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RESEARCH ARTICLE

# Olfactory Perceptual-Ability Assessment by Near-Infrared Spectroscopy Using Vertical-Slice Based Fuzzy Reasoning

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**ABSTRACT** The paper introduced a novel approach for automatic assessment of olfactory perceptual-ability of human-subjects using a functional Near Infrared Spectroscopy device. The assessment requires fuzzy functional mapping from spectroscopic measurement to perceptual-ability using Type-2 fuzzy reasoning. The novelty of the work lies in Vertical Slice Based General Type-2 Fuzzy Reasoning which employs fuzzy meet and union between the planes of type-2 measurement and observation spaces using the classical definition of t-norms and s-norms. The results of the meet and the union computation are later used as the Lower and Upper Firing Strength of the fired rule to determine the structure of the inference. Experiments undertaken confirm the efficacy of the proposed technique over traditional functional mapping, involving neural networks, regression analysis, and the like. The proposed technique of olfactory perceptual-ability can be directly employed to determine the thresholds for recognition-probability and discrimination-probability, when submitted to the subject in presence of aromatic noise. An analysis is undertaken to measure the computational overhead, which is found of the order of $O(m.n)$ and run-time complexity of 94.78 ms, where $m$ and $n$ respectively represent discretizations in the vertical slice and features respectively. A statistical test undertaken confirms the superior performance of the proposed system with others at 95% confidence level.

**INDEX TERMS** Assessment of subjective olfactory perceptual-ability, type-2 fuzzy logic, functional near-infrared spectroscopy (f-NIRs), vertical-slice based generaltype-2 fuzzy reasoning.

## I. INTRODUCTION

Perception refers to the cognitive processes involved in understanding and interpreting stimuli [1]. Olfactory Perceptual-Ability is concerned with measuring the power/ability of recognizing and assessment of olfactory stimuli/aroma [2]. The paper attempts to extract the olfactory perceptual-ability of healthy/brain-diseased subjects using whole brain functional Near-Infrared Spectroscopy (f-NIRs). Because of possible introduction of noise from undesired neighborhood channels, the assessment of olfactory perceptual-ability is greatly influenced by noisy measurements [3]. The paper introduces Type-2 fuzzy logic to eliminate the possible noise induced uncertainty from the assessment of olfactory perceptual-ability.

The pre-frontal lobe and the frontal lobes in the human brain respectively are responsible for odor recognition and encoding in long-term memory [4], [5]. The paper aims at assessing the olfactory perceptual-ability of human subjects based on 2 experimentally determined parameters, hereafter called Recognition-probability and Discrimination-probability [6], [7]. Such study would have interesting

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applications in early diagnosis of people, suffering from the Alzheimer's disease [8], [9]. There exist traces of works on electroencephalography (EEG) based perceptual-ability assessment of odors [10]. However, until now there is hardly any work on functional Near Infrared Spectroscopic (f-NIRs) based assessment of odors. This paper attempts to develop one f-NIRs device driven hemodynamic response analysis and assessment of odors. The merit of using the f-NIRs device lies in better spatial resolution than EEG. In addition, run-time complexity of the f-NIRs based olfactory perceptual -ability assessment is smaller than its EEG counterpart [11].

The f-NIRs devices employed measure the change in oxygenated and deoxygenated blood response in the active brain regions due to olfactory stimulation [12], [13], [14], [15]. Thus the present research has 2-fold motivations. The first motivation is to recognize the olfactory stimuli presented to a subject from his/her oxygenated and deoxygenated brain response to the stimuli. This study in essence aims at determining sensitivity of the subject to an olfactory stimulus, when presented with aromatic noise (impurity) of different concentration levels. The first motivation has interesting applications in selecting people for tea/liquor industries, where flavor is an important ingredient for business. The second motivation of the present paper is to identify the brain regions involved in the decoding of olfactory stimuli. This would open up more biological insight on the role of different lobes/modules in the pre-frontal cortex in the process of recognizing olfactory stimuli.

The study is undertaken using an array of 8 sources and 8 detectors of the f-NIRs device, where the sources and detectors are mounted on the pre-frontal region of the subjects in a special arrangement, so that each detector is located within a vicinity of 30 mm from the source [16]. The sources are activated in a time-multiplexed mode, so that one source is on at a time while all other sources are off at the same time, ensuring that the detected response is due to a single source only. This helps identifying the active brain pathways between a source and a detector, indicating the brain location involved in the olfactory recognition process.

The f-NIRs response captured form a given source is not free from intra-subjective noise due to parallel thought processes, artifacts due to eye-blinking and/or non-voluntary motor activations by the subject. One approach to handle the intra-subjective variations in f-NIRs response at a given brain location is to employ a reasoning technique, capable of producing accurate results in identifying active brain lobes, even in presence of noise indicated above. Fortunately, the logic of fuzzy sets and in particular Type-2 fuzzy sets has shown remarkable performance in the past in handling the present situation. This inspired the authors to employ Type-2 fuzzy sets for the selected application.

It is important to mention here that there are two variants of type-2 fuzzy sets, called Interval Type-2 Fuzzy Sets (IT2FS) [17] and General Type-2 Fuzzy Sets (GT2FS) [18]. Although the variants have their own merits and demerits, we selected GT2FS induced perceptual-ability assessment for the following reasons. First, GT2FS-based reasoning employs consulting secondary membership functions of the antecedent propositions in a rule to arrive at a decision about the consequent. Later, the membership function of the inferred proposition is defuzzified to obtain a measure of the subjective olfactory perceptual-ability [19].

The original contribution of the paper lies in a new formulation of GT2FS based reasoning. The novelty in reasoning appears due to the incorporation of the following principles. First, in most of the type-2 research, the observation is represented by a given value $x'$ of the linguistic variable $x$. In the present context, the observation is a type-2 fuzzy set at primary and secondary membership plane for a given value of the linguistic variable. Such representation is required to instantiate the rules with multiple measurements in a session and multiple sessions in a day, which in turn is required for robust measurement for qualitatively better reasoning. Second, the GT2FS reasoning employed considers computation of fuzzy meet and union between the planes of type-2 measurement (undertaken in the training phase) and observation (undertaken in the test phase) spaces using the classical definition of t-norms and s-norms. The results of the meet and the union computation are later used as the Lower Firing Strength (LFS) and Upper Firing Strength (UFS) of the fired rules to determine the structure of the inference. Lastly the obtained inference is defuzzified by Karnik-Mendel Defuzzification algorithm and the defuzzified value is used as the measure of subjective perceptual-ability. The performance of the proposed GT2FS-based reasoning is compared with existing ones with respect to computational cost and run-time complexity. Statistical tests undertaken confirm the superiority of the proposed GT2FS-based reasoning with respect to the traditional ones.

The paper is divided into VII sections. In Section II, a schematic overview of the proposed principles of olfactory perceptual-ability assessment is introduced. Section III is concerned with GT2FS based type-2 fuzzy reasoning for perceptual-ability assessment. Section IV outlines one interesting technique for the assessment of olfactory perceptual-ability of a subject. Experimental details are covered in Section V. Performance analysis is undertaken in Section VI. Conclusions are listed in Section VII.

## II. PRINCIPLES AND METHODOLOGIES

Assessment of olfactory perceptual-ability includes: Data Acquisition and normalization of f-NIRs data, pre-processing and filtering, feature extraction, feature selection and perceptual-ability measurement using the selected features. Here, the pre-frontal lobe montage is employed to measure the changes in concentration of the oxy-hemoglobin and de-oxy hemoglobin at the given time point in each channels of the f-NIRs device. Fig. 1 provides an overview of the proposed scheme for olfactory perceptual-ability measurement.

