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an Society for Cognitive

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## Welcome Massage



## Mojtaba Zarei MD, PHD, FRCP

## Dear colleagues

It is a pleasure to welcome you to the 8th Iranian Human Brain Mapping Congress held at Shahid Beheshti University. Shahid Beheshti university is the fastest growing university in Iran with

emphasis on human resources and new technologies. Moreover, it is one of the major centers and pioneers of brain mapping science in Iran. Interest in Brain Mapping has grown considerably since we started this annual meeting. Given the interdisciplinary nature of brain mapping science, each year we welcome scientists with different backgrounds including neuroscience, medical sciences, bioengineering, mathematics, biophysics, psychology, computer science, etc. It has become the highlight of our activity when students and senior researchers, clinicians, scientists, policymakers and policy users are all getting together to discuss new findings and advanced technologies in the field of brain sciences. Our main endeavor is giving inspiration to younger generation by those who dedicated their lives to the advancement of science alleviating human suffering. This year we continue our slogan "Brain Mapping: From Molecule to Medicine". We are aspiring to provide a medium for both domestic and world-renowned scientists to discuss and collaborate to obtain a better understanding of the nervous system and the related diseases. If brain mapping has taught us only one thing, that would be the importance of networks for optimal functioning. For this reason and many more, we welcome international scientific collaboration. Iran has so much to offer in neuroscience in general, and brain mapping in particular. There is a wealth of talent and energy among our educated youth which should be put into good causes with appropriate mentorship and guidance. In recent years, many high-quality clinical types of research have been published in prestigious medical journals because of access to a wide range of patients and their keen participation in research. We hope that this can be extended into clinical neuroscience as well. I encourage you to engage with our participants to develop your line of contact and to establish new networks to enhance your research. If there is anything that I can do to help, do not hesitate to contact me. I hope you enjoy the program and social interaction.

## **Program Chair of IHBM 2021**

# Congress Program

|               | Day 1 (November 16)   | Day 2 (November 17)  |                   | Day 3 (November 18)   |  |
|---------------|---|--|-------------------|---|--|
| 8:30 - 9:00   | Welcome<br>- Citations from Quran<br>- National Anthem<br>- Mojtaba Zarei<br>(Chair Of the IHBM)                            | -  | E                 |   |  |
| 9:00 - 10:00  | <b>Thomas Nichols (Oxford, UK)</b><br>Title: Opportunities and<br>Reproducibility Challenges for<br>Population Neuroimaging | Charlotte Stagg (Oxford, UK)<br>Title: Oscillations and Inhibition:<br>Towards an Understanding of the<br>Neurophysiology of Motor<br>Learning               | thology Symposiu  | Laszlo CinKotai , Ildiko Kiss,<br>Carla Wanblad<br>(3DHISTECH, Hungary)<br>Title: 3DHISTECH = Perfect<br>Solution for the Pathologists                                      |  |
| 10:00 - 11:00 | <b>Saad Jbabdi (Oxford, UK)</b><br>Title: Computational<br>Neuroanatomy with Diffusion<br>MRI                               | Matthew Rushworth (Oxford, UK)<br>Title: Activation and Disruption of<br>a Neural Network for Learning<br>Choice Values and for Making<br>Novel Decisions    | Pa                |   |  |
|               |   | 11:00-11:30 Break Time   |                   |   |  |
| 11:30 - 12:30 | <b>Mojtaba Zarei (SBU, Iran)</b><br>Title: Simultaneous PET/MRI<br>Imaging  | Joshua Jacobs (Columbia, USA)<br>Title: Probing the Neural Basis of<br>Human Memory with Direct<br>Recordings of Place and Grid Cells<br>and Traveling Waves | T                 | <b>homas Bak (Edinburgh, UK)</b><br>Title: Brain and Language   |  |
| 12:30 - 13:30 | <b>Narjes Soltani (SBU, Iran)</b><br>Title: Approaches to MEG Data<br>Analysis  | <b>Pieter Roelfsema (Amsterdam,</b><br><b>Netherlands)</b><br>Title: Conscious Visual Perception<br>and Restoring it in Blindness                            | Title             | Alexandre Pouget (Geneva,<br>Switzerland)<br>e: A Neural Model of Ultra-fast<br>Learning with Language  |  |
|               |   | 13:30-14:30 Break Time   |                   |   |  |
| 14:30 - 15:30 | Student Oral Presentation   | <b>Sylvain Baillet (McGill, Canada)</b><br>Title: Neural Dynamics of Brain<br>Perceptual Inferences  | sium              | Hamid Karimi-Rouzbahani<br>(Cambridge, UK)<br>Title: Representational Connectivity<br>Analysis Reveals Bidirectional Flow<br>of Familiarity Information Across the<br>Brain |  |
| 15:30 - 16:30 | Student Oral Presentation   | <b>Winrich Freiwald (Rockefeller, USA)</b><br>Title: Neural Circuits of the Social<br>Mind   | Perception Sympos | <b>Neda Afzalian (IPM, Iran)</b><br>Title: Semantic Face Processing   |  |
| 16:30 - 17:30 | Student Poster Presentation   | Kenneth D. Miller (Columbia, USA)<br>Title: Three Easy Pieces: Attention,<br>Paradoxical Responses,<br>Disinhibitory Circuit                                 | Face              | Amirhossein Farzmahdi (Albert<br>Binstein College of Medicine, USA)<br>Title: Computational Principles of the<br>Face-processing System in Brain-<br>inspired Networks      |  |
| 1             | 7:30-18:00 Question and Answer  | 17:30-18:00 Question and Answer  |                   | 17:30-18:00 EndSession  |  |







