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RESEARCH ARTICLE

Detection of Orienting Response to Novel Sounds in Healthy Elderly Subjects: A Machine Learning Approach Using EEG Features

Sağlıklı Yaşlı Bireylerde Yeni Seslere Yönlendirme Yanıtının Tespiti: EEG Özelliklerini Kullanan Bir Makine Öğrenimi Yaklaşımı

Emine Elif Tülay[1]

ABSTRACT

Unexpected events in the environment elicit the orienting response that protects humans from dangerous situations and there is great importance in identifying these events, especially in aging. The aims of the current study are attempting to find which classification model exhibits the best performance by means of event-related spectral perturbation (ERSP) features based on EEG and to understand which frequency bands, and time windows, contribute most to the classification of external stimuli. The data of 20 healthy elderly participants were included in the study and the 3-Stimulation auditory oddball paradigm was applied to participants. Different classifiers including Support Vector Machine (SVM) with Linear and Polynomial kernels, Linear Discriminant Analysis (LDA), and Naive Bayes were fed by ERSP features obtained from varying frequency bands and time domains. The classification process was fulfilled using custom-written scripts via the FieldTrip Toolbox (version no: 20220104) integrated with the MVPA-light toolbox running under Matlab R2018b. The best performance was obtained by linear SVM which was fed by theta response (4 – 8 HZ) in the early time window (0.1 – 0.5 s) with 90% accuracy in the case of standard stimuli distinguished from novel stimuli. Delta responses also exhibit distinctive characteristics for standard and novel stimuli by running LDA (87% accuracy) and polynomial SVM (86% accuracy). These findings show that the delta and theta responses have contributed to detecting standard and novel sounds with remarkable performances of SVM and LDA.

Keywords: Delta, theta, auditory stimuli, machine learning

ÖZ

Çevrede meydana gelen beklenmedik olaylar, insanı tehlikeli durumlardan koruyan yönlendirici tepkiyi ortaya çıkarır ve bu olayların tespit edilmesi özellikle yaşlanma sürecinde büyük önem taşır. Mevcut çalışmanın amacı, EEG'ye dayalı olaya ilişkin spektral pertürbasyon (ERSP) özellikleri aracılığıyla hangi sınıflandırma modelinin en iyi performansı gösterdiğini bulmaya çalışmak ve hangi frekans bantlarının ve zaman pencerelerinin dış uyaranın sınıflandırılması için en çok katkıda bulunduğunu anlamaktır. 20 sağlıklı yaşlı katılımcının verileri çalışmaya dahil edilmiştir ve katılımcılara 3-Stimülasyon işitsel oddball paradigması uygulanmıştır. Lineer ve Polinom çekirdek fonksiyonlu Destek Vektör Makinesi (DVM), Lineer Diskriminant Analizi (LDA) ve Naive Bayes gibi farklı sınıflandırıcılar, değişen frekans bantlarından ve zaman alanlarından elde edilen ERSP öznitelikleri ile beslenmiştir. Sınıflandırma işlemi, Matlab R2018b altında çalışan MVPA-light araç kutusu ile entegre FieldTrip Toolbox (sürüm no: 20220104) aracılığıyla özel yazılmış komutlar kullanılarak gerçekleştirilmiştir. En iyi performans erken zaman penceresinde (0.1 – 0.5 s) teta yanıtı (4 – 8 HZ) ile beslenen lineer DVM tarafından standart uyaranların yeni uyaranlardan ayırt edilmesi durumunda %90 doğrulukla elde edilmiştir. Delta yanıtları ayrıca LDA (%87 doğruluk) ve polinom DVM (%86 doğruluk) çalıştırarak standart ve yeni uyaranlar için ayırt edici özellikler sergilemektedir. Bu bulgular, delta ve teta yanıtlarının, DVM ve LDA'nın dikkate değer performanslarıyla standart ve yeni seslerin algılanmasına katkıda bulunduğunu göstermektedir.

