Original article / *Araştırma*

Computational analysis of affective facial behavior in children with the specific learning disorder

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ABSTRACT

Objective: *Clinical characterization of facial behavior is getting more critical in psychiatric disorders; however, there are no objective measures of these expressions. Our study aims to investigate to affective facial behaviors in specific learning disorder (SLD), collect objective facial behavior information to help decision making, and examine the discrimination ability of these behaviors in SLD and healthy controls (HC).* ***Methods:*** *SLD and HC group watched three, 5-minute scenes from cartoon videos and between these scenes in 2-minute question session was applied. Openface software for video analysis used three machine learning algorithms and the performance of these algorithms tested on our data using SLD and HC groups as prediction class. ROC curves and AUC had been calculated.* ***Results:*** *Prediction models using three machine learning classifiers had been created independently with tenfold cross-validation. SVM method showed the highest AUC=0.76 with sensitivity 72%, specifity 96%.* ***Conclusion:*** *Computational identification of facial behavior in children a promising beginning for the technologies to aid psychiatrists in the evaluation of learning and other neurodevelopmental disorders. Quantitative assessment of facial expression in neurodevelopmental disorders are both beneficial and informative and in future may be used as an addition to traditional methods of psychiatric examination.* ***(Anatolian Journal of Psychiatry 2020; 21(4):429-434)***

Keywords: *facial behavior, machine learning, specific learning disorder*

Özgül öğrenme bozukluğu olan çocuklarda affektif yüz davranışının bilgisayarlı incelemesi

ÖZ

Giriş: *Yüz davranışları psikiyatrik bozuklukların hemen hepsinde önemli klinik bulguları içerir, fakat günümüzde bunun için herhangi bir nesnel ölçüm yöntemi yoktur. Çalışmamızın amacı özgül öğrenme bozukluğu (ÖÖB) olan çocuklarda nesnel yüz davranış verilerini toplamak, klinik karara yardımcı olmak ve sağlıklı kontroller (SK) ile bu verilerin ayrım değerini araştırmaktır.* ***Yöntem:*** *ÖÖB ve SK grubu, ortalama 5 dakika süren çizgi film sahneleri izlemiş, 2 dakikalık aralarda sorular sorulmuştur ve yüz davranışları video kaydına alınmıştır. Openface yazılımı video analizi için kullanılmıştır. ÖÖB ve SK grupları arasındaki verilerin ayrımı için SVM, naive-bayes, lojistik regresyon makine öğrenme yöntemleri kullanılmıştır. Performans testlerinden ROC eğrileri ve AUC değerleri elde edilmiştir.* ***Sonuçlar:*** *Makine öğrenme yöntemleri öngörme modelleri ayrı olarak 10 katlı çapraz geçerli kılma analizine tutulmuştur. AUC: 0.76, duyarlılık: %72, özgüllük: %92 ile SVM metodu en yüksek performansı göstermiştir.* ***Tartışma:*** *Çocuklarda yüz davranışının bilgisayarlı tanımlanması, ÖÖB ve diğer nörogelişimsel hastalıklarda psikiyatrik değerlendirmeye yardımcı olabilir. Gelecekte nörogelişimsel hastalıklarda geleneksel yöntemlerin yanında, nesnel yüz davranışın değerlendirilmesi bilgilendirici ve faydalı olacaktır.* ***(Anadolu Psikiyatri Derg 2020; 21(4):429-434)***

Anahtar sözcükler: *Yüz davranışı, makine öğrenmesi, özgül öğrenme güçlüğü*

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INTRODUCTION

Specific learning disorder (SLD) is a neurodevelopmental disorder characterized by difficulties in learning and academic skills which are not better accounted for by intellectual disabilities, visual-auditory defects, and other mental or neurological disorders.[1] SLD is affecting 2-10 percent of school-age children. Recent studies showed children with SLD also have lack of empathy skills and theory of mind deficits.[2-5] Decreased prosocial behavior to sadness and inability to understand faux pas may clinically essential to understand difficulties in daily living and social relationships.[5,6] Clinical assessment of non-verbal expressiveness and gestures may indicate these problems in prosocial behavior, empathy, and other social learning skills.