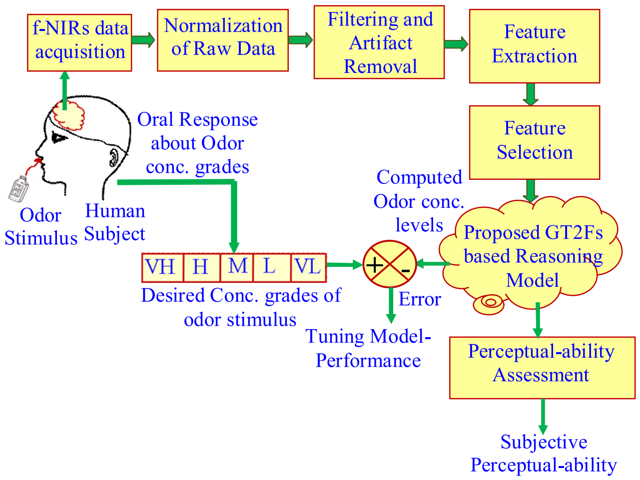



**FIGURE 1.** **Proposed block diagram to assess olfactory perceptual-ability of human subjects.**

### A. NORMALIZATION OF THE RAW DATA

Let us consider, 2 specific f-NIRs measurements, $\Delta_{HbO_\phi}(t)$ and $\Delta_{HbR_\phi}(t)$, respectively representing the increment in the oxygenated and deoxygenated blood concentration in the $\phi$-th channel at time instance $t$. It is well-known that in the Near-infrared spectra, $\Delta_{HbR_\phi}(t) < \Delta_{HbO_\phi}(t)$ holds well. So, normalization of $\Delta_{HbO_\phi}(t)$ and $\Delta_{HbR_\phi}(t)$ at a given channel $\phi$ requires computing the following 2 parameters:

$$\Delta_{HbO-\max} = Max_t(\Delta_{HbO_\phi}(t) : t_0 \leq t \leq T, \quad \forall\phi) \tag{1}$$

$$\Delta_{HbR-\min} = Min_t(\Delta_{HbR_\phi}(t) : t_0 \leq t \leq T, \quad \forall\phi) \tag{2}$$

where $t_0$ and $T$ indicate the beginning and the end time-point of an experimental trial for a selected stimulus on a given subject. The normalized value of the difference signal

$$\delta_\phi(t) = \Delta_{HbO_\phi}(t) - \Delta_{HbR_\phi}(t), \tag{3}$$

is computed by

$$\hat{\delta}_\phi(t) = \frac{(\Delta_{HbO_\phi}(t) - \Delta_{HbR_\phi}(t))}{\Delta_{HbO-\max}(t) - \Delta_{HbR-\min}(t)} \tag{4}$$

Now each session contains consecutive five trials with fixed duration of 15 seconds with a time-spacing of 5 seconds between two successive trials. The sampling rate of the f-NIRs device is 7.8 samples/sec [20]. Consequently, each trial includes $15 \times 7.8 = 117$ samples. Since the 15 seconds duration is divided into 3 time-windows, each window contains $117 / 3 = 39$ samples.

### B. PRE-PROCESSING AND FILTERING

The f-NIRs responses acquired are not free from artifacts. In fact, 3 distinct types of artifacts, such as i)physiological, ii) step and iii) spike artifacts often act as contaminations to f-NIRs data. Physiological artifacts contaminate f-NIRs response due to fluctuation heart-beat, Mayer wave, respiration and above all eye-blinking. Step artifacts induce f-NIRs data due to change in environment, such as lighting condition and also instrumental noise. Spike (also called, motion) artifacts come into play due to relative shift/decoupling in the location of optodes placed and their assigned positions on the scalp [21], [22], [23]. The last type often causes abrupt changes in the f-NIRs data. One common approach to eliminate artifacts is to employ a digital filter of desired pass-band. Here, a Chebyshev type Band-Pass Filter (BPF) [24], [25] of bandwidth 0.1 to 5 Hz is selected. The choice of the filter is fixed by its sharp roll-off around the selected cut-off frequencies. Finally, an Independent Component Analysis (ICA) [26] is undertaken to determine the 20 independent components of the f-NIRs response corresponding to 20 channels.

### C. FEATURE EXTRACTION

Next, the filtered 20 individual components are fed to the feature extraction module to extract the important set of features. The total 15 second duration of a trial is divided into 3 equal time-windows of 5 second each. Let, the normalized difference signal $\hat{\delta}_{i,\phi}(t)$ denote the $i$-th feature of the $\phi$-th channel for $i = 1$ to $n$ and $\phi = 1$ to $M$. Let T be the sampling interval. Then the discrete features $\hat{\delta}_{i,\phi}(t)$ is expressed as $\hat{\delta}_{i,\phi}(kt)$, for $k = 0, 1, 2, \ldots, K$. Two distinct types of features, called static and dynamic features, are used in the present context. The static features at fixed time points $t = kT$ for integer $k = 0, 1, 2, \ldots, (K-1)$ are listed below:

1) Signal mean ($m$) of HbO blood concentration,
2) Signal variance ($\sigma$) of HbO blood concentration,
3) Signal slope ($\tau$),
4) Skewness ($sk$) of HbO blood concentration,
5) Kurtosis ($ku$) of HbO blood concentration
6) Time to reach maximum value of HbO blood concentration from the onset of the stimulus,
7) Area under the normalized difference signal $\hat{\delta}_{i,\phi}(t)$,
8) Root Mean Square (RMS) value of HbO and
9) Average energy ($E$).

The dynamic features, on the other hand, are obtained by taking the difference of static features over successive sampling intervals [27]. For example, for the static feature $\hat{\delta}_{i,\phi}(kt)$, the dynamic feature $i$ from the $\phi$-th channel is obtained by

$$\Delta\delta_{i,\phi}(kT) = \hat{\delta}_{i,\phi}(kT) - \hat{\delta}_{i,\phi}((k-1)T) \tag{5}$$

for $i = 1$ to $n$ and $\phi = 1$ to $M$, $k = 0, 1, 2, \ldots, (K-1)$.

In the present application, we have $9 \times 3 = 27$ static features and $9 \times 2 = 18$ dynamic features. Consequently, we have $27 + 18 = 45$ features for each channel, thereby providing $M \times n = 20 \times 45 = 900$ features per individual subject. The product: $M.\ n$ being large enough, a feature selection algorithm is required to select fewer features from $M.\ n$ features.

### D. FEATURE SELECTION

Several interesting feature-selection algorithms are available in the current literature on pattern recognition [28]. Principal Component Analysis (PCA), for instance, is one of such algorithms that utilize the principles of linear independence of the eigen vectors of a real symmetric co-variance matrix constructed from the feature space of the given training instances. Among other well-known feature-selection algorithms, 2 popular techniques: Sequential Forward Search (SFS) and Sequential Backward Search (SBS) need special mentioning [29]. However these algorithms too are not free from all shortcomings. One fundamental limitation of these algorithms is Nesting effect, where features once selected in SFS (discarded in SBS) cannot be discarded (selected) once again. Additionally, none of these approaches optimally select the best set of features [30]. Evolutionary algorithms have shown promising applications in optimal feature selection with reference to the given criteria [31], [32]. This paper employs Differential Evolution (DE) algorithm to optimally select the top $N$ out of $n$ features with an aim to optimize the given criteria. The choice of DE is induced by the authors' previous experience of using the algorithm [31], [32] along with its high computational speed, fewer control parameters and faster convergence among the evolutionary and swarm class of algorithms.

The following 2 objective functions are optimized jointly in solving the DE-induced feature selection algorithm.

Let $f_{i,R,x}$ be the $i$-th feature of the $x$-th data sample belonging to class $R$, $f_{i,R,y}$ be the $i$-th features of the $y$-th data sample belonging to class $R$. Similarly, $f_{i,R',y}$ be the $i$-th features of the $y$-th data sample belonging to different class $R'$ where, $R' \neq R$. Let $N$ be the total number of features, $n$ be the reduced number of features with $n \leq N$. Here, $J_1$ be a measure of intra-class separation, and $J_2$ be a measure of inter-class separation.

$$J_1 = \sum_{\forall R} \sum_{\forall i} \sum_{\forall x} \left\| f_{i,R,x} - f_{i,R,y} \right\| \tag{6}$$

$$J_2 = \sum_{\forall i} \sum_{\substack{\forall R', \forall R \\ R' \neq R}} \sum_{\substack{\forall x \in R \\ \forall y \in R'}} \left\| f_{i,R,x} - f_{i,R',y} \right\| \tag{7}$$

Now, we need to maximize $J_2$ to maintain large inter-class separation, and minimize $J_1$ to reduce intra-class separation. Let $J$ be the composite objective function aiming at maximizing $J_2$ and minimizing $J_1$ jointly,

$$J = \frac{J_1}{\lambda + J_2} \tag{8}$$

where $\lambda$ is a positive component. A positive value of $\lambda$ in [0.01 10] is chosen to optimize $J$ using a meta-heuristic optimization algorithm. Although any meta-heuristic algorithm could have been employed to handle the problem, Differential Evolution algorithm has been selected here for its proven performance, such low computational overhead, small size and also our familiarity with the algorithm for around one decade. Finally, 20 best features (optimally selected) out of 900 extracted features are transferred to generate training instances of the proposed reasoning module.

### E. GENERATION OF TRAINING INSTANCES

Here, for each basic olfactory stimulus, 6 sessions per subject is considered, where each session includes 5 trials for healthy and brain-diseased persons. Consequently, for 25 healthy subjects we have 25 × 10 stimuli × 6 sessions/stimulus × 5 trials/session = 7500 training instances and for 5 brain-diseased person, 5 × 10 stimuli × 6 sessions/stimulus × 5 trials/session = 1500 training instances are generated, thereby yielding 7500 + 1500 = 9000 training instances. Further, 3 different levels of concentration is considered for each stimulus. Thus, a total of 9000 × 3 = 27000 training instances is generated to serve the purpose.