Anahtar Kelimeler: Delta, teta, işitsel uyaran, makine öğrenmesi

[1] (Assist. Prof.) Mugla Sitki Kocman University, Faculty of Engineering, Department of Software Engineering, Muğla, Turkiye

ORCID: E.E.T. 0000-0003-0150-5476

Corresponding author:
Emine Elif TÜLAY
Mugla Sitki Kocman University, Faculty of Engineering, Department of Software Engineering, Muğla, Turkiye
E-mail address: eliftulay@mu.edu.tr

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1. INTRODUCTION

Human brains are affected by different types of stimuli and produce stimuli-specific responses. According to the literature, unexpected novel events like a car horn in traffic elicit the Orienting Response (OR), which leads to the automatic detection of sudden changes in the environment (Debener, Makeig, Delorme, & Engel, 2005; Berti, Vossel, & Gamer, 2017) by disrupting ongoing thoughts and actions, and prepares the human on a physiological, behavioral, and cognitive level (Lynn, 1966). In other words, the sensory change detection mechanism based on the OR protects humans from dangerous situations despite the fact that a considerable number of studies support that OR is influenced by habituation (Barry, 2009; Cavanagh, Kumar, Mueller, Richardson, & Mueen, 2018).

Although there are many neuroimaging techniques like fMRI, PET/SPECT, or MEG, EEG is the most widely used to investigate brain responses in the cognitive domain due to its being technically and economically more practical. Moreover, different neurophysiological features like Event-related Potential (ERP) and Event-related oscillations (EROs) were investigated to understand the mechanism of attentional processes (Başar-Eroğlu, Başar, Demiralp, & Schürmann, 1992; Basar, Demiralp, Schürmann, Basar-Eroglu, & Ademoglu, 1999; Başar, Başar-Eroglu, Karakaş, & Schürmann, 2001; Başar-Eroğlu & Demiralp, 2001; Berti et al., 2017; Behforuzi et al., 2019) of rare stimuli in various paradigms. Especially event-related delta and theta oscillations have been associated with perception and attention (Harmony, 2013; Güntekin & Başar, 2016; Karakaş, 2020). There are a number of feature extraction methods available for measuring ERO. Event-related spectral perturbation (ERSP) (Delorme & Makeig, 2004) is one of the most important measurements of oscillatory activities to understand the mechanisms of cognitive processes (Makeig, 1993; Wei, Zhao, Yan, Duan, & Li, 1998).

Neuro-cognitive processes for unexpected events are affected by age (Li & Lindenberger, 2002; Berti et al., 2017). According to the studies based on ERO in the literature, the decrease of delta ERO in a visual oddball paradigm (Emek-Savaş, Güntekin, Yener, & Başar, 2016) and cued Go/Nogo Paradigm (Schmiedt-Fehr & Başar-Eroglu, 2011) was associated with aging. On the other hand, the findings of Huizeling, Wang, Holland, & Kessler (2021) revealed that older adults present different ERO patterns during attentional control to compensate for cognitive decline. Moreover, Schmiedt-Fehr, Dühl, & Basar-Eroglu (2011) supported that there may be modality-specific changes with age, and the brain responses of older adults could be affected more during visual stimuli in comparison to auditory stimuli in early stages, whereas Ho et al., (2012) found that the healthy elderly group showed higher delta power than the young group during auditory stimuli.

When the findings in the literature were considered, it could be said that there is no consensus about the mechanism of attentional processing of elderly subjects among researchers. Especially with the rise in machine learning (ML) approaches and methods that have outstanding robustness and adaptability, researchers can objectively and efficiently differentiate neural responses to external stimuli (Saeidi et al., 2021). In the last decade, various ML techniques have been applied to EEG signals for understanding affective processing (Alarcao & Fonseca, 2017; Wang & Wang, 2021; Rahman et al., 2021), attentional processing (Lotte et al., 2018), and even for detecting medical conditions (Hosseini, Hosseini, & Ahi, 2021; Chung & Teo, 2022). Among the different features of EEG data used in the literature, ERO in the Time-Frequency domain provides more information about temporal, spectral, and spatial dynamics of cognitive processes (Aliakbaryhosseinabadi, Kamavuako, Jiang, Farina, & Mrachacz-Kersting, 2019). However, various studies showed that ERP features also had promising classification performances for stimuli classification (Parvar et al., 2014; Tjandrasa & Djanali, 2018; Akhter, Lawal, Tanvir, & Ahmed, 2020; Borra & Magosso, 2021).

