Analysis of fMRI Signals from Working Memory Tasks and Resting-State of Brain: Neutrosophic-Entropy-Based Clustering Algorithm

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This study applies a neutrosophic-entropy-based clustering algorithm (NEBCA) to analyze the fMRI signals. We consider the data obtained from four different working memory tasks and the brain’s resting state for the experimental purpose. Three non-overlapping clusters of data related to temporal brain activity are determined and statistically analyzed. Moreover, we used the Uniform Manifold Approximation and Projection (UMAP) method to reduce system dimensionality and present the effectiveness of NEBCA. The results show that using NEBCA, we are able to distinguish between different working memory tasks and resting-state and identify subtle differences in the related activity of brain regions. By analyzing the statistical properties of the entropy inside the clusters, the various regions of interest (ROIs), according to Automated Anatomical Labeling (AAL) atlas crucial for clustering procedure, are determined. The inferior occipital gyrus is established as an important brain region in distinguishing the resting state from the tasks. Moreover, the inferior occipital gyrus and superior parietal lobule are identified as necessary to correct the data discrimination related to the different memory tasks. We verified the statistical significance of the results through the two-sample t-test and analysis of surrogates performed by randomization of the cluster elements. The presented methodology is also appropriate to determine the influence of time of day on brain activity patterns. The differences between working memory tasks and resting-state in the morning are related to a lower index of small-worldness and sleep inertia in the first hours after waking. We also compared the performance of NEBCA to two existing algorithms, KMCA and FKMCA. We showed the advantage of the NEBCA over these algorithms that could not effectively accumulate fMRI signals with higher variability.

Keywords: Neutrosophic set; entropy; clustering; functional magnetic resonance imaging signal; working memory; resting state.
1. Introduction

The analysis of functional magnetic resonance imaging (fMRI) signals has an important role in determining brain activation patterns. But the complexity of these signal datasets makes their analysis difficult. The first experiments on fMRI signals were performed by Beliveau et al.\(^1\) An fMRI dataset is a collection of large number of data sample in a Euclidean space, which can be expressed as

\[
X = [x_{ij}], \quad i = 1, 2, \ldots, x; \quad j = 1, 2, \ldots, y, \tag{1}
\]

where \(X\) denotes a matrix of fMRI dataset and \(x_{ij}\) is a signal value in a Euclidean space at position \(ij\). Here, \(x\) and \(y\) refer to the number of rows and columns in \(X\). In that matrix, each row indicates time, and each column indicates the region of interest (ROI) in the human brain. Hence, the dimension of the matrix is defined by \(x \times y\).

The fMRI signals of a particular timestamp that varies over a short period of neuronal activity are called a hemodynamic response.\(^2\) Examination of the blood oxygenation level-dependent (BOLD) fMRI signals allows to obtain indirect information about activation patterns throughout the brain associated with many brain functions such as cognition, sensory processing or motor control.\(^3\)

There are numerous applications of fMRI signal analysis in the literature related to the hemodynamic response of the human brain. Among others, research interest in resting brain (in the absence of a task or stimulus) analysis has increased.\(^4\) Biswal\(^5\) observed that resting-state signals exhibited spatial and temporal correlation patterns, and based on them established a method, termed as resting state functional connectivity (RSFC).\(^6\) Many studies identified abnormal neuronal activity related to neurological and psychiatric disorders.\(^7\) Recent research on functional resting state\(^8\) and working state\(^9\) in healthy subjects has developed significant importance in the field of neuroscience.

1.1. Related works

Several approaches for analyzing fMRI signals have been evolved in recent years. For example, Worsley and Friston\(^10\) adopted a statistical approach for variance analysis of fMRI signal. Friston et al.\(^11\) performed a multivariate analysis of fMRI signals using standard multivariate statistics and linear models. Xiong et al.\(^12\) performed parametric and nonparametric statistical tests to investigate the brain activation process. Lange and Zeger\(^13\) proposed a Fourier transform-based model to study the brain activation process using the fMRI signals. Chen and Christensen\(^14\) showed that brain tasks could be spatiotemporally separable using statistical independent component analysis (ICA) on fMRI signals.

Clustering is one of the most widely utilized approaches by researchers to study the activation patterns of fMRI signals. The primary purpose of clustering is to split fMRI signal values into similar and dissimilar groups based on distance parameters.\(^15\) Clustering of fMRI signal values is, however, one of the challenging tasks in computer science and machine learning because it is arduous often to construct clusters of fMRI signal values by differentiating similar patterns from dissimilar patterns based on preset distance parameters. A clustering process can be explained in terms of fMRI dataset \(X\) (Eq. \(\text{1}\)). The problem associated with a hard clustering technique is to find a partition \(C = \{c_1, c_2, \ldots, c_p\}\) for \(X\) by satisfying the following conditions:

\[
X = \bigcup_{i=1}^{p} c_i, \quad c_i \neq \emptyset \quad \text{for} \quad i = 1, 2, \ldots, p, \tag{2}
\]

\[
c_i \cap c_j = \emptyset \quad \text{for} \quad i, j = 1, 2, \ldots, p; \quad i \neq j. \quad \tag{3}
\]

There are two main types of clustering techniques: (a) hard clustering and (b) soft clustering.\(^16\) Both these types of clustering techniques differ in terms of deciding the association of data to a particular group. In hard clustering, fMRI signal values are completely associated with a specific cluster. That is, signal values are entirely associated with a specific cluster or not. The K-Means clustering algorithm (KMCA) is one of the frequently used methods in the type of hard clustering.\(^17\) Goutte et al.\(^18\) used KMCA to study the similarity patterns in the activation of the fMRI signals in different parts of the voxels. The K-means++ algorithms\(^19\) and K-medians algorithms\(^20\) are the advanced version of KMCA. KMCA, K-means++ and K-medians algorithms attempt to cluster data by minimizing the distance function.