### F. TYPE-2 FUZZY REASONING FOR PERCEPTUAL-ABILITY ASSESSMENT

After feature selection is over, the f-NIRs features are fed to a Type-2 fuzzy reasoning module to determine the centroid of the Type-2 fuzzy inference. The centroid is a measure of odor concentration grade of the subject for a given olfactory stimulus.

## III. GT2FS BASED REASONING FOR PERCEPTUAL-ABILITY ASSESSMENT

This section provides detailed design of GT2FS based reasoning for the assessment of perceptual-ability from f-NIRs features during recognition and discrimination of aromatic substances.

### A. CONSTRUCTION OF TYPE-2 FUZZY MEMBERSHIP FUNCTION

Let $f_1, f_2, \ldots, f_n$ be $n$ features for the proposed reasoning problem and $y_j$ is a measure of odor concentration of a selected aroma by a given subject. Let $f_i$ is $\widetilde{A}_i$ be a fuzzy proposition used to build up the antecedent part of the fuzzy rule $j$, and $y_j$ is $B_j$ is a fuzzy proposition to develop the consequent of the same rule. Here, $\widetilde{A}_i$ for $i = 1$ to $n$ are vertical slice based GT2FS given by $< f_i, \mu_{\widetilde{A}_i(f_i)}(u) >$, where $\mu_{\widetilde{A}_i(f_i)}(u)$ is the vertical slice at a given $f_i$ for $m$ discretizations $u_1, u_2, \ldots, u_m$ along the $u$-axis. Similarly, $\widetilde{B}_j$ is a vertical slice based GT2FS consequent given by $< y_j, \mu_{\widetilde{B}_j(y_j)}(u) >$. The vertical slices GT2FS $\widetilde{A}_i$ and $\widetilde{B}_j$ are obtained from 6 sessions in a day, where each session includes 5 trials, thereby obtaining 30 instances in a day.

To construct $\widetilde{A}_i$, 30 daily samples of feature $f_i$ collected over 10 days. Let the measurement $l$ of $f_i$ on day $v$ be denoted by $f_{i,l,v}$. Thus for $l = 1$ to 30, we obtain the mean

$$\bar{f}_{i,v} = \frac{\sum_{l=1}^{30} f_{i,l,v}}{30} \tag{9}$$

and variance

$$\sigma_{i,v}^2 = \frac{\sum_{l=1}^{30} (f_{i,l,v} - \bar{f}_{i,v})^2}{30} \tag{10}$$

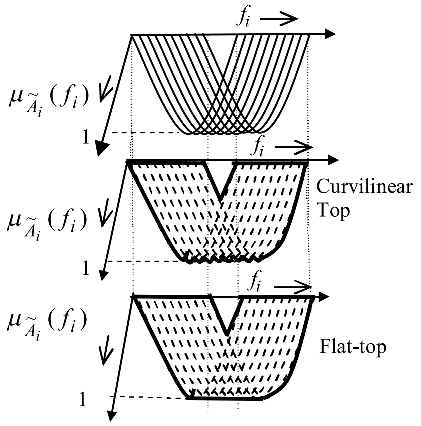



**FIGURE 2.** Construction of T2FS. (a) Type-1 MFs for ten days, (b) Computing union of Type-1 MFs, (c) Flat top approximation of fig. (b).

to construct one type-1 Gaussian MF: $A_{i,v}$, for $v = 1$ to 10. A vertical slice based GT2FS is constructed using type-1 $A_{i,v}$, $v = 1$ to 10 by the following 2 steps.

1) First a footprint of uncertainty (FOU) [33] is constructed for $\widetilde{A}_i$ with Lower Membership Function (LMF) and Upper Membership Function (UMF) obtained by

$$LMF = \underline{\mu}_{\widetilde{A}_i}(f_i) = \underset{\forall v}{Min}(\mu_{A_{i,v}}(f_i)), \quad (11)$$

$$UMF = \overline{\mu}_{\widetilde{A}_i}(f_i) = \underset{\forall v}{Max}(\mu_{A_{i,v}}(f_i)). \quad (12)$$

In order to maintain the convexity criteria of the proposed GT2FS, the peaks of the constituent type-1 MFs are joined with a straight line of zero slope, resulting in a flat-top approximation [34] (Fig. 2(a-c)).

2) Now, at the measurement points $f_i = f_i'$, an isosceles triangle with peak $= 1$ is drawn to represent $\mu_{\widetilde{A}_i(f_i')}(u)$, the secondary plane.

For construction of $\widetilde{B}_j$, the concentration grade of the odor stimulus obtained from the oral response of the subject is evaluated from each session comprising 5 trials, and thus for 6 sessions in a day, 6 measures of concentration grades are available [35]. A Gaussian type-1 MF is constructed with mean and variance respectively as the mean and variance of 6 oral responses. Thus for 10 days, 10 such type-1 Gaussian MFs are available, which are used to develop an IT2FS like the one presented to construct the IT2FS $\widetilde{A}_i$.

Now, for construction of the vertical slice GTFS with the observed data, the experiment includes $g$ sessions, each containing $h$ trials for feature $f_i$ for $i = 1$ to $n$, where all sessions are taken on the same experimental day. A type-1 Gaussian MF $A'_{i,j}$ is computed for each session $j$ with mean $\mu'_{i,j}$ and variance $\sigma^2_{i,j}$. Next a GT2FS $\widetilde{A}'_{i,j} = G(\mu'_{i,j}, \sigma^2_{i,j})$ is constructed for $j = 1$ to $s$ using steps similar to adopted for construction of vertical slice GT2FS from measured data.

The vertical slice $\widetilde{A}'_i =< f_i, \mu_{\widetilde{A}'_i(f_i)}(u) >$ formed is expected to have small spread along the $u$-axis as the data samples are collected on the same day.

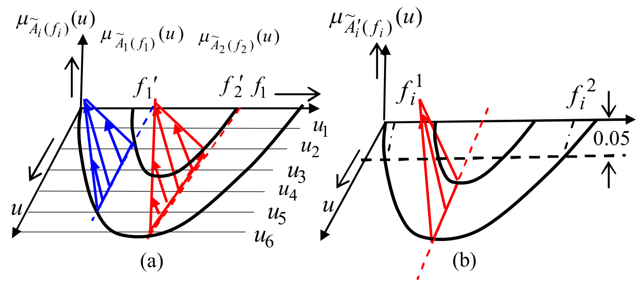



**FIGURE 3.** Construction of the vertical slice GT2FS with the (a) measured data and (b) observed data.

## B. SECONDARY MEMBERSHIP COMPUTATION

The following steps are adopted to evaluate the secondary membership functions.

1. Due to the centre of the footprint of uncertainty (FOU) yields maximum certainty, thus the secondary membership $\mu_{\widetilde{A}_i(f_i')}(u_{mid})$ have a peak ($\approx 1$) at the center, where $u_i = u_{mid} = (\overline{u}_i + \underline{u}_i)/2$, here $u_i$ be the primary membership at a given measurement point $f_i = f_i'$, lying within the FOU, whereas, $\overline{u}_i$ and $\underline{u}_i$ are the maximum and minimum values of primary membership $u_i$ lying on the FOU.
2. The secondary membership $\mu_{\widetilde{A}_i(f_i')}(u_i)$, exponentially decaying towards the boundaries of the FOU from its centre. The rate of decay is controlled by a parameter $\eta > 0$. Formally,

$$\mu_{\widetilde{A}_i(f_i')}(u_i) = \mu_{\widetilde{A}_i(f_i')}(u_{mid}).\exp(-\eta\,|u_{mid} - u_i|), \quad (13)$$

for $\overline{u}_i \leq u_i \leq \underline{u}_i$. The value of controlling parameter $\eta$ is selected adaptively by computing the difference between odor concentration grade obtained from the proposed model and verbal response of the subject-evaluated score about odor concentration grade (Fig. 3(a)).

## C. ARCHITECTURE OF GT2FS BASED REASONING

Consider one typical rule $j$ to compute the recognition-ability aroma $j$ given by If $f_1 is \widetilde{A}_{1,j}, f_2 is \widetilde{A}_{2,j}, \ldots, f_{n,j} is \widetilde{A}_{n,j}$, Then $y$ is $\widetilde{B}_j$. Let $\mu_{\widetilde{A}_i(f_i)}(u)$ be the vertical plane at linguistic variable $f_i$ for the primary membership u in the GT2FS $\widetilde{A}_i$ for the fuzzy proposition: $f_i$ is $\widetilde{A}_i$ . The fuzzy reasoning module attempts to derive type-2 fuzzy inference $y$ is $\widetilde{B}_j$, indicating the oral scores of olfactory stimulus for known MFs of the measurements: $f_i$ is $\widetilde{A}_i$ for all $i$.

