ECG HEART-BEAT CLASSIFICATION USING MULTIMODAL IMAGE FUSION

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ABSTRACT
In this paper, we present a novel Image Fusion Model (IFM) for ECG heart-beat classification to overcome the weaknesses of existing machine learning techniques that rely either on manual feature extraction or direct utilization of 1D raw ECG signal. At the input of IFM, we first convert the heart-beats of ECG into three different images using Gramian Angular Field (GAF), Recurrence Plot (RP) and Markov Transition Field (MTF) and then fuse these images to create a single imaging modality. We use AlexNet for feature extraction and classification and thus employ end-to-end deep learning. We perform experiments on PhysioNet’s MIT-BIH dataset for five different arrhythmias in accordance with the AAMI EC57 standard and on PTB diagnostics dataset for myocardial infarction (MI) classification. We achieved an state-of-an-art results in terms of prediction accuracy, precision and recall.

Index Terms— AlexNet, ECG, heart-beat classification , multimodal fusion.

1. INTRODUCTION
ECG heart-beat investigation is important for early diagnosis of cardiovascular diseases such as arrhythmias and myocardial infarction (MI) as ECG is the best source to provide electrophysiological pattern of depolarization and repolarization of the heart muscles. Arrhythmias is a heart rhythmic problem which happens when electrical signals coordinating heart-beats causes heart to beat irregularly. Myocardial Infarction, also called heart attack, is a serious threat to human life and is caused due to the blockage of oxygen-rich blood to the heart, thus resulting in severe cardiac arrest and can be dangerous for patient’s life [1].

ECG is a reliable tool to interpret the cardiovascular condition. However, ECG heart-beat classification is an uphill task for researchers due to the complex and non-stationary nature of the ECG signal [2]. Thus, computer based approaches for intelligent and automatic identification of abnormalities in heart-beat are in demand.

Earlier methods for heart-beat classification using ECG signal were dependent upon manual feature extraction using signal processing [3] and statistical techniques [4]. The disadvantages with these conventional methods are the separation of feature extraction part and pattern classification part and the expert knowledge about the input data and selected features [5]. Moreover, hand-crafted features may not invariant to noise, scaling and translations and thus can lead to the problem of generalization on unseen data.

Outstanding performance of deep learning models especially the performance of CNN in computer vision [6] and image classification [7] has gained attention of researchers since the deep learning models are capable of automatically learning hierarchical features directly from the data and promote end-to-end learning. Recent deep learning models use 1D ECG signal or 2D representation of ECG by transforming ECG signal to images. 2D representation of ECG provides more accurate heart-beat classification compared to 1D [8]. Furthermore, multimodal fusion of 2D representation of ECG achieved highest accuracy as compared to single ECG modality [9].

However, existing fusion methods rely on concatenation or decision level fusion [10]. There is room for improvement in fusion techniques that can provide better results while not sacrificing efficiency. To address the shortcomings of existing fusion models for ECG heartbeat classification, in this paper, we propose image fusion model (IFM) that fuses three gray scale images to form a single three channel image containing both static and dynamic features of input images and thus achieved better classification results while taking care of dimensionality as well.

The key contributions of the presented work are:

1. We propose a novel image fusion model (IFM) that fuses three gray scale images to form a single three channel image containing features of input images and thus achieved better classification results. The proposed model not only promotes the end-to-end learning but also computationally efficient by keeping dimensionality of the fused features equal to the dimensionality of single modality feature.
2. At the input of the IFM, converting heartbeats of ECG signal to images using Gramian Angular Field (GAF), Recurrence Plot (RP) and Markov Transition Field (MTF), preserves the temporal correlation among the samples of time series and thus we achieve better classification performance as compared to the existing methods of transforming ECG to images using spectrograms or methods involving time-frequency analysis.

2. RELATED WORK

Since 2D form of ECG signals such as images perform better than 1D raw ECG data [8], a big chunk of existing work related to ECG heart-beat classification includes conversion of ECG to images. In [11], ECG signal is converted into spectro-temporal images. Multiple dense CNNs were used to capture both beat-to-beat and single-beat information for analysis. Authors in [12] converted heart-beats of ECG signals to images using wavelet transform. A six layer CNN was trained on these images for heartbeat classification. In [13], well known pretrained CNNs such as AlexNet, VGG-16 and ResNet-18 are trained on spectrograms obtained from ECG. Using a transfer learning approach, the highest accuracy of 83.82% is achieved by AlexNet. In [14], ECG heart-beats were transformed to 2D grayscale images and then CNN was used for feature extraction and classification.

Multimodal fusion enhances the performance as compared to individual modalities by integrating complementary information from the modalities. A Deep Multi-scale Fusion CNN (DMSFNet) is proposed in [15] for arrhythmia detection. Proposed model consists of backbone network and two different scale-specific networks. Features obtained from two scale specific networks are fused using a spatial attention module. CNN and attention module based multi-level feature fusion framework is proposed in [16] for multiclass arrhythmia detection. Heart-beat classification is performed by extracting features from various layers of CNN. It is observed that combining the attention module and CNN improves the classification results.

