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ECG SIGNAL CLASSIFICATION USING WAVELET TIME SCATTERING, SUPPORT VECTOR MACHINE AND CONTINUOUS WAVELET TRANSFORM

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ABSTRACT

The Electrocardiogram (ECG) is the most useful and powerful tool used in hospitals to analyse the cardiovascular status and check health, a standard for detecting and diagnosing heart rhythms abnormality. In recent years, cardiovascular health has attracted much attention. However, Traditional doctors' consultations have disadvantages such as delayed diagnosis and high misdiagnosis rate, while cardiovascular diseases have the characteristics of early diagnosis, early treatment and early recovery. Therefore, it is essential to reduce the misdiagnosis rate of heart disease. This project is implemented to train/classify ECG signal into 3 different classes named as Cardiac Arrhythmia (ARH), Congestive heart failure (CHF), Normal Sinus Rhythms (NSR). This paper train/classifies electrocardiogram (ECG) signals using wavelet time scattering and support vector machine (SVM) and the results compared with continuous wavelet transform. The effect of classification accuracy evaluated using ECG recordings from Physio Net databases for the classification of ECG Signals.[6]

1. ELECTROCARDIOGRAM

An electrocardiogram (ECG) is a simple test that can be used to check your heart's rhythm and electrical activity. Sensors attached to the skin are used to detect the electrical signals produced by your heart each time it beats.These signals are recorded by a machine and are looked at by a doctor to see if they're unusual. An ECG may be requested by a heart specialist (cardiologist) or any doctor who thinks one might have a problem in the heart, including your GP[1].The test can be carried out by a specially trained healthcare professional at a hospital, a clinic. Despite having a similar name, an ECG isn't the same as an echocardiogram, which is a scan of the heart.

An ECG is often used alongside other tests to help diagnose and monitor conditions affecting the heart. It can be used to investigate symptoms of a possible heart problem, such as chest pain, palpitations (suddenly noticeable heartbeats), dizziness and shortness of breath.

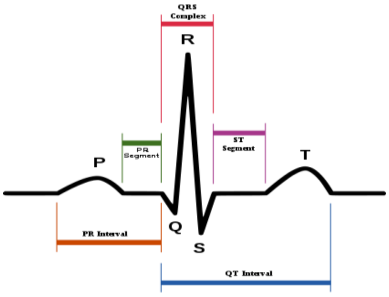

Fig. 1 ECG signal

I. Cardiac Arrhythmia (ARH):

Arrhythmias, also known as cardiac arrhythmia, heart arrhythmia, or dysrhythmia, are irregularities in the heartbeat, including when it is too fast or too slow. A heart rate that is too fast – above 100 beats per minute in adults – is called tachycardia, and a heart rate that is too slow – below 60 beats per minute – is called bradycardia. Some types of arrhythmias have no symptoms. Symptoms, when present, may include palpitations or feeling a pause between heartbeats. In more serious cases, there may be light-headedness, passing out, shortness of breath or chest pain. While most cases of arrhythmia are not serious, some predispose a person to complications such as stroke or heart failure. Others may result in sudden death.

II. Congestive Heart failure :

Heart failure (HF), also known as congestive heart failure (CHF) and cardiac failure (CCF), is a set of manifestations caused by the failure of the heart's function as a pump supporting the blood flow through the body; its signs and symptoms result from a structural and/or functional abnormality of the heart, that disrupts its filling with blood or its ejecting of it during each heartbeat. Signs and symptoms of heart failure commonly include shortness of breath, excessive tiredness, and leg swelling. The shortness of breath is usually worse with exercise or while lying down, and may wake the person at night. A limited ability to exercise is also a common feature. Chest pain, including angina, does not typically occur due to heart failure.

III. Normal Sinus rhythm :

A sinus rhythm is any cardiac rhythm in which depolarisation of the cardiac muscle begins at the sinus node. It is characterised by the presence of correctly oriented P waves on the electrocardiogram (ECG). Sinus rhythm is necessary, but not sufficient, for normal electrical activity within the heart.

The term normal sinus rhythm (NSR) is sometimes used to denote a specific type of sinus rhythm where all other measurements on the ECG also fall within designated normal limits, giving rise to the characteristic appearance of the ECG when the electrical conduction system of the heart is functioning normally. However, other sinus rhythms can be entirely normal in particular patient groups and clinical contexts, so the term is sometimes considered a misnomer and its use is sometimes discouraged.

2. WAVELET TIME SCATTERING

Wavelet time scattering yields representations insensitive to translations in the inputs signal without sacrificing class discriminability. One can use the representations as inputs to a classifier which specify the duration of translation invariance and the number of wavelet filters per octave.

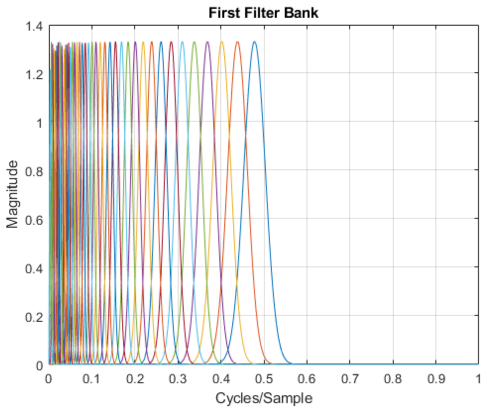

Fig. 2 Wavelet Scattering Filter Bank

3. SUPPORT VECTORMACHINE

In machine learning, support-vector machines (SVMs, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

When data are unlabelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The support-vector clustering algorithm, created by Have Siegelman and Vladimir Vapnik, applies the statistics of support vectors, developed in the support vector machines algorithm, to categorize unlabelled data.

