Prediction of children age using patterns of auditory event-related potentials

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***Abstract*—Many studies showed a relationship between auditory event-related potentials (ERP) and brain development. Particular attention was paid to N1, the ERP component, which reflects auditory detection and discrimination, and N2, which indicates attention allocation and phonological analysis. This study applied logistic regression algorithm (LRA) with regularization to classify children and adolescents to three age groups - 4-6, 7-12 and 12-18 years by individual amplitudes and latencies of P1, P2, N1 and N2, components of auditory ERPs. The Kruskal-Wallis H-test indicated significant group differences in amplitudes of P1 with $p < 6.67e^{-5}$, N1 with $p < 2.34e^{-7}$, N2 with $p < 5.95e^{-5}$ and latencies of P1 with $p < 1.14e^{-5}$ and P2 with $p < 2.57e^{-3}$. The classification accuracy between all three age groups was 0.63, macro-average and micro-average area under the curve (AUC) - 0.79 and 0.70. Classification accuracy of one age group against the rest was 0.71, 0.45 and 0.75 with AUC - 0.91, 0.50 and 0.76 for 4-6, 7-12 and 12-18 age group, respectively. The most informative feature for the correct age group recognition, which was reflected in the largest positive change of odds ratio, was amplitude of N1. The obtained results confirm association of the N1 amplitude with brain maturation and demonstrate sensitivity of LRA in detection of individual age using patterns of auditory ERPs.**

***Index Terms*—age, development, auditory ERPs, machine learning**

I. Introduction

The brain shows marked development from childhood to adolescence, which includes changes in dendritic branching, synaptogenesis, and myelination [1]. These neuronal processes lead to an increase in the brain volume due to gray matter changes [2]. The brain electrophysiological activity reflects these developmental changes, which in turn could be detected in patterns of electroencephalogram (EEG) [3].

Many studies have been conducted on age determination at resting-state EEG [4] and auditory event-related potentials (ERP) [5]. Auditory discrimination continues to develop even after middle childhood and adolescence with three clearly distinguished developmental periods: 5 to 12 years, 13 to 16 years and adulthood, with no clear developmental progression within each of these periods [6].

Studies, that explores the relationship of individual components of auditory ERPs with aging using pure tones, auditory and audiovisual speech paradigms revealed that older adults showed a consistent pattern of inhibitory deficits, manifested as increased P50 and N1 amplitudes and an absent or significantly reduced N2 [7]. N1 latency decreased with aging at Fz and Cz electrodes [8]. The N1 amplitude at Cz decreased from childhood to adolescence, and the N2 amplitude showed a significant decrement for both Cz and Fz. The P1 and P2 latencies demonstrated the pattern of shortening as the age increased; P1, P2 amplitudes showed significant linear increase with maturation [9], [10].

The majority of aforementioned studies reported the group differences in the auditory ERPs. Particularly, it has been previously shown that loudness-dependent auditory ERPs change with brain maturation [11]. This study aimed to predict individual age using amplitudes and latencies of P1, P2, N1 and N2 of auditory ERPs in response to sounds with different loudness. The features of ERPs were used in logistic regression model (LRA) with regularization in attempt to classify children and adolescents to three age groups - 4-6, 7-12 and 12-18 years. Using a linear weight analysis, we planned to find out which of the ERPs components makes the most significant contribution to the difference between the age groups.

II. Materials and methods

A. Participants

Thirty two children and adolescents participated in the study. To solve the task of age classification by evoked potentials, they were divided into three groups (N=7, age range 4.14-6.42; N=16, 7.08-11.98; N=9, 12.04-17.98).

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All participants and their guardians provided written informed concern before all experimental procedures. Protocols of the studies were approved by the Ethical Committee of the Institute of Higher Nervous Activity and Neurophysiology of RAS following the Helsinki declaration guidelines.

B. Experiment design

During EEG recording, participants were presented with a muted video, and tones of different loudness (50, 60, 70 and 80 dB) with duration of 100 ms played in headphones in a random sequence.

C. EEG recording and analysis

EEGs were recorded with 32 channels that were placed based on 10-20 electrode system. Electrooculogram (EOG) artefacts have been removed using independent component analysis (ICA) and the corresponding EOG channel after high-pass filtering with cutoff frequency of 1 Hz then a band-pass filter having cutoff frequencies of 0.1 and 40 Hz was applied.

The EEG epochs were estimated in the time interval (-200, 700 ms) relative to the presented stimulus onset with dropouts on the threshold $\pm$ 3 STD of amplitude and baseline (-0.2, 0.0). The amplitudes and latencies of ERPs were evaluated at FCz channel.

The Kruskal-Wallis H-test for independent samples was applied to check statistical differences in the ERP components between three age groups.

D. Feature space

Amplitudes and latencies of P1, P2, N1 and N2 ERPs components were used as features for classification. Thus features space was $X \in \mathbb{R}^8$, where 8 - number of ERPs components.

For classification of the age group three random individual ERPs from different groups were selected for the test set and all remaining participant ERPs were used for training multinomial LRA.

E. Classification metrics

Balanced accuracy (BA), receiver operating characteristic (ROC) curve and area under that curve (AUC) were used to assess the quality of the models.

F. Logistic regression

Logistic regression algorithm (LRA) was used to model the probability of a certain class and could be utilized as supervised multinomial classification algorithm. In order to prevent overfitting, LRA was used with L_2 regularization. L_2 regularization parameter was set to $\left[1e^{-10}, 1e^{9}\right]$. k-fold stratified cross validation was applied to training set for selecting the best parameter using the best balanced accuracy score.