The current study aimed to examine mainly two aspects of the classification of three sound stimuli applied to healthy elderly subjects. First, to attempt to find which classification model exhibits the best performance by means of ERSP features. Second, to understand which frequency bands, and time windows, contribute most to the classification of external stimuli. For this purpose, different classifiers were run on delta and theta responses at different time windows (please see Section 2.3). It was hypothesized that novel sound stimuli would be differentiated from the other type of sound stimuli with the delta and theta powers, especially in the early time window. Also, it was estimated that higher performances would be obtained by means of Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) classifiers.

2. METHODS AND MATERIALS

2.1 Dataset

In the current study, a public dataset (Cavanagh, 2021) was adopted (available at https://openneuro.org/datasets/ds003490/versions/1.1.0) including EEG signals of 25 healthy elderly subjects. The data of 20 participants (8 female, 12 male) were included in the study, disregarding the remaining 5 participants due to persistent artifacts or noise in their recordings. Out of these 5 participants, the epoch numbers of 2 participants were below 20, and the data of 3 participants were too noisy (muscle artifacts and spikes). The mean age was 68.8 (Standard deviation: 17.5) years. The inclusion criteria for the participants were as follows; Mini-Mental State Exam (MMSE) score ≥ 26. All participants provided written informed consent (Cavanagh et al., 2018).

The 3-auditory oddball paradigm was applied to participants during EEG recording. In the paradigm, there were three stimuli named standard (440 Hz sinusoidal tones, and 80 dB), target (660 Hz sinusoidal tones, and 80 dB), and novel distractors that are naturalistic sounds (Bradley & Lang, 1999), varying with each presentation (65 dB with an inter-quartile range of +/− 6.5 dB). The total number of stimuli is 200, including 140 standard, 30 target, and 30 novel. Each stimulus was presented for 200 ms and a random inter-trial interval (ITI) was selected from a uniform distribution of 0.5 to 1 second for the novel condition, and 950 to 1450 ms for both the standard and target conditions. The subjects mentally counted the target sounds (Cavanagh et al., 2018).

The EEGs of participants were recorded using the 64 channel Brain Vision system with a sampling rate of 500 Hz. During the recording, a CPz electrode served as reference, and an AFz electrode served as ground.

2.2 EEG Data Analysis

All the steps of EEG data analysis including preprocessing, feature extraction, and classification were fulfilled using custom-written scripts via the FieldTrip Toolbox (version no: 20220104) (Oostenveld, Fries, Maris, & Schoffelen, 2011) running under Matlab R2018b (MathWorks, Natick, MA, U.S.A.).

2.2.1 Preprocessing

Unlike the reference study by Cavanagh et al. (2018), a different pre-processing pipeline has been applied to data. The processing steps were described below;

1- *Importing data*: All conditions for each subject were imported to the Matlab platform by segmenting the data around the stimulus onset (−2000 to 2000 ms) and selecting 30 channels (F7, F5, F3, F1, Fz, F2, F4, F6, F8, T7, C5, C3, C1, Cz, C2, C4, C6, C8, P7, P5, P3, P1, Pz, P2, P4, P6, P8, O1, Oz, O2) apart from 64 channels. During the importing process, the data were re-referenced to an average reference of selected channels. Also, each epoch was baseline corrected according to the mean amplitude of−200 to 0 ms pre-stimulus time window. Finally, the discrete Fourier transform (DFT) filter was applied for removing the line noise.

2- *Removing artifacts:* The trials that contain fast muscular artifacts, jumps, and uncommon patterns were eliminated manually to enhance the efficiency of the next step, Independent Component Analysis (ICA).

3- *Applying ICA:* To remove eye movements, heartbeat effects, and spiky patterns, the fast ICA method[1] was used. After decomposing the data into sources, components that spectrally and topographically correspond to related artifacts were selected and removed, and the cleaned data was reconstructed.

4- *Detrending:* In this step, slow low-frequency drifts were removed per trial.

5- *Divide data into separate conditions:* The data that include all types of stimuli (target, standard, novel) were divided into separate sub-data based on the conditions per participant.

1 https://github.com/fieldtrip/fieldtrip/blob/master/external/fastica/fastica.m

6- *Removing residual bad trials:* The trials in each sub-data were checked by visual inspection, and bad trials were manually removed from the data.

7- *Equalizing the number of epochs among conditions:* The trials were then matched between conditions for each participant separately. The minimum number of trials was determined across all conditions per participant and after calculating the number of remaining trials for any conditions that were large, the calculated number of randomly selected trials was removed from the sub-data. In case a participant had less than 20 trials for a condition, the data were excluded from the dataset.