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Symposium

# **Neural Mechanisms** of Face Perception

from Neuroimaging to **Computational Modelling of the Brain** 

# **18 November 2021**



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# HBM Abstracts

Abstract No. 8001 (Oral Presentation)

## Separating subtypes of insomnia disorder based on structural and functional brain images: a preliminary machine learning study

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## Introduction

Insomnia disorder (ID) is a prevalent mental illness, characterized by difficulty in falling asleep and/or getting back to sleep after wake-up, associated with physical diseases, lower quality of life, higher motor vehicle accidents, depressive symptoms, emotion dysregulation, and memory impairment. There is an ongoing debate regarding ID's subtyping. Several behavioral and neuroimaging studies suggested that various subtypes of ID with distinct pathophysiology exist. However, their neurobiological underpinnings are poorly understood. Our aim was to test the hypothesis whether unimodal and/or multimodal neuroimaging can separate two main ID subtypes, namely, paradoxical and psychophysiological insomnia, from each other and from healthy control subjects based on the whole-brain neuroimaging matrices.

## **Materials and Methods**

We obtained demographic information, T1-weighted images, and resting-state fMRI from 34 patients with ID and 48 healthy controls. The outcome measures were voxel-wise values of gray matter volume, cortical thickness, low-frequency fluctuation, degree centrality, and regional homogeneity. Subsequently, we applied support vector machine to classify subjects via individual and combined imaging measures.

## Results

Our multimodal classification results were superior to unimodal approaches, as we achieved 81% accuracy to separate psychophysiological vs. control, 85% for paradoxical vs. control, and 87% for paradoxical vs. psychophysiological.

## Conclusions

This preliminary study provides initial evidence that structural and functional brain measures can help to distinguish two common subtypes of ID from each other and from healthy controls.

## Does Sleep-Disordered Breathing Affect CSF- and Imagederived Phenotypes in Alzheimer's Disease? A Multimodal Neuroimaging Study

Mohammad Akradi<sup>\*1</sup>, Amir Ebneabbasi<sup>\*1</sup>, Tara Farzane-Daghigh<sup>1</sup>, Mojtaba Zarei<sup>1</sup>, Alexander Drzezga<sup>2</sup>, Simon B. Eickhoff<sup>3, 4</sup>, Masoud Tahmasian<sup>1</sup>

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## Introduction

Sleep-disordered breathing (SDB) and Alzheimer's disease (AD) are prevalent conditions with a rising socioeconomic burden. Although SDB might affect cognitive decline, it is unclear whether and how it could be associated with neural/cerebrospinal fluid (CSF) markers of AD. We hypothesized that individuals with SDB have greater A $\beta$  deposition and lower glucose metabolism and voxel-based morphometry (VBM). Moreover, those CSF- and image-derived phenotypes mediate the relationship between SDB and cognitive status.

## **Materials and Methods**

We obtained 169 individual data (AD/SDB+: 34/14, MCI/SDB+: 77/40 and CN/SDB+: 58/28) from the ADNI database. Participants who had three imaging modalities [i.e., AV45 PET, Fluorodeoxyglucose (FDG) PET and magnetic resonance imaging (MRI)], baseline lumbar puncture (CSF A $\beta$ 42 and P-tau) and mini-mental state examination (MMSE) were selected. PET and MRI images were non-linearly registered to the MNI152. PET values were divided by cerebellar vermis for intensity normalization. PET/VBM measures were parceled to Schaefer-100. For each parcel and modality, a two-way analysis of covariance (ANCOVA) with main factors of "Group" and "SDB" was separately applied. Two mediation models were performed. For both models, SDB and MMSE were defined as exogenous (X) and endogenous (Y) variables, respectively. Mediators were A $\beta$ , FDG and VBM (Fig 1A) and CSF A $\beta$ 42 and P-tau (Fig 1B).

