

Single-Trial EEG Classification Using Logistic Regression Based on Ensemble Synchronization

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Abstract—In this paper, we propose an ensemble synchronization measure across all EEG channel pairs of a cluster based on Frobenius norm of the phase synchronization matrix, in a 0–1 scale enabling a direct comparison between clusters with different number of channels. Using this metric, we studied the intrahemispheric EEG synchronization in the lower gamma band (30–40 Hz) during 1229 single trials of an audio–visual integration cross modal task (CMT) recorded from five patients with schizophrenia and five healthy control subjects. Using ensemble synchronization measure and response latency of single trials recorded during the CMT as features for logistic regression, we could classify each single trial of EEG as belonging to a patient with schizophrenia or a healthy control subject with 73% accuracy, with an area under receiver operating characteristics curve of 0.83. We also propose a likelihood rating to denote the possibility of a subject belonging to the schizophrenia group.

Index Terms—Cross modal task (CMT), Frobenius norm, Hilbert transform, logistic regression, multichannel measure, phase synchronization.

I. INTRODUCTION

HUMAN cognitive functions involve the functional integration among different brain regions that are specialized for certain aspects of cognitive processing [1]. To perform even a simple task, the brain simultaneously employs multiple functionally distinct areas. Phase synchrony of neuronal oscillations has been postulated to be an important mechanism for binding together the activity of different brain regions in order to generate a unified perceptual experience from multiple sensory stimuli. This has been referred to as the *binding problem* by Treisman [2]. Phase synchronization has been implicated in sensory perception [3], attention modulation [4], memory processes [5],

neural communication [6], synaptic plasticity [7], action planning [8], task execution [9] etc. Schizophrenia, a neuropsychiatric condition characterized by aberrant brain connectivity [1], has been shown to be associated with task specific abnormal synchrony in scalp EEG channels [10]. Therefore, we examined scalp EEG phase synchronization across different brain regions during the performance of an audio–visual integration task, in the hope of differentiating subjects with schizophrenia from healthy controls using a novel ensemble synchronization-based classification metric.

Task specific single-trial EEG classification, based on signatures of brain activities, has remained a challenging problem [11]–[13]. In the past, differentiation of patients with schizophrenia from healthy controls has been attempted using artificial neural networks on EEG with 71% accuracy [14]. In this study, our focus was on single-trial EEG classification between schizophrenia and healthy groups. The need to use single trials came from our intent of developing a real-time system capable of performing such a classification. Here, we studied ensemble phase synchronization as a feature for classification, where the ensemble would encompass all brain regions involved in performing those cognitive tasks where a difference in performance between subject groups is expected. We chose to study intrahemispheric ensemble synchronization in lower gamma band, which is involved in long-range coordination [15], as there are reports suggesting dysfunctional long-range coordination in schizophrenia [16], [17].

In the next section, we describe the experiment and data acquisition. In Section III, we present a theoretical description of the quantitative methods used to process the data. In Section IV, we present the results. The paper concludes with a Conclusion section.

II. EXPERIMENT AND DATA

A. Subjects

Scalp EEG of five right-handed patients with schizophrenia and five healthy right-handed healthy control subjects were randomly selected from an EEG data base of schizophrenia and healthy subjects acquired as part of a funded research project at the National Institute of Mental Health and Neurosciences (NIMHANS), Bangalore, India. The earlier study had the approval of the NIMHANS Ethics Committee, thus conforming to the ethical standard laid down in the 1964 Declaration of Helsinki. Written informed consent was obtained from all participants, prior to enrolling them into the study. The sociodemographic details of all the subjects are given in

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TABLE I

DEMOGRAPHIC AND CLINICAL CHARACTERISTICS OF PATIENTS WITH SCHIZOPHRENIA AND HEALTHY CONTROLS (UPPER PANEL) ALONG WITH BETWEEN-GROUP COMPARISONS ON THE ABOVE VARIABLES (LOWER PANEL)

Variable	Patients with Schizophrenia (SZ)		Healthy Control subjects (HS)	
	Mean	CI	Mean	CI
Age (years)	31.8	±12.1	23.8	±1.8
Sex (male/female)	4/1		3/2	
Education (years)	10.4	±6.9	15.6	±1.9
Duration of Illness (months)	37.8		-	-

Variable	Significance level		Chi squared test for independence	
	$t_{(df)}$ Statistic	p-value	$\chi^2_{(df)}$ Statistic	p-value
Age (years)	$t_{(8)} = 1.8$	0.1	$\chi^2_{(8)} = 10$	0.26
Sex (male/female)			$\chi^2_{(1)} = 0$	1
Education (years)	$t_{(8)} = -2$	0.08	$\chi^2_{(6)} = 7$	0.32
Duration of Illness (months)			$\chi^2_{(4)} = 5$	0.29

CI – 95% confidence interval, df – degrees of freedom.

