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Studying the Distinction between Emotions in fMRI Data by Using Temporal Network Theory

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Abstract

Purpose: Our purpose in this study was to investigate the distinction between emotional states and the performance of the brain during different feelings by using temporal network theory.

Materials and Methods: For investigating the distinction between emotions, we chose functional magnetic resonance imaging data acquired during the display of an emotional audio-movie. In order to derive dynamic functional connectivity and create time-graphlets, we used spatial distance method and for studying the features of the temporal network, we applied different temporal network measures.

Results: Considering statistical comparisons, two global measures of temporal efficiency and reachability latency showed a significant difference between at least one pair of emotional states and we observed different meaningful regions in each temporal centrality measure.

Conclusion: The results of this analytic method showed that the brain network pattern during the expression of different emotional states is different compared to one another and also varies through time.

1. Introduction

During the recent years, the most recent neuroimaging methods and analytic approaches have made it possible to study connectivity patterns in the whole-brain scale. One of these methods is functional Magnetic Resonance Imaging (fMRI). In fMRI clinical usage, the amount of activity of brain regions and exploring the connectivity between regions may include important information which may lead the way of quantifying the information in fMRI images. Therefore, in examining the connectivity and cerebral activities, methods of connectivity analysis and type of stimulation are crucial. In this regard, many studies [1-9] have been done so far where the brain is in resting state or applying different stimulations which have led to know more about the function of the brain at the time of occurrence in the different internal and external conditions in the human brain.

There are many methods for analyzing fMRI data. In recent years, the interest to use the evaluation of Dynamic Functional Connectivity (DFC) has increased. There are many approaches to derive and quantify DFC. Thompson

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et al. [10], for the first time, introduced temporal network theory and related metrics regarding the network neuroscience and in order to derive DFC and create time-graphlets, they introduced the Spatial Distance (SD) method with the approach of weighted Pearson correlation. They illustrated that this method is able to compute unique connectivity estimates for each time point. They showed the ability of this method for investigating the dynamic function of the brain through analyzing the resting state fMRI dataset (one session with open eyes and another session with close eyes).

In cognitive neuroscience, the studying of emotions is one of the interests of researchers. Therefore, we investigate the distinction between emotions through using temporal network measures in an fMRI dataset acquired during applying a natural complex stimulus.

When a long-term complex natural stimulation is applied to obtain fMRI data, this dataset could be closer to the real world conditions. Investigating such data leads to elicit the brain responses that depict cerebral conditions and dynamics in natural events [11]. Therefore, this study tries to analyze fMRI data acquired during the display of an emotional audio-movie to represent different aspects of brain performance during the expression of different emotions and distinction among such emotions.

In this research, we chose the spatial distance method for deriving dynamic functional connectivity and the temporal network theory for quantifying the connectivity. In order to investigate the different features of the temporal network, we used different measures.

Finally, we concluded that this analytic method could show that the brain network pattern during the expression of different emotional states was different and such a pattern would also change in time.

Further in this article, in the materials and methods section, we will explain the database, extracting time series of emotions, deriving DFC, and investigating temporal graphs. In the results section, we point out the findings of the research and ultimately, we will engage in the specific discussion.

2. Materials and Methods

In this research, in order to use the temporal network theory for quantifying DFC estimates, we considered Regions Of Interest (ROIs) as nodes. We used the SD method to estimate dynamic functional connectivity between the nodes and we applied some of the temporal network measures for investigating time-graphlets. Finally, for performing statistical comparisons, we applied the non-parametric permutation test to the measures.

2.1. Dataset

In this study, we used fMRI data [11] acquired from 20 healthy right-handed persons (12 men and 8 women, average age of 26.6) during long-term stimulation using "Forrest Gump" audio-movie. Functional images were acquired using a 32–channel-head coil on a whole-body 7-Tesla Siemens MAGNETOM scanner with TR=2 s and TE=22 ms. Totally 3599 volumes were recorded for each participant [11].

In this research, we used pre-processed BOLD data (bold_dico_dico7Tad2grpbold7Tad_nl) and the data of the two subjects were excluded from the analysis, due to problems in image reconstruction (sub_4) and distortion correction (sub_10).

2.2. Regions of Interest

Forty-four Regions of Interest were chosen from Harvard-Oxford Atlas, including visual and auditory cortices and regions engaged in emotions (see Table 1).

Extracting time series of ROIs was done using FSL (https://fsl.fmrib.ox.ac.uk), SPM12 (https://www.fil.ion.ucl.ac.uk/spm/software/spm12), and MATLAB (MarsBar Toolbox (http://marsbar.sourceforge.net)) software.

