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Review Article

Classification Techniques in Machine Learning for Age-related Electroencephalography Data Analysis

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ABSTRACT

Electroencephalography (EEG) is used to measure event-related potentials in neuroscience. Age-related changes can alter the EEG signals as well as neurological diseases. Understanding EEG signals is beneficial to the diagnosis, prediction and prevention of neurological disorders, including neurological rehabilitation and the brain-computer interface. EEG data analytic application is a new frontier in neuroscience and neuroengineering. In this review article, EEG analysis during the resting state, working memory tasks and brain aging is briefly discussed. Several classification techniques in machine learning are discussed and compared in terms of aging, including the support vector machine, K-nearest neighbor, decision tree, random forest, multilayer perceptron, logistic model tree and Naïve Bayes. Dealing with big data analysis using machine learning will be a mega trend in the future, including EEG data.

Keywords: aging; electroencephalogram; feature classification; feature extraction; machine learning

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INTRODUCTION

Electroencephalography (EEG) is emerging rapidly as a useful tool in neuroscience. EEG records the electrical activity inside the brain, and it is often called an electro-physiological monitoring method. EEG has been applied in the diagnosis of neurological disorders and diseases, brain-computer interface and in other studies to investigate the complex structure of the brain. Understanding the process of brain aging is very important. Several neu-roimaging techniques have been used for such studies including functional magnetic resonance imaging (fMRI), computerized tomography (CT), and EEG[1-3].

In such studies, EEG is not only been applied during the patient's resting state, but also in work-memory tasks as memory decline is one of the earliest symptoms in both healthy aging and neurodegenerative diseases. Several types of analysis have been adopted to study the EEG in aging patients. The classical power spectral analysis[1], EEG signal complexity[4], functional connectivity and network topology[5] are the main techniques used to study age-related EEG. Machine learning techniques have not been widely applied to classify the healthy age-related EEG. Various machine learning algorithms can be used to clas-sify the EEG signals not only in the patient's resting state but also with a working memory (WM) load as well.

BRAIN WAVES AND ELECTROENCEPHALOGRAM

EEG is emerging rapidly as a useful tool in neu-roscience. EEG records the electrical activity inside the brain, and it is often called an electrophysiological moni-toring method. EEG is not only being researched for its use in diagnosis of neurological diseases, but it is also providing information to help scientists better understand the complex human brain and its functionalities. EEG has five major frequency bands with amplitudes of up to 100 microvolts, the Delta, Theta, Alpha, Beta and Gamma bands which relate to behaviors as shown in Table 1. EEGs can be recorded invasively or non-invasively. To record the EEG from the surface of the scalp dry or wet electrodes are used. The position of the electrodes is based on the international 10-20 system of electrode placement as shown in Figure 1. The electrodes are labelled according to the brain region and odd numbers represent the left hemisphere and even numbers represent the right hemisphere of the brain[6]. A new electrode naming system modified combinatorial nomenclature (MCN) uses 10%, 20%, 30%, 40%, and 50% of inion-to-nasion distance[7,8]. The MCN system renames the four electrodes from T3 to T7, T4 to T8, T5 to P7, and T6 to P8.

Table 1 The EEG frequency bands and behavior

Waves	Frequency bands (Hz)	Behavior trait
Delta	0.3-4	Deep sleep
Theta	4-8	Deep meditation
Alpha	8-13	Eyes closed, awake
Beta	13-30	Eyes opened, thinking
Gamma	30 and above	Unifying consciousness

