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Full Length Article

ECG based Atrial Fibrillation detection using Sequency Ordered Complex Hadamard Transform and Hybrid Firefly Algorithm

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ABSTRACT

Electrocardiogram (ECG), a non-invasive diagnostic technique, used for detecting cardiac arrhythmia. From last decade industry dealing with biomedical instrumentation and research, demanding an advancement in its ability to distinguish different cardiac arrhythmia. Atrial Fibrillation (AF) is an irregular rhythm of the human heart. During AF, the atrial moments are quicker than the normal rate. As blood is not completely ejected out of atria, chances for the formation of blood clots in atrium. These abnormalities in the heart can be identified by the changes in the morphology of the ECG. The first step in the detection of AF is preprocessing of ECG, which removes noise using filters. Feature extraction is the next key process in this research. Recent feature extraction methods, such as Auto Regressive (AR) modeling, Magnitude Squared Coherence (MSC) and Wavelet Coherence (WTC) using standard database (MIT-BIH), yielded a lot of features. Many of these features might be insignificant containing some redundant and non-discriminatory features that introduce computational burden and loss of performance. This paper presents fast Conjugate Symmetric Sequency Ordered Complex Hadamard Transform (CS-SCHT) for extracting relevant features from the ECG signal. The sparse matrix factorization method is used for developing fast and efficient CS-SCHT algorithm and its computational performance is examined and compared to that of the HT and NCHT. The applications of the CS-SCHT in the ECG-based AF detection is also discussed. These fast CS-SCHT features are optimized using Hybrid Firefly and Particle Swarm Optimization (FFPSO) to increase the performance of the classifier.

1. Introduction

ECG describes the electrical action of the human heart. The changes in voltages during repolarization and depolarization of the heart fibers are monitored by placing electrodes at different places on the chest and on the limb leads. The ECG signal is either printed on graph paper or displayed on a computer monitor. The benefits of ECG are its portability, prompt accessibility and flexibility. Computerized ECG classification can also help reduce health care costs. In the biomedical industry, there is an ongoing quest for the early detection of heart abnormalities using ECG signals.

This paper aims at developing an intelligent, inexpensive and flexible ECG-based automatic arrhythmia (irregular heart beat) detection system. The method includes signal preprocessing and feature extraction techniques to obtain the discriminative features of the ECG signals that correspond to a cardiac condition. These ECG features are classified using supervised learning techniques. Abnormal cardiac beat recognition is a crucial step in the detection of heart diseases. During AF the electrical discharges in the atrium are fast or rapid. Morphology changes can be observed through the changes in the ECG recordings. The clear indication of AF is irregular 'RR' interval and the absence of 'P' wave.

Since AF beats are occasional (rarely occurring), doctors sometimes have to depend on incidental examinations of AF. It would be quite inconvenient for doctors to go through the Electrocardiogram manually, especially for the cases where the occurrence of AF beats are random, and a long-term monitoring is required to detect the abnormal activity for further processing.

Fig. 2 describes information about the relative amplitudes and time intervals of each ECG beat, are called morphological transitions. The morphology (P, QRS complex, T and U waves) also called as features of ECG signal. Morphology changes due to the abnormalities in the heart. AF is such morphological abnormality present

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in the heart diseases. In this work CS-SCHT is utilized as a feature extraction strategy instead of using traditional [1,2] feature extraction methods. Waveform changes in the AF signal are given in Fig. 1. Techniques based on RR interval are proposed by Moody [3] and Tateno [4], and P wave based methods are presented by Mohebbi [5] had some limitations. When the ECG changes quickly between rhythms or when AF takes place with regular ventricular rates, the methods based on RR interval fails in the accurate detection. The absence of 'p' wave is difficult due to its small amplitude.

Different techniques and transformations proposed earlier in literature for extracting features from an ECG signal are explained in [6]. Various algorithms for the feature extraction of ECG signal are Karhunen–Loeve transform (KLT) [7], Wavelet Transform (WT) [8] and the Discrete Cosine Transform (DCT) [9,10]. The Fast Fourier Transform (FFT) performs a signal transformation from time to frequency domain for some applications [11]. The DCT is widely held for its optimum energy compaction property because the division of the average energy of the signal is grouped into a comparatively few constituents of the DCT-coefficients. The DWT [12] is familiar for its analysis for image and signal processing in multi-resolutional pattern. In the real-time applications advanced fast algorithm like Hadamard Transform (HT) [13] is used. Hadamard transform is used to reduce the computational complexity is applied for real values only, whereas complex Hadamard Transform (CHT) can be applied for both real and complex values. SCHT is considered for its fast computation. Advantage of applying CS-SCHT over HT is its low memory requirement and very low computational complexity of order log_2M for M data samples.

