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Analysis of acupuncture principle on subjects using k Singular Value Decomposition

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ABSTRACT

Promising fMRI(functional Magnetic Resonance Imaging) analysis methods have provided insight into the brain networks and brought reconciliation to acupuncture effects. In this present study , Ksvd(k Singular Value Decomposition) Technique is employed to identify the brain network involved in acupuncture activation for a old age shaky hand subject. Task analysis mostly employ 'seed voxel' method ,where a voxel or group of voxel's averaged time course from the seeding area is correlated with the time course of each voxel over the entire brain to generate connectivity maps . In Ksvd analysis , a dictionary is constructed and trained to identify the activated voxels of single subject . In this acupuncture analysis study, brain behavior after short stimuli , such as MA at acupoint LI 11,GB 34, identifies change with amygdale brain network for pain perception and pain modulation, sensory motor cortex for shaky hand were identified and these specific effect arise from the cooperation of brain regions engaged in Task and rest fMRI .

Key words : fMRI , Ksvd , MA , LI 11,GB 34,sensory motor cortex, pain perception.

1. INTRODUCTION

fMRI ,investigatation on the hemodynamic BOLD effect, has come to dominate the brain mapping field due to its minimal invasiveness, no radiation exposure, good spatial resolution and wide availability. In previous decade an increasing number of studies applied fMRI to investigate acupuncture stimulation. Acupuncture is one of the most important therapeutic modalities in traditional Chinese medicine (TCM). It utilizes fine needles that may pierce through specific anatomical points (named '*acupoints*') so that certain healing effects are produced[1]. Meta-analusis for verum acupuncture stimuli confirmed brain activity within many of the regions ,brain stem,cerebellum.[2]Acupuncture studies in fMRI did not quantify and explicitly distinguish subjects into de-qi and sharp pain based on needle sensations, which made striking discrepancies between results of different studies. What are the de-qi related BOLD responses, that is, are they dominated by activation or deactivation? What is the relationship between the de-qi related and the sharp pain related BOLD responses?The different regions were defined as regions of interest (ROIs) and correlated with the scores from the needling sensations.[3] Neuroimaging studies have shown that acupuncture stimulation activates the brain regions, primary somatosensory cortex , secondary somatosensory cortex , anterior cingulate cortex insular cortex, prefrontal cortex, amygdala, hippocampus, periaquaductal gray and hypothalamus.[6]The comparisons between different resting states disclosed the discrepancies between the pre and post needling effects in the Brain[4].The canonical HRF is the basis of a parametric model that estimates changes in the fMRI blood oxygen level dependent (BOLD) signal. The major problem in the hypothesis-driven method is the nonadaptivity of the canonical HRF [7]. To overcome these drawbacks, a variety of data-driven methods have been suggested[8] including PCA, ICA. In this study , a manual acupuncture at acupoint LI 11,GB 34 for a shaky hand aged subject is analysed to identify the difference in activation in sensory motor cortex using Ksvd, a multivariate analysis method, as this method has the potential of exploring the effect of acupuncture on brain activities.

2. MATERIALS AND METHODS

In this fMRI experiment of single trial, slices of images are acquired for 110 scans , with each image consisting of roughly 200,000 voxels. Though a good number of these voxel consist solely of background noise and can be excluded from further analysis, the data that needs to be analyzed is staggering. The second author with in clinical practice for over 25 years, administered acupuncture manually. Stainless steel needles used for LI 11,GB 34 are 0.2 mm in diameter and 40 mm in length. The experiment is repeated twice for the same subject with rest fMRI in between and have 2 runs for comparison of analysis which facilitates population inference. The subjects eyes were closed,so they can't observe the procedures.

2.1 SUBJECT AND ACUPUNCTURE

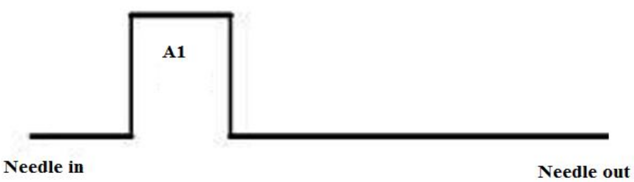

Figure:1Block run with acupuncture stimulation points and Rest fMRI.

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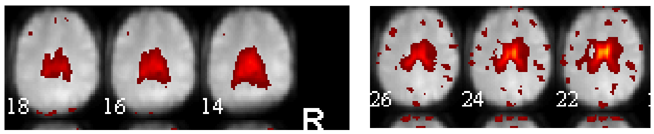

Figure 2:Activation reduced due to acupuncture in accupoint GB 34 and LI 11.Sagittal output is shown .

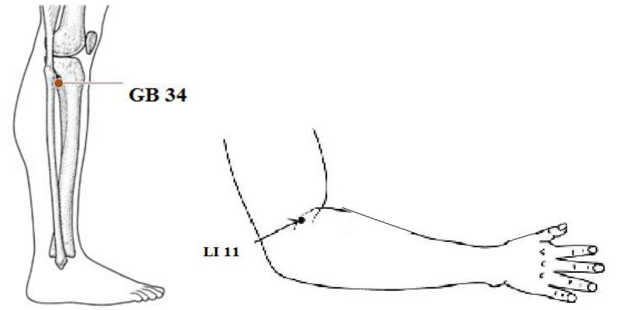

Figure 3:Acupoint GB 34 and LI 11 for improving the localization in sensory motor cortex.