In the last decade, soft clustering approaches have been increasingly utilized in fMRI signal analysis due to their robustness in dealing with inherent
uncertainties. Fuzzy set theory has often been used in the development of soft clustering methods. In a soft clustering method, fMRI time series values \( t_{ij} \in X \) can have a certain fuzzy membership value to multiple groups. The boundaries of fuzzy membership value are defined in such a way that region of the fMRI signal values has a nonzero membership but not complete membership. That is, the boundaries consist those fMRI signal values in such a way that \( 0 < \mu \tilde{X} (t_{ij}) < 1 \). Here, \( \mu \tilde{X} \) denotes the fuzzy membership function for the fuzzy set \( \tilde{X} \), and \( \mu \tilde{X} (t_{ij}) \in [0, 1] \) is referred to the fuzzy membership value of \( t_{ij} \) in \( \tilde{X} \). There are many fuzzy set-based clustering algorithms available in the literature. For example, Baumgartner et al. used a fuzzy set-based clustering algorithm, called the fuzzy clustering algorithm (FCA), in fMRI signals to identify activation patterns in different brain regions. Moser et al. employed FCA in clustering fMRI signals to separate different levels of activation in the brain. Baumgartner et al. showed that FCA is more robust than correlation analysis for identifying different levels of activation in the brain. To cluster magnetic resonance imaging (MRI) of people with Parkinson’s disease (PD), Huang et al. presented a fuzzy set and KMCA-based clustering algorithm, called fuzzy KMCA (FKMCA). It is worth noting that some new neuroimaging techniques have been developed in the context of MRI, e.g. three-dimensional convolutional neural networks can be used for patient classification with Alzheimer’s disease. Meyer and Chinrungruang proposed a new clustering algorithm using spectral estimation and dimension reduction concepts for clustering the fMRI signals. In recent years, the new advanced techniques of clustering and classifications have been proposed. An example in this respect is a methodology based on keypoint clustering and Self-Organized Neural Network (SONN) which is able to distinguish between background and foreground elements in video sequences. Explaining the image classification can be performed through the model-agnostic framework where middle-level object properties are used as blocks continuing the classifying images. The classification methodology is also used to predict the forces of different fingers during a task. These works offer the opportunity to create effective interface controlling, e.g. robotic hands. Many studies identified abnormal neuronal activity related to neurological and psychiatric disorders. Recent research on functional resting state and working state in healthy subjects has developed significant importance in the field of neuroscience.

1.2. Motivation and contributions

The statistical and clustering techniques described above have a number of drawbacks. These are summarized as follows:

(i) Linear correlation-based techniques are not able to discover significant patterns from fMRI signals. These techniques often ignore uncorrelated fMRI signals while analyzing patterns. However, other approaches based on kernel support vector machine (SVM) are also reliable for detecting brain patterns from fMRI signals.

(ii) Hard clustering technique, i.e. KMCA is more reliable than statistical techniques in discovering patterns from fMRI signals. But, KMCA is acutely vulnerable to the assumption of pre-set centroids of clusters. This problem always affects the performance of KMCA.

(iii) Soft clustering techniques (i.e. FCA and FKMCA) facilitate the description of uncertainty in fMRI signals only with degree of memberships. These techniques consider the fuzzy membership values of signals in the interval \([0, 1]\). During the clustering process, linear correlation-based techniques do not consider the information inherent in the fuzzy membership values. However, the study showed that the inherent information of events (e.g. fMRI signals) can be quantified in terms of their relative fuzzy membership values using the concept of entropy.

(iv) Clustering techniques (as described above) are used to analyze fMRI signals by dividing them into groups (i.e. clusters) in such a way that a group of similar fMRI signals (i.e. a cluster) is separated from a group of dissimilar fMRI signals (i.e. other clusters) based on some distance criterion. Therefore, researchers used clustering techniques to separate fMRI signals by forming different clusters to extract hidden features. However, clustering techniques do not ensure that the fMRI signals in a specific cluster are correlated with each other.
The above discussion shows that an effective clustering algorithm is needed that can deal with the limitations mentioned in (i)–(iv) as well as the inherent uncertainties of the fMRI signals. Recently, a study by Singh and Rabadiya demonstrated the effectiveness of neutrosophic set theory (NS) to cluster fMRI signals. Based on NS, Singh proposed a clustering algorithm, called neutrosophic-entropy based clustering algorithm (NEBCA). They demonstrated the application of NEBCA in clustering MRIs of PD patients. The main advantage of NEBCA is that it can represent the uncertainties of events using three different membership functions, viz., true, indeterministic and false. This robustness of NEBCA has not been studied in other domains. This motivates us to apply NEBCA to the analysis of fMRI signals. In this study, we made five contributions, which are listed as follows:

(1) First, we present the notion of NS followed by its mathematical definition. To represent fMRI signal values into NSs, neutrosophic membership functions (NMFs) are introduced. The NMFs help to determine the memberships of any fMRI signal value with respect to three degrees of memberships. In this way, each of the fMRI signal values is transformed into different NSs.

(2) Second, we use the neutrosophic entropy (NE) formula to measure the uncertainties with respect to the degree of memberships of each NS. In this way, each of the fMRI signal values is transformed into NE values.

(3) Third, NEBCA is used in this study to perform clustering of the NE values of the fMRI signals. NEBCA employs the Euclidean distance metric to perform the clustering. The major objective of this metric is to find the best clusters for NE values by keeping the distance between the NE values and the cluster centroids to a minimum.

(4) Fourth, fMRI signals from four working memory tasks, namely global processing task (GLO), semantic task (SEM), phonological task (PHO) and local processing task (LOC) are selected for the study. In this study, fMRI signals from resting-state (RES) of brain are also used for experimental purpose. The fMRI signals were obtained from the Harmonia project 2013/08/M/HS6/00042 founded by the Polish National Science Centre.

By applying NEBCA to these fMRI signals, different densities of clusters are generated. Finally, these clusters are analyzed to identify the following:

- **The differences between fMRI signals obtained from four memory tasks, viz., GLO, SEM, PHO and LOC, and**
- **The differences between fMRI signals obtained from four memory tasks with fMRI signals of RES.**

(5) Fifth, finally, this study focuses on discovering activation patterns of neurons in the human brain based on the clustered fMRI signals. Such activation regions in the brain are represented by employing the automated anatomical labeling (AAL) atlas.

The performance of NEBCA is compared with KMCA and FKMCA. Empirical results show the effectiveness of NEBCA over the selected clustering algorithms.

The structure of this paper is described as follows. Section 2 presents the overview of NS and related concepts. In Sec. 3 materials and methods are discussed. Empirical results based on statistical evidence are presented in Sec. 4. Conclusions followed by the direction for future works are discussed in Sec. 5.

2. Theoretical Basis

This section provides background for NS.

**Definition 1 (NS[32]).** Let Z be a universe of discourse. An NS $L^\ast$ is a representation of an observation $z \in Z$ in the form of $\delta T(z), \delta I(z), \delta F(z)$ \in $L^\ast$, and $0 \leq \delta T(z) + \delta I(z) + \delta F(z) \leq 3$. Here, these functions $\delta T: Z \rightarrow [0,1], \delta I: Z \rightarrow [0,1] and \delta F: Z \rightarrow [0,1]$ are called true, indeterministic and false membership functions of $z \in Z$. In the NS $L^\ast$. On the other hand, $\delta T(z), \delta I(z) and \delta F(z)$ denote the true membership, indeterministic membership and false membership values of $z$ in the NS $L^\ast$, respectively. Here, NS $L^\ast$ defined for the observation $z$ on the universe of discourse $Z$ restricts the values of $\delta T, \delta I$ and $\delta F$ in the subset of $[0,1]$.