With regard to the labeling that was done on movie seconds (entirely for all the characters), we extracted the time series of five emotions of happiness, fear, love, anger, and sadness. The length of each emotion was considered different: 68 s for fear, 126 s for happiness, 84 s for love, 128 s for anger and 208 s for sadness.

Table 1. ROIs extracted from Harvard-Oxford Atlas

Number of ROI	Name of ROI	Abbreviation
1	Angular gyrus	AG
2	Central opercular cortex	CO
3	Cuneal cortex	CN
4	Frontal medial cortex	FMC
5	Frontal operculum cortex	FO
6	Frontal orbital cortex	FOC
7	Heschl's gyrus (includes H1 and H2)	H
8	Inferior frontal gyrus, pars opercularis	F3o
9	Inferior frontal gyrus, pars triangularis	F3t
10	Inferior temporal gyrus, anterior division	T3a
11	Insular cortex	INS
12	Intracalcarine cortex	CALC
13	Lateral occipital cortex, inferior division	OLi
14	Lingual gyrus	LG
15	Middle temporal gyrus, anterior division	T2a
16	Middle temporal gyrus, posterior division	T2p
17	Middle temporal gyrus, temporooccipital part	TO2
18	Occipital fusiform gyrus	OF
19	Occipital pole	OP
20	Parahippocampal gyrus, posterior division	PHp
21	Parietal operculum cortex	PO
22	Planum polare	PP
23	Planum temporale	PT
24	Subcallosal cortex	SC
25	Superior temporal gyrus, anterior division	T1a
26	Superior temporal gyrus, posterior division	T1p
27	Supracalcarine cortex	SCLC
28	Temporal occipital fusiform cortex	TOF
29	Left Accumbens	Accbns.L
30	Left Amygdala	Amy.L
31	Left Caudate	Caud.L
32	Left Hippocampus	Hip.L
33	Left Lateral Ventricle	VL.L
34	Left Pallidum	Pall.L
35	Left Putamen	Put.L
36	Left Thalamus	Thal.L
37	Right Accumbens	Accbns.R
38	Right Amygdala	Amy.R
39	Right Caudate	Caud.R
40	Right Hippocampus	Hip.R
41	Right Lateral Ventricle	VL.R
42	Right Pallidum	Pall.R
43	Right Putamen	Put.R
44	Right Thalamus	Thal.R

2.3. Deriving DFC and Investigating Temporal Graphs

The Sliding Window (SW) method is one of the most common methods for estimating DFC [12,13]. In this method, the Pearson correlation approach is usually used to calculate the connectivity. The SW method uses the temporal proximity of time points to compute the correlation and the parameter of window length can strongly affect the results. The Tapered Sliding Window (TSW) method is similar to the SW method but uses the weighted correlation approach to compute the connectivity and considers more weight for time points that are closer to the window center. Both SW and TSW methods create DFC estimates with low temporal sensitivity and their results depend on the window length parameter.

We used spatial distance method to derive DFC. SD method uses all the time points and allocates weights to them based on their spatial similarity. Therefore, due to this type of weighting, in the calculation of correlation between the two nodes at each time point, the effect of all of the nodes is considered. SD method is a method through which each time point receives a weight vector that is used in the weighted Pearson correlation, therefore, it is possible to obtain unique connectivity estimation for each time point. This method can provide an accurate estimate of DFC with the highest temporal sensitivity.

After the connectivity times series were obtained by applying the SD method on time series of each emotion (in every individual), we applied Fisher Transformation and Box-Cox Transformation (within limits of λ in connectivity time series between -25 to 25 with an increase of 0.1). Then, every connectivity time series was standardized.

Binary time-graphlets were created using a thresholding method based on variance (in each connectivity time series, adjusting each edge of less than two standard deviations to zero).

Finally, we calculated temporal degree centrality, temporal closeness centrality, fluctuability, volatility, temporal efficiency, and reachability latency (see [10] for more details about the SD method and temporal network

measures). The codes for performing all the analyses in this research were developed in MATLAB.

2.4. Statistics

For statistical comparisons, we used the non-parametric permutation test. In between-group comparisons, null distributions were created with 100,000 permutations and all the comparisons were two-tailed. All of the permutations were created separately between each pair of emotions. In global measures, we considered test statistic as the mean difference and in nodal measures, the test statistic was considered as Spearman rank correlation coefficient. We used Bonferroni-corrected for multiple comparisons ($p \leq 0.005$). In order to determine which nodes are higher than the centrality probability, 1000 permutations were performed in which the nodal order for each subject was shuffled and then was averaged over subjects, therefore 44 null distributions were created. The distribution with the largest 950th value was selected for the significance threshold of $p < 0.05$.