## Results

ANCOVA tests demonstrated eight significant regions (p-value < 0.05) in four networks where all modalities are overlapped; right intraparietal sulcus, bilateral posterior cingulate cortex, right temporo and parietooccipital, right temporoparietal junction and left inferior parietal lobe. Those overlapped regions were used to calculate  $A\beta$ /FDG/VBM values for each subject and entered as mediators for the mediation model. Our mediation analyses indicated that SDB indirectly predict MMSE through VBM and CSF P-tau.

#### Conclusions

Consistent with our hypotheses, SDB might affect VBM and CSF P-tau which ultimately modulate cognitive status. Our findings suggest that SDB may be considered as a risk factor of AD.



Figure 1. A) a five-factor mediation model, paths coefficients and p-values. SDB and MMSE were defined as exogenous (X) and endogenous (Y) variables, respectively. A $\beta$ , FDG and VBM were entered as mediators. B) a four-factor mediation model, paths coefficients and p-values. SDB and MMSE were defined as exogenous (X) and endogenous (Y) variables, respectively. Cerebrospinal fluid (CSF) A $\beta$ 42 and CSF P-tau were entered as mediators.

## Evaluation of the effect of changing the parameters of transcranial direct current stimulation in regions involved in major depression disorder by Finite Element Method

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## Introduction

Major depression disorder (MDD) is caused by dysfunction of the prefrontal regions [1]. In this study, the effect of changing the stimulation parameters, including current Intensity, area, thickness, and geometry of the electrode as well as the presence or absence of gel and sponge on the electrode in the electric field Intensity generated in LDLPFC and RDLPFC regions as regions involved in major depression disorder has been investigated.

## **Materials and Methods**

The method used in this research is the finite element method. To create a 3D model of the brain, MRI images are first segmented using SPM software. Then each of the segmented regions of the brain, including gray matter, white matter, cerebrospinal fluid, skull, and scalp by CAT software. It becomes a 3D volume model, and finally, headreco software is used to meshing the final model. The meshed model is used to perform finite element simulation using SimNIBS software.

## Results

The results show that increasing the current Intensity does not affect increasing or decreasing the regions involved in the stimulation while leading to an increase in the electric field Intensity in the stimulated regions. Also, increasing the area of the electrode has led to an increase in the regions involved in the stimulation, and at the same time, has led to a decrease in the Intensity of the electric field. Other factors also have a little effect on the Intensity of the electric field caused by the stimulation.

## Conclusions

Increasing the Intensity of the current leads to an increase in the Intensity of the electric field in the excited brain regions. Increasing the sizes of the electrode leads to a decrease in the Intensity of the electric field. Increasing the thickness of the electrode does not affect the Intensity of the electric field caused by the excitation.

## References

[1] Grimm, S., et al., Imbalance between left and right dorsolateral prefrontal cortex in major depression is linked to negative emotional judgment: an fMRI study in severe major depressive disorder. Biological Psychiatry. 2008.

Table 1: values of electrical conductivity of brain regions

| Brain Regions       | Electrical Conductivity (S/m) |
|---------------------|-------------------------------|
| White Matter        | 0.126                         |
| Gray Matter         | 0.275                         |
| Cerebrospinal Fluid | 1.654                         |
| Skull               | 0.01                          |
| Scalp               | 0.465                         |
| Electrode           | 29.4                          |



Figure 1: Mean electric field contour induced by 2 mA current in a square electrode with a length of 5 cm and a thickness of 5 mm in the white matter of the brain

## Classification of ADHD and HC based on Neural Correlates of Sleep Quality

Tara Farzane-Daghigh<sup>1</sup>, Mohammad Akradi<sup>1</sup>, Mojtaba Zarei<sup>1</sup>, Tim Silk<sup>2</sup>, Fateme Samea<sup>1</sup>, Masoud Tahmasian<sup>1</sup>

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## Introduction

ADHD is one of the most prevalent neurodevelopmental disorders in children and adolescents. ADHD is associated with high rates of comorbidities such as sleep disturbances which are considered a risk factor for the development of ADHD or a symptom of it. Due to the overlapped symptoms of ADHD and sleep disturbances, we hypothesized that a machine learning-based classification can separate ADHD and healthy control (HC) individuals based on their sleep neural correlates.

## **Materials and Methods**

We used the NICAP, a multimodal dataset (MRI and rsfMRI images) including 197 ADHD and HC individuals. Grey Matter Volume (GMV) as a surrogate of structural measure and fALFF, Degree Centrality, and ReHo as surrogates of functional measures were calculated based on 453 parcels for each measurement from three atlases (400 Schäfer cortical parcels, 36 Brainnetome subcortical parcels, and 17 Buckner cerebellar parcels) for all subjects. Sleep neural correlates were assessed using the Pearson correlation of individuals' structural and functional values with their sleep quality score from the Adolescent Sleep-Wake Scale. The FDR corrected features (p<0.05) were used as ADHD and HC predictors in random forest and SVM models. For both models, the hyperparameters were tuned using the grid search.