The BIFORE (Binary Fourier Representation) [14] or HADAMARD transform contains two levels ($\pm$). It is used in various applications like signal processing, data compression algorithms, data encryption, quantum computing, etc. But the disadvantage of using this real Hadamard transform is that it can be applied only to real values. This limitation can be avoided by using Complex Hadamard Transform (CHT). CHT is a four-valued (± 1, $\pm j$) sequence. CHT includes high ordered matrices and Kronecker products. CHT with sequency order is called SCHT. Sequency measures how fast the elements of a specific row vector of the Hadamard transform matrix vary over a normalized time base t ϵ [0, 1]. SCHT coefficients are complex numbers consisting of both real & imaginary parts and they are not conjugate symmetric. Hence, more memory is needed to store the coefficients for analysis and synthesis in transform implementation. Hence a novel version of SCHT which surpasses the previous one called Conjugate Symmetric Sequency Ordered Complex Hadamard Transform (CS-SCHT) whose spectrum is conjugate symmetric. As CS-SCHT spectrum is conjugate symmetric, only half of spectral coefficients are required for combination and investigation. This, in turn, shrinks the memory requirement in processing for the applications such as real-time image watermarking and spectrum estimation. The overall classification flow diagram is shown in Fig. 3.

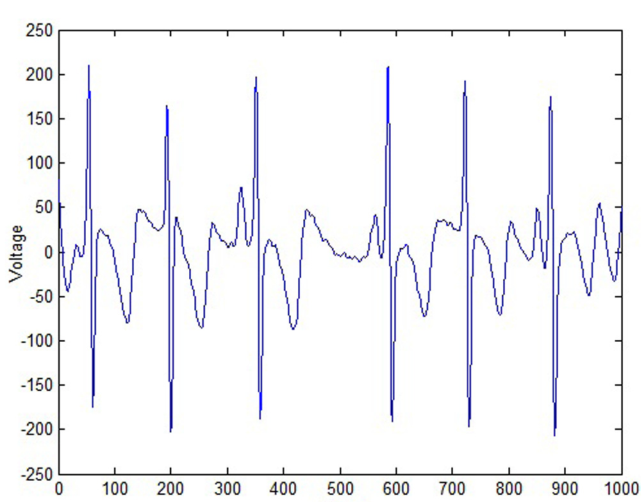

Fig. 1. AF signal.

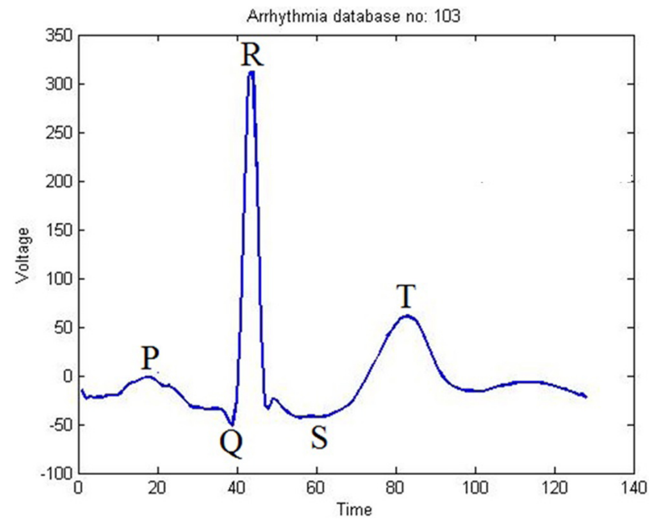

Fig. 2. Normal ECG signal.

2. Pre processing

The preprocessing step divided into three stages: Removing noise, Segmenting the ECG into beats [15] and Resampling all beats into equal size of 128 samples. The noise from the ECG signal is removed using Savizky – Golay [16] smoothing filter (also called digital smoothing polynomial filter or least-squares smoothing filter) in which the signal-to-noise ratio is improved by using a method of Linear Least Squares (LLS). This filter is applied with a window size of 15 and a polynomial order of 13. This filter can be implemented with LLS, minimizes the noise by considering the sum of squared differences between the signal constellation. Then obtained signals are segmented into beats by detecting the 'R' peaks. The detected R peaks of the ECG signal are shown in Fig. 4. From the MIT- BIH database [17] AF data files of 26 patients and Normal Sinus Rhythm files of 18 patients are used to detect AF. All the MIT-BIH database was not sampled at 360 samples per second. The sampling rate of a normal signal is 128 Hz and AF signal is 250 Hz. After segmentation, obtained ECG beats are of different lengths (sizes). We used 'resample' Matlab command to make all the beats into equal size of 128 samples for easy comparison shown in Fig. 5.

3. Feature extraction

Feature extraction is the important step in the detection of heart arrhythmia. Each ECG beat consists of large number of features and many of them might be insignificant. In this paper CS-SCHT extracts the features of each cardiac beat.