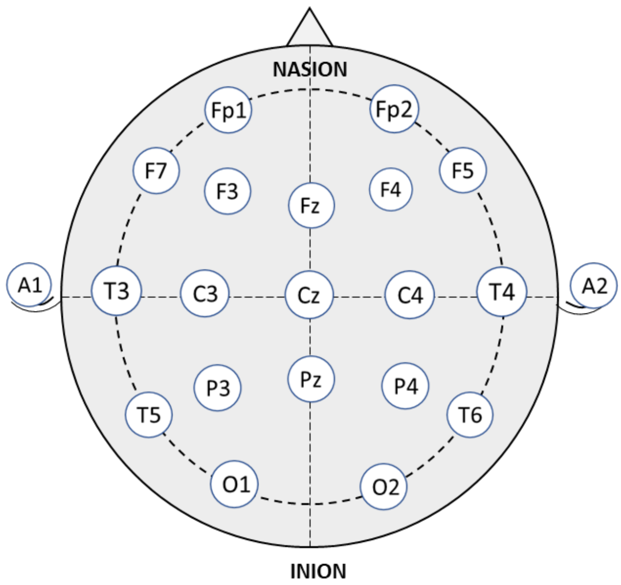

Figure 1 The international 10-20 system for EEG electrode placement

ELECTROENCEPHALOGRAM AND AGING

Aging causes subtle changes in brain size, memory, vasculature and cognitive abilities[9]. With aging, the brain declines as other organs in the body decline in a normal healthy person. The changes do not occur to the same degree in all brain areas during aging[10]. Memory is affected by aging in healthy people in terms of memory tasks because some brain areas may be not easily accessible to be studied[9]. In 2015, 30 million people were affected by neurodegenerative disorders, including Alzheimer's disease (AD)[11]. AD affects 1 in 9 for adults over 65 years old, and 1 in 3 for 85 years and older[12]. It is estimated that by 2050 there will 150 million people with AD, with a predicted cost for their care of two trillion US dollars by 2030[13,14]. Neurodegenerative diseases are mostly considered as age-related and it is the elderly community primarily suffering from these diseases. Positron emission tomography (PET) and magnetic resonance imaging (MRI) have been used to study the tau pathology and β-amyloid plaques which are the major causes of AD[15,16]. It has been shown that β-amyloid plaques is differentially associated with tau tracer retention in healthy aging and found to be higher in healthy older adults compared to younger adults[17].

Aging is not the only risk factor for brain disease, but the question is how the aging is associated with brain disorders and diseases. The most important problem at this time is to identify the root cause of brain diseases and curing them. The EEG is a non-invasive and excellent temporal resolution technique in neuroscience. It is important to identify aging biomarkers and differentiate the healthy age groups of infants, young and middle-age adults and elderly. In addition, it is necessary to solve the complex problems of brain organization. In the elderly community, mostly memory is affected during the process of aging. The elderly population is most vulnerable to neurodegenerative diseases. Age-dependent brain electrical signals have distinct features to classify them from other cognitive mental states. In recent years, machine learning has been introduced in signal analysis. Classical time and frequency domain analysis is being merged with machine learning to enhance the interpretation of EEG results.

Human brain aging is non-uniform and all body parts decline with age. The brain changes throughout a human life more than any other body parts. The frontal lobes of the brain are involved in activities such as planning and execution of tasks, working memory and other executive functions and this brain area is the last to mature, and may not be fully developed until 35 years of age[18]. To better understand the brain and its complex organization and functional networks and sub-networks, understanding aging and the processes of aging is important. Cognitive functions testing shows different results in different age groups. Cognitive functions involve memory, processing and active brain networks to store and retrieve information. The study of visual tasks has revealed information regarding learning abilities while performing the task.

AGE-RELATED CHANGES IN RESTING STATE EEG

A recent study reported that delta power was associated with executive performance in older people compared to young people and this suggested that slow frequencies (<7Hz) power decreases as age increases linearly[19]. In the elderly group, the theta band power was reported to be reduced topographically in the posterior region compared to younger adults[1]. Similarly, in the eyes open test, alpha frequency is reduced in older adults compared to younger adults in the right hemisphere. Earlier studies reported that compared with closed eyes, the open eyes condition was associated with reduced EEG signal and power in each band in young adults and children compared to other age groups[20,21]. Other studies reported that in resting state EEGs, the delta, theta and alpha bands showed reduced amplitude and increased beta activity in older adults compared with young adults[22,23]. Decreased beta band activity has been associated with reduced general health and cognitive impairment in elderly patients[24]. Increased delta and theta power, decreased mean frequency and changes in coherence were found in cases of dementia or mild cognitive impairment (MCI), or caused by healthy aging[25,26].

