

# Classification of Sleep Apnea using ECG-Signal Sequency Ordered Hadamard Transform Features

Padmavathi Kora  
Associate Professor  
Department of ECE  
GRIET

Ambika Annavarapu  
Assistant Professor  
Department of ECE  
GRIET

Priyanka Yadlapalli  
Assistant Professor  
Department of ECE  
GRIET

Nagaja Katragadda  
Assistant Professor  
Department of ECE  
GRIET

## ABSTRACT

Sleep apnea is a potentially serious breath disorder. This can be detected using a test called as Polysomnography (PSG). But this method is very inconvenient because of its time consuming and expensive nature. This can be overcome by using other methods like Respiratory rate interval, ECG – derived respiration and heart rate variability analysis using Electrocardiography (ECG). These methods are used to differentiate sleep apnea affected patients and normal persons. But the major drawback of these is in performance. Hence, in this paper this disadvantage is overcome by considering Sequency Ordered Complex Hadamard Transform (SCHT) as a feature extraction technique. A minute to minute classification of thirty – five patients based on sensitivity, specificity and accuracy are 93.74%, 96.15% and 95.6%.

## General Terms

Preprocessing, Feature Extraction, Classifier

## Keywords

ECG, SCHT, Sleep Apnea, SVM

## 1. INTRODUCTION

Sleep apnea (SA) is a breathing disorder in which one will experience pauses in breathing or shallow breaths for 10 to 20 seconds more than 30 times per hour during sleep. This disorder leads to other side effects like morning headaches, leg swelling, and day time sleepiness. SA is classified into three classes namely, central SA (CSA), obstructive SA (OSA) and mixed SA. Most patients about 84% are affected by OSA, because it can be detected neither by blood test nor by any physical change of patient's body. This leads to heart stroke, blood pressure, obesity, arrhythmias, and even diabetes.

Presently, a gold standard for sleep apnea detection is PSG using electroencephalography (EEG), electrooculogram (EOM), ECG, body movement and, nasal airflow. But implementation of PSG experiences practical problems like time consuming and high expense.

Alternative approaches for PSG for apnea detection are developed basing on EEG, ECG, snoring, or pulse oximetry. In them ECG is widely used signal, because feature extraction of ECG signal can be extracted accurately than remaining signals. For example, Bsoul et al. [15] combined RR interval, Yilmaz et al., [16] used feature extraction from a respiratory rate (RR) interval as a classifier input, and introduced such features as inter-quartile range, mean absolute deviation, and median value. and ECG-derived respiration signal (EDR) [17] for real time SA monitoring using a support vector machine (SVM) classification, extracting approximately 111 features in each minute of an ECG segment. Heart Rate Variability (HRV) and wavelet analysis have also been used for ECG

initial processing [18, 19]. k-nearest neighbor [20], SVM [4,21,22], and artificial neural network (ATNs) [18,22] are other classification techniques. In this test 12 channels requiring at least 22 wire attachments overnight to a patient to record ECG.

In this paper, alternative SA using Sequency ordered Complex Hadamard Transform (SCHT) as feature extraction is established as shown in Fig??. The features extracted using SCHT are then applied to a minute based Support Vector Machine (SVM) classifier.

## 2. SYSTEM MODEL

ECG data of thirty – five patients are considered for eight – hour 12 lead ECG signal is digitized with 12 – bit resolution. Each one minute ECG recording is labeled as 'Ap' and 'No', and placed in three different classes as shown in Table I depending on Apnea – Hypopnea Index (AHI). If AHI of 100 minutes is greater than 15, the patients are placed in apnea patient class. Class B recordings of time between 5 and 99 minutes contain the AHI index between the range of 5 and 15. If the apnea minutes are less than 5 the patient will come under normal Class C patients.