In NS, $\delta T, \delta I and \delta F$ are called the neutrosophic membership functions. A graphical representation of
the NMFs is shown in Fig. 1. In this figure, true ($\delta T$) and false ($\delta F$) are depicted in $x$ and $y$-axes, respectively. If universe $Z$ is discrete and finite, then $z_i \in Z$ ($i = 1, 2, \ldots, n$) can also be represented in terms of a NS. This kind of representation of NS is referred to as single-valued neutrosophic set (SVNS) [2]. It is defined as follows.

**Definition 2 (SVNS).** An SVNS $L^*$ in the universe $Z$ is defined with respect to neutrosophic membership functions, viz., $\delta T : Z \rightarrow [0, 1], \delta I : Z \rightarrow [0, 1]$ and $\delta F : Z \rightarrow [0, 1]$. Such SVNS can be expressed as:

$$L^* = \{(z_1, \delta T(z_1), \delta I(z_1), \delta F(z_1)) \mid z_1 \in Z\}.$$  

(4)

Here, $\{(\cdot, \cdot, \cdot, \cdot)$ denotes the collection of neutrosophic membership values of each $z_i \in Z$. In Eq. (4), the summation symbol indicates aggregation of observations; hence, the “+” signs signify a set-theoretic aggregation operator.

If the universe $Z$ is continuous and infinite, then NS $L^*$ can be expressed in terms of a unit interval $z_i \in Z$ as

$$L^* = \{(z_i, \delta T(z_i), \delta I(z_i), \delta F(z_i)) \mid z_i \in Z\}.$$  

(5)

Each observation $z_i \in Z$ can be represented in terms of NS $L^*$ using its three membership functions (i.e. $\delta T$, $\delta I$ and $\delta F$); and together called the NMFs. Description of NMFs is given in the following.

**Definition 3 (NMFs).** For any observation $z_i \in Z$, its NMFs can be defined with the help of following formulas:

$$\delta T(z_i) = \frac{z_i - Z_{\min}}{Z_{\max} - Z_{\min}}$$  

(6)

$$\delta F(z_i) = 1 - \delta T(z_i)$$  

(7)

$$\delta I(z_i) = \sqrt{\delta T(z_i)^2 + \delta F(z_i)^2}.$$  

(8)

In Eq. (6), $Z_{\min}$ and $Z_{\max}$ can be defined as:

$$Z_{\min} = \min\{z_1, z_2, \ldots, z_n\},$$  

(9)

$$Z_{\max} = \max\{z_1, z_2, \ldots, z_n\}.$$  

(10)

Here, “min” and “max” denote the minimum and maximum operations, respectively.

Entropy can be used to quantify the inherent uncertainties in any observation. Such measurement of uncertainties with respect to SVNS can be obtained using NE, which is defined in the following.

**Definition 4 (NE).** The NE of an SVNS $L^*$ at $z \in Z$ is denoted as a measure $E(L^*)$, where $L^* = \{(z, \delta T(z), \delta I(z), \delta F(z)) \mid z \in Z\}$, which can be defined as follows:

$$E(L^*) = 1 - \frac{1}{3} \left[\delta T(z) + \delta I(z) + \delta F(z)\right]$$  

(11)

Here, $X_1 = |\delta T(z) - \delta T(z)^e|$, $X_2 = |\delta I(z) - \delta I(z)^e|$, and $X_3 = |\delta F(z) - \delta F(z)^e|$. In Eq. (11), $\delta T(z)^e$, $\delta I(z)^e$ and $\delta F(z)^e$ represent the complements of $\delta T(z)$, $\delta I(z)$, $\delta F(z)$, respectively.

3. Materials and Methods

This section contains the description of the datasets, followed by the methodology used to analyze the datasets.

3.1. Description of datasets

Datasets from the resting-state procedure and four working memory tasks were analyzed. Sixty-six participants undergoing acquisition from MR were selected from 5354 volunteers who responded via online advertisement. Selection was conducted in two steps: (1) questionnaires (Chronotype Questionnaire, Epworth Sleepiness Scale, and the Sleep-Wake Assessment); (2) genotyping of the PER3 gene, by which 73 participants (divided into morning and evening chronotypes) were selected. The MR acquisition (resting state procedure and four tasks) was...
performed in two sessions: morning and evening. The order of the sessions as well as the versions of the tasks (there were two equivalent versions of each task) were counterbalanced between participants. The onset of each experimental session was adjusted to the chronotype of the subjects: participants of the morning type underwent MR acquisition between 08:00 and 09:00 a.m., and between 5:00 and 6:00 in the evening session; participants of the evening type — between 09:20 and 10:20 a.m. in the morning session, and 6:20 and 7:20 p.m. in the evening session. Participants were asked to adhere to wake and sleep schedules and to sleep at least 8 hrs during the week before and throughout the experiment. The quality and duration of sleep were monitored using actigraphs. The experiment was conducted on one day (if the morning session was the first) or on two days (if the evening session was the first).

On the experimental days, morning chronotypes woke up at 6:50 a.m. (mean, standard deviation (SD): 30 min) and evening types woke up at 08:15 a.m. (mean, standard deviation (SD): 25 min). Participants were asked to abstain from alcohol during the previous week and from caffeine on the experimental days. The detailed information on the tasks is given as follows:

(a) Experimental tasks: This study uses fMRI signals obtained from four working memory tasks: GLO, SEM, PHO, and LOC. To investigate the brain’s activation patterns, we also select the fMRI signals of the brain’s resting state (i.e. RES). The 116 regions of interest (ROIs) are defined according to the AAL brain atlas.

(b) Sessions: Two sessions were conducted to acquire fMRI signals from GLO, SEM, PHO, LOC, and RES: (a) morning and (b) evening.

(c) Phases: At first, participants were exposed to memory sets and allowed to memorize them. The response signals associated with this phase are called encoding. Next, the participants were asked to recognize the memory sets from the test sets. The response signals associated with this phase are called retrieval.