Non-verbal behavior has a vital role in human communication and has a fundamental part of the mental examination. Facial expressions give much information about mental/affective status and social intention. Clinical characterization of facial behavior is getting more critical in psychiatric disorders; however, there are no objective measures of these expressions. Experienced clinicians can understand this subtle behavior, but it is a problematic and subjective assessment, so automated systems become a topic in this area.[7,8] The automatic facial analysis had shown significant success to define indicators in depression eight and post-traumatic stress disorder.[8] Cohn et al.[9] demonstrated facial behavior and vocal prosody could be used to detect depressive symptoms. Alghowinem et al.[10] shown head movement during interview significantly different between depressed and healthy subjects. Girard et al. demonstrated that automatic facial expression analysis was consistent with manual coding.[11] Recent studies are mostly focused on depressive symptoms; thus, these methods may provide utility to clinical assessment in neurodevelopmental disorders.

Our study aims to investigate to affective facial behaviors in SLD, collect objective facial behavior information to help decision making, and examine the discrimination ability of these behaviors in SLD and healthy subjects.

METHODS

Participants

The study was performed as a cross-sectional, controlled, single center study. The SLD patient group were recruited from the Ondokuz Mayıs University Medical Faculty Hospital, Department of Child and Adolescent Psychiatry. The healthy control group (HC) was recruited from volunteer relatives of health workers in the same hospital. The diagnoses of the patient group were made by child and adolescent psychiatry residents, according to the DSM-5 criteria. Twenty children aged between 7 and 12 years diagnosed with SLD, and age and gender-matched 20 healthy children compromised groups. WISC-R, as an intelligence test done by experienced psychologist and a score of >80 on the test was included in the study. The exclusion criteria for the patient group were; neurological disorders, unstable or chronic medical diseases, comorbid psychotic disorders, diagnosis of schizophrenia, autism spectrum disorder or bipolar disorder in a participant, parent or sibling. The HC group was recruited from participants with age and gender characteristics, had no history of medical illness or psychiatric disorder and who obtained >80 scores in the WISC-R test.

Psychiatric procedures

After evaluation of diagnosis defined for the study, all participants and their families were informed orally and gave consent in writing for psychiatric evaluation and video recording. Psychiatric comorbidity was controlled using the Schedule for Affective Disorders and Schizophrenia for School-Age Children Present Version (KSADS-P). KSADS-P[12,13] applied by a trained child and adolescent psychiatry specialist and the WISC-R[14,15] was applied by psychologist for evaluating performance and verbal scores.

Video recording

Both SLD and HC group watched three, 5-minute scenes from cartoon videos and between this scene in 2-minute question session was applied. Every scene had the main character, and its feelings in the scene had asked both groups in Likert version (happy/sad/angry/frightened). Video 1 had a scene from the Lion King, has feelings of fear and anger. Video 2 had a scene from Tom and Jerry has a feeling of joy and humor. Video 3 had a scene from the Bambi, has a sense of sadness. Videos are shown in a 1200x800 computer monitor, and both group faces were recorded with an HD Nikon camera with 1200X800 resolution placed 30 cm away from the monitor.

Video analysis

We used Openface software for video analysis.[16] The Openface is a real-time Facial Action Unit (AU) intensity estimation and occurrence detection system based on appearance (histograms of oriented gradients) and geometry features (shape parameters and landmark locations).[16] AU terms taken from Facial actions coding system (FACS) can be used to identify visually recognizable facial muscle movements and to use facial expressions.[17] We used a subset of 9 most reliable AUs recognized by OpenFace[18] (Table 1). We used Openface to extract the AUs from the whole recording video watching session of a patient. AU intensity scores at each video frame had been recorded. For an illustration of sample AU intensity scores from recordings, see Figure 1.