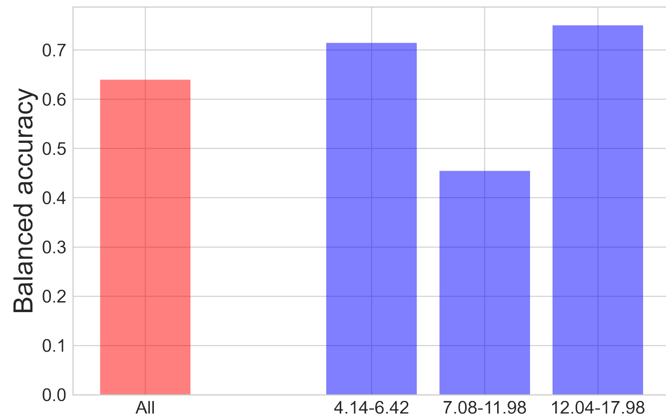

Fig. 1. Balanced accuracy for all three age groups - red bar and for each group separately (the one group versus the rest two) - blue bars

G. Feature interpretation

Evaluated linear filters allowed us to interpret the change of odds ratio (OR) "(1)", "(2)", where P_1 and P_2 were the probability of the sample belonging to the interested or the rest groups, respectively, when the value of an individual feature x_i changed and if all other features remained constant.

$$OR = \frac{P_1}{P_2} \tag{1}$$

$$\frac{OR_{x_i+1}}{OR} = e^{a_i} \tag{2}$$

III. Results

A. Age group differences

The Kruskal-Wallis H-test showed significant group differences in amplitudes of P1 (median = 0.82, std = 1.62; median = 1.99, std = 1.63; median = 0.87, std = 1.01) with $p < 6.67e^{-5}$, N1 (median = 1.88, std = 2.28; median = -0.33, std = 2.80; median = 2.92, std = 2.37) with $p < 2.34e^{-7}$, N2 (median = -2.82, std = 5.21; median = -5.70, std = 3.31; median = -2.91,

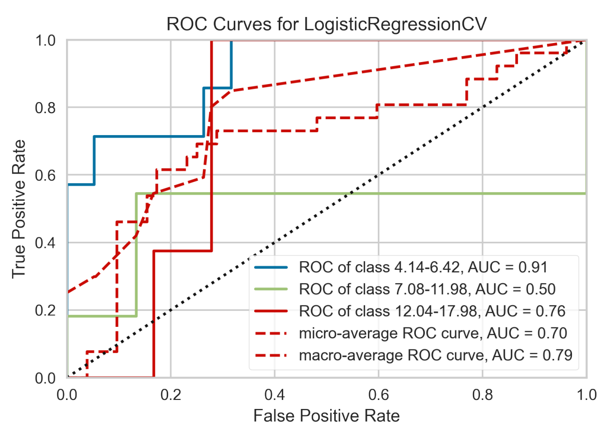

Fig. 2. Macro/micro-average ROC curves for all three age groups and for each group separately (the one group versus the rest two)

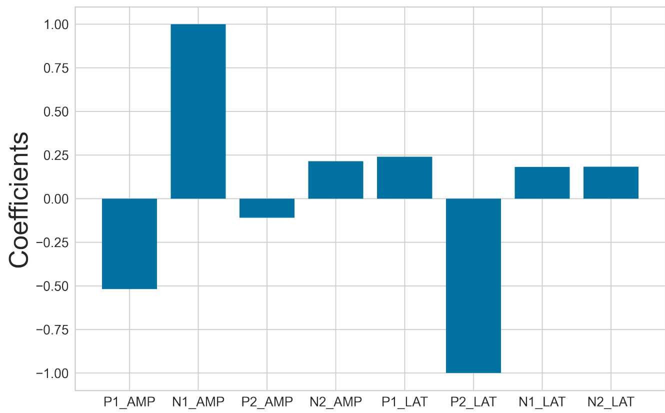

Fig. 3. Logistic regression coefficients for amplitudes and latencies of P1, P2, N1 and N2 of ERPs components

std = 2.69) with $p < 5.95e^{-5}$ and latencies of P1 (median = 88, std = 19.87; median = 80, std = 14.22; median = 70, std = 18.82) with $p < 1.14e^{-5}$ and P2 (median = 128, std = 18.88; median = 133, std = 21.58; median = 156, std = 17.63) with $p < 2.57e^{-3}$.

B. Result of multinomial classification

The classification accuracy between all three age groups was 0.63, macro-average and micro-average ROCs with 0.79 and 0.70 AUCs “Fig. 1”, “Fig. 2”. The one age group against the rest classification accuracy was 0.71, 0.45 and 0.75, ROCs with 0.71, 0.45 and 0.75, ROCs with 0.9, 0.50 and 0.76 AUCs

for each age group, respectively, “Fig. 1”, “Fig. 2”. The most informative feature for correct age group recognition, was amplitude of N1, which was reflected in the largest positive change of odds ratio “Fig. 3”.

IV. Discussion

The observed high recognition probability of individual EEG belonging to specific age group confirms that loudness-dependent auditory ERPs reflect brain developmental changes. Particularly, our findings indicate a strong association of the N1 amplitude with brain maturation [8] and slow developmental progression within 5-12 age period [6] that reflected in poor classification accuracy of this group ERPs against the rest two age groups.

Conventional division of children and adolescents by age groups and the impossibility of separating groups inside clearly distinguished developmental periods of middle childhood (4-12 years) confirms the need to create a regression model that will look for individual rather than group differences for personalized prediction of psychophysiological age of children and adolescences.

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