(d) Process to obtain fMRI signals of different tasks:

- GLO: In GLO, participants were presented with a collection of graphics characterized by a series of overlapping similarities. The fMRI signals were recorded for both the encoding and retrieval phases in the morning and evening sessions. In this study, fMRI signals of 52 participants from the GLO are selected for experimental purposes.
- SEM: In SEM, participants were presented with a collection of semantic words. This collection consisted of words from both Polish and English languages. The fMRI signals were recorded for both the encoding and retrieval phases in the morning and evening sessions. From the SEM, fMRI signals of 48 participants are selected for experimental purposes.
- PHO: In PHO, participants were presented with four meaningless words from Polish and English. The fMRI signals were recorded for both the encoding and retrieval phases in the morning and evening sessions for this task. The fMRI signals of 55 participants were selected for the experiment from PHO.
- LOC: In LOC, participants were presented with sets of graphics. Here, the stimuli in the sets differed only by a specific detail related to the GLO. In this case, fMRI signals were obtained for both the encoding and retrieval phases in the morning and evening sessions. The fMRI signals of 48 participants were selected from the experiment from LOC.
- RES: In RES, participants were not involved in any activity associated with the memorization of sets. The experiments were conducted for recording the stimuli in the morning and evening sessions. The fMRI signals of 48 participants were selected from this source for the study.

(c) Data pre-processing: To illuminate the possible dissimilarities in data organization between the encoding and retrieval phase of memories, we preprocessed the fMRI time series as follows. For each experimental task (GLO, SEM, PHO, and LOC), all data segments associated with the experiments’ encoding and retrieval phases were extracted from the fMRI recordings and formed in order of appearance in the new time series. Thus, finally, for each task, we considered fMRI data related to the encoding and retrieval phases separately.

Description of datasets is summarized in Table 1.
In Eq. (13), each \( L_{ij} \) is denoted as

\[
L_{ij} = \{ (t_{ij}, \delta T(t_{ij}), \delta F(t_{ij})) | t_{ij} \in X \},
\]

where \( \delta T(t_{ij}) \), \( \delta F(t_{ij}) \), and \( \delta I(t_{ij}) \) are called the true membership, indeterministic membership and false membership values of \( t_{ij} \), respectively. In Eq. (14), \( \delta T(t_{ij}) \) and \( \delta F(t_{ij}) \) can be defined using NMFs Eqs. (6)–(8) as

\[
\delta T(t_{ij}) = \frac{t_{ij} - \mu_{\text{min}}}{\mu_{\text{max}} - \mu_{\text{min}}}, \quad \delta F(t_{ij}) = \frac{1 - \delta T(t_{ij})}{\delta T(t_{ij})}.
\]

In Eq. (15), \( \mu_{\text{min}} \) and \( \mu_{\text{max}} \) can be defined as

\[
\mu_{\text{min}} = \min(t_{11}, t_{12}, \ldots, t_{xy}), \quad \mu_{\text{max}} = \max(t_{11}, t_{12}, \ldots, t_{xy}).
\]

### Algorithm 1. Pseudocode of NEBCA

**Input:** An fMRI time series dataset in the form of matrix \( X \) (Eq. (20)).

1. Define SVNS for each \( t_{ij} \in X \) denoted by \( L_{ij} \), and express them into the matrix form as \( L \) (Eq. (22)).
2. Determine NE value of each \( L_{ij} \) using NE function denoted by \( E(L_{ij}) \) (Eq. (21)), and express them into the matrix form as \( H \) (Eq. (20)).
3. Select \( \eta \) number of clusters as \( \mathbb{Z} \), where \( j = 1, 2, \ldots, \eta \).
4. Set \( i = 1/\text{*Initialization of iterator*} / \text{while } i \leq \text{Iterations} \text{ do}
5. (a) Select set of randomly initialized cluster centroids (Eq. (22)) as

\[
V(ir = i) = [v_1(ir = i), v_2(ir = i), \ldots, v_{\eta}(ir = i)].
\]

6. (b) Determine the Euclidean distances between NE values and the centroids (Eq. (22)).
7. (c) Based on the minimum Euclidean distance, allocate all NE values to the respective cluster having closest centroid.
8. (d) Update centroid of each cluster (Eq. (22)).
9. (e) \( i = i + 1 \).

**Output:** clustered fMRI time series dataset.

### Step 3. Determine NE value for SVNS

For each SVNS \( L_{ij} \in \mathbb{L} \), determine NE value with respect to NMFs of \( L_{ij} \), which is denoted as \( E(L_{ij}) \). It is expressed in the form of matrix as

\[
H = \begin{bmatrix}
E(L_{11}) & E(L_{12}) & \cdots & E(L_{1\eta}) \\
E(L_{21}) & E(L_{22}) & \cdots & E(L_{2\eta}) \\
\vdots & \vdots & \ddots & \vdots \\
E(L_{x1}) & E(L_{x2}) & \cdots & E(L_{x\eta})
\end{bmatrix},
\]
In Eq. (20), each $E(L_{ij})$ is defined using Eq. (21) as
\[
E(L_{ij}) = 1 - \frac{1}{3} [\delta T(t_{ij}) + \delta I(t_{ij}) + \delta F(t_{ij})]
\times J_1 J_2 J_3.
\] (21)
Here, $J_1 = |\delta T(L_{ij}) - \delta T(L_{ij})^\prime|$, $J_2 = |\delta I(L_{ij}) - \delta I(L_{ij})^\prime|$, and $J_3 = |\delta F(L_{ij}) - \delta F(L_{ij})^\prime|$.

Step 4. Define number of clusters: For the clustering process, $\eta$ number of clusters are selected as $Z_j$, where $j = 1, 2, \ldots, \eta$.

Step 5. Select centroid of each cluster: Choose individual centroid of each cluster, which is randomly defined as
\[
V(itr = 1) = \{v_1(itr = 1), v_2(itr = 1), \ldots, v_\eta(itr = 1)\}. \tag{22}
\]
Here, $itr = 1$ denotes the first iteration of the algorithm. Hence, $V(itr = 1)$ indicates the set of all centroids in this iteration.

Step 6. Compute the distance: Calculate the Euclidean distance $E_d(E(L_{ij}), v_j(itr = 1))$ between NE value $E(L_{ij}) \in \mathbb{H}$ and the centroid $v_j(itr = 1) \in V(itr = 1)$ using the formula as
\[
E_d(E(L_{ij}), v_j(itr = 1)) = \arg \min_j [(E(L_{ij}) - v_j(itr = 1))^2]. \tag{23}
\]
If $v_j(itr = 1) \in V(itr = 1)$ is the closest centroid to $E(L_{ij})$, then it is assigned to the $j$th cluster $Z_j$.

Step 7. Accumulate all NE values to the respective cluster: Assign $\forall E(L_{ij}) \in \mathbb{H}$ to the cluster $Z_j$ in terms of minimum Euclidean distance.
In this way, all $E(L_{ij})$ are accumulated to preset number of clusters.