Table I: Classes of Apnea

Class	Name of apnea	Apnea – Hypopnea Index (AHI)
Class A	Apnea Patient class	$AHI \geq 15$
Class B	Border line Class	$5 \leq AHI < 15$
Class C	Normal Patient Class	$AHI < 5$

### 2.1 Preprocessing

The preprocessing consists mainly of three phases

- Noise removing
- ECG signal segmentation into beats
- Change of non – uniform beats into uniform

The raw ECG is passed through Savitzky – Golay FIR smoothing filter to remove noise by using a technique called Linear Least Square (LLS). The noise minimization using LLS is carried out by considering the sum of squared differences between the signal assemblages. These obtained filtered non – uniform signals are segmented into beats detecting the 'R' peaks. The attained non - uniform samples are resampled to 200 uniform samples.

## 2.2 Feature Extraction

### 2.2.1 Sequency Ordered Complex Hadamard Transform

Discrete orthogonal transforms are used to make digital systems faster. These are used to transform the characteristics of a signal by altering its domain to understand signal without complexity. An orthogonal transform called BIFORE or HT is represented in (2) is established on Walsh functions by taking only two amplitude levels  $\{\pm 1\}$  forming a rectangular waveform.

A Hadamard matrix,  $H_M$ , is defined as a square matrix of dimension  $M \times M$  in which all elements are '1'. All records of a matrix are  $\pm 1, 2$ . Any two divergent rows of the matrix are orthogonal, that is,

$$H_M^T H_M = H_M H_M^T = N I_M \quad (2)$$

where  $H_M^T$  is the transpose of  $H_M$  and  $I_M$  is the identity matrix of dimension  $M \times M$ . In reality, a Hadamard matrix is a symmetric matrix whose row and column vectors are orthogonal to each other. The orthogonality property remains unaffected although the row and column vectors or sign of row and column vectors are exchanged as explained by equation (2).

But the major disadvantage of HT is it can be useful only to real - valued signals, but in real time applications complex values are also to be considered. So, Hadamard transforms are replaced by a comprehensive form called CHT, which comprises the values as  $C = \{\pm 1, \pm j\}$  where  $j = \sqrt{-1}$ . The advantage of CHT is it does not require any additional computational cost because of its complex elements as represented in equations (3) and (4). The orthogonality and simplicity of real HT are not altered because of CHT exclusively dealing with complex - valued signals in DSP applications. CHT is constructed on recursive formula consist of the higher order matrix diagonalising and Kronecker product multiples.

Ordered Hadamard matrices are obtained by organizing the rows of matrices in various ways. Sequency order is chosen in all different orderings as it is more equivalent to Fourier Transform frequency domain representation (3).

SCHT is a discrete orthogonal transform which is made up of the components  $\{\pm 1, \pm j\}$  and the row vectors of the transform matrix are organized in an ascending order of sequency. Sequency expel to the number of times that the row vector of a matrix crosses the imaginary axis in the unit circle above a normalized time base  $0 \leq k \leq 1$  such that each crossing represent a row of a SCHT matrix. SCHT implementation is modest than DFT in terms of hardware organization and computational convolution.

SCHT is implemented by using the extended version of conventional Rademacher functions called as complex Rademacher functions (CRD). CRD are used for both odd and even symmetry though they are incomplete orthogonal set of functions with odd symmetry. CRD is defined as follows:

$$CRD(0, k) = g(y) = \begin{cases} 1, & k \in \left[0, \frac{1}{4}\right) \\ j, & k \in \left[\frac{1}{4}, \frac{1}{2}\right) \\ -1, & k \in \left[\frac{1}{2}, \frac{3}{4}\right) \\ -j, & k \in \left[\frac{3}{4}, 1\right) \end{cases} \quad (3)$$

$$\text{and } CRD(0, k + 1) = CRD(0, k) \quad (4)$$

where period  $K = 1$ . Another simpler approach to define CRD over a normalized time base  $k \in [0, 1)$  is as follows:

$$CRD(0, k) = e^{\frac{jncsgn(e^{j2\pi t})}{4\sqrt{2}}} \quad (5)$$

which maps the real-valued  $t$  to the element from the set  $\{\pm 1, \pm j\}$  where  $csgn(y)$  is defined for any nonzero complex number  $y = y_1 + jy_2$  as follows:

$$csgn(y) = sgn(y_1) + jsng(y_2) \quad (6)$$

where  $sgn(\cdot)$  represents the signum function. But if  $y$  is a real number, it can be shown that  $csgn(y) = sgn(y)$ .