The shortcoming in the existing fusion methods is that they depend mostly on concatenation fusion. Concatenation creates the problem of the curse of dimensionality and high computational cost, results in the degradation of accuracy. To address the shortcomings of existing works, in this paper, we propose a novel image fusion model that fuses input images to form a single three channel image containing both static and dynamic features of input images and thus achieved better classification results while taking care of dimensionality as well.

3. PROPOSED METHOD

In this section we will explain the proposed image fusion model (IFM) as shown in Fig. 1.

3.1. ECG Signal to Image Transformation

At the input of the proposed model, we transform the heartbeats of input ECG signal into GAF, RP and MTF images.

3.1.1. Image formation by Gramian Angular Field (GAF)

The image formed by Gramian Angular Field (GAF) represents time series in a polar coordinate system rather than conventional cartesian coordinate system.

Let \( X \) be a real valued time series of \( n \) samples such that \( X = \{x_1, x_2, x_3, ..., x_i, ..., x_n\} \) we rescaled \( X \) to \( X_s \) so that the value of each sample in \( X_s \) falls between 0 and 1. Now we represent the rescaled time series in polar coordinate system by encoding the value as the angular cosine and the time stamp as the radius. This encoding can be understood by the following equation.

\[
\begin{align*}
\phi &= \arccos(x_{i0}) \\
r &= \frac{t_i}{N}
\end{align*}
\]  

(1)

where \( x_{i0} \) is the rescaled \( i \)th sample of the time series, \( t_i \) is the time stamp and \( N \) is a constant factor to regularize the span of the polar coordinate system [17]. The angular perspective of the encoded image can be fully utilized by considering the sum/difference between each point to identify the temporal correlation within different time intervals. In this paper we used a summation method for Gramian Angular Field and is explained by the following equation

\[
GAF = \cos(\phi_i + \phi_k)
\]  

(2)

The image formed by GAF for a single heartbeat is shown in Fig. 2.

Fig. 1: Complete Overview of the proposed Image Fusion Model.

Fig. 2: GAF, RP and MTF Images.
### 3.1.2. Image formation by Recurrence Plot (RP)

Periodicity and irregular cyclicity are the key recurrent behaviors of time series data. The recurrence plots are used as visualization tool for observing the recurrence structure of a time-series [18]. A recurrence plot (RP) is an image obtained from a multivariate time-series, representing the distances between each time point.

Let \( q(t) \in \mathbb{R}^d \) be a multi-variate time-series. Its recurrence plot is defined as

\[
RP = \theta(\epsilon - ||q(i) - q(j)||)
\]

In equation (3), \( \epsilon \) is threshold and \( \theta \) is called heaviside function.

Since our ECG signal is univariate, for our case, \( d = 1 \). The image formed by RP is shown in Fig[2]

### 3.1.3. Image formation by Markov Transition Field (MTF)

We used the method described in [17] to encode ECG signal into images. Consider the time series \( X \in \mathbb{R}^v \) such that \( X = \{ x_1, x_2, x_3, \ldots, x_l, \ldots, x_n \} \). The first step is to identify its \( Q \) quantile bins and assign each \( x_l \) to the corresponding bins \( q_k (k \in [1, Q]) \). Next step is to construct a \( Q \times Q \) weighted adjacency matrix \( W \) by counting transitions among quantile bins in the manner of a first-order Markov chain along the time axis. The Markov transition field matrix is given by

\[
M = \begin{bmatrix}
      w_{1k} & w_{2k} & \cdots & w_{lk} \\
      w_{1k} & w_{2k} & \cdots & w_{lk} \\
      \vdots & \vdots & \ddots & \vdots \\
      w_{1k} & w_{2k} & \cdots & w_{lk} 
\end{bmatrix}
\]

where \( w_{lk} \) is the frequency with which a point in quantile \( q_k \) is followed by a point in quantile \( q_l \).

We use 10 bins for the discretization and encoding of ECG heartbeats into images. The image formed by MTF is shown in Fig[2]

### 3.2. Image Fusion Model

After image formation from ECG heart-beat, we combine these three gray scale images to form a triple channel image (GAF-RP-MTF) which contains both static and dynamic features of the input images and thus enhance classification performance. A triple channel image is a colored image in which GAF, RP and MTF images are considered as three orthogonal channels like three different colors in RGB image space. We use AlexNet, (CNN based model) [7] for feature extraction and classification tasks and thus employ end-to-end deep learning where feature extraction and classification parts are embedded in a single network as shown in Fig[1]

### 4. EXPERIMENTS AND RESULTS

We experiment on PhysioNet MIT-BIH Arrhythmia dataset [25] for heartbeat classification and PTB Diagnostic ECG dataset [26] for MI classification. For our experiments, we used ECG lead-II re-sampled to the sampling frequency of 125Hz as the input.