Step 8. Update the centroid of each cluster: Define new centroid for each cluster as
\[
v_j(itr = itr + 1) = \frac{1}{|S_j|} \sum_{E(L_{ij}) \in S_j} E(L_{ij}); \tag{24}
\]
\[(j = 1, 2, \ldots, \eta).\]

In Eq. (24), $S_j$ denotes the set of all $E(L_{ij})$ assigned to the $j$th cluster $Z_j$.

Step 9. End the procedure of clustering: Stop the clustering process when the centroid of each cluster stops changing or NEBCA reaches the preset maximum number of iterations denoted by $\text{Iterations}$.

The pseudocode of NEBCA is summarized in Algorithm 1. The time complexity of NEBCA depends on two factors: (a) the dimension of the fMRI time series dataset (i.e. $x \times y$) and (b) the maximum number iterations (i.e. $\text{Iterations}$). Therefore, the aggregate time complexity of NEBCA based on Steps 1–9 is $O(x \times y \times \text{Iterations})$.

4. Results and Discussion

This section describes the experimental results based on the application of NEBCA on five different fMRI signals obtained from the GLO, SEM, PHO, LOC and RES.

4.1. Clustering of fMRI signals

NEBCA is applied to perform clustering of fMRI signals originating from GLO, SEM, PHO, LOC and RES. Therefore, the NE values are calculated for each ROI and time step, and clustering is performed between the vectors of NE estimated for successive instances. The number of clusters (i.e. $\eta$) is
set to 3, which is considered appropriate as per the study carried out by Goutte et al. After obtaining the clusters from each of the algorithms, viz., KMCA, FKMCA and NEBCA, labels are assigned to the clusters based on their dimensions. This means that a cluster with large dimensions is called *High Dimension Cluster (HDC)*, a cluster with medium dimensions is called *Medium Dimension Cluster (MDC)*, and finally, a cluster with low dimensions is called *Low Dimension Cluster (LDC)*. The LDC, MDC and HDC obtained from KMCA, FKMCA and NEBCA for a typical participant are shown in Figs. 3(a)–3(f). We used the Uniform Manifold Approximation and Projection (UMAP) method to reduce system dimensionality and consider all ROIs. Moreover, we performed similar calculations for other clustering techniques used in the paper FKMCA and KMCA. All results are depicted in Figs. 3(a)–3(f). From this figure, it is observed that NEBCA is able to form three well-separated clusters in the Euclidean space.

![Cluster visualization](image)

Fig. 3. A sample of cluster visualization of fMRI signals prepared by UMAP method: (a) UMAP reduction for NEBCA, RES evening (b) UMAP reduction for NEBCA, SEM encoding morning (c) UMAP reduction for KMCA, RES evening (d) UMAP reduction for KMCA, SEM encoding morning (e) UMAP reduction for FKMCA, RES evening (f) UMAP reduction for FKMCA, SEM encoding morning.
whereas it is not so clear in the case of other considered algorithms.

The differences between estimated HDC, MDC and LDC (obtained from NEBCA) become apparent when the means of their respective NE values are compared. These differences are shown only for GLO (phase: encoding, session: morning) in Fig. 4. From this figure, these differences are easily visible between the clusters of different dimensions. The signals belonging to LDC and MDC are the most volatile, while they are much smoother for HDC. Moreover, these differences are also visible with respect to the phases: encoding and retrieval.

To systematically investigate the effectiveness of the clustering algorithms (viz., KMCA, FKMCA and NEBCA), we calculate the probability density function (PDF) of the elements in the clusters obtained for each participant. The distributions of the elements in HDC with respect to GLO, LOC, PHO, SEM and RES (phases: encoding and retrieval, sessions: morning and evening) are shown in Fig. 5. Even a cursory examination of the distributions reveals differences between the tasks and RES. For example, the distribution of elements for the LOC characterizes the highest central part (session: evening) compared to the others. On the other hand, the distribution for RES shows very thin tails. To compare the results more quantitatively, statistical features such as skewness and kurtosis are derived from the distributions for HDC, MDC and LDC (phases: encoding and retrieval, sessions: morning and evening), which are depicted in Tables 2 and 3, respectively. Results obtained from NEBCA show that the distribution for the RES has the most symmetric shape (the least skewness). However, when only the tasks are considered, LOC shows the most symmetric distributions of the number of elements.
Table 2. A comparison of the skewness values of NEBCA with KMCA and FKMCA in terms of the number of fMRI signals belonging to HDC, MDC and LDC for different tasks (phases: encoding and retrieval, sessions: morning and evening) and RES (sessions: morning and evening):

<table>
<thead>
<tr>
<th>Task</th>
<th>Phase</th>
<th>Session</th>
<th>HDC (skewness)</th>
<th>MDC (skewness)</th>
<th>LDC (skewness)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>KMCA</td>
<td>FKMCA</td>
<td>NEBCA</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>KMCA</td>
<td>FKMCA</td>
<td>NEBCA</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>KMCA</td>
<td>FKMCA</td>
<td>NEBCA</td>
</tr>
<tr>
<td>GLO</td>
<td>Encoding</td>
<td>Morning</td>
<td>−0.04</td>
<td>0.35</td>
<td>−2.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−0.38</td>
<td>0.23</td>
<td>−1.38</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−0.45</td>
<td>0.08</td>
<td>−1.08</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>−0.64</td>
<td>−0.0011</td>
<td>−1.00</td>
</tr>
<tr>
<td>SEM</td>
<td>Encoding</td>
<td>Morning</td>
<td>−0.67</td>
<td>0.43</td>
<td>−0.06</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−0.01</td>
<td>0.44</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.15</td>
<td>0.75</td>
<td>−1.59</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>0.99</td>
<td>0.54</td>
<td>−0.41</td>
</tr>
<tr>
<td>GLO</td>
<td>Retrieval</td>
<td>Morning</td>
<td>−0.05</td>
<td>0.17</td>
<td>−1.66</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.12</td>
<td>0.27</td>
<td>−1.76</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>−0.54</td>
<td>0.03</td>
<td>−1.90</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−0.37</td>
<td>0.15</td>
<td>−1.40</td>
</tr>
<tr>
<td>LOC</td>
<td>Retrieval</td>
<td>Morning</td>
<td>0.46</td>
<td>0.36</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.82</td>
<td>0.23</td>
<td>0.40</td>
</tr>
<tr>
<td>PHO</td>
<td>Retrieval</td>
<td>Morning</td>
<td>0.30</td>
<td>0.21</td>
<td>−0.41</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>0.21</td>
<td>−1.30</td>
</tr>
<tr>
<td>RES</td>
<td></td>
<td>Morning</td>
<td>0.28</td>
<td>−0.45</td>
<td>−0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.08</td>
<td>0.13</td>
<td>−0.35</td>
</tr>
</tbody>
</table>

