A Type-2 Fuzzy Approach Towards Cognitive Load Detection Using fNIRS Signals

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***Abstract*— The main notion of this paper is to identify the cognitive load during a mental arithmetic task experiment using fNIRS signals. The first objective is to classify the difficulty level and the state of inactivity during the given task. To identify the classes, the feature vectors have to undergo all the possible steps of a pattern classification problem. In this paper, we have developed a novel Feature Selection technique to reduce the dimension of the feature vectors by omitting the redundant features. For this purpose, an objective function depending upon the class density or likelihood functions is optimized using the well-known Differential Evolution algorithm. General type-2 fuzzy classifier is used for subsequent classification step. The proposed Feature selection technique gives a satisfactory accuracy results over principal component analysis. Also the fuzzy classifier outperforms the other well-known classifier like support vector machine, k-nearest neighborhood. The load of a subject undergoing the experiment is measured at a particular class relying upon the mean type- 1 fuzzy value of all feature entities.**

Keywords—Brain computer interfacing, functional near-infrared spectroscopy, fuzzy type-2 classifier, principal component analysis, differential evolution algorithm.

I. INTRODUCTION

In recent years, development of brain computer interfacing (BCI) [1]-[2] systems has taken a considerable amount of concentration from scientific communities. The main purpose of BCI research is to model and develop systems with an intention to create a direct communication medium between brains and outside world without involving muscles or peripheral nervous system for those who are suffering from motor-neuron disease [3]. In BCI, external visual or auditory stimuli are provided to the user. With user's intention, brain signals in terms of electric potential or concentration change of hemoglobin in blood vessels of inner tissue are generated. These signals are acquired and classified such that the user's intention can be executed to control external devices or computer such as wheel chair [3]-[5], mind-driven motion of robots [6]-[8], thought-controlled driving [9]-[10], and also prosthetic devices [11]-[12]. There are two types of signal acquisition technique namely invasive and non-invasive. To avoid surgical approach and high cost, nowadays scientists are prone towards using non-invasive techniques like Electroencephalogram (EEG) [13], functional Nera Infrared Spectroscopy (fNIRS) [14], functional Magnetic Resonance Imaging (fMRI) [15] to collect brain signals.

In this paper, we have used fNIRS signals for cognitive load detection in mental arithmetic task experiment. In case of fNIRS signal, the change in the optical properties due to change in the concentration of oxy-hemoglobin (HbO) and deoxy-hemoglobin (HbR) in the blood vessels of the tissues is captured [14]. The photons of the light within the near infrared range can penetrate the several outer layers of the brain including the cranium, meninges and the fluid surrounding the brain. The light undergoes several optical phenomena like scattering, diffusion, refraction, reflection. The amount of the reflected photons from the inner tissues comes out several centimetres above the scalp with respect to the source location. It is captured using the appropriately placed IR source-detector pairs and the attenuation is computed using the modified Beer-Lambert law [14]. The change of attenuation can also be expressed linearly in term of change in concentration of [HbO] and [HbR] as,

$$\Delta A = \left(\alpha_{HbO}\Delta c_{HbO} + \alpha_{HbR}\Delta c_{HbR}\right)BL, \tag{1}$$

where, α_x is the specific light intensity (mol^{-1}m^{-1}) and c_x is the concentration of the absorber (mol), *B* is the differential path length factor, and *L* is the distance between source and detector (m). *x* is used as the dummy index for HbO and HbR.

fNIRS signals have huge importance in developing BCI systems using motor imagery signal in driving data to cognitive load detection with the help of mental arithmetic (MA) [16] task as it provides us with both spatial and temporal information unlike EEG and fMRI, which have high values of only one of them. For mental arithmetic task, the fNIRS signals are taken from the prefrontal region of the brain [16].