#### Results

117 participants (64% male, 39% ADHD,  $13\pm1.5$  years old, mean sleep and ADHD score of 2.74 and 5.57) from NICAP were entered into this study. Among 1812 features, 184 remained significant after the FDR correction. After the first random forest application, we selected the first 43 important features with importance>0.01 (The top 24 predictors are shown in Figure 1). We again applied the random forest with the selected 43 features. The accuracy, sensitivity, specificity, and ROC are 0.72, 0.83, 0.61, and 0.70, respectively. For the SVM model with all 184 features, the accuracy, sensitivity, specificity, and ROC are 0.72, 0.33, 1, and 0.46, respectively.

#### Conclusions

The results of our study indicate the importance of sleep and how discriminative sleep neural correlates might be in ADHD. It also May help to determine which underlying sleep neural features are related to ADHD and it might be helpful regarding the high rates of comorbidities and difficult ADHD diagnosis.



Figure 1: Top 24 classification predictors and their importance values

## Multimodal Brain Metastasis's Tumor and Edema Segmentation Using Generative Adversarial Networks

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## Introduction

Metastatic brain tumors (MBTs) are the most common complication of systemic cancer. MRI Imaging plays an essential role in MBTs for evaluation, analysis and treatment making plans. Segmentation of MBTs is a challenging problem with many inherent problems, as restricted training data. Recently many Deep Learning (DL) models have been developed to tackle this problem [1-2]. This study aimed to segment MBTs and edema using multimodal neuroimaging data by a DL model.

## **Materials and Methods**

We used multimodal data (Gadolinium-enhanced T1-weighted, T2- weighted, and FLAIR) of 43 participants who have been scanned at the Imaging Center of Imam Hossein Hospital (Iran). In the goal of comparison, we registered all modalities of each individual together, and after that, we transferred all data to standard space (MNI). An expert radiologist labeled metastasis and edema in all modalities. We used the Pix2Pix [3] network which used 85% data for the train and the rest data for test after quality assurance and preprocessing. Pix2Pix is a general-purpose solution to image-to-image translation. This network uses a "U-Net [4]"-based architecture for generator and a convolutional "PatchGAN" classifier which only penalizes structure at the scale of image patches. For the goal of the evaluation, we first calculated the model's accuracy and precision and secondly calculated the dice correlation between our outcome and labels.

#### Results

Our model worked acceptably according to the results obtained from the model evaluation criteria and segmented the tumor with good performance. Table 1. is shown the result of the evaluation of our model, and the performance of the model based on dice correlation was 0.95. For one of the participants, the result of our model is shown in Figure 1.

## Conclusions

We developed a DL model to segment metastatic brain tumors, and edema including T1-weighted, T2- weighted, and FLAIR. This model was able to segment MBTs with high accuracy and detect metastases larger than 5 mm.

## References

[1] Azimi P, Mohammadi HR, Benzel EC, Shahzadi S, Azhari S, Montazeri A. Artificial neural networks in neurosurgery. J Neurol Neurosurg Psychiatry. 2015 Mar;86(3):251-6.

[2] Jalalifar, Ali, et al. "A brain tumor segmentation framework based on outlier detection using one-class support vector machine." 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE, 2020.

[3] Lin, Nancy U., et al. "Response assessment criteria for brain metastases: proposal from the RANO group." *The lancet oncology* 16.6 (2015): e270-e278.

[4] Creswell A, White T, Dumoulin V, Arulkumaran K, Sengupta B, Bharath AA. Generative adversarial networks: An overview. IEEE Signal Processing Magazine. 2018 Jan 10;35(1):53-65.

| Table | 1: | eva. | luat | tion | measurements |  |
|-------|----|------|------|------|--------------|--|
|       |    |      |      |      |              |  |

| PSNR | Dice | SSIM |
|------|------|------|
| 32   | 96.3 | 93   |



Figure 1: network output example

## Auditory Midbrain Implant: Primary Auditory Cortex Responses to Electrical and Acoustical Stimulation

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## Introduction

Auditory midbrain implant (AMI) is a new type of central auditory prothesis that is designed for electrical stimulation within the central nucleus of the inferior colliculus in patients with no implantable cochlea, such as neurofibromatosis type 2(NF2). The main aim of our study was to compare the primary auditory cortex (A1) local field potential (LFP) responses, LFP-Area, Peak-Amplitude, On-set, Off-set and Peak-Latency, in acute cats' experiments, using the A1 neuronexus probe, to electrical stimulation of ICC and acoustical stimulation to search effectivity of AMI for auditory perceptions sensation.

#### **Material and Method**

After normalization of the five characteristics including LFP-Area, Peak-Amplitude, On-set, Off-set, and Peak-Latency from the signal for each response and averaging, electric and acoustic responses were compared to each other by using the Mann-Whitney rank sum statistic test. In total, 224 recording-stimulation pairs were compared.