3.1. Conjugate Symmetric-Sequency Ordered Complex Hadamard Transform (CS-SCHT)

The row vectors of real Hadamard matrices can be arranged in a number of ways to obtain the ordered Hadamard matrices.

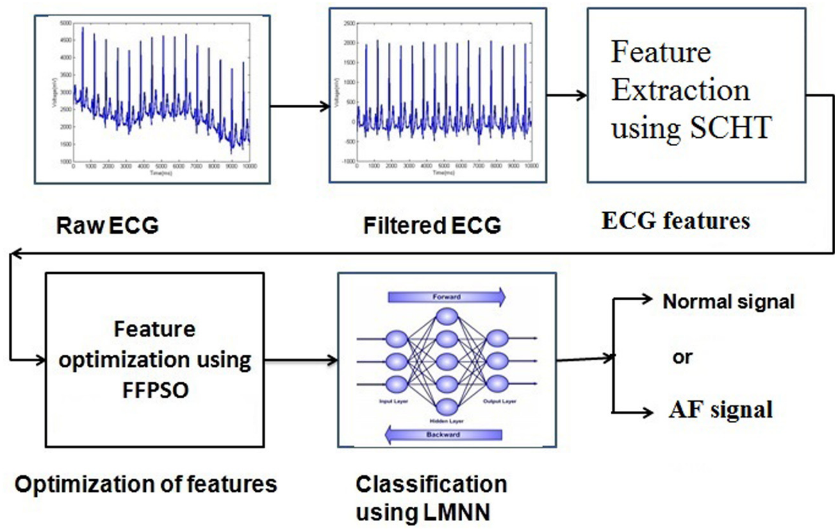

Fig. 3. ECG classification using CS-SCHT features.

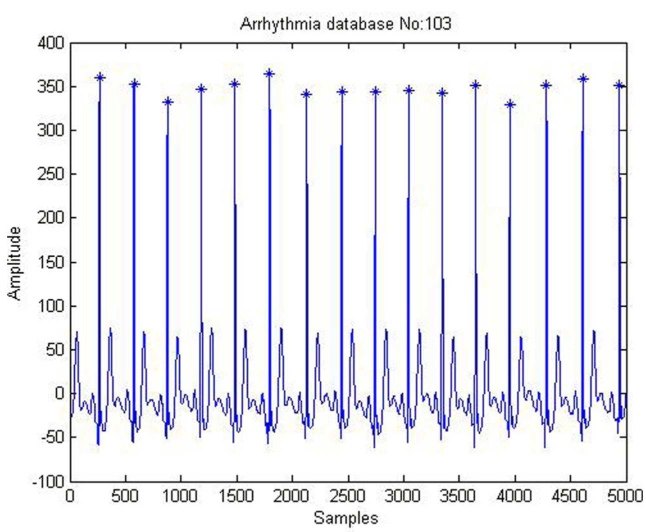

Fig. 4. ECG R peak detection.

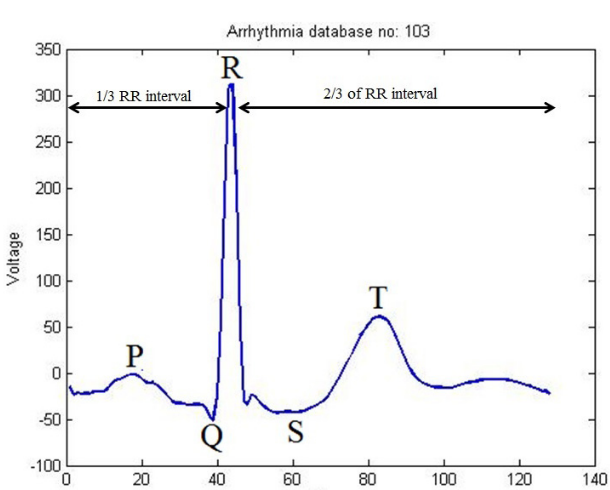

Fig. 5. ECG beat segmentation.

Sequency order is widely preferred due to its analogy to Fourier transform and its applicability in digital signal processing and communications. Sequency measures how fast the elements of a specific row vector of the Hadamard transform matrix vary over a normalized time base k ϵ [0, 1). Hence, it is also interesting to explore the orderings of complex Hadamard transforms for some particular applications. Complex Hadamard Transform (CHT) with a sequency order known as Sequency-Ordered Complex Hadamard Transform (SCHT). Complex plane within the normalized time t, that is The construction of the SCHT matrices is based on the complex Rademacher functions which are the extended complex version of conventional Rademacher functions. The row vectors of an SCHT matrix are arranged in an increasing order of zero crossings in the unit circle of a, $0 \leqslant k \leqslant 1$.

SCHT may have significance in signal processing as the discrete Fourier transform (DFT). CHT with natural ordering called natural-ordered complex Hadamard transform (NCHT) [18]. The NCHT may be seen as another ordered version of CHT where its ordering follows the WHT matrix. The NCHT is related to the SCHT in some manner.