This paper aims for the detection of cognitive load on the basis of the fuzzified output of the feature vectors. The difficulty level is classified using general type-2 [17]-[19] classifier based on the assumption that difficulty level of problems may seem different to different subjects. Though the difficulty level of the problems are defined pre-experimentation, there exists some uncertainty in finding out appropriate difficulty level for each problem for each subject taking part in the experiment. The general type-2 fuzzy classifier is used, as it provides better perspective in defining the uncertainty than the normal type-1 fuzzy classifier. The second novelty of this work lies in the feature selection (FS) step, where likelihood based objective function is designed with necessary mathematical approach. This selection technique identifies the most appropriate features from the original feature vector depending upon the class conditional density functions by optimizing a cost function using Differential Evolution (DE) [20] algorithm.

The paper is organized as follows. Section II describes the proposed framework including a proposed FS technique and fuzzy classifier for difficulty level determination and cognitive load detection. Section III covers up the experimental set up that includes the timeline of the used stimulus. In section IV the performance of the classifier with statistical analysis is included. At last, the paper is concluded in section V.

II. Proposed Framework

The goal of our work is to classify the different difficulty levels along with the state of inactivity encountered during mental ability task experiment. Since it is a classification problem, the solution procedure includes four major steps – preprocessing, feature extraction (FE), feature selection (FS), classification. During preprocessing stage, the noise and any other artifacts are filtered out and the signals of interest are gathered for further use. After the noise-removed signals are accumulated, suitable features are extracted from the raw discrete time data streams. To remove any redundancy present in the feature vectors obtained in the previous step, FS technique must be used, such that in subsequent stage, the classifiers can be trained properly and the chance of getting over trained or under trained can be avoided for better classification accuracy. In this section, we proposed a novel approach towards feature selection and a generalized type-2 fuzzy set (GT2FS) based classifier. These approaches are illustrated below with sufficient details.

A. *Preprocessing and Noise Rremoval*

While conducting the experiment, it is certain that various kinds of noises cause disturbance in the data stream of fNIRS. These noises can be divided into two categories in broad sense - experimental noise, physiological noise [21]. Experimental noise or error is generated from the motion artifacts such as head motion which results in the dislocation of optodes. These can be visualized in the fNIRS data as spike artifacts due to abrupt change in light intensity as the optodes change their positions. Physiological noise includes several kinds of artifacts due to heartbeat (1-1.5 Hz), blood pressure fluctuations or Mayer wave (around 0.1 Hz), respiration (0.2 – 0.5 Hz) [21] etc.

There are several band pass and advance adaptive filtering techniques are available [21] for removal of these noises. During this work we have used Chebyshev band pass filter with cutoff frequencies 0.1 Hz and 0.6 Hz such that majority of these physiological noises such as Mayer wave, respiration noise are removed. In the next step advanced filtering using Independent Component Analysis (ICA) [22]-[23] has been used for removal of many other physiological noises. ICA helps in restoring original hemodynamic signal from noisy multi-source data by first isolating the main IC and then accumulating the ICs along with the primary IC using the associated weights derived from their *t*-values.

B. *Likelihood based Feature Selection*

Let $\mathbf{X}_{N\times D}=\{\vec{X}_1,\vec{X}_2,\ldots\vec{X}_N\}$ be a set of N pattern vectors or data points, each having D features. Given such $\mathbf{X}_{N\times D}$ matrix, the object is to find a feature matrix $\mathbf{x}_{N\times n}$, where $n\le D$. The notion of this FS technique is to select the features which involve in significant increment of likelihood of a feature vector as a whole within its own class and decrement of likelihood in other classes. The probability of the feature vector $\vec{X}_i^c$ with prior information that class c has already appeared in the experiment is given by $p(\vec{X}_i^c/c)$. Similarly, the probability of the feature vector $\vec{X}_i^c$ with prior information that class d has already appeared in the experiment is given by $p(\vec{X}_i^c/d)$. Now if an iterative optimization technique is used, objective is to maximize the difference between intra and inter-class likelihood function which can be expressed mathematically as,

$$p(\vec{X}_i^c/c)-\tfrac{1}{K-1}\sum_{\forall d,d\neq c}p(\vec{X}_i^c/d)\,. \tag{2}$$