#### Results

Comparing electric and acoustical responses of the LFP-Area, LFP-Peak and the LFP-threshold had shown no significant difference. This similarity indicates the effectivity of AMI to produce auditory perceptions sensation. In LFP-latencies' comparisons we have find a significant shorter time delays between acoustical and electrical stimulations responses, which represented the time that acoustical stimuli need to reach the ICC.

#### Conclusion

We also found that each acoustical stimulation level (dB re SPL) change, corresponded to electrical stimulation levels (dB re 1 $\mu$ A) with the coefficient of 4 to produce the similar LFPs in A1. These inadequate coefficients can cause neuronal damage, which can cause a decrease in the LFP responses during the experiment time. Our data demonstrated that the AMI could selectively activate different neuronal populations in the ICCs to effective auditory perception sensation. We also found that for the constant firing of neurons during the time and do not produce neuronal damage, we need to decrease our electrical stimulation levels by <sup>1</sup>/<sub>4</sub> (dB re 1 $\mu$ A).



Fig.1: LFP-character comparisons in On-BFs between acoustic and electric data. In each figure, one of the six characters and comparison statics results are shown. NS means not statistically significant differences between two groups, \*\*\* means p<0.001, and \*\* means p<0.01.

|         | LFP-     | Area     | Three    | shold    | Onset I  | atency   | Offset I | Latency  | Peak An  | nplitude | Peak L   | atency   |
|---------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| Groups  | Acoustic | Electric |
| Median  | 0.612    | 0.593    | 1.000    | 0.913    | 0.904    | 0.760    | 0.927    | 0.837    | 0.725    | 0.670    | 0.958    | 0.826    |
| Mad     | 0.254    | 0.254    | 0.098    | 0.078    | 0.085    | 0.168    | 0.123    | 0.170    | 0.236    | 0.230    | 0.060    | 0.106    |
| Min     | 0.079    | 0.043    | 0.666    | 0.750    | 0.486    | 0.211    | 0.584    | 0.367    | 0.151    | 0.253    | 0.731    | 0.526    |
| Max     | 1.003    | 1.000    | 1.000    | 1.000    | 1.000    | 1.000    | 1.000    | 1.000    | 1.000    | 1.000    | 1.000    | 1.000    |
| Average | 0.5971   | 0.608    | 0.939    | 0.909    | 0.895    | 0.762    | 0.880    | 0.793    | 0.669    | 0.656    | 0.939    | 0835     |
| n       | 87       | 87       | 98       | 98       | 110      | 110      | 87       | 87       | 87       | 87       | 117      | 117      |
| P Value | =0.37    | 4 (NS)   | <0.01    | . (**)   | <0.001   | . (***)  | <0.001   | L (***)  | =0.17    | 6 (NS)   | <0.001   | (***)    |

Table 1: LFP characteristic group comparisons and their statistical values. Active sites (n), median absolute division (MAD), minimum (MIN), maximum (MAX), value of statistical probability (P value), \*\*\* highly statistically significant, \*\* mediocre statistically significant, NS not statistically significant.

## The Effect of Language Priming on the Activation Level of Motor Cortex in Action/Non-Action Language Conditions

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## Introduction

According to the research on embodiment hypothesis, patients with motor dysfunctions have variety of problems with action-language related to their dysfunctional bodypart [1]. There is a relative engagement of the motor cortical system in various language-related functions, not exclusively those of motor preparation for articulation or motor simulation [2]. To study the effect of language type (in regard with action relatedness) on motor system, we recorded the motor cortex data of participants in action/object language production in primed vs nonprimed conditions. The significance of this study is to investigate the role of motor cortex in different language functions.

## **Materials and Methods**

We recorded the cortical electric activity of 27 English-language-learners (Right-handed, Upper/Intermediate) while doing a picture description task, including 4conditions: Object/Action picture description with and without syntactic priming. Subjects were instructed to produce a single sentence to describe the presented pictures. The EEG was recorded continuously using 64-channel EEG out of which, 18 were used in motor analysis[3]. Moreover, Behavioral data were analyzed using repeated-measures within subject ANOVA (2\*2) design (Action relatedness (Action, Object description) \* Priming (Primed, NonPrimed).

#### Results

Our behavioral results confirmed a main effect of Priming in both response accuracy (F(1,26)=27.09, p<0.001) and response times (F(1,26)=15.11, p=0.001) (higher RA and faster RT in primed conditions). Neither main effect of Action-relatedness nor interaction between Action-relatedness and Priming were seen (Figures 1).

Our EEG analyses revealed a significant main effect of Priming between 200-350ms post-stimulus onset. This is the time-window related to stimulus evaluation and categorization (the same time-window as P300). While both primed conditions maintain relatively similar ERPs, being explained by the effect of Priming, non-primed conditions start to show differential ERPs at around 400ms post-stimulus. These results represent different underlying processing Action vs Object description while unprimed.