Complex Rademacher Functions and their Matrices

Rademacher functions [19] are incomplete orthogonal set of functions having odd symmetry and they are being used to form other function series which exhibit either odd or even symmetry or both. In this subsection, we extend the real Rademacher functions and define complex Rademacher functions (CRD) over a normalized time base $0 \leqslant t \leqslant 1$ as follows: where period T = 1. Another simpler approach to define complex Rademacher functions over a normalized time base t ϵ[0, 1) is as follows:

$$CRD(0,k) = f(x) = \begin{cases} 1, & k\varepsilon[0,1/4) \\ j, & k\varepsilon[1/4,1/2) \\ -1, & k\varepsilon[1/2,3/4) \\ -j, & k\varepsilon[3/4,1) \end{cases} \tag{1}$$

and CRD (0, t + 1)= CRD (0,t)

$$CRD(0,k+1) = e^{-\frac{j\pi csgn(e^{2\pi k})}{\sqrt{2}}} \tag{2}$$

which maps the real-valued t to the element from the [1,-1,j,-j] where csgn(x) is defined for any nonzero complex number x = x1 + jx2 as follows:

$$sgn(x) = sgn(x1) + jsgn(x2) \tag{3}$$

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where sgn represents the signum function. But if x is a real number, it can be shown that csgn (x)=sgn (x). The definition of signum function is given in Eq. (3). Half of the elements of the real Rademacher functions are introduced by the complex element j. This holds the orthogonality property of the Rademacher functions. For non-negative integer r, the complex Rademacher function series can be defined as follows:

$$CRD(p,k) = CRD(0, 2^p k) \tag{4}$$

where p = 0, 1, 2,. . .m−1. This mean that CRD (p, k) can be obtained by CRD (0, k), CRD (1,k) and CRD (2,k) in the horizontal direction by a factor of 2^p. The complex Rademacher matrices are the discrete versions of the complex Rademacher function series. By sampling the complex Rademacher function series at N = 2^m equally spaced locations within the normalized time t, complex Rademacher matrices can be obtained. Let R_m be the complex Rademacher matrix of dimension $n \times 2^m$.

Then, the p_{th} row of R_m is defined as

$$R_n(p,l) = CRD\left(p, \frac{4l+1}{2^{m+2}}\right) \tag{5}$$

where p = 0, 1, . . ., m−1 and l = 0, 1,. . ., 2^{m-1}. Let us, as an example, consider M = 8. Then, the 3 × 8 complex Rademacher matrix is

$l \rightarrow$	0	1	2	3	4	5	6	7
$2^P\left(\frac{4l+1}{2^{m+2}}\right)$	1/32	5/32	9/32	13/32	17/32	21/32	25/32	29/32
$2^P\left(\frac{4l+1}{2^{m+2}}\right)$	2/32	10/32	18/32	26/32	34/32	42/32	50/32	58/32
$2^P\left(\frac{4l+1}{2^{m+2}}\right)$	4/32	20/32	36/32	52/32	68/32	84/32	100/32	113/32

$$R_3 = \begin{bmatrix} 1 & 1 & j & j & -1 & -1 & -j & -j \\ 1 & j & -1 & -j & 1 & j & -1 & -j \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \end{bmatrix}$$

CS-SCHT Matrices

With the CRD matrices defined, the CS-SCHT matrices are generated based on the products of the rows of CRD matrices. Let H_N be the CS-SCHT matrix of size M x M where M = 2^m. Then, it is defined as

$$H_N(m,k) = \prod_{r=0}^{m-1} R_n(r,k)^{b_r} \tag{6}$$

where $R_n(r,k)$ is the (r^{th}, k^{th}) element of the CRD matrix, m is the binary number and b_r is the binary value at position r. Let $R_n(r)$ for $r = 0, 1, \ldots, m-1$ be the r^{th} row vector of the CRD matrix, let $\odot$ be the operator for the element using element vector multiplication. For example, H_8 can be expressed using Eq. (6) as

g		$H_8(m,k)$
000	$\rightarrow$	1
001	$\rightarrow$	$R_3(0,k)$
010	$\rightarrow$	$R_3(1,k)$
011	$\rightarrow$	$R_3(1,k) \odot R_3(0,k)$
100	$\rightarrow$	$R_3(2,k)$
101	$\rightarrow$	$R_3(2,k) \odot R_3(0,k)$
110	$\rightarrow$	$R_3(2,k) \odot R_3(1,k)$
111	$\rightarrow$	$R_3(2,k) \odot R_3(1,k) \odot R_3(0,k)$

$$H_8(m,k) = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & j & j & -1 & -1 & -j & -j \\ 1 & j & -1 & -j & 1 & j & -1 & -j \\ 1 & j & -j & -1 & -j & 1 & j & 1 \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\ 1 & -1 & j & -j & -1 & 1 & -j & j \\ 1 & -j & -1 & j & 1 & -j & -1 & j \\ 1 & -j & -j & -1 & -1 & j & j & 1 \end{bmatrix}$$

The row index values 0, 1 and 2 refer to the ones found in binary bit positions of the decimal value r. The transformation matrices depicting the entries of the CHT are the SCHT matrices.