2.2.2 Feature Extraction: ERSP Analysis

To obtain the feature sets based on ERSP values for the classifier, the sensor-level time-frequency decomposition with complex Morlet wavelets was conducted on each trial of clean data for each condition, each selected channel (F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, O1, Oz, O2), and for all participants. A Morlet function with three cycles was used to calculate the time-frequency transform between 1 and 15 Hz with 0.5 Hz frequency resolution, and the wavelet coefficients were estimated for 10 ms steps between −2000 s and 2000 ms. Time-frequency representations (TFRs) were baseline-corrected with respect to the −1000 to −500 ms pre-stimulus period for slow oscillations (delta and theta bands).

2.3 Classification Analysis

The Fieldtrip integrated MVPA-light toolbox (Treder, 2020) was used to assess whether the ERSP features of EEG could be used to detect novel stimuli in healthy elderly subjects. For this purpose, several classifiers were employed, including Linear SVM, Polynomial SVM, LDA, and Naive Bayes (NB) with default hyperparameters[2] of the MVPA-light toolbox. These hyperparameters can be listed as follows: For SVM, a default search grid was used to automatically determine the best c parameter. When the polynomial kernel was used, gamma was set to 1/(number of features), coef0 was set to 1 and degree was set to 2. For LDA, shrinkage regularization was used and the shrinkage regularization parameter (lambda) was calculated automatically using the Ledoit-Wolf formula[3]. For NB, probabilities were modeled using Gaussians and every class had an equal probability. The class means and variances were estimated for every feature for training. At testing time, the maximum a posteriori (MAP) rule was applied to assign a sample to the class with the maximum posterior probability.

Prior to training the classifier, nested z-scoring was used to avoid the flow of information from the test set flowing into the processing of the train set. Also, a 10-fold cross-validation method was used to train classifiers that were applied for the average of time-frequency points in a specific time and frequency ranges using selected EEG channels as features. The training process with cross-validation was repeated 5 times with new randomly assigned folds to obtain robust results. After that, all test folds and repetitions were averaged to reach the final result. The performance of the classifier was evaluated using the confusion matrix and accuracy metrics.

During the classification analysis, the spectral-temporal searchlight analysis was implemented by using different frequency bands, and time of interest to distinguish novel stimuli from target and standard stimuli. For each classification model, EEG channels were included as features in the delta (1.5 – 4 Hz) frequency band with 0.1– 0.7 s time windows of interest, theta (4 – 8 Hz and 5.5 – 8 Hz) with 0.1 – 0.5 s and 0.5-0.7 s time windows of interest. The time windows and frequency ranges were determined by visual inspection of grand averages (please see Fig. 1 and Fig. 2).

3. RESULTS

Fig. 1 and Fig. 2 depict the grand averages of ERSP values in the delta and theta frequency bands, respectively, over the average across all electrodes (please see Section 2.2.2) for all types of sound stimuli applied to healthy elderly subjects. In both Figures, the left plot represents target stimuli, the middle plot represents standard stimuli, and the right box represents novel stimuli.

2 https://github.com/fieldtrip/fieldtrip/blob/master/ft_statistics_mvpa.m
3 https://github.com/treder/MVPA-Light/blob/master/external/cov1para.m