3. Results

Using the SD method, we created the temporal network in each emotion for each subject. In the following, we represent the results of applying each measure to temporal networks after performing statistical comparisons.

3.1. Centrality Measures

For statistical comparisons in centrality measures, we used Spearman rank correlation as the test statistic in the non-parametric permutation test.

Table 2. Statistical comparison of temporal degree centrality between two emotions

			Temporal Degree Centrality	
			ρ	P-value
Happiness	-	Anger	0.0674	0.6626
Happiness	-	Fear	-0.2295	0.1319
Happiness	-	Love	-0.0569	0.7117
Happiness	-	Sadness	0.0515	0.7370
Fear	-	Anger	0.3706	0.0135
Fear	-	Love	0.2842	0.0626
Fear	-	Sadness	0.0316	0.8391
Sadness	-	Anger	0.1924	0.2106
Sadness	-	Love	-0.0634	0.6817
Anger	-	Love	0.2781	0.0669

Considering Table 2 and Table 3, no significant correlation was found between the pair of emotions in temporal degree centrality and temporal closeness centrality, which shows the nodes have different centrality properties in emotional states.

Table 3. Statistical comparison of temporal closeness centrality between two emotions

			Temporal Closeness Centrality	
			ρ	P-value
Happiness	-	Anger	-0.0710	0.6470
Happiness	-	Fear	0.1584	0.3031
Happiness	-	Love	0.1690	0.2722
Happiness	-	Sadness	0.1435	0.3536
Fear	-	Anger	-0.0582	0.7104
Fear	-	Love	0.0382	0.8070
Fear	-	Sadness	0.1576	0.3070
Sadness	-	Anger	0.3443	0.0229
Sadness	-	Love	0.0912	0.5558
Anger	-	Love	-0.1166	0.4472

3.2. Measures of Fluctuability, Volatility, Reachability Latency, and Temporal Efficiency

The results of statistical comparisons of global measures are presented in Tables 4 to 7. The test statistic was the mean difference. Considering Tables 4 to 7, throughout the global level of the network, two measures of temporal efficiency and reachability latency could at least show a significant difference between a pair of emotions.

Table 4. Statistical comparison of fluctuability between pair-emotions

			Fluctuability	
			diff-mean	P-value
Happiness	-	Anger	-0.1697	0.9367
Happiness	-	Fear	2.6267	0.0766
Happiness	-	Love	1.9917	0.2353
Happiness	-	Sadness	-1.0252	0.6242
Fear	-	Anger	-2.7964	0.1207
Fear	-	Love	-0.6350	0.5986
Fear	-	Sadness	-3.6518	0.0435
Sadness	-	Anger	0.8555	0.7154
Sadness	-	Love	3.0169	0.1298
Anger	-	Love	2.1614	0.2724

diff-mean is the difference between maen value.

In fluctuability (Table 4) and volatility (Table 5), there was no significant difference between the pair of emotions.

Table 5. Statistical comparison of volatility between pair-emotions

			Volatility	
			diff-mean	P-value
Happiness	-	Anger	10.3386	0.1224
Happiness	-	Fear	7.1883	0.3515
Happiness	-	Love	7.2322	0.2956
Happiness	-	Sadness	12.8432	0.0359
Fear	-	Anger	3.1502	0.6896
Fear	-	Love	0.0439	0.9954
Fear	-	Sadness	5.6549	0.4392
Sadness	-	Anger	-2.5047	0.6856
Sadness	-	Love	-5.6110	0.3885
Anger	-	Love	-3.1064	0.6611

In temporal efficiency (Table 6), between sadness and love that significant difference was created among them, love has a higher mean value than the sadness, thus in love compared to sadness, there are shorter temporal paths.

Table 6. Statistical comparison of temporal efficiency between pair-emotions

			Temporal Efficiency	
			diff-mean	P-value
Happiness	-	Anger	-0.0253	0.9281
Happiness	*-*	*Fear*	*-0.0470*	*0.0002*
Happiness	*-*	*Love*	*-0.0511*	*< 0.0001*
Happiness	-	Sadness	0.0161	0.0265
Fear	-	Anger	0.0217	0.7954
Fear	-	Love	-0.0041	0.8499
Fear	*-*	*Sadness*	*0.0631*	*< 0.0001*
Sadness	-	Anger	-0.0414	0.2343
Sadness	*-*	*Love*	*-0.0672*	*< 0.0001*
Anger	-	Love	-0.0257	0.6336

In reachability latency (Table 7), between anger and love that significant difference was created among them, anger has a higher mean value than the love, hence in love than anger, the information transfer was faster.