Thus, the overall objective function considering all the feature vectors of all the classes can be written as,

$$J=\sum_{\forall c}\sum_{\forall i,i\in c}\left(p(\vec{X}_i^c/c)-\tfrac{1}{K-1}\sum_{\forall d,d\neq c}p(\vec{X}_i^c/d)\right). \tag{3}$$

Let, $\vec{X}_i^c$ be the i^{th} vector belong to class *c*, $\vec{\mu}^c$ be the mean vector of class *c*, Σ^c be the co-variance matrix of class *c* and $p(\vec{X}/c)\sim N(\vec{\mu}^c,\Sigma^c)$. By modifying equation (2) and neglecting higher order terms, we have,

$$J=L_1-\lambda.L_2\,, \tag{4}$$

where, scale factor $\lambda\in(0,10]$

$$L_1=\sum_{\forall c}\sum_{\forall i,i\in c}\left(\frac{1}{K-1}\sum_{\forall d,d\neq c}L_1^d-L_1^c\right), \tag{5}$$

$$L_2 = \sum_{\forall c} \sum_{\forall i, i \in c} \left(\frac{1}{K-1} \sum_{\forall d, d \neq c} \frac{1}{(2\pi)^{\frac{n}{2}} \left|\Sigma^d\right|^{\frac{1}{2}}} - \frac{1}{(2\pi)^{\frac{n}{2}} \left|\Sigma^c\right|^{\frac{1}{2}}} \right), \quad (6)$$

$$L_1^d = \frac{1}{2.(2\pi)^{\frac{n}{2}} \left|\Sigma^d\right|^{\frac{1}{2}}} (\vec{X}_i^c - \vec{\mu}^d)^T \Sigma^{d^{-1}} (\vec{X}_i^c - \vec{\mu}^d), \quad (7)$$

$$L_1^c = \frac{1}{2.(2\pi)^{\frac{n}{2}} \left|\Sigma^n\right|^{\frac{1}{2}}} (\vec{X}_i^c - \vec{\mu}^c)^T \Sigma^{c^{-1}} (\vec{X}_i^c - \vec{\mu}^c). \quad (8)$$

Equation (4) is maximized using Differential Evolution (DE) algorithm. To initialize population vectors, string vectors of dimension *D* consisting of '1' (true) and '0' (false) are constructed. The true value at a position indicates the inclusion of the feature value of that particular index into the lower dimensional feature vectors. These low dimensional feature vectors are used to obtain the value of the cost function of equation (4) assuming that their original class definitions have not been changed. The string vectors are updated iteratively using DE/rand/1/bin [20] technique. The scale factor λ is chosen experimentally to maintain a compatibility between the two values L_1 and L_2. After optimization the best string vectors found so far is used for reduction of the original feature vectors. Now, when a new unknown feature vector comes into sight for testing, this string vector helps the recognizer to down select the features.

C. Classification and Load Detection

The next step after feature selection is classification. The Gaussian fuzzy membership functions for each feature entity are developed for different subjects for a particular class. If there is *S* number of subject available for the experiment, then we obtain *S* number of Gaussian membership curve for a particular feature entity in a class. We also consider the secondary membership to be Gaussian in nature where the mean and variance are computed using the information from upper membership (UMF) and lower membership function (LMF) [17]-[18].

There exists different kind of rules for type reduction [19] of a general type-2 fuzzy sets. When a feature vector with unknown class label is given to the system, we compute the type-1 membership value of a feature entity by the following mathematical expression,

$$\mu'_F(x) = \frac{\sum_{\forall \mu_F(x)} J(x, \mu_F(x)).\mu_F(x)}{\sum_{\forall \mu_F(x)} J(x, \mu_F(x))}, \quad (9)$$

where, $\mu_F(x)$ is the primary membership value of feature F at a value x and $J(x, \mu_F(x))$ is the secondary membership value of the primary membership $\mu_F(x)$. The summation is taken over all the primary membership values found from the *S* number of subjects between UMF and LMF. We find all of the membership values of all the features for all the classes and store them in matrix *F* whose rows are indicating the membership values of the features for a class and columns are indicating the membership value of a feature entity in all the classes.