3.2. Fast CS-SCHT Algorithm using Factorization method

Let H_M be any CS-SCHT [20] matrix of size M × M. Then, it is a square matrix defined by

$$H_M = \begin{bmatrix} H_{M/2} & H_{M/2} \\ H_{M/2}S_{M/2} & -H_{M/2}S_{M/2} \end{bmatrix} . P_m$$

where $M = 2^m$ and P_m is the permutation matrix.

$$S_{2^{m-1}} = \begin{bmatrix} I_{2^{m-2}} & 0 \\ 0 & jI_{2^{m-2}} \end{bmatrix}$$

and $I_{2^{m-2}}$ is the identity matrix of order $2^{m-2} \times 2^{m-2}$. In this way, an M × M CS-SCHT matrix can be constructed using the CS-SCHT matrices of size (M/2) × (M/2), and the CS-SCHT matrix of order 8x 8, which is expressed as

$$H_8 = \begin{bmatrix} H_4 & H_4 \\ H_4S_4 & -H_4S_4 \end{bmatrix} . P_m$$

A well-organized algorithm for calculating the CS-SCHT is formulated using the sparse-matrix factorization method. In order to understand the factorization method, for M = 8, then H_8 matrix will become

$$H_8 = \begin{bmatrix} H_4 & 0 \\ 0 & H_4 \end{bmatrix} \begin{bmatrix} I_4 & 0 \\ 0 & S_4 \end{bmatrix} \begin{bmatrix} I_4 & I_4 \\ I_4 & -I_4 \end{bmatrix} . P_m$$

H_4 can be again factorized and represented in terms of H_2 as,

$$H_8 = \begin{bmatrix} H_2 & 0 & 0 & 0 \\ 0 & H_2 & 0 & 0 \\ 0 & 0 & H_2 & 0 \\ 0 & 0 & 0 & H_2 \end{bmatrix} . \begin{bmatrix} I_2 & 0 & 0 & 0 \\ 0 & S_2 & 0 & 0 \\ 0 & 0 & I_2 & 0 \\ 0 & 0 & 0 & S_2 \end{bmatrix} .$$

$$\begin{bmatrix} I_2 & I_2 & 0 & 0 \\ I_2 & -I_2 & 0 & 0 \\ 0 & 0 & I_2 & I_2 \\ 0 & 0 & I_2 & -I_2 \end{bmatrix} . \begin{bmatrix} I_4 & 0 \\ 0 & S_4 \end{bmatrix} . \begin{bmatrix} I_4 & I_4 \\ I_4 & -I_4 \end{bmatrix} . P_m$$

where

$$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}, S_2 = \begin{bmatrix} 1 & 0 \\ 0 & j \end{bmatrix}, S_4 = \begin{bmatrix} I_2 & 0 \\ 0 & jI_2 \end{bmatrix}$$

and P_m is the permutation matrix. Decomposition of 8-point CS-SCHT [19] into three stages as shown in Fig. 6. Each stage requires eight subtractions/additions. Apart from first stage remaining stages involves complex multiplications by j to compute the 8-point CS-SCHT. Total mathematical requirements needed are $(M/4)log_2(M/2)$ complex multiplications and $Mlog_2M$ complex addition/subtractions, where $M = 2^m$ and m is the number of stages. The hardware implementation of the complex mathematical computations can be obtained by swapping and negation operations. In similar procedure H_{128} matrix is generated. Each ECG beat of 128 samples is multiplied with CS-SCHT matrix of order 128X128 in order to transform it into Hadamard domain. (See Fig. 6).

4. Feature optimization

Feature selection methods are to determine the most relevant features to classify the given datasets and to improve the accuracy of the classification results. The present study gives a new technique for the detection of two cardiac conditions(Normal and AF) using nature inspired optimization techniques in combination with three classifiers (K-nearest neighbor (KNN), (Support Vector Machines) SVM and (Levenberg Marquardt Neural Network) LMNN). FFPSO is a nature-inspired meta-heuristic optimization algorithm, which can be effectively used to identify the changes in the ECG by finding the optimized features (key features) of each cardiac beat. For the detection AF, these features are given to the KNN, SVM and LMNN classifiers.