WORKING MEMORY TASK AND BRAIN AGING

The brain aging process is accompanied by cognitive decline and neurophysiological and structural changes within the brain[27,28]. Memory capacity decreases during the progressive brain aging process[29,30]. Different frequency bands exhibited correlations with aging while performing memory tasks. One study reported the alpha band showed age-related changes (decrease with aging) in connectivity in memory tests[31]. Other than EEG, functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG) have been applied to evaluate age-related changes in elderly brain[32,33]. Low beta activity was found to be associated with poor visual performance of elderly subjects and increased beta activity with high visual performance in younger subjects[34]. The EEG beta band power has been correlated with visual attention task in the occipital region[34,35]. Decreased EEG synchronization was found in elderly adults compared with young adults in the alpha and beta bands during visual working memory tasks[36]. The WM has been utilized as a firm tool to investigate alterations in EEG signals of healthy and diseased elderly patients. Synchronization likelihood was applied to investigate differences in AD and MCI, and found significantly decreased alpha and beta bands in AD and significantly higher in MCI in the alpha band (8-10 Hz) during a visual WM task[37]. A good classification of healthy and AD subjects was obtained using the complexity of brain signals using a WM task[38].

NETWORK ANALYSIS

Human learning abilities can be improved, and various neuroimaging techniques have been introduced for human learning studies over the past few decades. Improving the cognitive skills might help the elderly community to develop their capabilities and perform better in their daily work. Human brain areas continuously communicate with each other in different frequency ranges. The connectivity and network architecture can also inhibit some network features in different mental states related to age. In a resting state condition, the MCI small-world architecture presents midway topological properties between AD subjects and healthy controls, confirming the hypothesis that MCI is an intermediate step along the disease progression[39]. The brain areas communicate with the brain and form subnetworks to perform various tasks. Graph theory has been used over the past decade to evaluate brain network performance. The construction of brain networks from connectivity data describes the most commonly used network features e.g. local and global efficiency, clustering coefficients and path length[40]. In a study of Cognitive Reserve (CR), younger participants low in CR exhibited greater mean coherence than younger participants high in CR, whereas the opposite pattern was observed in older participants, with greater coherence in older participants high in CR suggesting the possibility of a shift in the relationship between CR and brain connectivity during aging[41].

Various imaging techniques have been used to investigate the brain network connectivity in older healthy and dementia patients, including MCI and AD. fMRI-based studies have been used in task-based and resting state fMRIs (rs-fMRI) to investigate brain networks[42]. Task-based fMRI studies have shown stronger connectivity in the frontal regions in elderly patients[42,43]. A resting state fMRI study investigated the default mode network

(DMN) and found memory decline in normal older patients and others with neurodegenerative disorders[3]. In a young versus old study, age-related functional connectivity changes were found to be associated with cognitive decline[44]. Graph theory-based studies found lower local and global efficiencies in elderly groups compared to younger patients using fMRI[45,46]. Graph theory has been mostly utilized for brain network connectivity and topological analysis on EEG signals.

AD patients have been found to have almost 10% decreased local efficiency in the eyes closed state as compared to healthy elderly[47]. Feature extraction and machine learning algorithms are used to automatically classify EEG data into classes[48]. Distinct features have been used to separate the EEG signals of elderly from young and middle-aged people. Fractal dimension has shown significant results and it has been demonstrated that age follows an upside-down parabolic shape as the age increases from young adult to elderly above 80 years of age[4,49]. Another study reported that the sample entropy of an EEG signal changed with the sleep state in middle-aged and elderly subjects and this variation of sleep state was highly consistent in each subject in both age groups[50]. By using the EEG prominent features, EEG signals can be classified automatically into different age groups.

FEATURE EXTRACTION AND CLASSIFICATION

Feature extraction is an important step in data processing and classification in machine learning. It is used to find the most suitable and compact set of informative features from raw data. Different feature selection techniques are used to select the optimal features from a feature set in order to improve the accuracy and performance of the model. Numerous classification algorithms are used to classify the EEG signals by using EEG features as input to the classifier. Every machine learning technique has a different impact on the classification model depending on the size of the dataset, noise, and computational cost.

