet was adopted as the classifier in the training procedure and tested on real-world data. Compared to four different baseline data augmentation methods, the AF detection accuracy is further improved by signals generated from Welch-GAN. Experiments also show that signals generated from Welch-GAN is more robust to motion artifact than baseline augmentation methods.

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