TABLE II

TREATMENT STATUS AND CLINICAL CHARACTERISTICS OF PATIENTS WITH SCHIZOPHRENIA

Schizophrenia Patient Identifier	Age of onset of illness (years)	Illness duration (months)	Treatment status (see legend)
SZ003	39	6	NN
SZ007	30	120	MF
SZ010	24	36	RT
SZ012	17	3	NN
SZ013	34	24	MF

NN- Neuroleptic-naïve; MF- medication-free for 2 months or more; RT- on regular treatment.

TABLE III

TOTAL NUMBER OF TRIALS SELECTED FOR EACH CATEGORY AND STIMULUS TYPE

Stimulus type	Total selected trials	Healthy control subjects	Schizophrenia subjects
Congruent	376	200	176
Incongruent	360	190	170
Neutral	493	259	234

Table I, while the clinical details are listed in Table II. Statistically significant difference between groups for each variable was evaluated by conducting independent two sample t -test. Results of Pearson's chi-squared test for independence have been reported for sake of completeness. A larger sample is required to draw conclusions from these metrics confidently.

B. Equipment Configuration

The EEG was acquired using a 70-channel Neuroscan SynAmps acquisition system (Compumedics, Charlotte, USA). An electrode cap with the 10–10 International system of electrode placement was used. This included 64 monopolar scalp

electrodes and four bipolar electrodes for EOG, EKG, and EMG. Acquisition was controlled using ACQUIRE, Neuroscan's proprietary acquisition software. Impedances for all electrodes were reduced to a range of 5–10 K Ω . A high-pass filter of 0.1 Hz and a low-pass filter of 100 Hz were used at the time of recording. Sample frequency was set to 1000 Hz. Stimulus delivery was controlled by STIM2 (Compumedics, Charlotte, USA), a stimulus presentation system which includes a dedicated audio system and a four-button response pad for collection of finger-press responses from the subjects. The subjects were seated in a comfortable cushioned chair in a darkened, sound-attenuated room facing a 17" CRT monitor at eye-level which was connected to the STIM2 system.

C. Cross Modal Task (CMT)

This is an audio–visual integration task administered as an event-related paradigm and designed to engage multimodal perceptual integration processes in the brain. The subjects were simultaneously presented with an image on a computer monitor and a sound through earphones. The gestalt image could be a human male or female face or a scrambled image. The sound could be a snippet of a human male or female voice or white noise. The subject's task was to pay close attention to both the visual and auditory stimuli and to respond by appropriate button press if the gender of the face in the image and the voice in the sound matched (*congruent trials*, index finger press), or did not match (*incongruent trials*, middle finger press) or if there was no discernible face or voice (*neutral trials*, ring finger press). Trials in which no image was presented, served as *null trials* to provide stimulus free baseline while also ensuring that the intertrial interval is random.

Of a total of 256 trials for each subject, 25% each were congruent, incongruent, neutral, and null trials. The sequence of image-voice combination was prespecified according to a pseudorandom list such that the appearances of each stimulus type were approximately equal during any interval. Half of the incongruent trials had male face—female voice pairings and the other half had female face—male voice pairings. For the neutral task, the scrambled image and white noise clipping were paired.

At the onset of each trial, a fixation cross-hair was presented which lasted for 2060 ms before being replaced by the probe image. Stimulus onset for both visual and auditory stimuli was 2060 ms after trial onset. The size of visual stimuli was 180×200 px which subtended a visual angle of 6.9° vertically and 6.2° horizontally at a viewing distance of 60 cm. The duration of both visual and auditory stimuli was 500 ms. The fixation cross-hair reappeared 1500 ms after the stimulus offset, with intertrial interval being 5070 ms. Fig. 1 captures the sequence of events for each trial in the CMT EEG experiment.

The data on acquisition was band pass filtered between 0.5 and 80 Hz and notch filtered at 49–51 Hz to remove the ac-line noise. ECG and EMG channels were removed. Artifacts were rejected upon visual inspection and by ICA-based methods using ADJUST toolbox [18], [19] in EEGLAB [20] a MATLAB toolbox for processing EEG.