Support Vector Machine (SVM)

SVM is a linear classifier that can be used in classification and regression problems. SVM was developed by Vapnik as a robust prediction method based on astatistical learning framework Vapnik–Chervonenkis theory[51]. For a given set of training data points, with each labeled with a class, the SVM model plots them into a hyperplane assigning them to a class maximizing the gap between two classes. SVM is advantageous for data with high dimensional spaces, and is memory efficient and effective in binary and multiclass classifications. SVM has been widely used in EEG signal classification including AD, sleep stages, and emotion recognition[52-55].

K-Nearest Neighbor (KNN)

KNN is a non-parametric method used for both class classification and regression. The KNN working principle is to store all available samples and classify new data points based on similarity to the available class/category. For a new data point KNN uses a distance measure to find the nearest neighbor and predict the class[56]. KNN has been used to study AD, seizure detection, human sleep stages, and emotion recognition[56-59].

Decision Tree (DT) C4.5

DT is a tree structure-based method used for both classification and regression in machine learning. DT starts with a root node and features act as nodes, decision rules are represented with edges, and leaf is the class and pruning is used to remove the unwanted branches[60]. DT models are easy to prepare, and require less preparation as DT does not require normalization and scaling of data. Outliers and missing values have notably less influence on DT data. DT has been effectively used to classify the EEG data for epilepsy, AD, and sleep stages.[60-62].

Random Forest (RF)

RF is one of the ensembles learning techniques used in both regression and classification. RF is based on a bagging modification and it constructs the combination of de-correlated trees and obtains the output of average from the trees. Multiple decision trees are used to predict the class by using a majority vote based on the separation of data[63]. In order to grow the decision tree, the combination of bagging and random selection of features is utilized. Random forest has been used in human emotion recognition, AD, and sleep stage classification[64,65].

Multilayer Perceptron (MLP)

MLP is an artificial neural network classifier, which utilizes a machine learning back propagation technique for training[66]. MLP consists of a minimum of three layers including input, hidden and output layers. MLP is sometimes referred as a "vanilla" neural network, when it contains a single hidden layer. It is used to classify the data which is nonlinear. For example, the MLP classifier has been applied to classify EEGs in dementia, MCI, AD, and epilepsy[67-69].

Table 2 Advantages and disadvantages of various classification methods

Classifier	Advantages	Disadvantages
K-Nearest Neighbor	• It is a simple technique and easy to implement. • No training phase makes it faster	• Sensitive to noise • Requires large space • Testing phase is slow
Support Vector Machine	• It can easily handle complex and nonlinear data • It is easier to work with compared to other methods • It is a non-parametric learning technique	• Poor performance with a high number of features • Requires more Training time
Decision Tree	• It requires no domain knowledge to construct the decision tree • Easy to implement • It is effective with high dimension data It is efficient and Robust with noisy data	• Restricted to single output attribute • Performance is dependent on the type of data set, which can make it unstable
Random Forest	• It is efficient with large datasets • It can handle large numbers of variables with deletion • It is considered as one of the most accurate algorithms	• Overfitting problem with noisy data • It slows down with a large number of trees in real time prediction
Multi-Layer Perceptron	• It is easy to train and can handle noisy data • It is efficient in nonlinear complex and high dimensional problems	• Overfitting of data • Requires high computational time and it is difficult to interpret the process • To an extent dependent variables effect each independent variable
Naïve Bayes	• It is simple to implement • It has good computational efficiency • It is more efficient with larger datasets	• Performance decreases with small datasets • It is not very effective when dependency exists among the variables
Logistic Model Tree	• It combines decision tree learning and logistic regression • It can be constructed efficiently and is easy to interpret	• It can suffer masking problems in multiclass cases • Higher computational complexity

Logistic Model Tree (LMT)

LMT is machine learning model that combines decision tree learning and logistic regression. This technique utilizes logistic regression to build models to select the attributes and regression of the leaves of higher levels of the tree[70]. LMT has been applied for use in seizure detection in epilepsy, and to predict the AD and MCI by using EEG signals[71,72].