#### Conclusions

Priming affects both object description and action description in a relatively similar pattern.

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Figure 2

## Multimodal Brain Metastasis's Tumor and Edema Tracking Using GOTURN Network

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## Introduction

Tracking brain tumors is proven to be helpful for clinicians to pathology assessment [1]. This will be more critical when scientists struggling with brain metastasis which are tumors that have moved from other parts of body into the brain. They are various in structure, texture, and shape; thus, they are hard to recognize and even expertise using different modalities along with T1-weighted MRI to recognize them. In this study, we used a deep neural network architecture to trace the metastasis using multimodal neuroimaging data automatically.

## **Materials and Methods**

We used multimodal data (Gadolinium-enhanced T1-weighted, T2- weighted, and FLAIR) of 43 participants who have been scanned at the Imaging Center of Imam Hossein Hospital (Iran). The Generic Object Tracking Using Regression Networks (GOTURN) [3] tracking algorithm was used to predict metastasis in each slice. The GOTURN defines a tracker architecture based on image comparison. The architecture contains two convolutional networks. In this model, the target object was input into one network, and the search region of the next frame was fed into the other convolutional network for finding the target. The output of the two networks was the input of fully connected layers.

We had used metastasis tracking in our previous work by using only T1-weighted MRI on traditional Convolutional Neural Network (CNN) [4], therefore our previous results were compared to those of this new approach in terms of three well-known evaluation quantities in tracking concepts are "Success," "Precision," and "Frame Per Second" (FPS).

## Results

Analyzing multimodal data with GOTURN tracking algorithm had better performance than the traditional CNN, which used only one neuroimaging modality to trace metastasis. The results of these approaches and metastasis tracking are shown in Table.1, and Figure 1.

## Conclusions

The performance of metastasis tracking was improved by firstly using multimodal neuroimaging data and, and secondly utilizing GOTURN. This accurate metastasis tracking can increase the intuition of related researchers by indicating the approximated location of it as prior information.

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Table 1: evaluation measurements

| Approach name | Success | Precision | FPS |
|---------------|---------|-----------|-----|
| CNN           | 65      | 89        | 22  |
| GOTURN        | 61      | 90        | 100 |





Figure 1: the result of Tumor tracking in four frames ( a to d ) movie link: https://drive.google.com/file/d/1AxHWLvxwzK8shI-LvlWO-GkZ-SiaafUa/view?usp=sharing

## Investigation of Mental Engagement using a Frequency-based Index in Steady-State Visually Evoked Potentials

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## Introduction

One of the most popular paradigms in BCI systems is Steady State Visually Evoked Potentials (SSVEPs), which is a response to flickering visual stimuli[1]. BCI tasks usually require a high cognitive workload, along with a protracted working duration, which can lead to a decrease in vigilance, errors and task failure. The Task Engagement Index (TEI) is a ratio of EEG power bands (beta/(alpha+theta)) that can be used to assess how cognitively engaged a person is in a task. In this study, TEI was utilized to assess user engagement with SSVEP stimulation.

## Method

An online available SSVEP dataset [2] containing 16 channels of EEG signals acquired from 5 healthy individuals while looking at a green flickering LED light at 5Hz, 6Hz, 7Hz, and 8Hz frequencies for 30\_seconds each was used. In this research, only 3 channels of Oz (due to its proximity to the visual cortex), F3 and F4 were used. The TEI values were then calculated for each stimulus frequency .Finally, the performance of different users was evaluated (by comparing the TEI values with accuracy obtained based on the CCA approach).

#### Results

Fig. 1 shows the TEI values for the three mentioned channels and the four stimulus frequencies. The accuracy rate of target frequency detection based on the CCA approach [3] is also provided in these charts to assess the strategy.

#### Conclusions

It can be concluded that TEI can be used in SSVEP\_based BCI systems to provide a user distraction alert system. Since 8Hz is in the alpha range, the index's superior performance at this frequency and in the occipital area makes sense.

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Fig. 1: TEI and CCA accuracy rate values for the four stimulus frequencies in (a) Oz, (b) F3 and (c) F4 channels Excluding participant No.3, the TEI values in the 8Hz frequency and Oz channel are correlated with the CCA method's results.

## Machine learning based clustering analysis for the effects of cardiac arrest on the brain intracellular pH levels

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## Introduction

In this paper we consider the important biologic issue and its analysis by mathematical model. There are pH levels for the cells, which is a function of local perfusion. Low intracellular pH causes the production of free radicals and affects the calcium balance of cells, which may lead to cell death. Therefore, the study of pH dynamics is worth predicting cell death after stroke and cardiac arrest.