After getting the matrix *F*, we find the average membership value in a particular by summing along the column of a matrix, expressed as,

$$\bar{\mu} = \frac{\sum_{\forall F} \mu'_F}{\#\ features} \quad (10)$$

The class with highest average membership value is the class corresponds to the unknown feature vector.

After determining the class, we now compute the load on each subject by the value of the average membership in a class.

III. Experimnts and Results

This section includes a brief description of fNIRS device used, experimental setup along with subject and stimuli details, and experiments: to i) extract fNIRS features, ii) select the most significant features from a large pool of extracted features, iii) detect cognitive load for easy, moderate and hard mental tasks, iv) compare the classifier performance and v) to validate classifier performance using McNemar's statistical test.

A. fNIRS Device

The experiment has been performed at Artificial Intelligence Lab, Jadavpur University, where the brain response of human subjects is captured using a popular brain-imaging device called fNIRS (Fig. 1). The selection of this device for the present problem is obvious because of its non-invasiveness, capability to localize and measure blood oxygenation, low-cost and portability [24]. It can be shown form Fig. 1(b) that fNIRS band that has been used in this experiment, comprising 4 infra-red (IR) light sources (sensors) and 10 detectors. The path from IR source to detector of an fNIRS device is termed as channels, which provides a measure of oxy-hemoglobin (HbO) and de-oxy-hemoglobin (HbR) blood concentration. Therefore, the present fNIRS band captures brain images from 16 channels when the band is attached to the forehead of human subjects during the experiment.

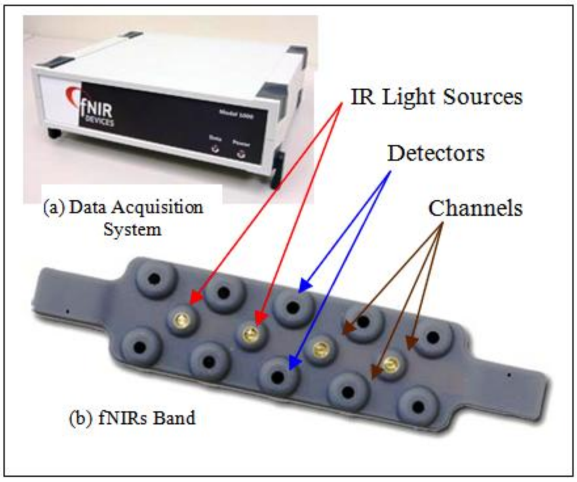

Fig. 1. fNIRS device to capture brain images during cognitive tasks

B. *Experimental Set-up*

Fig. 2 shows an experimental framework; where a subject is asked to perform mental mathematical/logical operations only by pointing the correct answer from a set of four options. fNIRS band is placed on her forehead to measure cerebral blood flow during the trial. Eight such healthy subjects of ages between 22 and 26 years are selected to perform the experiments. They are instructed to restrict their movement in order to avoid unwanted movement-related artifacts.

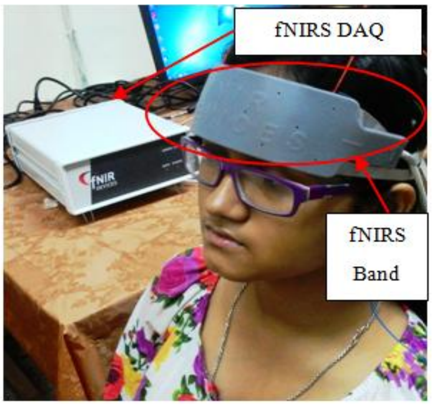

Fig. 2. A subject is performing cognitive tasks while brain images are captured using fNIRS device

An experimental trial contains five mental mathematical/logical problems, each of 20 seconds and a 5-second rest between each problem. For the present problem, three kinds of experimental trial have been prepared based on three difficulty levels: easy (E), moderate (M) and hard (H). Each subject has to perform each of these three trials for 7 times, resulting in 35 experimental instances for each difficulty level. The cognitive load of the subjects is also classified into three distinct levels including low, medium and high, depending on the difficulty levels: E, M and H respectively.