Let $f_1 = f_1', f_2 = f_2', \ldots, f_n = f_n'$ be a measurement point. The secondary grade of membership at $f_i = f_i'$ is a vertical slice, represented by an isosceles triangle (Fig.3 (a)). In other words, the triangular vertical plane contains a set of type-2 MFs $\mu_{\widetilde{A}_i(f_i')}(u)$ for $u = u_1, u_2, \ldots, u_m$. It is noted that, in the present application the value of m is selected optimally as a used-defined positive integer. Let $\mu_{\widetilde{A}'_i(f_i')}(u)$ be the observed MF for $i = 1$ to n features. For selection of $f_i = f_i'$, $i = 1$ to n, first the end-points of the UMF are identified satisfying the following criterion. Let $f_i = f_i^1$ and $f_i^2$ be the 2 end-points, such that $UMF_i(f_i^1) = UMF_i(f_i^2) = th$, where the threshold $th = 0.05$ is selected optimally (Fig.3(b)). For optimal selection of th, Evolutionary algorithm is employed to maximize the accuracy of the proposed model. The location of the vertical plane is fixed at $f_i = f_i' = (f_i^1 + f_i^2)/2$. This is repeated for $i = 1$ to n.

The following steps are adopted for automated reasoning using vertical slice based general type-2 fuzzy sets.

1. Obtain the fuzzy meet operation between $\mu_{\widetilde{A}_i(f_i')}(u)$ and $\mu_{\widetilde{A}_i'(f_i')}(u)$ for $i = 1$ to $n$. The fuzzy meet operation computes the t-norm of $\mu_{\widetilde{A}_i(f_i')}(u)$ and $\mu_{\widetilde{A}_i'(f_i')}(u)$ for a given feature $i$, $\forall u \in \{u_1, u_2, \ldots, u_m\}$, and saves the result in a set $P_i$, where

$$P_i = \{\mu_{\widetilde{A}_i(f_i')}(u) \cap \mu_{\widetilde{A}_i'(f_i')}(u) : \forall u \in \{u_1, u_2, \ldots, u_m\}\} \quad (14)$$

2. Next, a set $S_1$ is constructed, where

$$S_1 = \{p_1 t p_2 t \ldots t p_n | p_1, p_{2,\ldots,} p_n \in P_1 \times P_2 \times \ldots \times P_n\}, \quad (15)$$

for $p_i \in P_i$ for $i = 1$ to $n$ and $t$ denotes the t-norm operation. Here, $p_1 t p_2 t \ldots t p_n$ denotes a cumulative t-norm computed pair-wise in order from the left to the right.

3. Similarly,

$$S_2 = \{p_1 s p_2 s \ldots s p_n | p_1, p_{2,\ldots,} p_n \in P_1 \times P_2 \times \ldots \times P_n\} \quad (16)$$

is computed, where $s$ denotes the s-norm operation and $p_i \in P_i$ for $i = 1$ to $n$. Here, $p_1 s p_2 s \ldots s p_n$ denotes a cumulative s-norm computed pair-wise in order from the left to the right.

4. Lastly, the largest element from $S_1$, called the Greatest Lower Bound (GLB), and the smallest element from $S_2$, called the Least Upper Bound (LUB) are computed for the $j$-th fired rule as follows.

$$GLB_j = p_1' t p_2' t \ldots t p_n' \quad (17)$$

where, $p_1' t p_2' t \ldots t p_n' \geq p_1 t p_2 t, \ldots t p_n \in P_1 \times P_2 \times \ldots \times P_n$ and

$$LUB_j = p_1'' s p_2'' s \ldots s p_n'' \quad (18)$$

where $p_1'' s p_2'' s \ldots p_n'' \leq p_1 t p_2 t, \ldots t p_n \in P_1 \times P_2 \times \ldots \times P_n$.

5. Finally, Lower Firing strength (LFS) and Upper Firing strength (UFS) for the $j$-th fired ruleare defined as in (19) and (20) respectively.

$$LFS_j = Min(LUB_j, GLB_j), \quad (19)$$
$$UFS_j = Max(LUB_j, GLB_j). \quad (20)$$

### D. TYPE-2 FUZZY (T2FS) INFERENCE GENERATION

Given a consequent GT2FS $\widetilde{B}_j$, the inference generation involves 2 main steps.

1. a) A type-reduction is performed from GT2FS to IT2FS by taking the product of primary membership $u$ and secondary membership $\mu_{B_j(y_j')}(u)$ for all $u$ lying inside the FOU for a given value of $y_j = y_j' \in Y_j$, thus producing a set $S_j$, as in (19).

$$S_j = \left\{u.\mu_{\widetilde{B}_j(y_j')}(u) \middle| u \in J_{y_j} = \{u_1, u_2, \ldots, u_m\} \subseteq [0, 1], \text{for} \, y_j = y_j', \quad \forall y_j \in Y_j\right\} \quad (21)$$

b) Identify the positive elements of $S_j$ (by dropping zero elements) and call the resulting set $S_j'$.

$$S_j' = \{s_j \in S_j | s_j > 0\} \quad (22)$$

c) Compute the Revised Upper Membership Function (*R-UMF*) and Revised Lower Membership Function (*R-LMF*) of the consequent Fuzzy Set for Rule $j$ at $y_j = y_j'$ by taking the smallest and the largest element of set $S_j'$.

$$R - UMF(y_j') = \overline{\mu}_{\widetilde{B}_j'} = \text{largest element in } S_j' \quad (23)$$
$$R - LMF(y_j') = \underline{\mu}_{\widetilde{B}_j'} = \text{Smallest element of} S_j'. \quad (24)$$

The R-UMF and R-LMF are shown by firm lines in Fig. 4.

2. Compute the following transformation to obtain the resulting IT2MF $\widetilde{B}_j' = [\underline{\mu}_{\widetilde{B}_j'}, \overline{\mu}_{\widetilde{B}_j'}]$, where

$$\underline{\mu}_{\widetilde{B}_j'} = \min(LFS_j, \underline{\mu}_{\widetilde{B}_j}) \quad (25)$$

and

$$\overline{\mu}_{\widetilde{B}_j'} = \min(UFS_j, \overline{\mu}_{\widetilde{B}_j}) \quad (26)$$

7. Now for multiple firing rules, the union of the type-2 fuzzy interfaces is given by

$$\mu_{\widetilde{B}'} = \bigcup_{\forall j} \mu_{\widetilde{B}_j'}, \quad (27)$$

where, the inferred IT2MF $\widetilde{B}_j' = [\underline{\mu}_{\widetilde{B}_j'}, \overline{\mu}_{\widetilde{B}_j'}]$, is

$$\overline{\mu}_{\widetilde{B}'} = \max_{\forall j}(\overline{\mu}_{\widetilde{B'}_j}) \quad (28)$$
$$\underline{\mu}_{\widetilde{B}'} = \min_{\forall j}(\underline{\mu}_{\widetilde{B'}_j}) \quad (29)$$

8. Next, to evaluate the left and right end point centroids, we perform the well-known Enhanced Karnik-Mendel (EKM) defuzzification technique [36]. Finally, the centroid ($C$) is measured by taking the average of $C_{lower}$ and $C_{upper}$, where $C_{lower}$ be the left end point centroid and $C_{upper}$ be the right end point centroid.

$$C = \frac{C_{lower} + C_{upper}}{2} \quad (30)$$

Here, the centroid $C$ is represented as the quantitative grades of odor concentration in [0, 100] scales, which is perceived by the subject. The architecture of the proposed Vertical-Slice based GT2Fs model is illustrated in Fig. 4.

An error metric for aroma $R$ of a subject is evaluated by $E_R = |D_R - C_R|$ for optimal parameter selection in the training phase and to compare the relative merit of the proposed type-2 fuzzy technique with the state-of the-art techniques in the test phase. Here, $D_R$ be the desired concentration grade obtained from the oral response of a subject about the perceived concentration grade of a given odor stimulus $R$ and $C_R$ be the computed odor concentration grade obtained from the GT2Fs based reasoning model.