4.1. Firefly Algorithm (FFA):

Firefly Algorithm (FA) is used to solve many engineering problems like, congestion management in deregulated environment [21], optimizing real power loss and voltage stability limit [22]. FA is formulated by Xin-She Yang, is a meta-heuristic optimization algorithm, which is constructed by mimicking firefly light intensity behavior in nature. The FA algorithm is based on the flashing behavior-based search for finding the mating partners and move to the fireflies within the optimum position in the structure. FA algorithm consists of two main parts, namely the light intensity brightness and attractiveness. The light intensity brightness determines the direction of movement, attractiveness part describes the distance moved by Firefly.

The light intensity attraction of firefly is calculated using the formula

$$I = \frac{I_0}{e^{\gamma rij}} \tag{7}$$

where I_0 is the maximum fluorescence intensity firefly and γ is the observation coefficient and r_{ij} is spatial distance between fireflies i and j. Firefly's attractiveness is represented as follows:

$$\beta = \beta_0 e^{-\gamma r^2} \tag{8}$$

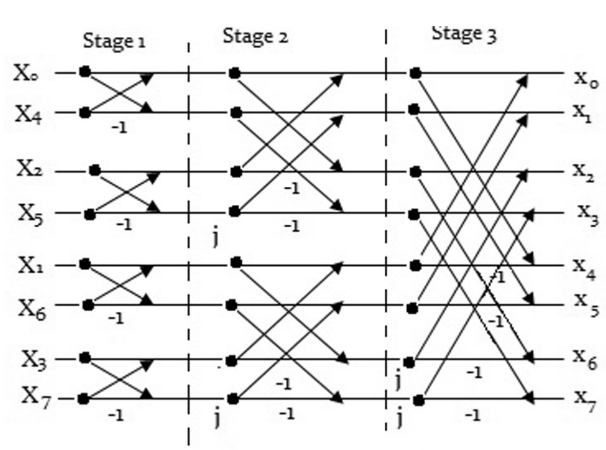

Fig. 6. Fast implementation of CS-SCHT.

4.2. Distance

The distance between any two fireflies is estimated using the distance formula.

$$r_{i,j} = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{9}$$

The Firefly i can be traveled towards the firefly j using the equation

4.3. Movement

$$x_i = x_i + \beta_0 e^{-\gamma r_{i,j}^2} (x_i - x_j) + \alpha \epsilon_i \tag{10}$$

The first-term in the above equation gives the present position of a firefly, the second-term represents the β (attractiveness) of a firefly (attraction of neighboring fireflies) and the third-term denotes the random-walk (random part) of a firefly.

$$x_i = x_i + \alpha(rand - 1/2) \tag{11}$$

A firefly will be directed towards the brighter one, and if there is no brighter one surrounding to it, then it will move arbitrarily as shown in Eq. (11). where the α is a random variable, and rand ϵ (0, 1).

4.4. Proposed hybrid FF and PSO (FFPSO) algorithm

The proposed hybrid FF-PSO [23] algorithm is used for optimizing ECG features. In this method faster computational convergence feature of PSO, is embedded on the characteristics of Firefly Algorithm (FFA), to increase the convergence speed to reach the global optimum point. The convergence of PSO depends upon parameters gbest and pbest. FFA algorithm starts with an initial random solution, after every iteration it modifies the solution until the global optimum is reached. The optimal solution obtained from FF algorithm depends upon the quality of the initial solution provided. In this proposed algorithm, the initial solution for the FFA is given by the optimal solution gained from the PSO algorithm. Since an initial best solution is given for FFA from the PSO, this Hybrid approach provides the better solution than individual PSO or FFA algorithms.

$$r_{px} = \sqrt{\sum_{j=1}^{d} (pbest_{i,j} - x_{i,j})^2} \tag{12}$$

The distance between xi and $gbest_i$, is the Cartesian distance

$$r_{gx} = \sqrt{\sum_{j=1}^{d} (gbest_{i,j} - x_{i,j})^2} \tag{13}$$

The position vectors xi of the FFPSO [24] is randomly mutated by using Eq. (10).

$$\begin{aligned} x_i(t+1) = {} & w x_i(t) + c_1 e^{-\gamma r_{px}^2} (pbest_i - x_i(t)) \\ & + c_2 e^{-\gamma r_{gx}^2} (gbest_i - x_i(t)) + \alpha(\gamma - 1/2) \end{aligned} \tag{14}$$

Firefly Algorithm can be used for two purposes:

i) Calculating the optimum value of a function.
ii) Reducing feature set of a population.

Algorithm: FFPSO

We have considered initial size of Population as 2086 beats (AF and normal).
Population was loaded using Matlab command X= xlsread (Normal and AF. xlsx).
The rows of X represents the features and the columns of X represents the size of population.
Calculated the fitness of the above features using objective function.
The maximum value of the fitness among all the population is stored.
If present fitness is greater than previous fitness.
Then feature i is moved towards feature j.
Calculated the new solution and updated the fitness value.
Then Sorted the features in descending order based on their fitness.