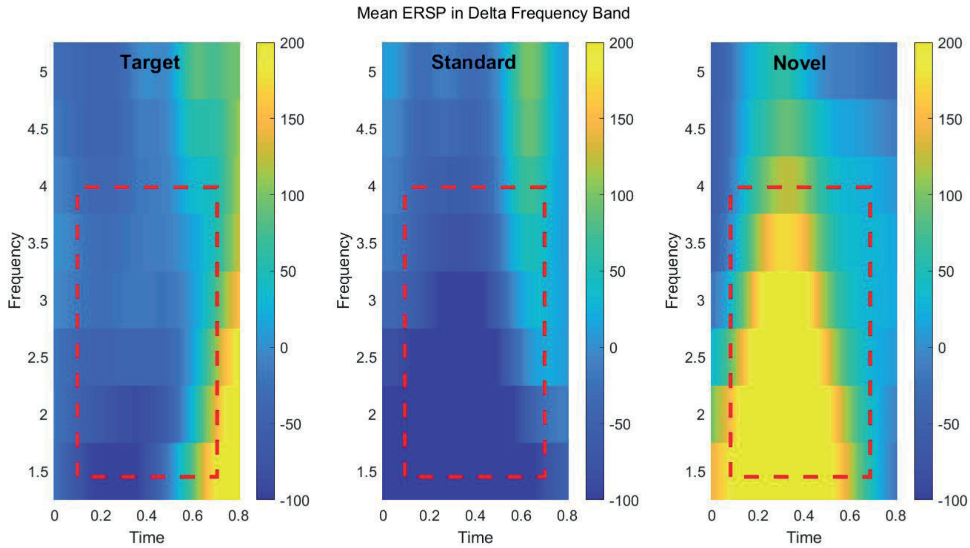

Figure 1. Time-Frequency Representations for all stimuli: Grand average of ERSP values in Delta frequency band over the averaged across all electrodes. Red dashed lines represent the ranges for frequency (1.5 – 4 Hz) and time (0.1 – 0.7 s) that were used by the classifiers as features.

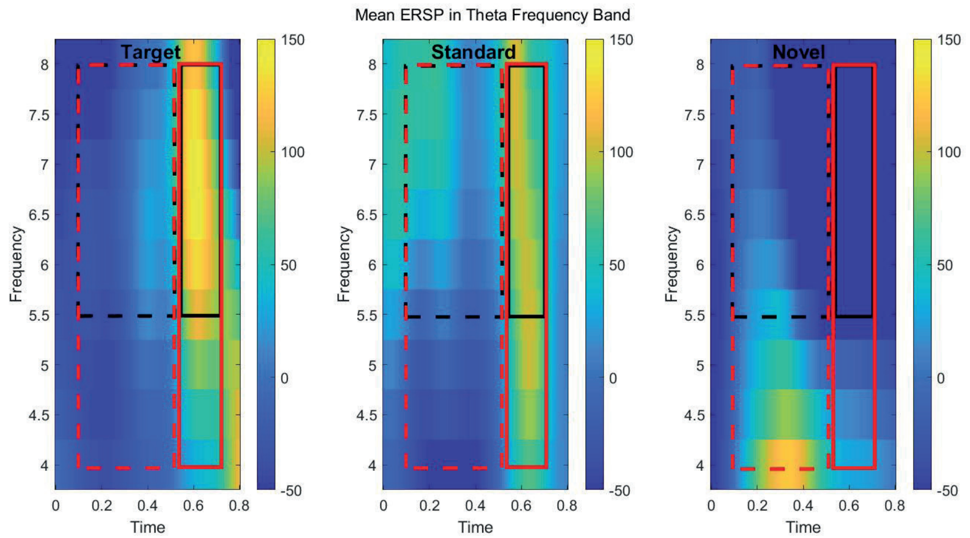

Figure 2. Time-Frequency Representations for all stimuli: Grand average of ERSP values in Theta frequency band over the averaged across all electrodes. Red dashed lines represent the ranges for frequency (4 – 8 Hz) and time (0.1 – 0.5 s), black dashed lines represent the ranges for frequency (5.5 – 8 Hz) and time (0.1 – 0.5 s), red solid lines represent the ranges for frequency (4 – 8 Hz) and time (0.5 – 0.7 s), black solid lines represent the ranges for frequency (5.5 – 8 Hz) and time (0.5 – 0.7 s). The time-frequency points in all these ranges were used by the classifiers as features separately.

The plots in Fig. 1 and Fig. 2 give us clues for the frequency and time ranges in order to perform spectral-temporal searchlight analyses for the classification process. Whereas one time-frequency range was used in the delta band (Fig. 1), four time-frequency ranges were determined in the theta band (Fig. 2). The ranges were also determined in light of the literature given in Section 1.

Fig. 3 depicts the results of the classification analyses by means of the accuracy metric for Linear SVM, Polynomial SVM, LDA, and NB classifiers (the bars from left to right) where different time-frequency points were used as features. The first (front) row shows the performances for delta (1.4-4 Hz) as the frequency of interest at 0.1-0.7 s times of interest, the second row shows the performances for theta (4-8 Hz) as the frequency of interest at 0.1-0.5 s times of interest, the third row shows the performances for theta (4-8 Hz) as the frequency of interest at 0.5-0.7 s times of interest, the fourth row shows the performances for theta (5.5-8 Hz) as the frequency of interest at 0.1-0.5 s times of interest, and the last (at the back) row shows the performances for theta (5.5-8 Hz) as the frequency of interest at 0.5-0.7 s times of interest. Fig. 3A represents the accuracy values for classifying target and novel stimuli, whereas Fig. 3B represents the accuracy values for classifying standard and novel stimuli.