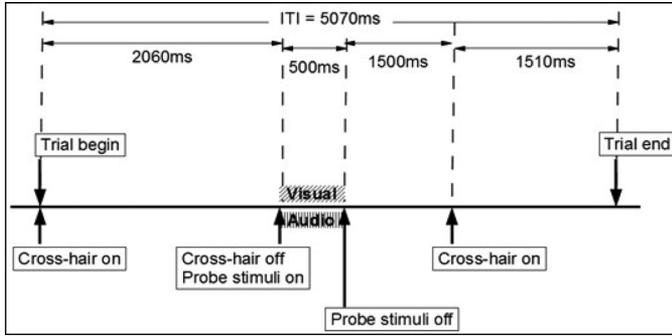


Fig. 1. Diagram illustrating the timeline for each trial in the CMT EEG experiment.

III. QUANTITATIVE METHODS

A. Hilbert Phase Synchronization

Let $s(t)$ be any time domain signal. Let us define analytic signal $\psi(t)$

$$\psi(t) = s(t) + j \cdot \hat{s}(t) = A(t) \cdot \exp(j \cdot \varphi(t)) \quad (1)$$

where $\hat{s}(t)$ is the Hilbert transform of the signal $s(t)$, $j = \sqrt{-1}$, $A(t)$ is the *instantaneous amplitude* (envelope), and $\varphi(t)$ is the instantaneous phase of the analytic signal $\psi(t)$. For phase to be free from influence of amplitude, the signal must be narrow band [21]. So we consider the lower gamma (30–40 Hz) band for the phase synchronization analysis, which is sufficiently narrow and also includes the 40-Hz representative component instead of entire gamma band [22] instead of the entire 30–80 Hz [23]–[26]. Instantaneous phase difference $\varphi(t)$ at time t is $\phi_{12}(t) = \phi_1(t) - \phi_2(t)$ where φ_1, φ_2 phases of first and second EEG channels of the pair are. Finally, we define the synchronization value s between a channel pair for window W_i as follows:

$$s_{12}(W_i) = \left| \frac{1}{|W|} \sum_{t=1}^{|W|} \exp(i \cdot \phi_{12}(t)) \right|^2 \quad (2)$$

where $|W|$ is the length of the analysis window W [27]. If $s = 1$ signal pairs are in perfect phase synchrony and if $s = 0$ the signals are in perfect phase asynchrony. If there are n number of EEG channels in a cluster an $n \times n$ symmetric matrix $A_n(t)$ is created whose ij th entry $a_{ij}(t)$ is the phase synchronization of i th and j th channels as calculated in (2).

The EEG signals acquired during the CMT were analyzed by segmenting into trials from 1 s before the stimulus onset till 2 afterward. The data were band pass filtered for lower gamma band using an equiripple FIR filter with the following specification: pass bands at 30 and 40 Hz; stop bands at 26 and 44 Hz; pass-band and stop-band attenuation of 0.5 and 40 dB, respectively. The analysis window length used for calculating phase synchronization was 400 ms, which was shifted by one time point at a time. We obtained two 35×35 symmetric matrices one for each hemisphere, as all eight channels on the center line are included in both hemispheres i.e., $((62 - 8)/2) + 8 = 35$ channels in each hemisphere.

B. Ensemble Synchronization Measure

We propose a quantitative measure to define an ordering of the synchronization matrices based on *Frobenius norm* of a matrix [28]. If a_{ij} is the ij th entry of a matrix A , then the *entry wise norm* $\|A\|_p$ is defined in (3) where p is a positive integer and n is the number of channels in the ensemble. We chose *Frobenius norm* $\|A\|_F$, by substituting $p = 2$ as follows:

$$\|A\|_p = \left(\sum_{i=1}^n \sum_{j=1}^n (a_{ij})^p \right)^{1/p} \quad (3)$$

$$\gamma = \sqrt{\frac{\|A\|_F^2 - n}{n^2 - n}}. \quad (4)$$

The ensemble measure is computed on a 0–1 scale as given in (4), where n is the number of channels in cluster. Here, a value of 0 corresponds to the lowest ensemble synchronization while 1 corresponds to highest. This enables comparison of different clusters using the proposed ensemble measure, thus one can tell which ensemble or which subject exhibits greater synchronization.