Table 3. A comparison of the kurtosis values of NEBCA with KMCA and FKMCA in terms of the number of fMRI signals belonging to HDC, MDC and LDC for different tasks (phases: encoding and retrieval, sessions: morning and evening) and RES (sessions: morning and evening):

<table>
<thead>
<tr>
<th>Task</th>
<th>Phase</th>
<th>Session</th>
<th>HDC (kurtosis)</th>
<th>MDC (kurtosis)</th>
<th>LDC (kurtosis)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>KMCA</td>
<td>FKMCA</td>
<td>NEBCA</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>KMCA</td>
<td>FKMCA</td>
<td>NEBCA</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>KMCA</td>
<td>FKMCA</td>
<td>NEBCA</td>
</tr>
<tr>
<td>GLO</td>
<td>Encoding</td>
<td>Morning</td>
<td>−1.88</td>
<td>−0.81</td>
<td>7.26</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−1.65</td>
<td>−0.86</td>
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<tr>
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<td></td>
<td></td>
<td>−1.13</td>
<td>−1.24</td>
<td>3.20</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−1.34</td>
<td>−0.86</td>
<td>−0.83</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−1.90</td>
<td>−1.108</td>
<td>−0.64</td>
</tr>
<tr>
<td>PHO</td>
<td>Encoding</td>
<td>Morning</td>
<td>−1.79</td>
<td>−0.20</td>
<td>4.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−0.55</td>
<td>−0.98</td>
<td>−0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−1.81</td>
<td>−1.30</td>
<td>4.88</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−1.32</td>
<td>−1.29</td>
<td>4.93</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>−1.74</td>
<td>−1.31</td>
<td>1.68</td>
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<td></td>
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<td>−1.11</td>
<td>−1.11</td>
<td>−0.32</td>
</tr>
<tr>
<td>PHO</td>
<td>Retrieval</td>
<td>Morning</td>
<td>−1.68</td>
<td>−0.99</td>
<td>1.28</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−1.53</td>
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<td>1.37</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−1.75</td>
<td>−0.86</td>
<td>−0.43</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>−1.55</td>
<td>−0.99</td>
<td>−0.09</td>
</tr>
</tbody>
</table>
elements in both the encoding and retrieval phases. GLO, SEM and PHO show a strong left-sided asymmetry in the distribution of the number of elements. A similar conclusion can be drawn when the distribution tails are analyzed for the RES and LOC. The lowest kurtosis with the thinnest tails of the distribution is observed with the RES and LOC.

4.2. Performance evaluation of NEBCA with existing algorithms

This section illustrates the results obtained by comparing the performance of NEBCA with existing clustering algorithms, namely KMCA and FKMCA. The performance of these algorithms is evaluated using the standard deviation (SD) values for HDC, MDC and LDC. Therefore, the SD values are calculated for the elements belonging to HDC, MDC and LDC. Therefore, the SD values are calculated for the elements belonging to HDC, MDC and LDC for GLO, SEM, PHO, LOC and RES with respect to the phases: encoding and retrieval, and the sessions: morning and evening. These statistics are shown in Table 4. From this table, it can be seen that NEBCA has the lowest SD values compared to KMCA and FKMCA for HDC in terms of each of the phases and the sessions. Statistical features of distribution of the number of elements in clusters (Fig 4), for example, leptokurtotic character of PDF, show stability of the clusters size formed by NEBCA in comparable to KMCA and FKMCA. In later case, the PDF distribution is very wide or binomial type for KMCA and FKMCA, correspondingly. Thus, the cluster sizes produced by these two algorithms vary strongly among participants. This confirms the stability of NEBCA in terms of clustering fMRI signals.

4.3. Analysis of NE distribution

A PDF comparison of the entropy values of the fMRI signals from GLO, LOC, PHO, SEM and RES is performed with respect to two individual clusters, namely HDC and LDC. Two different sessions (i.e. morning and evening) with their respective phases (i.e. encoding and retrieval) are considered for the analysis. The results of this study are shown in Fig 3. In this figure, the results for MDC are not shown because MDC and LDC are similar in terms of entropy volatility. It is evident that the estimated