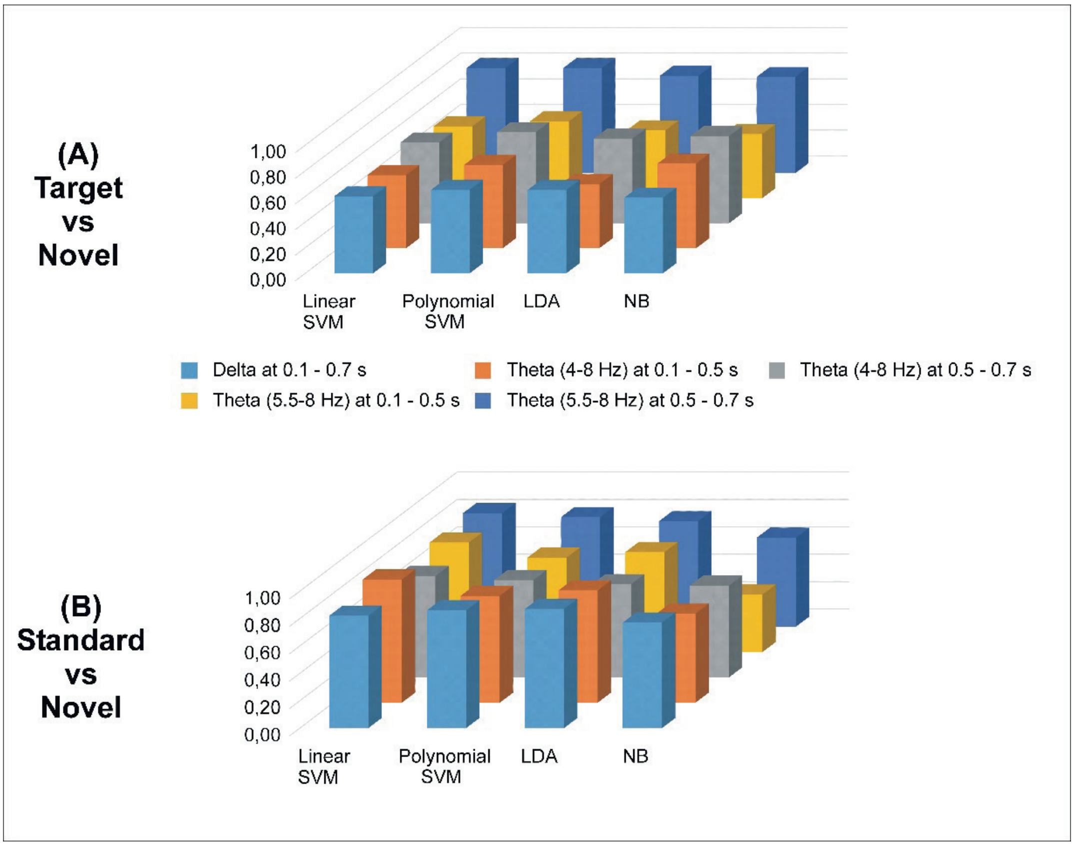

Figure 3. The classification performances by means of accuracy metric for Linear SVM, Polynomial SVM, LDA, and NB classifiers where different times and frequencies were used as features. (a) The performances to distinguish target and novel stimuli (b) The performances to distinguish standard and novel stimuli.

As seen from the bar graph (Fig. 3A), the best feature of EEG to distinguish novel stimuli from target stimuli is late theta (5.5 – 8 Hz at 0.5-0.7s) via all classifier models. Fig. 2 also supports this finding. However, early theta (0.1 – 0.5 s) in the same frequency range could not show the same performance. Moreover, when the theta frequency band was taken wider (4 – 8 Hz), the performances could not reach higher levels at both time windows. To distinguish novel stimuli from standard stimuli, whereas the performances of linear SVM, polynomial SVM, and LDA were close to each other, NB had a lower performance for all feature sets (Fig. 3B). Fig. 3A and 3B clearly showed that the performances of all classifiers were higher for distinguishing novel stimuli from standard stimuli than distinguishing novel stimuli from target stimuli by means of almost all feature sets, except late theta (5.5 – 8 Hz at 0.5-0.7s). All accuracies and confusion matrices (TP and TN rates) of the classification analysis obtained by running searchlight analyses by means of the temporal and spectral features of ERSP are summarized in Table 1.