C. Statistical Significance of Phase Synchronization

We test the null hypothesis H_0 , that the observed phase synchronization on a channel pair $s_{1,2}$ is not statistically significant or $H_0 : s_{1,2} = 0$. The decision rule used to test this hypothesis is: reject H_0 if $s_{1,2} > s_0$, where for a given p -value, s_0 is the $100 \times (1 - p)$ percentile of the distribution of s values obtained as phase synchronization between a large number of pairs of independent shifted-time surrogate signals [29]. For Hilbert transform-based pairwise phase synchronization over an analysis window of 400 ms, we observe $s_0 = 0.51$ when evaluated over 100 pairs of surrogate signals for a p -value of 0.05 or 95% significance level. We observe a high value for s_0 since the analysis window duration is small. The choice of window length is influenced by our desire to retain good temporal resolution to facilitate in capturing the changing dynamics.

Now, we conduct a similar null hypothesis significance testing on the proposed ensemble synchronization measure γ . The decision rule used to test null hypothesis H_0 , i.e., observed ensemble synchronization is not significant is to reject H_0 if $\gamma > \gamma_0$, where γ_0 is evaluated as the $100 \times (1 - p)$ percentile of the distribution of γ values evaluating on a large number of ensembles of independent shifted-time surrogate signals for a given p -value. Using the proposed ensemble synchronization measure γ , we observe $\gamma_0 = 0.51 (= s_0)$ for a 100 surrogate ensemble with 35 channels each for a p -value of 0.05. Even intuitively there is no reason to expect ensemble synchronization to be significant when pairwise synchronization is not or vice versa. As expected the statistical significance threshold for ensemble synchronization γ_0 is similar to the synchronization threshold for channel pair s_0 irrespective of the number of signals in the ensemble.

D. Logistic Regression

Let m, n be number of training examples, and features extracted from data. Transpose is denoted as $(\bullet)^T$. The feature matrix X is defined as follows:

$$X = [(x^{(1)})^T \ (x^{(2)})^T \ \dots \ (x^{(i)})^T \ \dots \ (x^{(m)})^T]^T$$

$$x^{(i)} = [1 \ x_1^{(i)} \ \dots \ x_j^{(i)} \ \dots \ x_n^{(i)}]. \quad (5)$$

Here $x^{(i)}$, of order $1 \times (n + 1)$, is the feature vector of i th example and $x_j^{(i)}$ is its j th feature. The extra dimension corresponds to the intercept term set to 1, i.e., $x_0^{(i)} = 1$. Now, i th example is represented as $(x^{(i)}, y^{(i)})$, where $y^{(i)}$ in (6) defines target class vector Y of order $m \times 1$:

$$y^{(i)} = \begin{cases} 0, & \text{healthy control} \\ 1, & \text{schizophrenia.} \end{cases} \quad (6)$$

The hypothesis function h is the sigmoid which restricts the output to $[0, 1]$ range. The output $h_\theta(x^{(i)})$ corresponding to $(x^{(i)}, y^{(i)})$ defined in (7), depends on a weight vector θ of length $1 \times (n + 1)$:

$$h_\theta(x^{(i)}) = \frac{1}{(1 + \exp(-x^{(i)} \cdot \theta^T))}. \quad (7)$$

The output $h_\theta(x^{(i)})$ is the score assigned to each single trial (i th example) and its predicted class is decided using (8) single trial (x^i, y^i) is given by

$$(x^{(i)}, y^{(i)}) = \begin{cases} \text{healthy control,} & \text{if } h_\theta(x^{(i)}) < 0.5 \\ \text{schizophrenia,} & \text{if } h_\theta(x^{(i)}) \geq 0.5. \end{cases} \quad (8)$$

The goal is to minimize a cost function by searching for a weight vector θ_{\min} such that a hyper plane partitions the examples into its respective classes with best possible accuracy. To avoid overfitting for training dataset leading to a loss of generalization, we perform regularization, penalizing the cost function with weights θ and degree of regularization is controlled by parameter λ .

E. Logistic Regression-Based Classification

We chose four features for the classifier viz. average hemispheric synchronization measures evaluated using the proposed ensemble measure (4) over a 300 ms window at three intervals— at stimulus onset (interval from stimulus onset to 300 ms afterward), at stimulus offset (interval from stimulus offset to 300 ms afterward) and at response time (interval from 400 to 100 ms prerresponse) apart from using response latency.

We restricted the trials that are used for the classification by the following criteria. Apart from rejecting trials at preprocessing stage, due to spurious signals, noise, etc., we chose only trials with a correct response. Further, we selected trials in which the response latency is at most two standard deviations away from the mean response latency for the subject under consideration. This ensures that trials where the subject responded either very quickly or delayed are not considered as they might have been a random guess due to haste or confusion. Summary of number of

trials selected for each category and stimulus type is presented in Table III.