Real Rademacher functions are partially introduced by the complex element  $j$  where  $j = \sqrt{-1}$  to compress the orthogonality property of the Rademacher functions. For non-negative integer  $p$ , the complex Rademacher function series can be defined as follows:

$$CRD(p, k) = CRD(0, 2^p k) \quad (7)$$

where  $p = 0, 1, \dots, m - 1$ . By constricting  $CRD(0, k)$  in the horizontal direction by a factor of  $2^p$  results in  $CRD(p, k)$ . By discretizing the CRD function series the CRD matrices are obtained i.e., sampling the CRD function series at  $M = 2^m$  equally spaced locations within the normalized time  $k$ . Let  $R_m$  be the CRD matrix of dimension  $m \times 2m$ .

Then, the  $p^{\text{th}}$  row of  $R_m$  is defined as

$$R_m(p, l) = CRD\left(r, \frac{1}{2^m} + \frac{1}{2^{m+2}}\right) = CRD\left(p, \frac{4l + 1}{2^{m+2}}\right) \quad (8)$$

where  $p = 0, 1, \dots, m - 1$  and  $l = 0, 1, \dots, 2m - 1$ .

Let us, as an example, consider  $M = 8$ . Then, the  $3 \times 8$  complex Rademacher matrix is fashioned in (9) by placing (3) and (4) in (8) and attained values are tabulated in TABLE II.

**TABLE II. Complex Rademacher matrix values for  $M = 8$**

$R_m(p, l)$	0	1	2	3	4	5	6	7
$R_m(0, l)$	$\frac{1}{32}$	$\frac{5}{32}$	$\frac{9}{32}$	$\frac{13}{32}$	$\frac{17}{32}$	$\frac{21}{32}$	$\frac{25}{32}$	$\frac{29}{32}$
$R_m(1, l)$	$\frac{2}{32}$	$\frac{10}{32}$	$\frac{18}{32}$	$\frac{26}{32}$	$\frac{34}{32}$	$\frac{42}{32}$	$\frac{50}{32}$	$\frac{58}{32}$
$R_m(2, l)$	$\frac{4}{32}$	$\frac{20}{32}$	$\frac{36}{32}$	$\frac{52}{32}$	$\frac{68}{32}$	$\frac{84}{32}$	$\frac{100}{32}$	$\frac{116}{32}$

$$R_3 = \begin{bmatrix} 1 & 1 & j & j & -1 & -1 & -j & -j \\ 1 & j & -1 & -j & 1 & j & -1 & -j \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \end{bmatrix} \quad (9)$$

Using complex Rademacher matrices, the SCHT matrices are created based on the products of the row vectors of complex Rademacher matrices. Let  $H_M$  be the SCHT matrix of size  $M \times M$  where  $M = 2^{mm}$ . Then, it is defined as

$$H_M(g, l) = \prod_{p=0}^{m-1} R_m(p, l)^{b_p} \quad (10)$$

where  $R_m(p, l)$  is the  $(p^{\text{th}}, l^{\text{th}})$  element of the complex Rademacher matrix,

$$g = b_{m-1}2^{m-1} + \dots + b_12^1 + b_02^0 \quad (11)$$

and  $b_p = 0$  or  $1$ . Let  $R_m(p)$ , for  $p = 0, 1, \dots, m-1$ , be the  $p^{\text{th}}$  row vector of the complex Rademacher matrix. For example, let us consider  $H_8$  (12) which can be achieved by using (10) and the values are tabulated in TABLE II. Equation (13) is obtained by substituting equation (3) in (12).