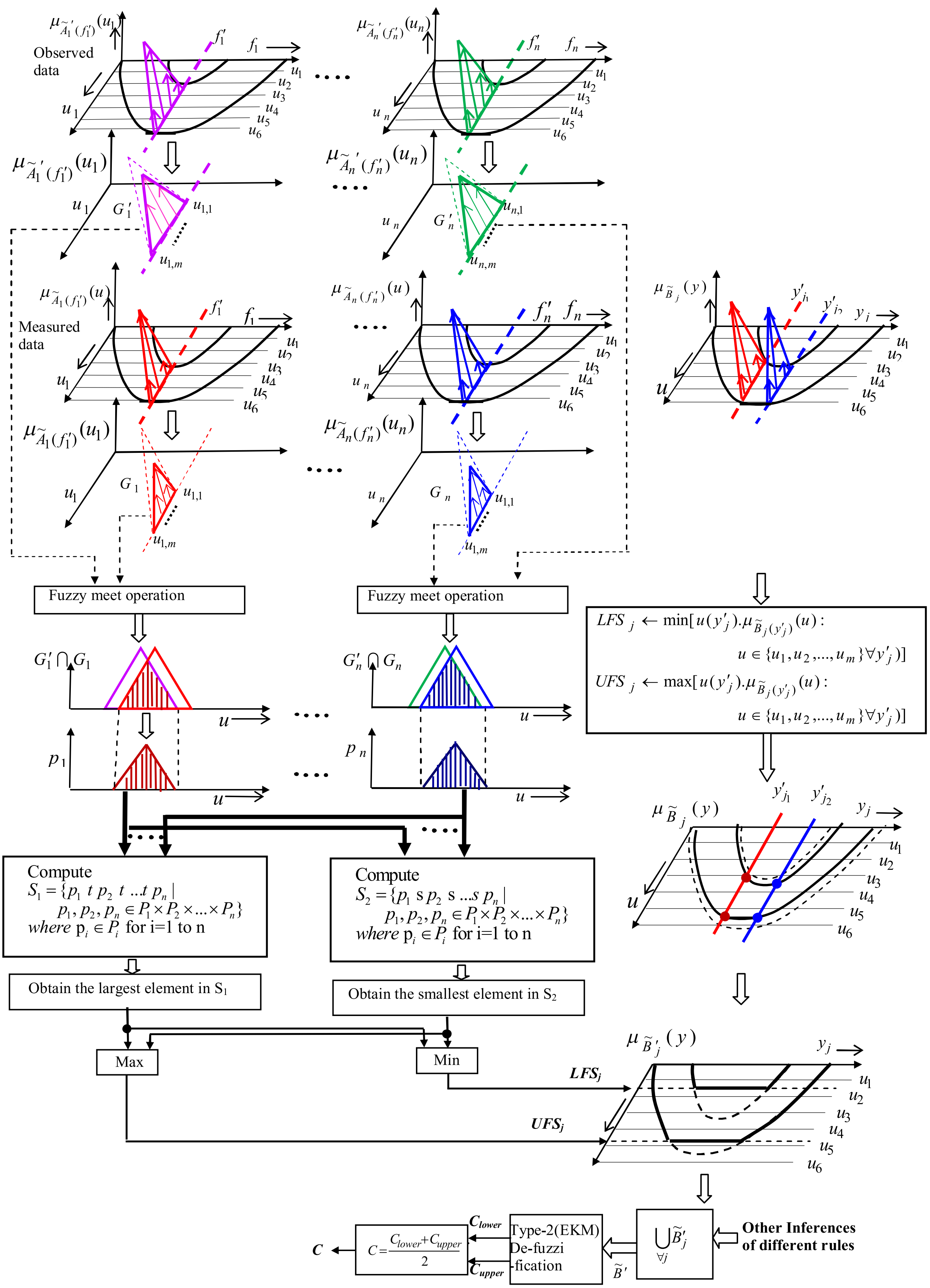



**FIGURE 4.** Inference generation for the proposed GT2FS based reasoning.

### 1) TIME-COMPLEXITY

The computation of the upper and lower firing strength is done by 2 ways. The first step we compute the largest value of $p_1tp_2t \ldots tp_n \forall u_m$ and the smallest value of $p_1sp_2s \ldots sp_n \forall u_m$ which requires the computational cost of $O(m.n)$ for s-norm computation and a complexity of $O(m)$ for t-norm complexity [19]. Here, $n$ denotes the number of linguistic variables in the antecedent and $m$ denotes the number of discretization along the $u_i$ axis. So the total computational cost of the above process is $O(m.n) + O(m) \approx O(m, n)$

### E. OPTIMAL PARAMETER SELECTION OF GT2FS REASONING MODEL

Parameter selection is here performed by a grid search algorithm [35] (Fig. 5). First, a random selection of parameters: $m$, $\eta$, $th$ and $\lambda$ in user-defined ranges: $m \in [4, 10]$, $\eta \in [0.1, 0.8]$, $th \in [0.02, 0.08]$, $\lambda \in [0.01, 0.09]$ is performed to initialize the feature selection and Vertical slice based GT2FS reasoning in order. An error metric $E_R = D_R - C_R$ for a given stimulus $R$ is computed, where $D_R$ be the oral response of the subject about concentration of the stimulus, and $C_R$ is the computed response by the GT2FS reasoning and defuzzification for the same stimulus. The process of feature selection, GT2FS reasoning and error estimation is continued for all stimuli $R$, and a metric $J = (\sum_{\forall R} E_R^2)^{1/2}$ is evaluated. The $J$ obtained for the current choice of parameter set is compared with previous $J$ obtained for the last assigned parameter set. The parameter set obtained for the smaller $J$ is saved. The above process is repeated for finitely large number of iterations $i_{\max}(= 10^4$, say). Finally, when iteration $i$ attains $i_{\max}$, the optimal parameters are recorded for on-line testing later.

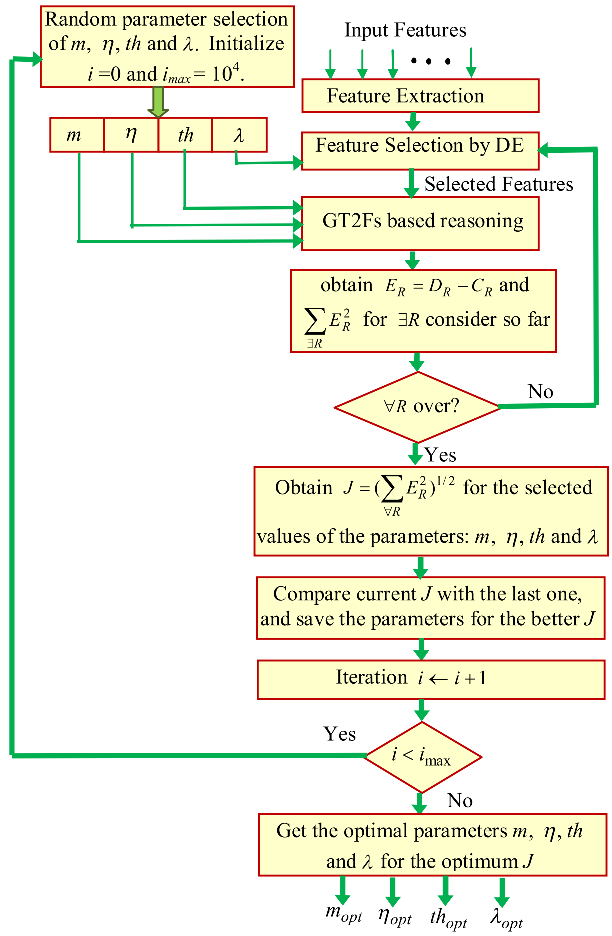



**FIGURE 5. Schematic Overview of the proposed grid search algorithm to obtain the optimal parameters *m*, $\eta$, *th* and $\lambda$ for the optimum *J*.**

## IV. OLFACTORY PERCEPTUAL-ABILITY ASSESSMENT

In this section we develop a measure of perceptual-ability in terms of recognition-probability and discrimination-probability.

### A. RECOGNITION PROBABILITY

Let $C$ be the centroid of the inferred type-2 MF, representing the model response about the concentration grade of the odor stimulus percieved by the subject and $\rho$ be the actual concentration of the aromatic substance presented to the subject. The following conditional probabilities are defined to measure the subjective perceptual-ability of a person with a minimum value $\alpha$ assuming that the concentration $\rho$ of the aromatic substance is limited to $\beta$.

$$P(C \geq \alpha | \rho \leq \beta) = \frac{p((C \geq \alpha) \cap (\rho \leq \beta)}{P(\rho \leq \beta)} \tag{31}$$

where

$$P((C \geq \alpha) \cap (\rho \leq \beta) = \frac{\frac{n(S_1|s_1 \in S_1 \text{ satisfying } C \geq \alpha \text{ and } \rho \leq \beta \text{ jointly})}{\text{Total no of points in} S}}{\frac{n(S|s \in S \text{ satisfying } \rho \leq \beta)}{\text{Total no of points in } S}}$$

$$= \frac{n(S_1|s_1 \in S_1 \text{ satisfying } C \geq \alpha \text{ and } \rho \leq \beta \text{ jointly})}{n(S|s \in S \text{ satisfying } \rho \leq \beta)} \tag{32}$$

and $n(S)$ and $n(S_1)$ are the cardinality of the sets $S$ and $S_1$ satisfying the selected conditions.