Table 1

Classification metrics after running spectral-temporal searchlight analyses

Classes	Frequency Bands	Time Windows	Linear SVM		Polynomial SVM		LDA		NB	
			TP/TN (%)	Acc	TP/TN (%)	Acc	TP/TN (%)	Acc	TP/TN (%)	Acc
Target vs Novel	Delta	0.1 - 0.7 s	70/55	0.60	82/40	0.65	80/57	0.65	48/67	0.59
	Theta 4-8 Hz	0.1 - 0.5 s	61/58	0.57	78/54	0.65	67/36	0.50	36/89	0.66
		0.5- 0.7 s	63/66	0.63	67/76	0.71	77/52	0.66	53/83	0.68
	Theta 5.5-8 Hz	0.1 - 0.5 s	59/53	0.56	75/46	0.60	66/43	0.53	47/48	0.50
		0.5- 0.7 s	75/85	0.82	75/87	0.82	76/80	0.76	60/85	0.75
Standard vs Novel	Delta	0.1- 0.7 s	88/69	0.82	89/86	0.86	90/84	0.87	74/83	0.77
	Theta 4-8 Hz	0.1- 0.5 s	95/87	0.90	84/73	0.78	94/72	0.82	43/79	0.65
		0.5- 0.7 s	68/75	0.74	66/86	0.71	80/52	0.68	46/86	0.67
	Theta 5.5-8 Hz	0.1 - 0.5 s	80/79	0.80	87/52	0.69	85/59	0.73	44/36	0.42
		0.5- 0.7 s	81/79	0.83	77/85	0.80	95/66	0.77	44/88	0.65

Acc: Accuracy, TP/TN: True Positive/True Negative

The findings revealed that the best performance (0.90 accuracy) was achieved with Linear SVM for the classification of novel stimuli and standard stimuli by means of early theta (4 – 8 Hz at 0.1 – 0.5 s). Also, the TP and TN values of the confusion matrix showed that the classifier was better at predicting standard stimuli (95%) than it was at predicting novel stimuli (87%). When the delta frequency band was used as a feature set, the performance of LDA (0.87 accuracy) and polynomial SVM (0.86 accuracy) surpassed the performance of linear SVM. Among all confusion matrix values for the classification of novel and standard stimuli, the most balanced prediction rates were achieved by polynomial SVM where the delta frequency band was used as the feature set (Table 1).

Moreover, both SVM classifiers were quite successful to differentiate two rare stimuli, target and novel. Linear SVM and polynomial SVM were much better at predicting novel stimuli (85%, and 87% respectively) than at predicting target stimuli (75% for both) with a 0.82 accuracy rate.

4. DISCUSSION AND CONCLUSION

The current study evaluated the delta and theta responses upon application of the 3-Stimulation auditory oddball paradigm by means of ERSP measurement, and the classification analyses were performed with varying selected features in frequency and time domains to understand which features have a higher contribution at identifying novel sounds. Moreover, different classifiers were used including SVM with Linear and Polynomial kernels, LDA, and NB to reveal which classifier exhibits good distinction for unexpected stimuli with which features. To the best of my knowledge, this is the first study that attempts to detect novel sounds with different traditional machine learning techniques fed with the ERSP features of EEG in various time-frequency ranges.

The most remarkable performances of the current study were obtained in the case that standard stimuli distinguished from novel stimuli and SVM, with both kernel types showing better performances followed by LDA. Furthermore, the other important observations of the spectral-temporal searchlight analyses revealed that the best classification performance was achieved by linear SVM (0.90 accuracy) which was fed by theta response (4 – 8 HZ) in the early time window (0.1 – 0.5 s). Delta responses also have distinctive characteristics for standard and novel stimuli. However, LDA (0.87 accuracy) and polynomial SVM (0.86 accuracy) were more powerful than the rest of the classifiers with delta response features. On the other hand, in the case to classify both rare stimuli, target, and novel, the best prominent feature was late theta (5.5-8 Hz), where SVM (both kernels) was used (0.82 accuracy). In general, the results revealed that novel sounds were distinguished from standard tones better than from target tones since whereas both novel and target tones were rare sounds which were the attended and/or oriented noises, standard tones were frequent sounds.