## **Materials and Method**

We examine the brain pH dataset and its relationship to heart attack using a machine learning algorithm. Clustering is a fundamental unsupervised learning. The primary goal of clustering is the grouping of data into clusters based on similarity, density, intervals or particular statistical distribution measures of the data space. We focus on features like, pH, Sex, Ethnicity, Age and Death type which collected by PNAS in Table1.

#### Results

The result represents five clusters or groups of populations, which means that in each of these clusters are similar in terms of age, sex, pH and Ethnicity as shown in Figure 3. We also find that according to the data from these dataset Figure 2.

## Conclusions

By using k-means method we analyzed the effects of cardiac arrest on changing brain intracellular pH level. In this paper we presented a general model in order to change brain cells pH level caused by cardiac arrest. The proposed model is useful to better understand the cardiac arrest affections.

## References

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|    | рН   | Sex | Ethnicity       | Age | DeathType |
|----|------|-----|-----------------|-----|-----------|
| 0  | 7.13 | М   | Caucasian       | 64  | Cardiac   |
| 1  | 6.50 | м   | Caucasian       | 63  | Cardiac   |
| 2  | 6.40 | м   | AfricanAmerican | 59  | Cardiac   |
| 3  | 6.53 | м   | Caucasian       | 52  | Cardiac   |
| 4  | 6.58 | м   | Caucasian       | 58  | Cardiac   |
|    |      |     |                 |     |           |
| 95 | 6.97 | м   | Caucasian       | 44  | Other     |
| 96 | 6.62 | м   | Caucasian       | 57  | Cardiac   |
| 97 | 7.03 | м   | Caucasian       | 61  | Cardiac   |
| 98 | 6.61 | м   | Caucasian       | 54  | Cardiac   |
| 99 | 6.99 | F   | Caucasian       | 38  | Cardiac   |



Table 1: Data frame of considered dataset



Figure3: Final Result and Clustering



Figure 2: left: Compare Age, pH and Ethnicity, right: Compare Age, pH and Sex

# The role of intrinsic brain networks in the link between sleep quality and familial risk of depression

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## Introduction

Individuals with a familial history of depression are at elevated risk of depression. In addition, studies have pointed out a connection between the familial risk of depression and poor sleep quality. Despite its potential contribution to the increased risk of depression, the neurobiological mechanisms of such a link remain to be understood. Thus, the present study aimed to investigate the functional connectivity (FC) of neural networks as a possible underlying link between sleep quality and the familial risk of depression.

## **Materials and Methods**

We selected 92 participants from the Human Connectome Project (HCP) and assigned them to two groups of high-risk (N=47) and low-risk (N=45) individuals based on their parental history of depression. Using participants' RS-FMRI data, we then preformed independent component analysis followed by dual regression to identify intrinsic brain networks. Lastly, using the General Liner Model (GLM), we set up t-tests to compare FCs of the networks between the two groups to assess the neural characteristics of (1) the familial risk of depression and (2) those of the interaction between sleep quality and the familial risk.

#### Results

We found no significant between-group differences (i.e., high-risk vs low-risk) in the FCs within or between the networks. The interaction of the risk status and sleep quality, however, revealed significant within-network differences. Specifically, the interaction was associated with decreased FC in the DMN (namely, the left middle temporal gyrus) and increased FC in the CEN (the left supramarginal gyrus and bilateral occipital cortex) in the high-risk group.

#### Conclusions

Our findings highlight aberrant FCs within the DMN and CEN as the neural connection between the family history of depression and sleep quality. Furthermore, poor cognitive performance and increased likelihood of rumination associated with the reported aberrant FCs might be the vulnerability factors for depression in high-risk individuals with poor sleep quality.

# Supervised Machine learning algorithms in psychological science

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## Introduction

Electroencephalography signals have been chosen as a functional tool for the concrete task in diagnosing psychological disorders [1]. Machine learning has shown great promise in helping EEG signals due to its capacity to learn feature representations from raw data. we employ Beck Depression Inventory (BDI) and Beck anxiety inventory (BAI) scores to diagnose related disorders.

## **Materials and Methods**

In our method, brain activity of subjects was recorded via EEG by using Mitsar 19 channel system according to the International 10-20 system. In order to remove interferences from EEG, all the EEG electrode contact impedances were maintained below 5 k $\Omega$ . Independent component analysis (ICA) algorithm has also been used to remove blinking, eye movements and muscles artifacts. To a high-pass filter with a cut-off frequency of 0.1 Hz, a low-pass filter with a cut-off frequency of 50 Hz, and a Notch filter with cut-off frequencies of 45 and 55 Hz were used. We applied regression, support vector machine (SVM), multi-layer perceptron (MLP) and k-nearest neighbor (KNN) supervised learning algorithms and compare their success in classification tasks.

#### Results

According to the rank of each coefficient, we have run the described algorithms for 148 features for BDI and 31 features for BAI. The MLP algorithm get more accuracy than SVM, KNN and regression as seen in Figure 1 and 2.