C. *Experiment 1: Feature Extraction*

Feature extraction (FE) is a very important step in pattern classification problem, since signals representing a specific pattern contains some primitive features that can best describe the pattern itself. In this experiment, we too select a list of features that can be used to extract necessary information from fNIRS data to detect the cognitive load of human subjects. We consider seven following feature sets.

(i) F_1: mean values of HbO concentration
(ii) F_2: mean value of HBR concentration
(iii) F_3: mean value of HbO + HbR concentration
(iv) F_4: mean value of HbO-HbR concentration
(v) F_5: standard deviation of HbO+HbR concentration
(vi) F_6: standard deviation of HbO-HbR concentration and
(vii) F_7: average slope of HbO-HbR concentration.

To perform FE, we start with fNIRS data acquired for three different levels of cognitive tasks: E, M and H. For each kind of difficulty level, we obtain HbO and HbR data, each having dimension of 35×16×40, where, 35 represents the number of experimental instances, 16 represents the number of channels of fNIRS and 40 represents the samples. To extract first feature set $F_{1,}$ we take mean of HbO data across samples recorded by each channel and obtain 16 features for each of 35 instances. Therefore, F_1 contains mean-HbO features having dimension of 35×16. In similar fashion, feature sets F_2-F_7 is prepared by determining their respective 16 features for 35 instances, which finally present a feature matrix of 35×112 dimension for each difficulty level.

A clear discrimination in concentration level from 16 channels has been observed for each feature set. For better understanding, we provide feature level discrimination between mean of HbO concentration determined from 16 channels, while the subject is performing cognitive tasks during one experimental trial. Fig. 3, 4 and 5 present the feature level discrimination between mean of HbO concentration determined from 16 channels for E, M and H levels respectively. It is evident from the figures that features become quite discriminating with the increase of the difficulty level while performing cognitive task.

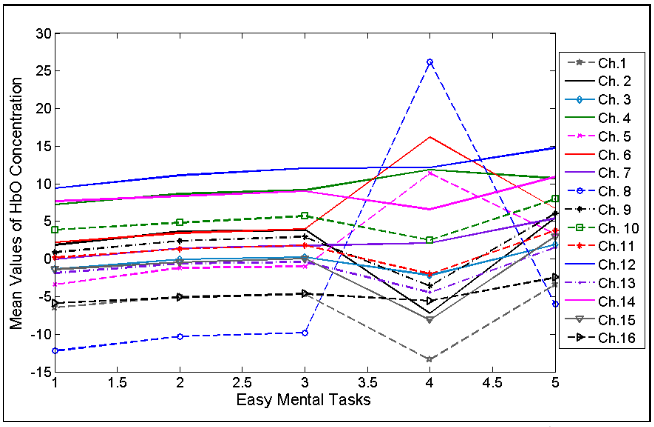

Fig. 3. Feature level discrimination between mean values of HbO concentration taken from 16 channels for easy cognitive tasks