<table>
<thead>
<tr>
<th>Task</th>
<th>Phase</th>
<th>Session</th>
<th>KMCA SD</th>
<th>FKMCA SD</th>
<th>NEBCA SD</th>
<th>KMCA SD</th>
<th>FKMCA SD</th>
<th>NEBCA SD</th>
<th>KMCA SD</th>
<th>FKMCA SD</th>
<th>NEBCA SD</th>
</tr>
</thead>
<tbody>
<tr>
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<td>Encoding</td>
<td>Morning</td>
<td>45.09</td>
<td>41.87</td>
<td>34.75</td>
<td>8.20</td>
<td>40.81</td>
<td>22.13</td>
<td>45.15</td>
<td>7.94</td>
<td>17.78</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>42.85</td>
<td>44.88</td>
<td>29.12</td>
<td>9.69</td>
<td>44.40</td>
<td>25.70</td>
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<td>6.51</td>
<td>8.92</td>
</tr>
<tr>
<td>SEM</td>
<td>Encoding</td>
<td>Morning</td>
<td>41.75</td>
<td>49.14</td>
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<td>14.96</td>
<td>49.79</td>
<td>22.77</td>
<td>39.27</td>
<td>10.01</td>
<td>11.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>42.23</td>
<td>46.38</td>
<td>37.20</td>
<td>21.25</td>
<td>46.50</td>
<td>30.63</td>
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<td>8.73</td>
<td>10.97</td>
</tr>
<tr>
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<td>Encoding</td>
<td>Morning</td>
<td>42.77</td>
<td>42.36</td>
<td>16.88</td>
<td>9.39</td>
<td>41.40</td>
<td>12.13</td>
<td>41.96</td>
<td>8.30</td>
<td>8.06</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>45.78</td>
<td>46.77</td>
<td>15.17</td>
<td>9.41</td>
<td>48.16</td>
<td>12.65</td>
<td>44.39</td>
<td>8.91</td>
<td>8.14</td>
</tr>
<tr>
<td>PHO</td>
<td>Encoding</td>
<td>Morning</td>
<td>45.86</td>
<td>41.66</td>
<td>32.92</td>
<td>11.20</td>
<td>41.28</td>
<td>22.67</td>
<td>44.32</td>
<td>6.22</td>
<td>14.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>39.26</td>
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<td>22.58</td>
<td>11.71</td>
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<td>18.00</td>
<td>39.31</td>
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<td>8.51</td>
</tr>
<tr>
<td>GLO</td>
<td>Retrieval</td>
<td>Morning</td>
<td>45.20</td>
<td>45.71</td>
<td>41.28</td>
<td>11.90</td>
<td>45.47</td>
<td>30.09</td>
<td>45.48</td>
<td>51.41</td>
<td>16.54</td>
</tr>
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<td></td>
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<td>9.41</td>
<td>45.69</td>
<td>22.32</td>
<td>44.45</td>
<td>6.29</td>
<td>18.17</td>
</tr>
<tr>
<td>SEM</td>
<td>Retrieval</td>
<td>Morning</td>
<td>39.05</td>
<td>46.75</td>
<td>32.25</td>
<td>16.08</td>
<td>45.93</td>
<td>28.73</td>
<td>40.69</td>
<td>7.08</td>
<td>9.11</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>39.94</td>
<td>44.73</td>
<td>36.07</td>
<td>16.17</td>
<td>45.65</td>
<td>32.43</td>
<td>40.90</td>
<td>3.75</td>
<td>10.53</td>
</tr>
<tr>
<td>LOC</td>
<td>Retrieval</td>
<td>Morning</td>
<td>46.39</td>
<td>46.01</td>
<td>15.39</td>
<td>9.21</td>
<td>45.08</td>
<td>12.75</td>
<td>45.10</td>
<td>7.34</td>
<td>7.73</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>42.41</td>
<td>16.60</td>
<td>14.34</td>
<td>8.09</td>
<td>111.64</td>
<td>11.53</td>
<td>41.34</td>
<td>165.14</td>
<td>8.30</td>
</tr>
<tr>
<td>PHO</td>
<td>Retrieval</td>
<td>Morning</td>
<td>42.93</td>
<td>44.37</td>
<td>29.32</td>
<td>11.43</td>
<td>44.21</td>
<td>17.23</td>
<td>43.59</td>
<td>5.99</td>
<td>20.70</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>44.52</td>
<td>48.33</td>
<td>32.54</td>
<td>39.52</td>
<td>50.33</td>
<td>26.6</td>
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<td>5.58</td>
<td>11.16</td>
</tr>
<tr>
<td>RES</td>
<td>—</td>
<td>Morning</td>
<td>42.71</td>
<td>43.86</td>
<td>19.90</td>
<td>8.65</td>
<td>38.09</td>
<td>14.36</td>
<td>43.95</td>
<td>4.23</td>
<td>9.05</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Evening</td>
<td>42.71</td>
<td>43.86</td>
<td>19.90</td>
<td>13.81</td>
<td>42.81</td>
<td>13.62</td>
<td>44.53</td>
<td>9.26</td>
<td>10.22</td>
</tr>
</tbody>
</table>
Fig. 6. The PDF of NE values for clustered fMRI signals from GLO, LOC, PHO, SEM and RES in HDC and LDC. Upper panel: encoding phase, lower panel: retrieval phase. The results for the MDC were not shown because their entropy values are similarly volatile to those of the LDC.

4.4. Comparison of NE values in different brain regions

In order to compare the properties of the signals obtained for the memory tasks (i.e. GLO, LOC, PHO, SEM) and RES with respect to the ROI coordinates, the clustered entropy values (i.e. the NE values) were averaged over time and participants with respect to experimental phase and session. The results of this analysis are shown in Fig. 8. As expected, the mean entropy values vary with ROI. The lowest values for both HDC and LDC are obtained for ROIs (according to the AAL atlas) that are mainly in the range of 45–70 (45, 46, 53, 54, 59, 60, 61, 54, 65, 66 and 70), corresponding to the sensory-motor, visual I and visual II regions in the resting state network (RSN). Consistent with the results presented previously, the signals for LDC exhibit a more volatile behavior comparable to that of HDC. Moreover, the dispersion of mean NE values with respect to all tasks is more pronounced in lower entropy values than RES. Thus, the distinction between working memory tasks and RES fMRI signals can be easily performed using NEBCA. Moreover, the detailed analysis of the PDF of NE values provides information about the time of the session and the type of the task. Figure 7 presents the PDF of the entropy values for randomly assigned clusters’ elements. The SEM and RES as representative results are only depicted. Compared to Fig. 6, HDC, MDC, and LDC are indistinguishable.

4.4. Comparison of NE values in different brain regions

In order to compare the properties of the signals obtained for the memory tasks (i.e. GLO, LOC, PHO, SEM) and RES with respect to the ROI coordinates, the clustered entropy values (i.e. the NE values) were averaged over time and participants with respect to experimental phase and session. The results of this analysis are shown in Fig. 8. As expected, the mean entropy values vary with ROI. The lowest values for both HDC and LDC are obtained for ROIs (according to the AAL atlas) that are mainly in the range of 45–70 (45, 46, 53, 54, 59, 60, 61, 54, 65, 66 and 70), corresponding to the sensory-motor, visual I and visual II regions in the resting state network (RSN). Consistent with the results presented previously, the signals for LDC exhibit a more volatile behavior comparable to that of HDC. Moreover, the dispersion of mean NE values with respect to all tasks is more pronounced in lower entropy values than RES. Thus, the distinction between working memory tasks and RES fMRI signals can be easily performed using NEBCA. Moreover, the detailed analysis of the PDF of NE values provides information about the time of the session and the type of the task. Figure 7 presents the PDF of the entropy values for randomly assigned clusters’ elements. The SEM and RES as representative results are only depicted. Compared to Fig. 6, HDC, MDC, and LDC are indistinguishable.
Fig. 8. Mean entropy and SD values in HDC and LDC for GLO, LOC, PHO, SEM and RES, obtained by averaging over time series during each experiment phase and participant. Upper panel: encoding phase, lower panel: retrieval phase. The y-axes for HDC and LDC are different for better visibility. The most prominent peaks are labeled with the anatomical regions. The results for the MDC were not shown because their entropy values are similarly volatile to those of the LDC.
HDC. The mean of NE for the RES typically exhibits larger values than its counterpart for the tasks, which is especially visible for the HDC. In the case of LDC, one could also observe a much higher SD values (sub-panels in Fig. 8) over participants in comparison to HDC. Based on the above facts, it can be concluded that results for HDC are the most informative, and they have been analyzed in detail in the following part of the article.