A confusion matrix is a table that is used to define the performance of a classification algorithm. A confusion matrix visualizes and summarizes the performance of a classification algorithm.

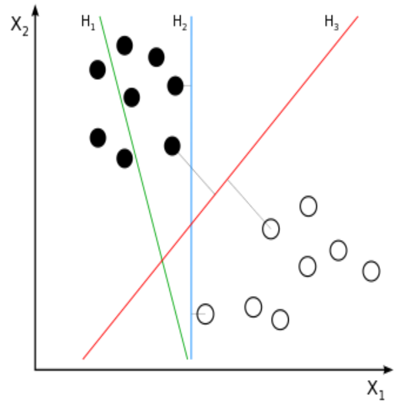

Fig. 3 SVM algorithm

4. METHODOLOGY

This uses ECG data obtained from three groups, or classes, of people: persons with cardiac arrhythmia, persons with congestive heart failure, and persons with normal sinus rhythms. In this 162 ECG recordings from three Physio Net databases: MIT-BI abnormal H Arrhythmia Database , MIT-BIH Normal Sinus Rhythm Database , and The BIDMC Congestive Heart Failure Database. In total, there are 96 recordings from persons with arrhythmia, 30 recordings from persons with congestive heart failure, and 36 recordings from persons with normal sinus rhythms. The goal is to train a classifier to distinguish between arrhythmia (ARR), congestive heart failure (CHF), and normal sinus rhythm (NSR).[2]

There are 113 records in the train Data set and 49 records in test Data. By design the training data contains 69.75% (113/162) of the data. Recall that the ARR class represents 59.26% of the data (96/162), the CHF class represents 18.52% (30/162), and the NSR class represents 22.22% (36/162). Examined the percentage of each class in the training and test sets. The percentages in each are consistent with the overall class percentages in the data set.[5]

In this wavelet time scattering network is implemented with the default filter banks: 8 wavelets per octave in the first filter bank and 1 wavelet per octave in the second filter bank. The invariance scale is set to 150 seconds.

After constructing the scattering network, obtained the scattering coefficients for the training data as a matrix. When you run feature Matrix with multiple signals, each column is treated as a single signal.

In order to obtain a matrix compatible with the SVM classifier, reshaped the multi-signal scattering transform into a matrix where each column corresponds to a scattering path and each row is a scattering time window. In this case, you obtain 1808 rows because there are 16-time windows for each of the 113 signals in the training data.[8]

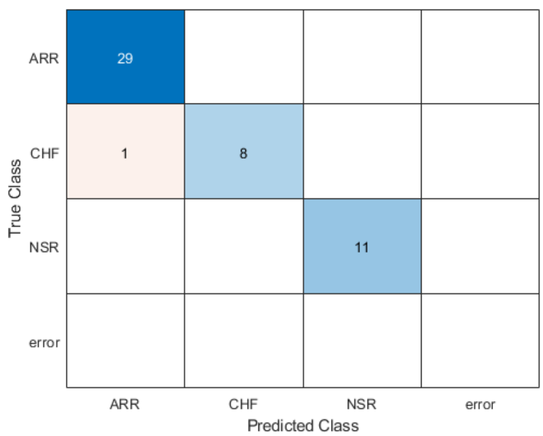

Fig. 4 Confusion matrix of wavelet scattering

The classification accuracy on the test dataset is approximately 98%. The confusion matrix shows that one CHF record is misclassified as ARR. All 48 other signals are correctly classified.

5. ECG SIGNALS CLASSIFICATION USING CONTINUOUS WAVELET TRANSFORM AND ALEXNET

Here we take a total of 500 samples. Out of the total of 500 samples we take 350 samples for the training data and 150 samples for the testing data. The number of samples used for the testing will be 50 from each section gives a total of 150 samples.

In this method first we convert the signals into images to be used as input to CNN for classification.[3]

All the signal coefficients are arranged to form a scalogram. Scalograms are then converted into images.

For ECG signal classification, we used pretrained deep CNN.Alex Net is used.[4]

The first step in the training is to read the images in the database folder.It includes images in the folder and the subfolder.

All the training images are stored in train images variable and test images are stored in test images.

Load the pretrained network and load all the layers of network. After defining all the layers and transfer options to start the training. The train network function takes the images and trained them according to the options.[7]

The training process gives the confusion matrix as

ARR	41 27.3%	0 0.0%	1 0.7%	97.6% 2.4%
CHF	4 2.7%	50 33.3%	0 0.0%	92.6% 7.4%
NSR	5 3.3%	0 0.0%	49 32.7%	90.7% 9.3%
	82.0% 18.0%	100% 0.0%	98.0% 2.0%	93.3% 6.7%

Target Class

Fig. 5 Confusion matrix of Continuous wavelet transform.

In the final training we see that the accuracy achieved is 96.67%, Which is good.

6. RESULT

In the first process the confusion matrix shows that one CHF record is misclassified as ARR. All the 48 other signals are correctly classified. And the accuracy is 98%.

In the second process four ARR misclassified as CHF and 5 as NSR. In the same way one NSR mis classified as ARR. The accuracy is 96.67%.

7. CONCLUSION

Wavelet time scattering and SVM classifier yields better results to classify ECG waveforms into one of the three diagnostic classes when comparing this with the ECG signal classification using continuous wavelet transform and Alex Net.

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