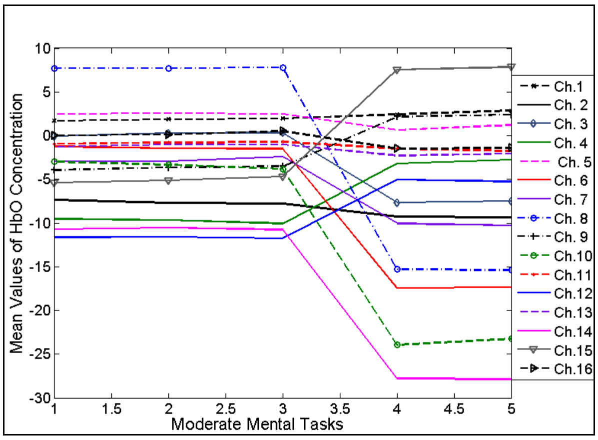

Fig. 4. Feature level discrimination between mean values of HbO concentration taken from 16 channels for moderate cognitive tasks

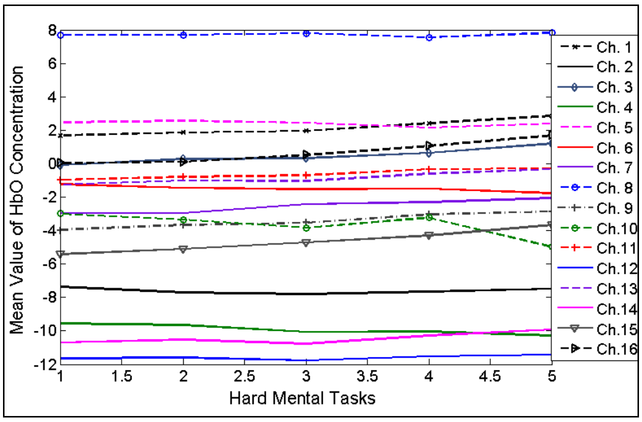

Fig. 5. Feature level discrimination between mean values of HbO concentration taken from 16 channels for hard cognitive tasks

Feature level discrimination has also been observed for the remaining six feature sets, when extracted for three difficulty levels. However, these graphs cannot be presented because of space complexity.

D. Experiment 2: Feature Selection

Selection of appropriate features is necessary to correctly classify any pattern recognition problem, if the extracted feature set is found significantly large. Having a large dimensional feature set (here, 112), this experiment also utilizes a DE-induced likelihood-based feature selection (FS) technique that optimally selects 25 most significant features for further classification.

The performance of the proposed FS technique is compared with the well-known principal component type-2 analysis (PCA), when the selected features are fed to the fuzzy classifier. Result is given in Table I, wherefrom it can be concluded from the table that the proposed FS technique provides better classification accuracy than PCA [25].

TABLE I: COMPARISON BETWEEN MEAN AND STANDARD DEVIATION OF FUZZY TYPE-2 CLASSIFIER WITH PCA BASED AND PROPOSED LIKELIHOOD BASED FS TECHNIQUE

Features Dimensions	Average Classifier Accuracy (in %)		Statistical Significance
	PCA + Fuzzy Type-2 Classifier	Proposed likelihood + Fuzzy Type-2 Classifier	
112 (Reduced to 25)	88.791 (0.01407)	**92.597 (0.01207)**	+

E. Experiment 3: Cognitive Load Detection for Different Difficulty Levels

This experiment deals with classification of cognitive load into three classes: low, medium and hard and also determine subjective load for E, M, and H levels of cognitive tasks. For this we determine fuzzy membership values for each level (class) of cognitive load: low, medium and hard. For a particular class, we quantified the range of fuzzy memberships (0,1] in three levels as shown in the Table II.

TABLE II: MEASUREMENT OF COGNITIVE LOAD ACCORDING TO AVERAGE FUZZY MEMBERSHIP VALUES

Range of Fuzzy Membership Values	**Cognitive Load**
0.0-0.3	Low
0.3-0.7	Medium
0.7-1.0	High

The membership ranges, as mentioned in Table II, are used to detect subjective load while the particular subject is offered easy, moderate and hard cognitive tasks one by one. The cognitive load for randomly selected four subjects are presented in Table III, which gives a clear indication that using the proposed technique, cognitive load differs subject to subject for the same degree of complexity.