Subjects were scanned in a 3.0 Tesla MR whole body Scanner. Functional images were collected in a sagittal orientation parallel to the AC-PC plane with 5 mm slice thickness using a single-shot gradient-recalled echo planar imaging (EPI) sequence. The EPI pulse sequence had the following parameters: TR = 1500 ms, TE is 40 ms, flip angle = 90 degree; matrix size = 64 × 64, FOV 240 × 240 mm^2, giving an in-plane resolution = 1.8 × 1.8 mm. The scan covered the entire brain . Structural scans were acquired using 3D MRI sequences with a voxel size of 1 mm^3 for anatomical localization.

2.2 Sparse k SVD

The natural signals can be compactly expressed, or efficiently approximated, as a linear combination of prespecified atom signals, where the linear coefficients are sparse (i.e., most of them zero). Sparse coding approximates an input signal, Y, by a sparse linear combination of items from dictionary D. K- SVD algorithm is a powerful iterative algorithm for training sparse dictionaries. The K-SVD algorithm can find the dictionary D that yields sparse representations for a set of training examples.[9]Specifically, this problem can be mathematically described by

$$\min_{\mathbf{D},\mathbf{X}}\{\|\mathbf{Y}-\mathbf{D}\mathbf{X}\|_F^2\} \quad \text{Subject to } \forall i, \|\mathbf{x}_i\|_0 \le T_0 \tag{1}$$

Where Y is the data elements , X the coefficients of the signal.T he K-SVD algorithm is a two step process:Sparse coding step,Code book update step. Exact determination of sparsest representations proves to be an NP-hard problem, approximate solutions are considered instead. The simplest ones are the Matching Pursuit (MP), the Orthogonal Matching Pursuit (OMP) algorithms.With estimated X, K-SVD puts only one column in the dictionary d_i and corresponding xj,the j^{th} row of X.This is solved using Single Value Decomposition (SVD)[8] .The columns of dictionary are sequentially changed and corresponding coefficients are updated.

2.3 Method of Optimal Direction (MOD) algorithm

This method closely follows the K-Means Algorithm.The sparse coding stage uses OMP algorithm .Assuming the coding for each example is known, the error is defined as

$$e_i = y_i - DX \tag{2}$$

Assuming X is fixed, an update to D such that the above error minimizes

$$D (n+1) = D (n) +\eta\ EX(n)T \tag{3}$$

Using infinitely many iteration and small η, leads to a steady state outcome and that is the MOD update matrix.MOD method assumes known coefficients at each iteration, and derives the best possible dictionary.After the dictionary learning with optimum k at each voxel, the non zero k atoms are used as the design matrix.Then F – map is calculated and degree of freedom should be imported to the SPM12 tool box to obtain the activation map for a given p- value.

3. INFERENCE AND DISCUSSION

Table 1: 110 acquisition arranged as columns against detrended voxels of whole brain.

ACQUISITION →

VOXEL ↑

d <63793x84 double>

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1	82.2515	82.4053	81.8371	77.3596	75.2151	74.4756	79.4847	79.2358	80.6912	76.9178	77.1285	73.7654
2	1	133.9937	138.5353	134.4815	128.0889	118.0494	117.6368	122.5055	126.6038	126.5847	124.2958	123.4914	122.5892
3	1	172.4408	178.5406	170.7320	164.2202	152.0621	150.1431	149.4925	153.7736	153.6070	155.6833	158.1413	156.1550
4	1	198.9870	203.1423	194.1587	190.6657	182.3289	181.6894	179.4811	180.4493	177.0769	180.8539	182.8240	187.0543
5	1	220.2983	215.5014	214.9262	211.4987	212.8435	211.2967	207.7710	205.9388	204.7985	209.0137	211.5402	216.3343
6	1	276.4870	267.7691	276.2149	272.3500	274.2171	268.5030	270.3071	272.0532	271.0068	271.6667	266.3572	274.5407
7	1	296.0802	286.5431	294.6693	288.4642	288.9788	283.9014	288.8715	294.5136	293.5052	291.8804	289.2347	293.4890
8	1	301.4125	297.6292	301.6100	291.9595	293.9425	284.5192	290.3934	292.6285	293.9923	293.3623	287.8698	293.0419
9	1	260.8670	262.0353	256.8342	251.9396	255.1557	249.5123	247.8221	254.6169	260.9785	263.0555	252.3220	257.0598
10	1	237.0295	241.8865	231.6328	226.5971	227.8668	223.1528	215.2885	230.1262	236.8205	240.7455	218.7480	226.7101
11	1	183.4683	191.1622	179.5898	180.0590	174.6770	174.9245	164.3077	183.7367	187.3820	189.1457	169.8435	177.7215
12	1	147.5307	152.0016	144.6203	141.6582	136.9510	139.2129	137.2056	148.0711	145.8257	142.5763	132.9859	140.5957
13	1	149.7963	155.9028	155.3624	151.0031	141.9545	141.7263	145.3379	149.2264	148.5921	144.0495	141.7042	142.2706
14	1	192.8478	200.7588	194.0103	186.5893	171.5238	173.6138	179.4563	184.7438	181.3534	178.2496	175.4358	174.6786
15	1	238.8628	249.2507	236.9001	229.2358	211.3102	213.1924	210.9233	216.4196	213.1265	215.4690	215.4155	213.0715
16	1	282.4556	286.2364	271.5078	267.0564	258.3273	261.6150	257.5315	257.6736	252.0572	254.5108	255.1354	259.1843
17	1	306.1774	301.2038	300.3136	295.1121	296.4709	296.5946	291.2440	290.3644	289.6250	294.6061	296.7797	299.1524
18	1	361.4662	352.3673	362.2669	356.5904	359.2468	351.9789	355.0126	356.8085	357.9047	356.8305	352.1212	357.4673
19	1	366.7707	356.9576	366.3979	360.5034	360.6996	354.0304	360.4198	367.6423	370.0008	365.0981	362.1468	362.6197
20	1	374.8267	370.2787	373.2672	364.1650	366.6650	355.1597	360.4729	363.1599	368.0050	363.5324	355.2193	357.8817