Naïve Bayes (NB)

Naïve bayes belong s to the family of probabilistic classifiers based on the Bayes theorem. NB applies the Bayes theorem and assumes independence among the features[73]. NB is best suited for functionality-dependent or completely independent either binary or multi-class classifications. The NB classifier has been applied to investigate EEG signals in AD, Parkinson's disease, epilepsy, and in the detection of depression[74-76].

In this review, the advantages and disadvantages of the aforementioned classifiers are presented in Table 2.

Feature extraction and classification in aging

Age prediction is more challenging in functional imaging than structural imaging[77] and BrainAGE. We investigated whether age-related changes are affecting brain EEG signals, and whether we can predict the chronological age and obtain BrainAGE estimates using a rigorous ML framework with a novel and extensive EEG features extraction. Methods: EEG data were obtained from 468 healthy, mood/anxiety, eating and substance use disorder participants (297 females. Feature extraction is the key element in machine learning models for the prediction of the data and its class. Fractal dimension, skewness, kurtosis and mean value of each electrode have been used as prominent features in age prediction studies. EEG signal coherence and cross correlation are considered significant features in the connectivity domain[78]. In the time domain and the frequency domain, zero crossing skewness, kurtosis, statistical features e.g. mean, median and standard deviations have been used for classification. For the complexity measure of EEG signals, sample entropy, Shannon entropy and permutation entropy have exhibited significance in not only ageing studies but in AD as well[77-79].

Linear discriminant analysis (LDA), support vector machine (SVM), K-nearest neighbor (KNN), decision tree (DT), Naïve Bayes, Random Forest (RF), Multilayer perceptron (MLP), logistic model tree (LMT), linear regression and neural network are a few algorithms majorly used for classification in AD and aging studies in EEG.

In EEG-based studies classification of brain signals has been used to predict brain age. Feature extraction is the process of obtaining the meaningful information from raw EEG signals. The classification techniques are used to characterize input data into the classes or groups. Machine learning techniques have been utilized to understand complex EEG signals. Features extraction and classification techniques, regression analysis, and deep learning have been used to investigate EEG signals[80,81]. Time domain, frequency domain, wavelet features and many other advanced linear and non-linear features are used to classify EEG data. To optimize a feature set, a feature selection technique is used select the optimal set of features. The feature selection technique is further subdivided into three groups, filter models, wrapper models and embedded models[82].

One study compared mild infarct dementia (MID) and AD and then compared the results with healthy subjects using the feature of mean spectral power[83]. In an AD classification study, amplitude modulation and spectral features were used and the EEGs were recorded using a 7-channel portable device[84]. An SVM algorithm was used to classify the AD group from a healthy elderly population and obtained 91.4% accuracy. IA classification using EEG amplitude features, time domain, frequency and power spectral features has shown a potential for machine learning[77]. Brain aging is not only important for studying differences in aging, but it is also important to understand the association between brain aging and neurodegenerative diseases. The study of brain aging can also help the clinical expert to better understand the memory decline affected by age-related issues in elderly patients. The utilization of various types of WM tasks might help the clinical expert to improve cognitive performance in elderly patients.

CONCLUSION

It is very important to investigate the differences between healthy age-related EEG and EEG with dementia, more specifically AD which is associated with aging. Certain EEG features including the spectral feature, statistical features, nonlinear features, and network features are promising features to classify the age-related EEG in the resting state and under a WM task state. Working memory plays a vital role in investigating alterations in healthy elderly EEG associated with memory decline. Nonlinear features including fractal dimension and entropy have shown correlations with EEG complexity with age and they can be further applied to evaluate age-related changes in EEG. Similarly, graph theory features are very important to help understand the functional connectivity and network characteristics in healthy aging brain networks. Numerous machine learning classifiers are available which can be applied to classify the EEG data. There is still a lack of investigations concerning age-dependent changes in human EEG and their associations with neurodegenerative diseases.

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CONFLICTS OF INTEREST

The authors declare no potential conflicts of interests.

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