Table 7. Statistical comparison of reachability latency between pair-emotions

			Reachability Latency	
			diff-mean	P-value
Happiness	-	Anger	0.5981	0.7500
Happiness	*-*	*Fear*	*6.9996*	*< 0.0001*
Happiness	*-*	*Love*	*7.3761*	*< 0.0001*
Happiness	-	Sadness	-4.8668	0.0085
Fear	*-*	*Anger*	*-6.4015*	*0.0003*
Fear	-	Love	0.3765	0.7530
Fear	*-*	*Sadness*	*-11.8664*	*< 0.0001*
Sadness	-	Anger	5.4649	0.0054
Sadness	*-*	*Love*	*12.2429*	*< 0.0001*
Anger	*-*	*Love*	*6.7780*	*0.0002*

3.3. High Levels of Centrality

The nodes with a higher level of centrality in each emotion were presented in Tables 8 and 9. In temporal degree centrality (Table 8), regions of SC and Accbns.R were the same in the states of anger and sadness (SC was also unveiled in state of love). In temporal closeness centrality (Table 9), Put.R was in common in the states of both love and sadness.

Considering Tables 8 and 9, in each emotion in temporal degree centrality and temporal closeness centrality, different regions became significant.

Table 8. Nodes with higher levels of temporal degree centrality in each emotion

	Temporal Degree Centrality				
	Anger	*Fear*	*Happiness*	*Love*	*Sadness*
Name of ROI	FMC	-	PHp	SC	SC
	SC	-	PO	-	Accbns.R
	Accbns.L	-	Hip.R	-	-
	Amy.L	-	-	-	-
	Thal.L	-	-	-	-
	Accbns.R	-	-	-	-

Table 9. Nodes with higher levels of temporal closeness centrality in each emotion

	Temporal Closeness Centrality				
	Anger	**Fear**	**Happiness**	**Love**	**Sadness**
Name of ROI	-	Caud.L	-	Put.R	VL.L
	-	-	-	Thal.R	Amy.R
	-	-	-	-	VL.R
	-	-	-	-	Put.R
	-	-	-	-	-
	-	-	-	-	-

In Figure 1, we illustrate the nodes with a higher level of temporal closeness centrality in sadness (in order to visualize spatial pattern, we used BrainNet Viewer software (https://github.com/mingruixia/BrainNet-Viewer)).
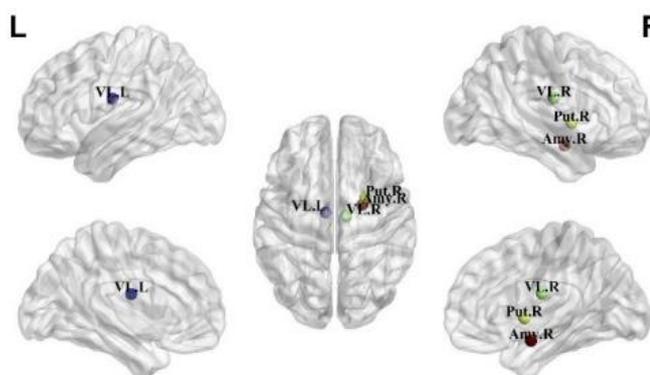
Figure 1. Nodes with a higher level of temporal closeness centrality in sadness

4. Discussion

We investigated the distinction between the emotions in a dataset with prolonged complex naturalistic stimulation representing the life of human beings.

We used the spatial distance method in stimulus-driven data for deriving dynamic functional connectivity and applied temporal network theory in order to investigate the distinction between emotions.

Considering the findings of this research, two global measures of temporal efficiency and reachability latency demonstrated a significant difference between at least a pair of emotion, and different significant regions observed in each temporal centrality measure. Also, centrality measures showed no significant correlation between the pair of emotions, so it is concluded that the nodes have different centrality properties in the emotions.

This study used the thresholding approach based on the variance in order to create binary connectivity matrices that are not completely optimized and can be improved. One of the limitations of this thresholding approach is the high risk of false positive connectivity.

In relation to study the features of the temporal network, except the used measures in this study, it is possible to use other measures of the temporal network.

Ultimately, we conclude that creating time-graphlets by dynamic functional connectivity estimates derived from the spatial distance method and evaluating network properties by applying temporal network measures could represent the distinction between emotions.

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