F. Classifier Performance

For each stimulus type, we trained a logistic regression classifier on randomly chosen subset of the selected trials that were divided into training set (65%) and testing set (35%) using a pseudorandom sequence. Then we compute the performance on testing dataset by using θ_{\min} obtained on the training set with regularization parameter set to 1. The performance of the classifier is evaluated using accuracy at single trial on training set in tandem with testing set which reflects the real-world scenario. Further, we report sensitivity, i.e., true-positive rate defined as ratio of true positives to actual number of positive in the total dataset using a threshold of 0.5, and false-positive rate defined as the ratio of false positives to the actual number of negatives in the dataset using a threshold of 0.5, this is equivalent to $(1 - \text{specificity})$.

G. Likelihood Rating

A likelihood rating $\text{lik}(s_j)$ is assigned to each subject s_j , which reflects the likelihood of the subject as belonging to schizophrenia category over healthy control. This rating ranges from 0 denoting healthy, to 1 denoting schizophrenia, computed as the average of scores assigned to all selected single trials $tr(s_j)$ belonging to subject s_j for a particular stimulus type, where score (i, s_j) is the score assigned to i th selected single trial defined as the predicted output of the classifier $h_{\theta_{\min}}(x^{(i)})$ (see (7)). If the likelihood rating is greater than threshold then the subject is termed as belonging to schizophrenia category, else to healthy category. In our study, a threshold of 0.5 is chosen for performing the subject level classification:

$$\text{lik}(s_j) = \frac{1}{tr(s_j)} \sum_{i=1}^{tr(s_j)} \text{score}(i, s_j) \quad (9)$$

$$s_j \in \begin{cases} \text{healthy control,} & \text{lik}(s_j) < \text{threshold} \\ \text{schizophrenia,} & \text{lik}(s_j) \geq \text{threshold.} \end{cases}$$

IV. RESULTS

A. Behavioral Results

The behavioral performance during the CMT trials is given in Table IV. The mean and 95% confidence interval for response accuracy and response latency for both groups across all the three stimulus types are listed. The mean difference in response latency between groups was statistically significant for congruent and incongruent but not for neutral stimulus type. Therefore, response latency for congruent and incongruent trials (but not the neutral trials) may be a good candidate for the classification task. The response latency among healthy controls is validated to be faster when compared to the patients with schizophrenia across stimulus type. Thus, neutral stimulus type might not be a good candidate for classification task in the feature space.

TABLE IV

COMPARISON OF BEHAVIORAL PERFORMANCE FOR BOTH SUBJECT CATEGORIES DURING CONGRUENT TRIALS (UPPER PANEL), INCONGRUENT TRIALS (MIDDLE PANEL), AND NEUTRAL TRIALS (LOWER PANEL) OF THE CMT

Stimulus Type		Congruent Trials	
Performance Metrics		Accuracy (%)	Latency (ms)
SZ	Mean	71.3	1323
	CI	8.8	42.1
HS	Mean	73.4	1070.2
	CI	11.2	33.4
t-test	$t_{(df)}$ Statistic	$t_{(8)} = -0.35$	$t_{(387)} = 9.39$
	p-value	0.73	2×10^{-16}
Stimulus Type		Incongruent Trials	
Performance Metrics		Accuracy (%)	Latency (ms)
SZ	Mean	65.8	1452
	CI	11.7	44.6
HS	Mean	70.8	1251.2
	CI	4.7	35.8
t-test	$t_{(df)}$ Statistic	$t_{(8)} = -0.66$	$t_{(370)} = 7.0$
	p-value	0.53	1.2×10^{-11}
Stimulus Type		Neutral Trials	
Performance Metrics		Accuracy (%)	Latency (ms)
SZ	Mean	95.7	890.1
	CI	8.1	36.6
HS	Mean	98.5	862.5
	CI	0.7	20.6
t-test	$t_{(df)}$ Statistic	$t_{(8)} = -0.93$	$t_{(511)} = 1.32$
	p-value	0.38	0.18

SZ- Patients with schizophrenia; HS- healthy control subjects; CI- 95% confidence interval; df- degrees of freedom.