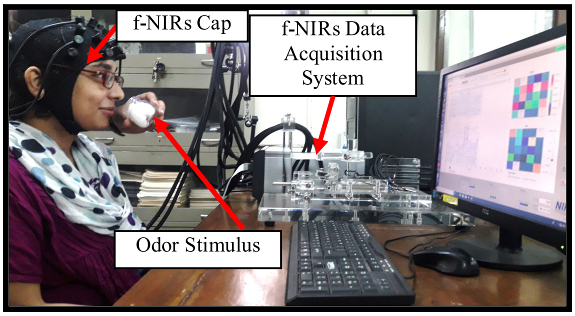
### B. DISCRIMINATION PROBABILITY

Let $\gamma$ be the concentration in parts per million (ppm) of an impurity added to an aromatic substance. A probabilistic measure is defined below to estimate the perceptual-ability of the subject in presence of impurity. Formula (31) provides an estimate of perceptual-ability $C$ with a minimum value alpha, assuming that the concentration of the aromatic impurity is less than a threshold $\beta$.

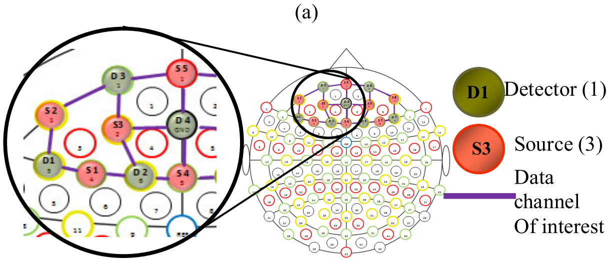
$$P(C \geq \alpha | \gamma \leq \beta) = \frac{P((C \geq \alpha) \cap \gamma \leq \beta}{P\gamma \leq \beta} \tag{33}$$

where

$$P((C \geq \alpha) \cap (\gamma \leq \beta) = \frac{\frac{n(S_2|s_2 \in S_2 \text{ satisfying } C \geq \alpha \text{ and } \gamma \leq \beta \text{ jointly})}{\text{Total no of points in } S}}{\frac{n(S|s \in S \text{ satisfying } \gamma \leq \beta)}{\text{Total no of points in} S}}$$




(a)




(b)

| | | | | |
|---|---|---|---|---|
| 2 - 3 | 5 - 3 | | 5 - 6 | 8 - 6 |
| 2 - 1 | 3 - 3 | 5 - 4 | 6 - 6 | 8 - 7 |
| | 3 - 4 | | 6 - 4 | |
| 1 - 1 | 3 - 2 | 4 - 4 | 6 - 5 | 7 - 7 |
| 1 - 2 | 4 - 2 | | 4 - 5 | 7 - 5 |

(c)

**FIGURE 6. (a) Experimental set-up, (b) source detector connection of pre-frontal_8 × 8 montage (c) Channel setup for pre-frontal lobe montage.**

$$= \frac{n(S_2|s_2 \in S_2 \text{ satisfying } C \geq \alpha \text{ and } \gamma \leq \beta \text{ jointly})}{\text{n}(S|s \in S \text{ satisfying } \gamma \leq \beta)} \tag{34}$$

In case ($\rho \leq \beta$) and ($\gamma \leq \beta$) are independent, the composite probability:

$$P(C \geq \alpha|\rho \leq \beta and \gamma \leq \beta)$$
$$= P(C \geq \alpha|rho \leq \beta) \times P(C \geq \alpha|\gamma \leq \beta) \tag{35}$$

holds. This formula provides the basis of perceptual-ability with a minimum value $\alpha$ assuming that $\rho$ of the aromatic substance is limited to $\beta$ and impurity of the aromatic noise $\leq \gamma$.

To assess the perceptual-ability of subjects, the $\beta$ is fixed up to a moderate finite value $\beta_{\min}(=10)$, selected optimally from various experimental events, and a suitable value of $\alpha$ is determined, so as to obtain a constant area in the fixed number of $v$ days' data by the left topmost rectangle, representing $\beta <$ 10 and $\alpha$ above a threshold $\alpha^{th}$. Here, the importance is to find $\alpha_{\min}$ for each subject. Thus subjects may be ranked in ascending order of $\alpha_{\min}$.

## V. EXPERIMENTS AND RESULTS

This section attempt to designing the following experiments of the olfactory perceptual-ability assessment of human subjects using the f-NIRs device. Experiment 1 deals with Hemodynamic response analysis for increasing concentration of aromatic substance. Experiment 2 provides automatic feature extraction for different concentration level of the olfactory stimulus. Experiment 3 provides the sensitivity analysis of the model parameters. Experiment 4 aims at perceptual-ability assessment of a subjects.

### A. FNIRS DATA ACQUISITION AND EXPERIMENTAL FRAMEWORK

The experiments on the assessment of olfactory perceptual-ability of a subject have been conducted in Artificial Intelligence laboratory of Jadavpur university, Kolkata, India. The whole brain f-NIRs (NIRScout$^{TM}$ imager) device, manufactured by NIRx Medical Technologies LLC, is used to capture the hemodynamic response of the subject. The whole brain f-NIRs data acquisition system and the experimental setup is shown in Fig. 6(a). The f-NIRs device contains 8 infrared (IR) sources and 8 infrared detectors to acquire the brain response of a subject during olfactory stimulation [35]. The combination of 8 source and 8 detectors forms $8 \times 8 =$ 64 data channels, among them, 20 channels are utilized for data acquisition, followed by nearest neighboring source-detector combinations according to 10-10 optode placement strategy. Fig. 6(b) shows the Topographic layout and the source-detector arrangement of the pre-frontal lobe. Fig. 6(c) identifies the possible combination of channels. For example, the channel 2-3 represents the IR pathway from source 2 to detector 3, and is positioned at the top left corner in the topographic layout.

### B. PARTICIPANTS

Thirty volunteers, in the age group of 20-45 years, participated in the experiment [37], [38] after maintaining all safety measures according to Helsinki declaration received in 2004 [49]. The participants include 25 healthy subjects with age below 45 years and 5 are suffering from the olfactory disorder. Among them 2 are suffering from Hyposmia (indicating reduced ability to detect odors), one from Anosmia (having complete inability to detect odors) and two from Parosmia (having inability to detect distorted odors).

### C. STIMULUS PRESENTATION FOR ORDER CLASSIFICATION

Each subject is advised to take a comfortable resting position to avoid possible pick-ups of muscles artifacts [39]. The experiment comprises three sessions, with three trials per session. Each odor is presented for 15 second duration with 3 different concentration levels (Low, Medium and High). Ten distinct smell stimuli (Rose water, Male perfume, Cumin seeds, coriander seeds, Coco powder, Sandal wood powder, Camphor oil, Eucalyptus oil, Hydrogen sulphide, Ammonia) have been used in various concentration values (High, medium and low). Next to assess the discriminating-ability of the basic aromatic substance in presence of aromatic noise the noise amplitude is gradually increased, so as to determine the threshold amplitude of noise at which the subject fails