TABLE III: SUBJECT WISE COGNITIVE LOAD DETECTION FOR 4 SUBJECTS CORRESPONDSTO TABLE II

Class / Subject	Load (In Alphabetic Form)		
	Easy	Moderate	Hard
1	Low	Medium	Medium
2	Medium	High	High
3	Low	Low	Medium
4	Medium	High	High

In order to detect cognitive load distribution of the subjects with increasing difficulty level, oxygenation level is captured from fNIRS and presented in Fig. 6 (a)-(d).

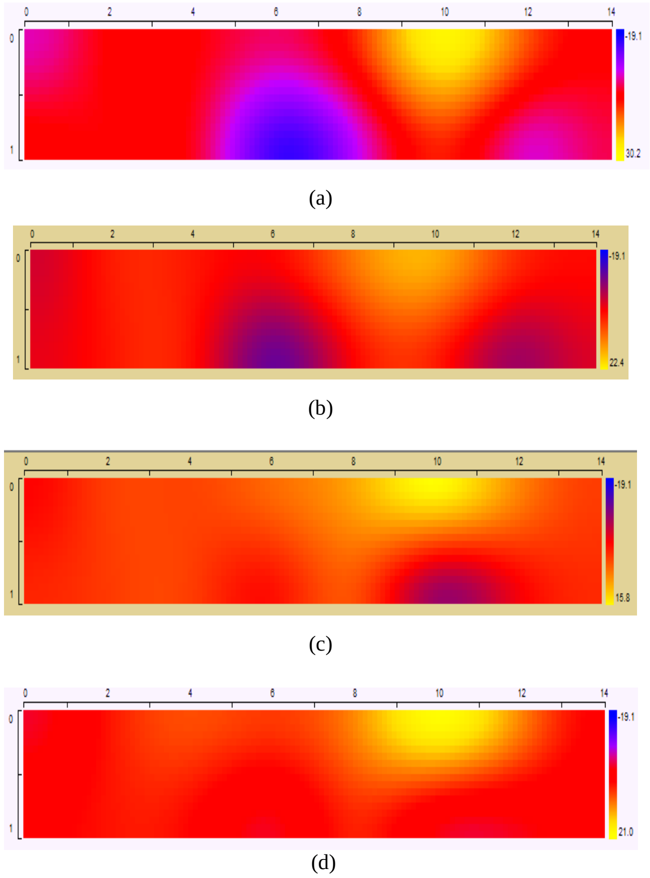

Fig. 6. Oxygenation level recorded from 14 sensor-detector pair. (a): inactive condition, (b): easy task, (c): moderate task, (d): hard task

From Fig. 6 (a)-(d), we can observe the change in oxygenated blood volume of a subject with the increase in difficulty level of a task. From the color bar shown in figure, it is clear that there is a high rise of brain activity with the increase in oxygenation, the highest of which is represented by yellow color, whereas the lowest brain activation is represented by blue color. Now, from fig. 6(a), it is evident that there requires less oxygenated blood during inactive (rest) situation. In addition, it is also prominent from fig. 6 (a) that in inactive situation, brain activity becomes low, which results in the appearance of blue region. Fig. 6 (b) shows the oxygenation level during easy task performance, where blue regions as well as its intensity tend to get lower. In fig. 6(c), difficulty level of the task becomes moderate, where the human brain needs to perform more activity, thus flow of oxygenated blood tends to get higher, so more reddish/yellowish region appears, whereas blue region decreases significantly. Lastly, Fig. 6 (d) shows the oxygenation for hard task. This task requires the highest brain activation, which is evident from only the red/yellow regions near the forebrain, and no de-oxygenation takes place.

F. Experiment 4: Proposed Classifier Performance

We have compared type-2 fuzzy classifier performance using proposed likelihood-based FS algorithm with linear support vector machine (LSVM) [26], k-nearest neighbor (kNN) [27] and support vector machine with radial basis function (SVM-RBF) [28] classifiers (Table IV). Table IV indicates that the proposed likelihood-based FS induced type 2 fuzzy classifier attains the highest classification accuracy (above 90% in each case) as compared to its standard competitors. The last column of the table represents statistical significance of the difference of the means of best two algorithms. Positive (+) significance means that if we use two-tailed test, then the t value of 49 degrees of freedom becomes significant at a 0.05 level of significance. Negative (-) significance indicates not statistically significant and 'NA' represents the cases for which two or more algorithms best accuracy results.