In standard FA, the method of updating the movement of fireflies is not faster. In general, it is useful for fireflies to find a new search space with a certain velocity to reach the global optimum point quickly. Therefore, the velocity term with modification for faster convergence is added to improve exploration and exploitation of the algorithm. In this present approach, attraction part of normal FFA is modified with PSO operator. Using PSO, each firefly in the swarm is attracted towards pbest and gbest. For each iteration the distance between its present location to gbest and pbest is calculated. Proposed modified algorithm enriches performance of the standard Firefly Algorithm and converges more quickly with less time.

5. Results and discussion

The algorithm has been implemented in Matlab 7.12.0. The experiment has been employed with a population size of 2086 for 50 generations. where beta (β) is 0.2 and alpha (α) have been set to 0.25. The initial value of acceleration coefficients c1 and c2 were set to 2.0. The inertial weight have been set to 0.5. The optimized features from the Hybrid Firefly Algorithm are given as the input for the LMNN so that its convergence speed and final accu-

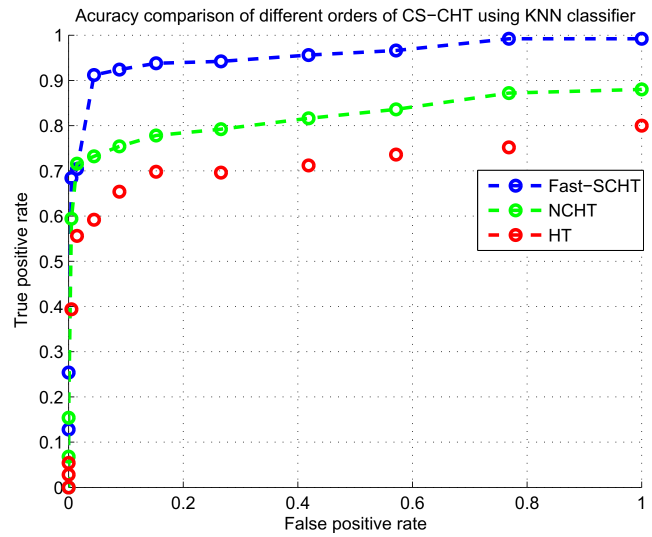

Fig. 7. Performance comparison of different orders of Hadamard Transform.

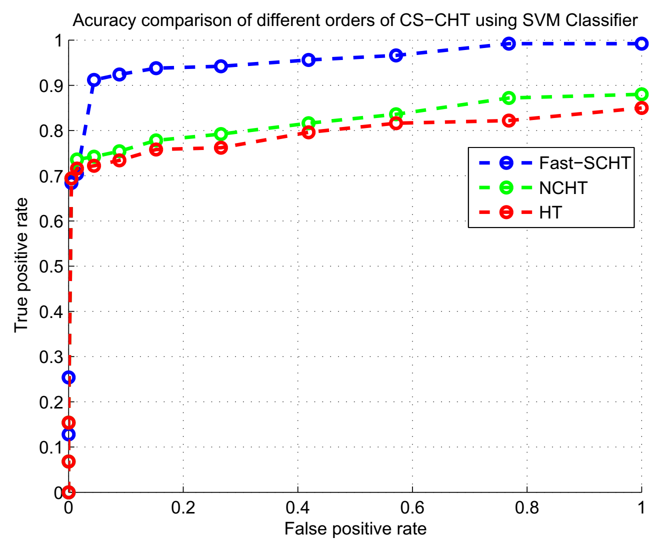

Fig. 8. Performance comparison of different orders of Hadamard Transform.

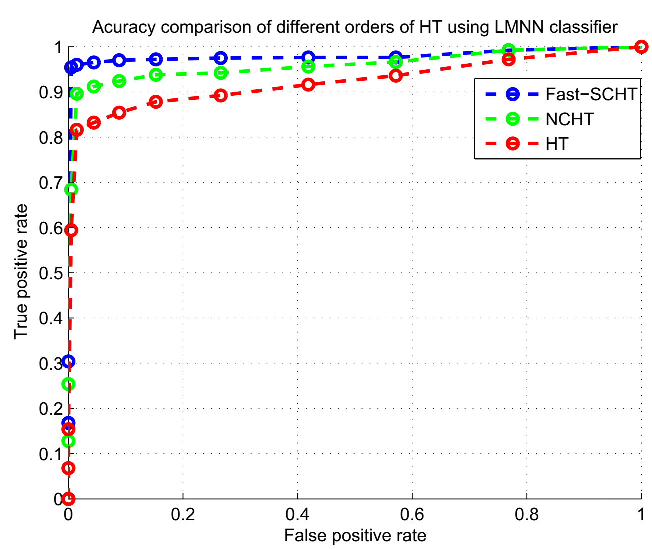

Fig. 9. Performance comparison of different orders of Hadamard Transform.

Table 1
Classification with KNN classifier.

