25_CONCORSO PUBBLICO, PER TITOLI ED ESAMI, PER LA COPERTURA A TEMPO DETERMINATO, DELLA DURATA DI CINQUE ANNI, SECONDO LA NORMATIVA CONCORSUALE AI SENSI DEL D.P.C.M. DEL 21 APRILE 2021, PER N. 1 POSTO DI RICERCATORE SANITARIO, CAT. D, LIVELLO D SUPER DA ASSEGNARE ALLA SC NEURORADIOLOGIA

PROVA I

1. Avendo a disposizione tecniche di risonanza magnetica strutturale quali analisi effettuerebbe su una patologia degenerativa? Con quali altri dati integrerebbe le informazioni della risonanza magnetica?

2. Cos'è un software Open Source e in cosa si distingue dagli altri?

3. Si traduca l'abstract dell'articolo sottostante

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A review on neuroimaging-based classification studies and associated feature extraction methods for Alzheimer's disease and its prodromal stages

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ABSTRACT

Neuroimaging has made it possible to measure pathological brain changes associated with Alzheimer's disease (AD) in vivo. Over the past decade, these measures have been increasingly integrated into imaging signatures of AD by means of classification frameworks, offering promising tools for individualized diagnosis and prognosis. We reviewed neuroimaging-based studies for AD and mild cognitive impairment classification, selected after online database searches in Google Scholar and PubMed (January, 1985–June, 2016). We categorized these studies based on the following neuroimaging modalities (and sub-categorized based on features extracted as a post-processing step from these modalities): i) structural magnetic resonance imaging [MRI] (tissue density, cortical surface, and hippocampal measurements), ii) functional MRI (functional coherence of different brain regions, and the strength of the functional connectivity), iii) diffusion tensor imaging (patterns along the white matter fibers), iv) fluorodeoxyglucose positron emission tomography (FDG-PET) (metabolic rate of cerebral glucose), and v) amyloid-PET (amyloid burden). The studies reviewed indicate that the classification frameworks formulated on the basis of these features show promise for individualized diagnosis and prediction of clinical progression. Finally, we provided a detailed account of AD classification challenges and addressed some future research directions.

Prova non estratta

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PROVA 2

1. Avendo a disposizione tecniche di risonanza magnetica diffusione quali analisi effettuerebbe su una patologia degenerativa? Con quali altri dati integrerebbe le informazioni della risonanza magnetica?

2. Cos'è Matlab e a cosa serve?

3. Si traduca l'abstract dell'articolo sottostante

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DeepAtrophy: Teaching a neural network to detect progressive changes in longitudinal MRI of the hippocampal region in Alzheimer's disease

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ABSTRACT

Measures of change in hippocampal volume derived from longitudinal MRI are a well-studied biomarker of disease progression in Alzheimer's disease (AD) and are used in clinical trials to track therapeutic efficacy of disease-modifying treatments. However, longitudinal MRI change measures based on deformable registration can be confounded by MRI artifacts, resulting in over-estimation or underestimation of hippocampal atrophy. For example, the deformation-based-morphometry method ALOHA (Das et al., 2012) finds an increase in hippocampal volume in a substantial proportion of longitudinal scan pairs from the Alzheimer's Disease Neuroimaging Initiative (ADNI) study, unexpected, given that the hippocampal gray matter is lost with age and disease progression. We propose an alternative approach to quantify disease progression in the hippocampal region: to train a deep learning network (called DeepAtrophy) to infer temporal information from longitudinal scan pairs. The underlying assumption is that by learning to derive time-related information from scan pairs, the network implicitly learns to detect progressive changes that are related to aging and disease progression. Our network is trained using two categorical loss functions: one that measures the network's ability to correctly order two scans from the same subject, input in arbitrary order; and another that measures the ability to correctly infer the ratio of inter-scan intervals between two pairs of same-subject input scans. When applied to longitudinal MRI scan pairs from subjects unseen during training, DeepAtrophy achieves greater accuracy in scan temporal ordering and interscan interval inference tasks than ALOHA (88.5% vs. 75.5% and 81.1% vs. 75.0%, respectively). A scalar measure of time-related change in a subject level derived from DeepAtrophy is then examined as a biomarker of disease progression in the context of AD clinical trials. We find that this measure performs on par with ALOHA in discriminating groups of individuals at different stages of the AD continuum. Overall, our results suggest that using deep learning to infer temporal information from longitudinal MRI of the hippocampal region has good potential as a biomarker of disease progression, and hints that combining this approach with conventional deformation-based morphometry algorithms may lead to improved biomarkers in the future.

Prova non estratta

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PROVA 3

1. Avendo a disposizione tecniche di risonanza magnetica funzionale fMRI quali analisi effettuerebbe su una patologia degenerativa? Con quali altri dati integrerebbe le informazioni della risonanza magnetica?

2. Cos'è R e a cosa serve?

3. Si traduca l'abstract dell'articolo sottostante

Diagnostic power of resting-state fMRI for detection of network connectivity in Alzheimer's disease and mild cognitive impairment: A systematic review

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Abstract

Resting-state fMRI (rs-fMRI) detects functional connectivity (FC) abnormalities that occur in the brains of patients with Alzheimer's disease (AD) and mild cognitive impairment (MCI). FC of the default mode network (DMN) is commonly impaired in AD and MCI. We conducted a systematic review aimed at determining the diagnostic power of rs-fMRI to identify FC abnormalities in the DMN of patients with AD or MCI compared with healthy controls (HCs) using machine learning (ML) methods. Multimodal support vector machine (SVM) algorithm was the commonest form of ML method utilized. Multiple kernel approach can be utilized to aid in the classification by incorporating various discriminating features, such as FC graphs based on "nodes" and "edges" together with structural MRI-based regional cortical thickness and gray matter volume. Other multimodal features include neuropsychiatric testing scores, DTI features, and regional cerebral blood flow. Among AD patients, the posterior cingulate cortex (PCC)/Precuneus was noted to be a highly affected hub of the DMN that demonstrated overall reduced FC. Whereas reduced DMN FC between the PCC and anterior cingulate cortex (ACC) was observed in MCI patients. Evidence indicates that the nodes of the DMN can offer moderate to high diagnostic power to distinguish AD and MCI patients. Nevertheless, various concerns over the homogeneity of data based on patient selection, scanner effects, and the variable usage of classifiers and algorithms pose a challenge for ML-based image interpretation of rs-fMRI datasets to become a mainstream option for diagnosing AD and predicting the conversion of HC/MCI to AD.

Prova Estratta

Elise Pereira