Table V provides the individual class performance by using confusion matrix of four different classes (easy, moderate, hard and inactivity) while implementing type-2 fuzzy classifier and proposed likelihood-based FS technique. Table V indicates that the classification accuracy for the individual class is high, over 90%.

TABLE IV: MEAN AND STANDARD DEVIATION OF CLASSIFIER ACCURACY USING PROPOSED LIKELIHOOD-BASED TECHNIQUE

Features Dimensions	Difficulty Level / Class	Average Classifier Accuracy (In %)				Statistical Significance
		L-SVM	KNN	SVM-RBF	Type-2 Fuzzy Classifier	
112 (Reduced to 25)	Easy	75.156 (0.01936)	77.431 (0.0)	83.174 (0.01493)	**93.797 (0.01949)**	+
	Moderate	72.309 (0.01584)	76.139 (0.01894)	80.197 (0.01346)	**92.647 (0.01719)**	+
	Hard	71.473 (0.01575)	73.164 (0.01795)	76.197 (0.01976)	**90.794 (0.01019)**	+
	Inactivity	74.794 (0.02941)	76.981 (0.01349)	76.197 (0.01976)	**93.147 (0.02009)**	+

TABLE V: CONFUSION MATRIX OF FOUR DIFFERENT CLASSES USING FUZZY TYPE-2 CLASSIFIER AND PROPOSED LIKELIHOOD-BASED FS TECHNIQUE

Predicted Class Actual Class	Easy	Moderate	Hard	Inactivity
Easy	**93.797**	2.458	1.0977	2.6473
Moderate	2.598	**92.647**	1.913	2.842
Hard	3.892	3.197	**90.794**	2.117
Inactivity	3.414	1.941	1.498	**93.147**

G. *Experiment 5: McNemar's Statistical Test*

McNemar's test [29] is one popular statistical test to compare the relative performance of the proposed algorithm with existing standard techniques. Here, we too apply McNemar's test to compare performance of the proposed likelihood-based feature selection induced type-2 fuzzy classifier with the above mentioned three standard classifiers including LSVM, kNN and SVM-RBF. The results of Mcnemar's test, as reported in Table VI depends on the value of the parameter *p*, where *p* indicates the estimated probability of rejecting the null hypothesis of a study question when that hypothesis is true. Table VI confirms that the proposed classifier outperforms all its competitors by a wider margin.

TABLE VI: STATISTICAL TEST

Classifier algorithm used for comparison (features:25)	REFERENCE ALGORITHM: LIKELIHOOD-BASED FS INDUCED TYPE-2 FUZZY CLASSIFIER	
	Z	p
L-SVM	36.257	p<0.00001
kNN	21.145	p<0.00001
SVM-RBF	7.145	p<0.00001

IV. CONCLUSIONS

This paper proposes an interesting approach to detect cognitive load of human subjects using fNIRS signal. Seven different feature sets are utilized here to identify right features to classify cognitive load. The fuzzy membership ranges have been defined to detect subjective load while the particular subject performs easy, moderate and hard cognitive tasks. Cognitive load distribution of the subject with increasing difficulty level is analyzed from the oxygenation level recorded using fNIRS device. It is clear from the experimental results that the proposed likelihood-based FS induced type 2 fuzzy classifier attains the highest classification accuracy (above 90% in each case) in comparison to its standard competitors including LSVM, kNN and SVM-RBF. Experiment also reveals that individual class performance (easy, moderate, hard and inactivity) by using type-2 fuzzy classifier and proposed likelihood-based FS technique is high, over 90%.

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