## Conclusions

This paper applies the machine learning algorithms to psychological diagnosis. since the number of features reduced, the stunning results produced after feature selection.

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<sup>th</sup> Iranian Human Brain Mapping Congress

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## Effects of interictal epileptiform discharges on cognitive performance, personal and clinical aspects of patients' life in drug-resistant epilepsy

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## Introduction

Cognitive impairments are one of the most frequent symptoms of epilepsy, affecting several aspects of patients' life [1]. However, its evaluation and treatment are challenging for clinicians. The relationship between interictal EEG findings and cognitive problems in patients with epilepsy has been studied for several years. Nevertheless, results are controversial and different definitions make it hard to combine available literature and synthesize evidence-based recommendations about their effects on cognition and personal and clinical aspects of patients' life.

## **Materials and Methods**

This cross-sectional study enrolled fifty-one adult patients with drug-resistant epilepsy, diagnosed based on the latest International League Against Epilepsy (ILAE) guidelines. We performed long-term EEG monitoring and comprehensive neuropsychiatric evaluation. IEDs were defined and classified based on the latest ILAE and American Clinical Neurophysiology Society's (ACNS) guidelines [2]. Interictal and ictal EEG findings, neuroimaging, disease characteristics, and personal data were collected.

## Results

Cognitive functions and quality of life were almost the same in IEDs frequency groups. We found that there is not any significant relationship between IEDs frequency and cognitive performance after controlling confounding factors. However, we showed that Marital status, age of onset, and seizure frequency were correlated with IEDs frequency. Brain MRI had a significant correlation with IEDs frequency, but further statistical analysis showed this is unreliable.

## Conclusions

Further studies are needed to clarify the exact pathophysiology of cognitive impairments in epilepsy and the role of IEDs.

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## Investigation of Phase Space Reconstruction to Reduce EEG channels for Imagined Speech Purposes

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## Introduction

The electroencephalographic (EEG) signal has many applications in the field of brain-computer interface (BCI) due to its non-invasive nature. For the practical application of BCI systems, reducing the number of channels for ease of use and increasing processing speed can be effective. In this research, a novel method is investigated for imagined speech tasks (IST).

### **Materials and Methods**

The algorithm of relative wavelet energy (RWE) is one of the classic tools to extract traditional features of EEG signals [1]. In this study, the phase space reconstruction (PSR) approach was used to reconstruct a one-channel of EEG into multidimensional space which shows its true attractor. The extracted features were classified using a support vector machine (SVM), by feeding the reconstructed data to the RWE. The PSR was implemented by time-delay embedding method which needs time delay (TD) and embedding dimension (ED) parameters. They were calculated by an extended version of Mutual information and false nearest neighbor algorithms. The dataset [2] including six-channel EEG were illustrated by blue in figure 1. It consists of five vowels /a/, /e/, /i/, /o/, and /u/ from 15 young adults in imagining pronunciations.

#### Results

The area around the T3, C3, Cz, C4, and T4 electrodes is more promising to detect the unspoken due to the homunculus being there, as well as the F7 electrode in the Broca area and the T5 electrode in the Wernicke area [3]. Here, C3 and C4 channels only exist in the database. All channels were reconstructed with ED = 2 and TD = 3. Then, the classification method is performed on each participant using RWE+SVM. The reconstructed C3 channel has better results than the other one-channel as well as six-channels as shown in Table 1. The mean accuracy is 27.43% for reconstructed C3 and 23.67% for six-channels, respectively.

## Conclusions

All of the reconstructed-channel+RWE+SVM show better classification results than six-channel+RWE+SVM which suggests the proposed method is practicable for few-channel BCI.

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| Subject                  | Reconstructed<br>F3 | Reconstructed<br>C3 | Reconstructed<br>P3 | Reconstructed<br>F4 | Reconstructed<br>C4 | Reconstructed<br>P4 | All of six<br>channels |
|--------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|------------------------|
| S01                      | 23.97               | 30.82               | 27.4                | 27.4                | 24.66               | 25.34               | 26.71                  |
| S02                      | 25.13               | 28.64               | 23.12               | 29.65               | 22.11               | 25.12               | 21.61                  |
| S03                      | 21.82               | 26.09               | 23.66               | 23.64               | 25.46               | 22.44               | 29.08                  |
| Mean of S01,<br>S02, S03 | 23.64               | 28.51               | 24.72               | 26.89               | 24.07               | 24.3                | 25.80                  |
| Mean                     | 24.52               | 27.43               | 26.13               | 25.54               | 25.59               | 25.09               | 23.67                  |

Table 1: Accuracy of the reconstructed channels and six-channel.



Figure 1: Electrode distribution for the EEG registers [2]. Six blue channels were selected for data recording in the database.







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