We resize the images to 227 x 227 to perform experiments with AlexNet. A drop out ratio of 0.5, momentum of 0.9 and \( L_2 \) regularization of 0.004 was used. we trained AlexNet till the validation loss stops decreasing further. The experimental results are discussed in section[5]

#### 4.1. PhysioNet MIT-BIH Arrhythmia Dataset

Forty seven subjects were involved during the collection of ECG signals for the dataset. The data was collected at the sampling rate of 360Hz and each beat is annotated by at least two experts. Using these annotations, five different beat categories are created in accordance with Association for the Advancement of Medical Instrumentation (AAMI) EC57 standard [19].

The original dataset has 21892 heartbeats, each of which is a 187-point time series. Since there is a class-imbalanced in the dataset as apparent from the numbers, we applied SMOTE [27] to upsample the minority classes. The final training and testing samples are 152456 and 21890 respectively.

The results of experiments in terms of recognition accuracies and their comparison with previous state-of-the-art are shown in Tables[1 and 3]

#### 4.2. PTB Diagnostic ECG dataset

Two hundred and ninety (290) subjects took part during collection of ECG records for PTB Diagnoses dataset. 148 of them are diagnosed as MI, 52 healthy control, and the rest are diagonsed with 7 different diseases. Each record contains ECG

### Table 1: Ablation Study on MIT-BIH Dataset

| Modalities             | Accuracies% | Precision% | Recall% |
|------------------------|-------------|------------|---------|
| GAF Images only        | 97.3        | 85         | 91      |
| RP Images only         | 97.2        | 82         | 93      |
| MTF Images only        | 91.5        | 86         | 89      |
| Proposed IFM           | 98.6        | 93         | 92      |

### Table 2: Ablation Study on PTB Dataset

| Modalities             | Accuracies% | Precision% | Recall% |
|------------------------|-------------|------------|---------|
| GAF Images only        | 98.4        | 98         | 96      |
| RP Images only         | 98          | 98         | 94      |
| MTF Images only        | 95.3        | 94         | 89      |
| Proposed IFM           | 98.4        | 98         | 94      |
Table 3: Comparison of heart beat Classification results of MITBIH Dataset with Previous Methods

| Previous Methods | Accuracies% | Precision% | Recall% |
|------------------|-------------|------------|---------|
| Izci et al. [14]  | 97.96       | -          | -       |
| Zhao et al. [15]  | 98.25       | -          | -       |
| Oliveria et al. [12] | 95.3     | -          | -       |
| Shaker et al. [21] | 98         | 90         | 97.7    |
| Kachuee et al. [22] | 93.4   | -          | -       |
| Proposed IFM     | 98.6        | 93         | 92      |

Table 4: Comparison of MI Classification results of PTB Dataset with Previous Methods

| Previous Methods  | Accuracies% | Precision% | Recall% |
|-------------------|-------------|------------|---------|
| Dicker et al. [13] | 83.82       | 82         | 95      |
| Kojuri et al. [23] | 95.6        | 97.9       | 93.3    |
| Kachuee et al. [22] | 95.9      | 95.2       | 95.1    |
| Liu et al. [24]    | 96          | 97.37      | 95.4    |
| Proposed IFM       | 98.4        | 98         | 94      |

signals from 12 leads sampled at the frequency of 1000Hz. However, in this paper, we used ECG lead II, and worked with healthy control and MI categories.

For experiments with AlexNet, the training and testing samples are 21892 and 2911 respectively. The results of experiments in terms of recognition accuracies and their comparison with previous state of art are shown in Tables 2 and 4.

5. DISCUSSION

The ablation study on both datasets prove that fused three channel image achieved higher accuracy than using single image modality as shown in Tables 1 and 2. Furthermore, Tables 3 and 4 show that the proposed fusion method achieved state-of-the-art results and beat previous methods, that depends upon concatenation fusion, in terms of recognition accuracy, precision and recall.

MTF requires the data to be discretized into $Q$ quantile bins to calculate the $Q \times Q$ Markov transition matrix, therefore the size of MTF images is $Q \times Q$. In this paper $Q = 10$. Thus, the size of MTF images is 10 x 10. For data fusion and to train the AlexNet, we resize 10 x 10 image to 227 x 227. This resizing causes redundancy in MTF images and is likely the reason why there is a drop in recall shown in Tables 3 and 4.

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7. CONCLUSION

In this paper, we propose a novel image fusion model for ECG heart beat classification. At the input of these frameworks, we convert the raw ECG data into three types of images using Gramian Angular Field (GAF), Recurrence Plot (RP) and Markov Transition Field (MTF). We first perform image fusion by combining three input images to create a three channel single image which serve as input to the AlexNet. Experimental results on two publicly available datasets prove the superiority of the proposed method over previous methods.

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