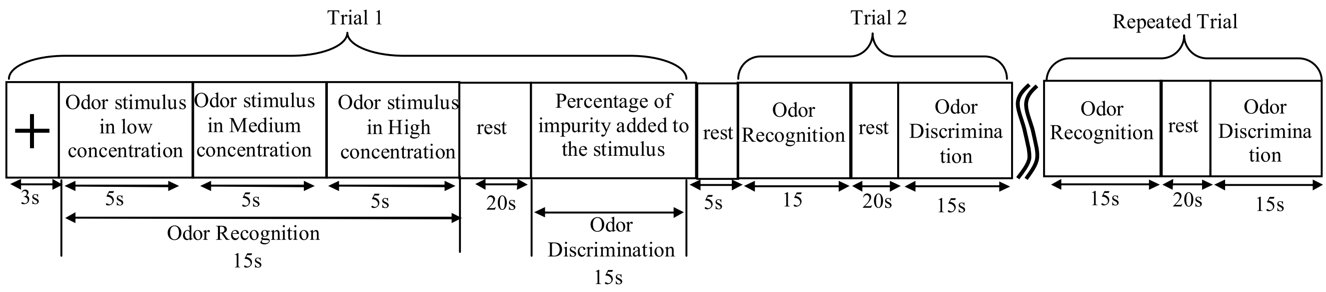



**FIGURE 7.** **Structure of the stimulus used with timing for olfactory perceptual-ability assessment.**

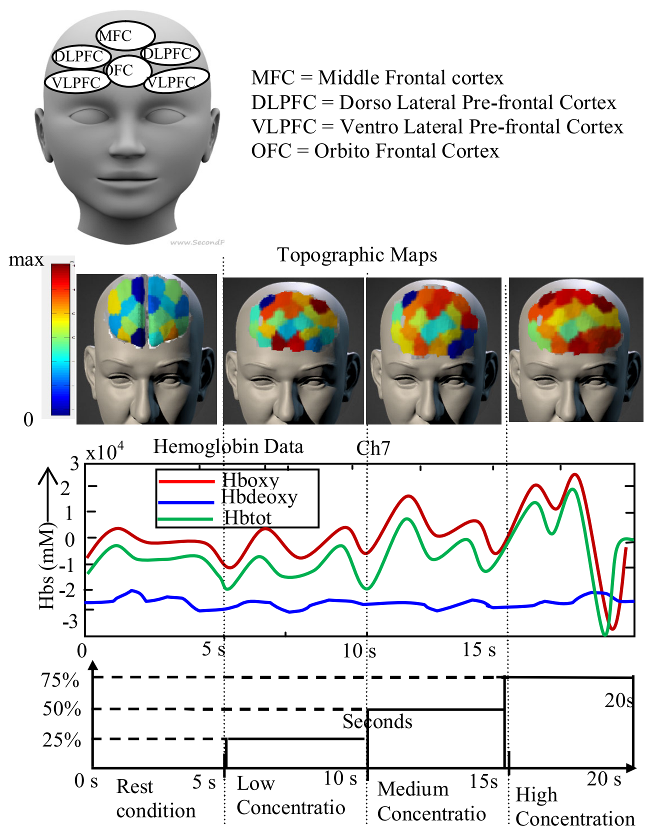



**FIGURE 8.** **Hemodynamic parameters and the topographic maps obtained during the different concentration levels of aromatic substance.**

to recognize the base olfactory stimulus. Experiments are conducted over 30 subjects and the threshold values of noise are determined for each subject for each pair of base and noisy aromatic stimuli. Fig.7 illustrates one sequence of olfactory stimuli.

### *D. EXPERIMENT 1: (HEMODYNAMIC RESPONSE ANALYSIS FOR INCREASING CONCENTRATION OF AROMATIC SUBSTANCES)*

This experiment attempts to determine the effect of increasing concentration of the solid (liquid) aromatic substance in gm/cc (gm/ml). The experiment begins with rest condition, before presentation of an aromatic stimulus. The rest period is continued for 5 seconds. After these 5 seconds,

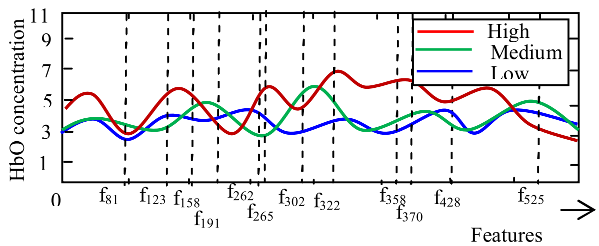



**FIGURE 9.** **Extracted f-NIRs feature to discriminate three different concentration levels of the aromatic substance.**

the concentration is increased by 25% and the hemoglobin concentration (in m-moles) is recorded by the f-NIRs system. Fig. 8 shows that the hemodynamic parameters like Oxy-hemoglobin blood concentration (Hboxy), De-oxy hemoglobin blood concentration (Hbdeoxy) and the total hemoglobin consumption (Hbtot) changes over time. Fig. 8 provides the hemoglobin concentration for increasing concentration of the aromatic substance. It is apparent from the figure that oxygen consumed (i.e., the difference of oxy-hemoglobin concentration and de-oxy-hemoglobin concentration) increases with increased concentration with aromatic substance.

The following biological implication follows directly from the topographic map [15] in Fig. 8.

1. Initially, the activation takes place in to the pre-frontal region.

2. The activation shifts to the middle frontal cortex (MFC) after 12 seconds duration from the presentation of the stimulus.

3. The activation of the orbito frontal cortex (OFC) [40] is reduced gradually (green colored pad in the Fig.8) with increased concentration of the aromatic stimulus.

4. With increased in concentration of the aromatic substance, the activation of the Dorso-lateral pre-frontal cortex (DLPFC) and Ventro-lateral pre-frontal cortex (VLPFC) are increased.

### *E. EXPERIMENT 2: (AUTOMATIC FEATURE EXTRACTION TO DISCRIMINATE 3 DEGREES OF CONCENTRATION LEVELS)*

The motivation of the present experiment is to discriminate the f-NIRs features for 3 concentration levels of Aromatic substance. We adopt Evolutionary Algorithm (EA) technique

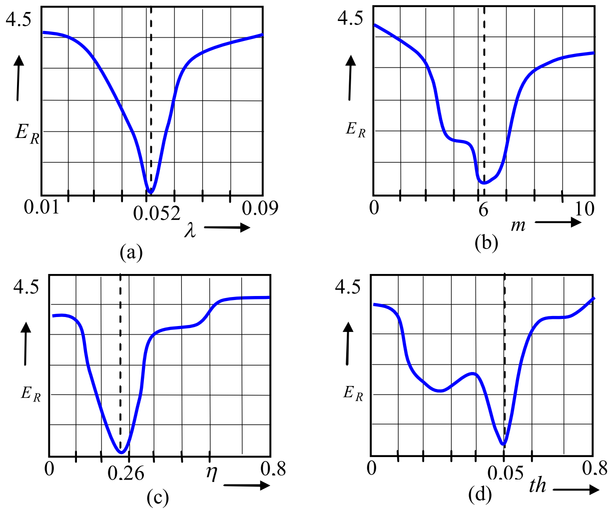



**FIGURE 10.** **(a-d) Parametric Sensitivity of error metric $E_R$ for the proposed GT2FS reasoning technique.**

to select the best possible f-NIRs features from the extracted f-NIRs features. EA selects most significant 20 features from a large dimension (=900 features) feature sets. Fig. 9 depicts these 20 optimal features from the feature value plot for three degrees of concentration levels. It is clear from the plot that the feature $f_{81}$ (mean HbO concentration of channel 4), $f_{123}$ (mean HbO concentration of channel 12), $f_{158}$ (mean HbO concentration of channel 18), $f_{191}$ (standard deviation of HbO concentration of channel 15), $f_{262}$ (avg. energy of channel 7), $f_{265}$ (avg. energy of channel 14), $f_{302}$ (avg. energy of channel 19), $f_{322}$ (skewness of channel 5), $f_{358}$ (skewness of channel 11), $f_{370}$ (skewness of channel 17), $f_{428}$ (kurtosis of channel 5), $f_{525}$ (kurtosis of channel 5) have the maximum inter-class separation.

### F. EXPERIMENT 3: SENSITIVITY ANALYSIS

A sensitivity analysis is undertaken to test optimality of $E_R$ with respect to 4 parameters $m$, $\eta$, $th$ and $\lambda$. Fig.10 provides the results of off-tuning the parameters from their optimal values, which shows a rise in $E_R$ for off-tuned parameter. It is important to note that the optimal values attained in our experiments are $\lambda = 0.052$, $th = 0.05$, $\eta = 0.26$, and $m = 6$.

### G. EXPERIMENT 4: PERCEPTUAL-ABILITY ASSESSMENT OF A SUBJECT

This experiment aims at measuring the perceptual-ability of a subject in two phases. In the first phase we identify the recognition probability of a subject and in the second phase, we can measure the discrimination probability of that subject (Fig.11). Now for a given $\beta(=56)$ and fixed no. of points in the left top area (over 5 days), the parameter $\alpha$ is evaluated by shifting the dotted line along $y$-axis. This is repeated for 30 subjects. Let the $\alpha$ -values obtained by the above process are $\alpha_1, \alpha_2, \ldots, \alpha_{30}$ for 30 subjects.