To facilitate comparison of working memory tasks with RES, entropy values (i.e. the NE values) are shown in Fig. 9. The differences between the corresponding entropy for the tasks and RES are estimated in Fig. 8. To distinguish for which ROIs the difference between RES and the tasks is statistically significant, we performed a two-sample $t$-test with unequal variances. From the results of this test, we can conclude that the ROIs whose activities differ most between the tasks and RES belong to a wide range of brain structures, such as the cuneus (ROIs: 45 and 46), the inferior occipital gyrus (ROIs: 53 and 54), the angular gyrus (ROIs: 65 and 66), or the superior (ROIs: 59 and 60) and inferior parietal lobules (ROIs: 61 and 62) and the right paracentral lobule (ROI: 70). The right and left inferior occipital gyrus (ROIs: 53 and 54) (from the AAL atlas) are most prominent in this regard. Moreover, the most significant deviation of the analyzed tasks from the RES was identified in the case of verbal tasks, i.e. PHO and SEM. This is clearly visible for the case of the SEM (encoding, evening) or the PHO (retrieval, morning). In both cases, the difference assumes the most extreme values compared to other tasks.

A deeper interpretation of the results show that the regions with the lowest entropy values (Fig. 8) are located in visual, parietal, and cerebellar areas. Among them are the angular gyrus (ROIs: 65 and 66) responsible for memory retrieval, the supramarginal gyrus (ROIs: 63 and 64) which combine multimodal sensory inputs, and the inferior occipital gyrus (ROIs: 53 and 54). This structure is involved in primary visual processing and is considered to be a part of the visual word form area engaged in word identification. Our results reveal that the inferior occipital gyrus is the best in distinguishing between fMRI signals of working memory tasks and RES. The visual stimuli (abstract objects and words) activated much more the visual areas than RES (see Fig. 8).

The use of NEBCA allows us to highlight subtle differences in the activity of specific brain regions associated with four different types of working memory tasks. The inferior occipital gyrus is such a structure that distinguishes PHO (in terms of processing pseudowords — a sequence of letters that resembles a real word) from the other working memory tasks. The superior parietal (ROIs: 59 and 60), involved in spatial orientation, attention, and language processing, is responsible for discriminating the task involving visual objects from tasks involving words and pseudowords. Our results suggest a strong activation of the right parietal lobe during the morning retrieval session, which can be explained by the confirmed involvement of the right parietal lobe in visual attentional processing during reading, and by a lower small-worldness and insufficient hemispheric synchronization when attentional processes could be more strongly engaged in task performance. The activity of a particular area of the inferior parietal lobule — the supramarginal gyrus (ROIs: 63 and 64), which is involved in phonological word choice distinguishes tasks involving words and pseudowords. The other region involved in this discrimination is the paracentral lobule (ROI: 70), part of which is the supplementary motor area, which takes part in a widespread frontoparietal network underlying working memory. The implementation of NEBCA allows us also to determine the diurnal variability of brain activity patterns. The visual representation of the absolute values from Fig. 8 is shown on the brain with AAL atlas in Fig. 10. It can be observed that the absolute values of the differences between RES and working memory tasks are generally higher in the morning session than in the evening. This could be explained by lower small-worldness in the morning, which was confirmed by our recent research. Also, Marek et al. showed a higher activation of the orienting attention system during the morning hours compared to the evening hours. The study by Schmidt et al. indicated that diurnal variations modulate neural activity related to task complexity and showed that the activity of the thalamus is higher in the morning when performing more complex tasks. Moreover, our previous study on resting state indicated increased functional connectivity between visual, sensorimotor networks and the thalamus in the morning hours, which is consistent with the current results. The only exception
Fig. 9. Differences between entropy values in HDC and LDC for GLO, LOC, PHO, SEM and RES, obtained by averaging over time series during each experiment phase and participant. Upper panel: encoding phase, lower panel: retrieval phase. The y-axes for HDC and LDC are different for better visibility. The most prominent peaks are labeled with the anatomical regions. The results for the MDC were not shown because their entropy values are similarly volatile to those of the LDC.

to the differences between RES and working memory tasks is SEM encoding, where values are higher in the evening. The explanation for this could be that greater neural involvement is required in the evening due to the global processing of the presented words. Folkard has shown that strategies for memorizing information vary according to the time of day. He observed that local processing dominates in the
morning hours, whereas it is global in the evening. In the SEM during the encoding phase, where semantically related words were presented, neural activity of the structures responsible for memorization is higher in the evening due to a favorable global strategy.

5. Conclusions and Future Directions

This study addressed the problem of clustering and analysis of fMRIs. For this purpose, a clustering algorithm based on neutrosophic set theory and neutrosophic entropy called NEBCA was adopted and applied to fMRI signals obtained from four working memory tasks and RES. Through clustering the signals related to temporal brain activity, three non-overlapping data clusters were determined and statistically analyzed. These clusters were compared to identify the differences between (a) fMRI signals from working memory tasks and (b) fMRI signals from working memory tasks and RES. Finally, the visualization of the results on the brain with an AAL atlas was used to indicate the variability of brain region patterns. The performance of NEBCA was compared with two existing algorithms, viz., KMCA and FKMCA. Using NEBCA, we were able to distinguish between different working memory tasks and RES, as well as detect subtle differences in the activity of brain regions. However, the statistical results showed that KMCA and FKMCA were not able to generate effective clusters from fMRI signals. The main reason was that these two existing algorithms were not able to accumulate fMRI signals with lower variability in the desired cluster.

Our analyses revealed that the inferior occipital gyrus (ROIs: 53 and 54) is crucial for discriminating between RES and the tasks, as visual objects activate the visual brain more than RES. Moreover, the same brain region allows us to distinguish the processing of pseudowords (PHO) from the other working memory tasks. In the case of the distinction between visual and verbal tasks, the most important was the superior parietal lobule (ROI 59), which is involved in spatial orientation, attention, and language processing. The use of the NEBCA also made it possible to determine the influence of the time of day on patterns of brain activity. Differences between working memory tasks and RES were larger in the morning, which could be explained by a lower index of small-worldness probably caused by sleep inertia in the first hours after waking up.

Possible future development of the proposed methodology may concern combining its efficiency with novel classification methods using, among others, neural network techniques. Moreover, NEBCA may be integrated with a brain–computer interface tool to analyze various functional working state and resting-state signals from patients with various neurological disorders.

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References


32. Y. Zheng and X. Hu, Concurrent prediction of finger forces based on source separation and classification of neuron discharge information, Int. J. Neural Syst. 31 (2021) 2150010.


44. J. A. Rice, Mathematical Statistics and Data Analysis (Cengage Learning, 2006).