TABLE V

SINGLE-TRIAL CLASSIFIER PERFORMANCE FOR EACH STIMULUS TYPE

Stimulus type	Congruent	Incongruent	Neutral
Training set accuracy %	74	71	61
Testing set accuracy %	73	69	59
True Positive Rate (TPR)	0.668	0.613	0.453
False Positive Rate (FPR)	0.212	0.23	0.29
Area under Curve	0.83	0.76	0.64

TABLE VI

LIKELIHOOD RATINGS ASSIGNED TO SUBJECTS IN EACH CATEGORY ACROSS STIMULUS TYPE

Likelihood ratings	Duration of Illness (months)	Congruent	Incongruent
Healthy Control Subjects	-	0.24	0.25
	-	0.36	0.51
	-	0.24	0.33
	-	0.35	0.39
Schizophrenia Subjects	-	0.36	0.37
	6	0.62	0.64
	120	0.82	0.73
	36	0.67	0.57
	3	0.49	0.38
	24	0.71	0.69

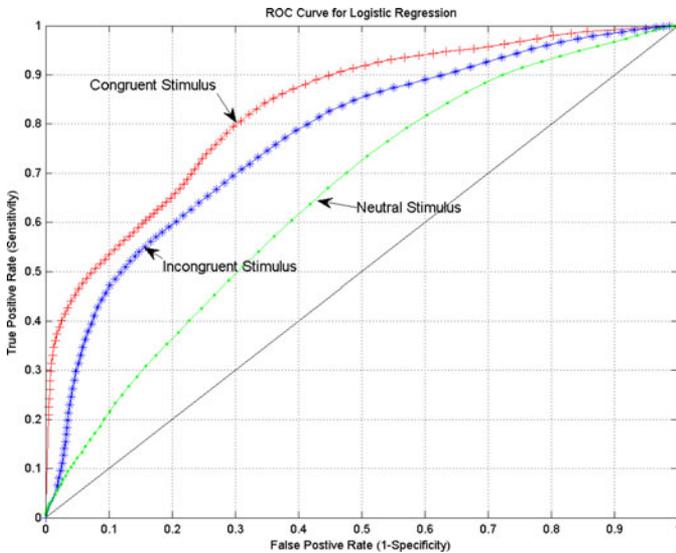


Fig. 2. ROC curve of the classifier for all three stimuli types.

B. Classifier Performance

The average performance of the classifier for each stimulus type separately trained and tested on 100 randomly selected training and testing sets is reported. The receiver operating characteristics (ROC) curve for the classifier performance is depicted in Fig. 2 for all three stimuli types. The area under the ROC curve measures the performance of the classifier. Higher

values of the area under the ROC curve indicate a statistically reliable classification performance.

In Table V, we report the average results of 100 training and testing phases for the performance metrics at single trial and at subject level for all three stimuli types. We observe single-trial average classification accuracy of around 73%, and area under the ROC curve of around 0.83. Thus, we observe that congruent stimulus type performs better than incongruent stimulus type, also confirmed by the ROC curve in Fig. 2. We also note that classification of single-trial using neutral stimulus type leads to 59% accuracy, which is closer to random guess, confirming our surmise that neutral stimulus type is not favorable for classification using our proposed features.

C. Likelihood Rating

The likelihood ratings assigned to all subjects belonging to both healthy and schizophrenia categories for both congruent and incongruent stimulus types are provided in Table VI. We can infer that the likelihood ratings are on the border, i.e., around threshold of 0.5, for those schizophrenia subjects, in whom the illness has set in very recently as reflected by the duration of illness specified in months.

V. CONCLUSION

EEG and MEG are noninvasive tools that acquire brain signals with high temporal resolution using scalp electrodes and provide valuable insights into the systems-level processing associated with rest and cognitive ability. Phase synchronization is one of the most effective signal processing tools to measure task specific ensemble activities of different brain regions specialized

for specific functions [30], [31]. We proposed the quantity γ in (4) to capture a multichannel Hilbert transform-based phase synchronization measure in 0–1 range, using which it is possible to compare ensembles for level of synchronicity.

If single-trial EEG classification is a challenging problem [13], then task-based classification of EEG of a patient with mental disorder relative to that of a subject without the disorder is even more challenging [14]. Here, we have attempted to develop a single-trial EEG-based classifier that differentiates congruent and incongruent EEG trials in a CMT as belonging to the schizophrenia group or the healthy control group. We have chosen four features for logistic regression from hemispheric ensemble synchronization at three specific intervals in addition to response latency. We believe this approach has good potential for developing a real-time system capable of estimating the likelihood of a subject belonging to the schizophrenia group based on their performance on certain cognitive tasks. One of our future goals will be to validate this method on a large data set, improvising it by including other frequency bands, while limiting to channel clusters relevant to the cognitive task under study.

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