Similarly, we can also measure the discrimination probability for a given $\alpha(=0.7)$ and the impurity concentration

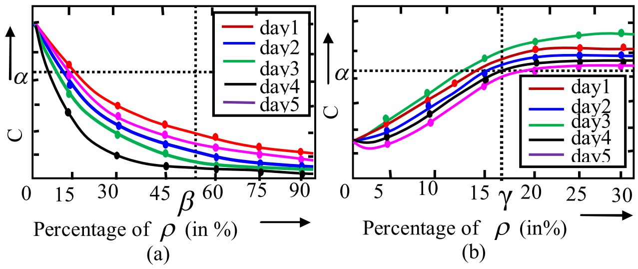



**FIGURE 11.** **Perceptual-ability assessment with the basis of (a) Recognition-Probability and (b) Discrimination- Probability of a subject.**

( $\gamma$ ) is evaluated by shifting the dotted line along the $x$-axis. Let the $\gamma$ value obtained by the above process are $\gamma_1, \gamma_2, \ldots, \gamma_\beta$ up to the maximum recognition threshold ( $\beta$ ). For 30 subjects we obtain $\beta_1, \beta_2, \ldots, \beta_{30}$. Then we rank subjects depending on the in-equality $\alpha_4 > \alpha_9 > \alpha_1 > \ldots > \alpha_2 > \alpha_7$ and $\beta_4 < \beta_9 < \beta_1 < \ldots < \beta_2 < \beta_7$ where subject 4 has the highest perceptual-ability and subject 7 has the least perceptual-ability. To rank subjects based on odor perceptual-ability, we undertake 3 steps. First we compute recognition probability and discrimination probability for $E_R$ 30 subjects, of which only 10 are shown in Table-1 for space limitation. Second, we take their product to compute perceptual-ability of the individual subjects. Lastly, we sort the subjects based on the descending order of their perceptual-ability. The ranks of the subjects thus obtained are indicated in the table itself.

## VI. PERFORMANCE ANALYSIS AND STATISTICAL EVALUATION

This section deals with the experimental basis of performance analysis of the proposed Type-2 fuzzy set induced reasoning techniques with the traditional and existing ones.

### A. PERFORMANCE ANALYSIS OF THE PROPOSED GT2FS METHODS

To compare the relative performance of the proposed type-2 fuzzy reasoning with the existing techniques, we employ the $E_R$ metric as the performance index of the proposed algorithm. Table-2 provides the results of metric obtained by the proposed type-2 fuzzy set based reasoning techniques against non-fuzzy reasoning algorithms [41], [42], [43], type-1 [44], and type-2 fuzzy algorithms [37], [45], [46], [47] are realized and tested with the best settings of parameters of individual algorithms for the present perceptual task. The list of parameters of all algorithms is illustrated in the Appendix section of the authors' previous paper (Table-IV of section A.3 in [35]). This experiment has been performed over 25 healthy subjects and 5 brain-diseased subjects, comprising 10 stimuli, including 6 sessions each, covering $30 \times 3 \times 10 \times 6 = 5400$ training instances. It is apparent from Table-2 that the proposed reasoning algorithm outperforms its nearest competitors by an error metric of 1.5%. Moreover, It is also observed form the same table that the run time complexity of the proposed

**TABLE 1.** Olfactory perceptual-ability assessment for ten subjects.

| Subjects | $\alpha$ | $\beta$ (in %) | $\gamma$ (in %) | $P(C \geq \alpha \vert \rho \leq \beta)$ | $P(C \geq \alpha \vert \gamma \leq \beta)$ | $P(C \geq \alpha \vert \rho \leq \beta) \times P(C \geq \alpha \vert \gamma \leq \beta)$ | % of Perceptual-ability Assessment | Rank of Subjects |
|---|---|---|---|---|---|---|---|---|
| Subject 1 | 0.721 | 18 | 15 | 0.6142 | 0.0663 | 0.0407 | 4.0 | 4 |
| Subject 2 | 0.755 | 16 | 14 | 0.4756 | 0.0884 | 0.0419 | 4.1 | 3 |
| Subject 3 | 0.851 | 14 | 12 | 0.5587 | 0.0791 | 0.0441 | 4.4 | 2 |
| Subject 4 | 0.877 | 9 | 6 | 0.6422 | 0.0753 | 0.0483 | 4.8 | 1 |
| Subject 5 | 0.673 | 20 | 17 | 0.5395 | 0.0633 | 0.0341 | 3.4 | 5 |
| Subject 6 | 0.899 | 43 | 27 | 0.3473 | 0.0432 | 0.0149 | 1.4 | 9 |
| Subject 7 | 0.344 | 47 | 17 | 0.2275 | 0.0587 | 0.0133 | 1.3 | 10 |
| Subject 8 | 0.589 | 28 | 22 | 0.4262 | 0.0688 | 0.0293 | 2.9 | 6 |
| Subject 9 | 0.793 | 31 | 25 | 0.5128 | 0.0443 | 0.0226 | 2.2 | 8 |
| Subject 10 | 0.437 | 35 | 30 | 0.7259 | 0.0396 | 0.0287 | 2.8 | 7 |

**TABLE 2.** Comparison of $E_R$ obtained by the proposed reasoning method against existing methods of a subject.

| Reasoning Techniques of comparison with optimal settings of parameters | No. of free param -eters | Error metric $E_R$ | Run-time in IBM PC Dual-core Machine |
|---|---|---|---|
| SVM with Gaussian Kernel based reasoning [41] | 4 | 4.241 | 56.28 |
| SVM with polynomial Kernel based reasoning [42] | 10 | 4.059 | 57.76 |
| BPNN based Reasoning [43] | 4 | 5.136 | 62.37 |
| Type-I Fuzzy sets based reasoning [44] | 3 | 8.349 | 46.28 |
| IT2FS based reasoning [45] | 2 | 3.579 | 45.71 |
| GT2FS based reasoning [46] | 5 | 2.931 | 95.48 |
| SA-GT2FGG [47] based reasoning | 5 | 1.042 | 96.42 |
| Semi-GT2FS based reasoning [38] | 11 | 1.584 | 95.39 |
| Vertical slice GT2FS based reasoning [35] | 3 | 0.097 | 94.92 |
| **Proposed Vertical slice GT2FS based reasoning model** | **4** | **0.042** | **94.78** |

GT2FS algorithm is 94.7 milliseconds, which is comparably less than the other existing GT2FS based techniques.

## B. STATISTICAL VALIDATION

To statistically validate the proposed reasoning technique we employ the well-known Wilcoxon Signed rank test [48]. Here, Algorithm $B$ is any one of the 7 algorithms listed in Table-3 and Algorithm $A$ is the reference algorithm (here reference is the proposed algorithm). To validate the $H_0$ be the null hypothesis, we evaluate the test statistics

$$W = \sum_{i=1}^{T_r} [sgn(E^A_{R,i} - E^B_{R,i}).r_i] \tag{36}$$

where, $E^A_{R,i}$ and $E^B_{R,i}$ are the measures of error metrics $E_R$ at the $i$-th training instances of algorithm $A$ and Algorithm $B$ respectively. $T_r$ be the total number of training instances and $r_i$ be the rank of the pair at $i$-th training samples. The results of the statistical test are provided in Table-3. The plus and minus value in the table represents the $W$ values of algorithm $A$ and $B$ which is significant or not significant. Here, 95% confidence level is achieved with the degree of significance, at the level of 0.05.

**TABLE 3.** Statistical analysis with the reference algorithm: Proposed GT2FS method.

| Existing of Reasoning Algorithm with optimal settings of parameters (values not included for space limitation) | Reference Algorithm: Proposed VGT2Fs Algorithm |
|---|---|
| Type-I Fuzzy sets based reasoning [44] | + |
| IT2FS based reasoning [45] | + |
| GT2FS based reasoning [46] | + |
| SA-GT2FGG [47] based reasoning | + |
| Semi-GT2FS based reasoning [38] | + |
| Vertical slice GT2FS based reasoning [35] | + |

## VII. CONCLUSION

The paper proposes a new approach to assess the olfactory perceptual-ability of human subjects using f-NIRS induced type-2 fuzzy reasoning. To measure perceptual-ability, computation of 2 parameters: recognition probability and discrimination probability are computed. Three experiments have been performed to measure olfactory perceptual-ability. The first experiment is undertaken with three different levels of concentration of the aromatic stimulus to measure the recognition threshold of the subject. The second experiment is concerned with noisy aromatic stimuli to determine discrimination threshold of the primary aromatic stimulus. The third experiment is performed to rank subjects based on their measure of perceptual-ability. A run-time complexity analysis envisages that the proposed algorithm outperforms its competitors by a large margin. Statistical tests undertaken by Wilcoxon Signed Rank test, also indicates relatively better performance of the proposed technique with its competitors by a confidence level of 95%. The proposed research outcome may find interesting and useful application as a bio-marker for the early Alzheimer's disease. It would also serve as a tool for the selection of tea-tasters based on their measure of olfactory perceptual-ability from brain-response to olfactory stimuli.

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