Table III. SCHAT matrix  $H_8(g, l)$  for  $M = 8$

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

$$H_8(g, l) = \begin{bmatrix} 1 \\ R_3(0, l) \\ R_3(1, l) \\ R_3(1, l) \odot R_3(0, l) \\ R_3(2, l) \\ R_3(2, l) \odot R_3(0, l) \\ R_3(2, l) \odot R_3(1, l) \\ R_3(2, l) \odot R_3(1, l) \odot R_3(0, l) \end{bmatrix} \quad (12)$$

$$H_8(g, l) = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & j & j & -1 & -1 & -j & -j \\ 1 & j & -1 & -j & 1 & j & -1 & -j \\ 1 & j & -j & 1 & -1 & -j & j & -1 \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\ 1 & -1 & j & -j & -1 & 1 & -j & j \\ 1 & -j & -1 & j & 1 & -j & -1 & j \\ 1 & -j & -j & -1 & -1 & j & j & 1 \end{bmatrix} \quad (13)$$

The positions of binary ones of decimal value  $g$  bring into being by the row index values 2, 1 and 0

### 2.3 Classifier

Classification of apnea and non – apnea minute based ECG recording is studied by SVM with a Gaussian radial basis function kernel. In classification phase, performance of SVM is checked using a 10 – fold cross validation (CV) scheme. In this set of samples are divided randomly into 10 approximately balanced and equal parts. At each time these subsets are excluded from total samples and remaining

samples are set for training. Percentage of correctly classified data by 10 – fold CV accuracy. 10-fold CV was also used to optimize two Gaussian kernel parameters during the learning phase:  $\gamma$ , the width of the Gaussian kernel and  $\sigma$ , which controls the trade-off between minimizing training errors and model complexity. In this proposed system, SVM classifier performance is evaluated on the test set using accuracy, sensitivity, and specificity defined as follows.

$$\text{specificity} = \frac{\text{True}_{\text{Negative}}}{\text{True}_{\text{Negative}} + \text{False}_{\text{Positive}}} \times 100 \quad (14)$$

$$\text{sensitivity} = \frac{\text{True}_{\text{Positive}}}{\text{True}_{\text{Positive}} + \text{False}_{\text{Negative}}} \times 100 \quad (15)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (16)$$

$TP$  ( $\text{True}_{\text{Positive}}$ )

= Count of all the correctly classified Normal beats

$TP$  ( $\text{True}_{\text{Negative}}$ )

= Count of all the correctly classified Abnormal beats

$FP$  ( $\text{False}_{\text{Positive}}$ )

= Count of Normal beats classified as Abnormal beats

$FN$  ( $\text{False}_{\text{Negative}}$ )

= Count of Abnormal beats classified as Normal beats

### 3. RESULTS & DISCUSSION

Based on various records of Apnea – ECG database efficiency of proposed method is calculated in terms of specificity and sensitivity in addition to the accuracy using the MATLAB tool for classification. Table IV represents the comparison of our proposed method with the previous methods.

Table IV Comparison of Proposed technique with previous techniques

Approach	Performance		
	Sensitivity	Specificity	Accuracy
Measure of minutes of sleep disordered respiration [1]	NA	NA	91
$SaO_2$ [2]	90.1	82.9	NA
$SaO_2$ and EEG [3]	91	83.3	88.5
$SpO_2$ and ECG[4]	79.75	85.89	84.40
EEG [5]	69.64	44.44	NA
ECG [6]	NA	NA	92.67
Fourier and Wavelet transform of HRV [7]	90.8	NA	NA
Bivariate autoregressive model of HRV [8]	NA	NA	85

RR interval based Classification [9]	NA	NA	89
ECG – SVM [10]	92.9	100	96.5
RI Waveform [11]	88.1	65.7	91.2
Nasal Pressure – ECG [12]	75	100	87.5
W – ECG with features [13]	81.37	79.09	80.14
W – ECG + PCA [14]	95.20	92.65	93.91
Proposed Method	93.74	96.15	95.6

#### 4. CONCLUSION

In this paper, we studied the ECG signal based sleep apnea detection and, further developed a novel form using SCHT as feature extraction and calculated the effectiveness in terms of sensitivity, specificity and accuracy. From the experimental results we conclude that the SCHT get the best accuracy than the previous methods.

In future we plan to enhance the performance of feature extraction using optimization, and then make it to work in real – time monitoring system and analyze the ECG signal of patients during sleep.

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