The findings in this study were in line with the previous studies that show the relation between delta (Güntekin and Başar, 2016) and theta (Karakaş, 2020) oscillatory responses and attentional processes. According to the literature, for stronger orientation coding, the main effects (peak latency) of the stimulus were found mostly at 300–500 ms post-stimulus onset for delta oscillations; however, general stimulus effects were found at time localization from 190 to 960 ms. For theta oscillations, whereas the main effects (peak latency) of the stimulus were found at 320–400 ms post-stimulus onset, a significant difference between target and non-target processing was obtained within 60–700 ms (Demiralp et al., 1999). In another study by Başar-Eroğlu et al. (1992), in responses to 3rd attended tones, there was a significant increase in the theta frequency band (frontal and parietal locations; 0-250 ms).

There were also common points with the studies that applied the ML approach. Aliakbaryhosseinabadi et al. (2019) ran the LDA classifier with three types of feature sets (time domain, frequency domain, and the combination of these two sets) obtained by the application of three modalities (auditory, visual, and audiovisual). However, the study focused on young adults rather than the elderly group. According to the results of this study, spectro-temporal features (combined feature set) had a higher accuracy than the other two feature sets for all modalities. Moreover, spectro-temporal features obtained upon application of auditory stimuli enable the classifier to attain remarkable performances for all brain regions, separately, in contrast to the current study which considered all the brain regions in one feature set. However, brain oscillations are selectively distributed in the whole brain (Başar, 2006). Therefore, feeding the classifier with a single feature set that includes the features obtained from all brain regions could provide more robust results.

Another study that attempted to classify standard and novel sounds by means of spatio-temporal patterns of discriminant electrophysiological responses to auditory stimuli was done by Aellen, Göktepe-Kavis, Apostolopoulos, & Tzovara (2021). In the study, the performances of deep learning (convolutional neural networks (CNN) with different techniques) and ‘traditional’ machine learning algorithms (Logistic Regression and SVM with ’rbf’ kernel) were compared. The findings revealed that the AUC scores of the different CNN architectures (Shallow CNN: 0.75; Deep CNN: 0.73; ResNet: 0.72) were significantly higher than the AUC of logistic regression (0.63) and the AUC of SVM (0.58). Although the study applied deep-learning techniques, the performance of the current study where EROs in the time-frequency domain were used as features in the ‘traditional’ machine learning approach was much better than in this study where only time-domain features were used. Moreover, in the current study, the preprocessing step that makes the data more suitable for ML (Akhter et al., 2020) was more comprehensive than in the study by Aellen et al. (2021).

There is great importance in identifying rare stimuli, which have an impact on attentional processing in the environment (Liebherr et al., 2021), especially as adults grow older (Riis et al., 2008). The current study has revealed promising classification results to identify the novel sounds. Also, unlike many classification studies in the literature, exhaustive preprocessing steps were applied before feature extraction, including various artifact removal methods for robust classification results. However, the performances would be improved by overcoming several limitations of the study and using different feature sets. As a major problem, it is not possible to understand the aging effect in the identification of novel stimuli. To overcome this limitation, it absolutely would be better to include the young healthy group in the study, even dividing them into subgroups. This inclusion will also be helpful to decide the best model in cases of different ages.

Moreover, undoubtedly, the faster brain oscillations, like alpha, beta, and gamma, in response to sound stimuli are also related to cognitive processes (Mäkinen, May, & Tiitinen, 2004; Başar & Güntekin, 2012; Başar, 2013; Villena-González, Palacios-García, Rodríguez, & López, 2018). For example, beta oscillations in response to novel stimuli elicited an OR (Haenschel, Baldeweg, Croft, Whittington, & Gruzelier, 2000). Therefore, it would be informative to examine the distinctive features of high frequencies for the identification of sound stimuli in future studies. It should also be acknowledged that the current study addressed the sound stimuli classification with a small sample set. It obviously would be better to increase the number of subjects for more robust results and to use different learning techniques such as deep learning.

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