Classifier	Sen	Spe	Accuracy
HT + KNN	53.2%	65.1%	51.2%
NCHT + KNN	73.5%	72.2%	73.22%
Fast CS-SCHT + KNN	92.35%	93.9%	92.17%

Table 2
Classification with SVM classifier.

Classifier	Sen	Spe	Accuracy
HT + SVM	71.0%	73.13%	70.12%
NCHT + SVM	76.2%	75.47%	72.13%
Fast CS-SCHT + SVM	95.5%	96.9%	96.74%

Table 3
Classification with LM NN classifier.

Classifier	Sen	Spe	Accuracy
HT + LMNN	91.2%	89.2%	80.9%
NCHT + LMNN	89.34.2%	89.2%	89.2%
Fast CS-SCHT + LMNN	99.97%	98.7%	99.3%

Table 4
Comparative study for detection of AF.

Studies	Approach	Sen (%)	Spe (%)	Acc (%)
Tateno et al. (2001) [4]	RR Interval	91.20	96.08	–
parvaresh et al. (2011) [25]	AR_coefficients	96.14	93.20	90.09
Lee et al. (2013) [26]	RR Interval	97.26	95.91	–
Zhou et al. (2014) [27]	SD & entropy	96.89	98.27	98.03
Padmavathi Kora et al. (2016) [28]	WTC features	100%	96.9%	99.1%
Proposed approach	Fast CS-SCHT	96.97	99.43	99.3

racy can be increased. Instead of using morphological feature extraction techniques, in this paper CS-SCHT is used as the feature extraction technique. The CS-SCHT gives best features for the classification. The performance of CS-SCHT is compared with classical HT, NCHT techniques. The HT, NCHT and CS-SCHT features are classified using SVM, KNN and LM NN as in the Tables 1–3. For measuring accuracy two parameters Sensitivity (Sen) and Specificity (Spe) are calculated using the following equations.

$$Spe = \frac{Correctly\_classified\_Normal\_beats}{Total\_Normal\_beats} X100 \tag{15}$$

$$Sen = \frac{Correctly\_classified\_AF\_beats}{Total\_AF\_beats} X100 \tag{16}$$

$$Accuracy = \frac{Correctly\_classified\_beats}{Total\_beats} X100 \tag{17}$$

Figs. 7–9 compare the accuracy performance of KNN, SVM and LMNN classifiers in terms of ROC curves. The classification accuracy of KNN classifier with CS-SCHT optimized features is 92.17% for the detection of AF. The classification accuracy of SVM classifier with CS-SCHT optimized features is 96.74% for the detection of AF. Results show that optimized CS-SCHT features in combination with LMNN classifier shows better results than KNN and SVM classifiers for the detection of AF. The classification accuracy of LMNN classifier with CS-SCHT features is 99.3% for the detection of AF. The work in [4] explored an experimental study based on the difference between RR intervals for extracting relevant features for the detection of AF. The values of sensitivity and specificity are 91.20% and 96.08%, respectively. (See Table 4).

The work presented in [25], used AR coefficients as features for classification AF using three different classifiers. AR coefficients are calculated for each 15 s data sequence length. The values of specificity and sensitivity are 93.20% and 96.14%, respectively. The work proposed in [26] used three statistical methods for the detection of AF. These techniques are tested on AF database and Normal database. The values of sensitivity and specificity are 97.2% and 95.91% respectively. The work proposed in [27] used RR intervals, and computed various operations like nonlinear or linear integer filtering, symbolic dynamics and the calculation of Shannon entropy. On-line analytical processing of the method can be achieved using this novel algorithm. The values of sensitivity, specificity and accuracy are 96.89%, 98.27% and 98.03% respectively.

The work proposed in [28] used WTC coefficients for the detection of AF. The WTC features for the normal and AF datasets are calculated. These features are optimized using PCA algorithm. The values of sensitivity, specificity and accuracy are 100%, 96.9% and 99.1% respectively.

From the experiments, this study concludes that the proposed beat feature optimization technique with CS-SCHT outperformed other three algorithms with the selection of a minimal number of relevant features using CS-SCHT. The proposed method shows the highest classification accuracy for the detection of AF. The CS-SCHT have been employed intelligently to select the most relevant features that could increase the classification accuracy while ignoring noisy and redundant features.

6. Conclusion

ECG is used to access the electrical activity of a human heart. In this study, our aim is to automate the above procedure so that it leads to correct diagnosis. Early diagnosis and treatment is of great importance because immediate treatment can save the life of the patient. The proposed fast CS-SCHT method is used to extract the features from each ECG beat then these features are compared to HT and NCHT algorithm. These fast CS-SCHT features are optimized to 20 features using FFPSO algorithm. The classification accuracy using CS-SCHT with LMNN classifier was 99.3% for the detection of AF. The experimental results shown that the proposed CS-SCHT method can extract more relevant features than the other methods proposed in the literature.

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