Table 2: K-10 , Iteration =30,Sparse dictionary learning using Ksvd Algorithm.

Sparse matrix(X)

	1	2	3	4	5	6	7
1	0	-0.2468	-0.2074	-0.3017	-0.0726	-0.3853	-0.5369
2	0.4112	0.5757	0.3064	0.2122	0	0	0
3	-0.1811	0	0	0	0	0.4237	0.5293
4	0.3004	0.1103	0	0.1838	0.1538	0	0
5	0	0	0	0	0	0	0.0264
6	0	0.2718	0.2725	0	0.1531	0.1356	0.1627
7	0	0	0.1225	0.3707	0.3401	0.3210	0.0792
8	-0.2570	0	0	-0.3372	-0.3424	-0.2169	0
9	-0.1263	-0.4681	-0.2880	0	0	0	0
10	-0.6087	-0.8751	-0.9097	-0.9862	-0.8821	-0.8367	-0.8546

Dictionary (D)

nksvd <63793x10 double>

	1	2	3	4	5	6	7	8	9
48272	1	0.0012	0.0012	0.0012	0.0012	0.0012	0.0012	0.0012	0.0012
48273	1	3.8277e-04	3.8035e-04	3.8747e-04	3.8057e-04	3.7811e-04	3.7515e-04	3.7898e-04	3.8229e-04
48274	1	0.0019	0.0019	0.0019	0.0019	0.0019	0.0019	0.0019	0.0019
48275	1	0.0041	0.0042	0.0042	0.0041	0.0041	0.0041	0.0041	0.0041
48276	1	0.0063	0.0063	0.0063	0.0062	0.0062	0.0062	0.0062	0.0062
48277	1	0.0069	0.0069	0.0069	0.0068	0.0069	0.0069	0.0069	0.0069
48278	1	0.0069	0.0069	0.0068	0.0068	0.0068	0.0068	0.0068	0.0068
48279	1	0.0067	0.0067	0.0067	0.0067	0.0067	0.0067	0.0067	0.0067
48280	1	0.0066	0.0066	0.0066	0.0066	0.0066	0.0066	0.0066	0.0066
48281	1	0.0069	0.0069	0.0069	0.0068	0.0069	0.0069	0.0069	0.0069
48282	1	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055
48283	1	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034
48284	1	9.5389e-04	9.6624e-04	9.5774e-04	9.8093e-04	9.8525e-04	9.6868e-04	9.8161e-04	9.8428e-04
48285	1	4.4505e-04	4.4654e-04	4.4645e-04	4.4451e-04	4.4312e-04	4.3413e-04	4.4152e-04	4.4557e-04
48286	1	0.0022	0.0022	0.0022	0.0021	0.0021	0.0021	0.0021	0.0021

The input scans are preprocessed in SPM12 for co registration, motion correction, slice time correction , Normalization and arranged as Y matrix as shown in table 1.Applying kSVD to Y results in sparse dictionary for optimum value of k-6.The activations projected in fig 2. implies that, before acupuncture on the specified acu points , the more voxels are seen in sensory motor cortex. After the acu point pressure, the region is equivalent to a healthy subject activation. Few highlights are also seen in fig 2. Which states that the activation may be due to hearing during experiment paradigm, lateral unwanted thinking, some expectations or disappointments , fear. With 30 iterations , the leaning is considerable for K=6.If the K value is above or below this, provides deviation in activation.

4. CONCLUSION

The acu point **LI 11,GB 34** activation on a shaky hand subject is analysed and the functional localization on the block paradigm using kSVD is obtained. Our fMRI study confirmed that acupuncture at these two point can activate certain cognitive-related regions in shaky hands patients. These results also explain methodology in acupuncture research.The future direction is to classify the healthy controls and ET subjects using the identified spatial map and time series. The only demerit is the deactivations could not be accountable.

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