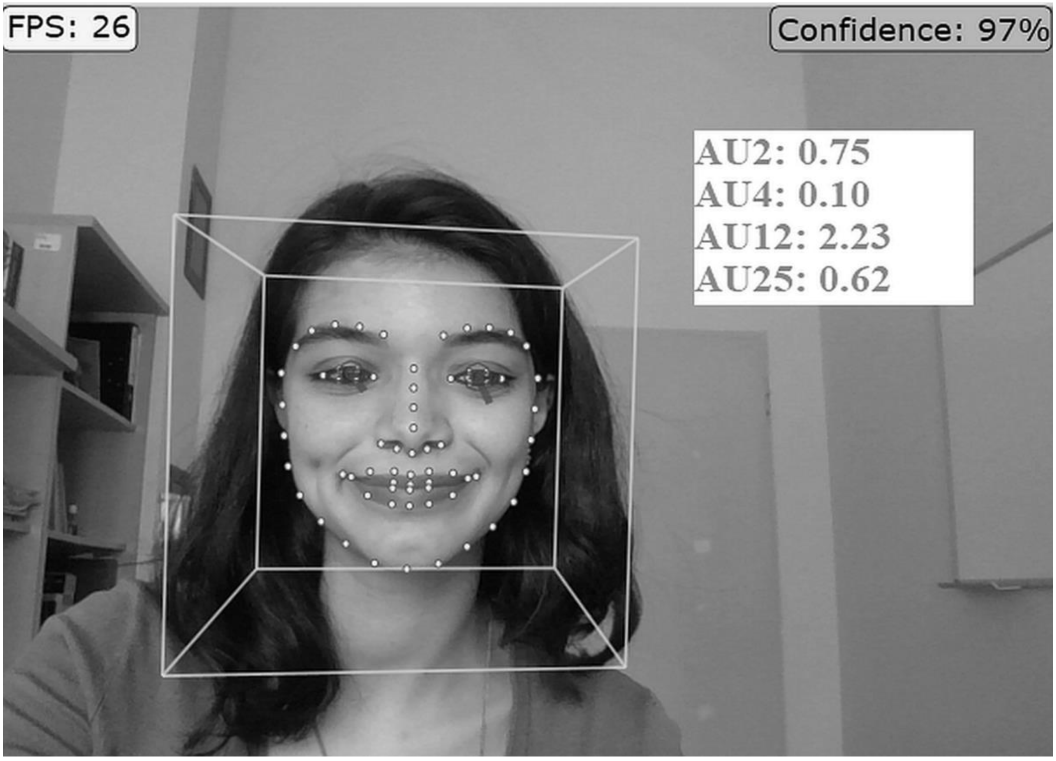

Figure 1. An example set of AU intensity scores for sample video frames

Statistical methods

The study data were evaluated using SPSS for Windows 21.0 software (SPSS Inc. Chicago, IL). Conformity of the variables to normal distribution was assessed visually (histogram and possibility graphs) and with analytical methods (Kolmogorov-Smirnov/Shapiro-Wilks tests). For values conforming to the normal distribution, chi-square test, and Student's t-test were used and for those not with normal distribution, the Mann Whitney U test.

Machine learning methods

Rapid Miner Studio Academic[19] software had been used for analysis and modeling. The data from videos had been pre-processed with the principal component analysis, which had applied for dimension reduction. We used three machine learning algorithms (Table 1) and the performance of these algorithms tested on our data using SLD and HC groups as prediction class. Ten-fold cross-validation used for both train and test sets. All subsets and means acquired by this process calculated for Receiver Operation Characteristic (ROC) curves and area under curve (AUC) had been calculated. Machine learning algorithm with the highest AUC had been chosen for results.

Ethical approval

Ethics board approval for the study was granted by the Clinical Research Ethics Committee of Ondokuz Mayıs University, numbered: B30.2.ODM.0.20.08, 681, dated 08/19.

Table 1. Action units and their muscular basis

Action unit	FACS name	Muscular basis
AU2	Outer brow raiser	m. frontalis
AU4	Brow lowerer	m. depressor glabellae, m. depressor super cillii
AU12	Lip corner puller	m. zygomaticus major
AU25	Lips Part	m. depressor labii inferioris

RESULTS

Forty children and parents initially invited into the LD and HC groups. In LD group four were excluded with a diagnosis of autism spectrum disorder and intellectual disability, two with psychiatric disorders diagnosed in first-degree relatives and one as he did not wish to continue with the tests. SLD group compromised 20 children, and HC was formed of 20 children age and gender-matched. Sociodemographic and clinical variables had shown in Table 2.

Action unit intensities compared between SLD and HC groups. HC group showed significantly high scores AU2 in video 1, video 2, and 3. Also, the HC group showed significantly high scores AU4 and AU25 in video 3, AU12 in video 2. Results had shown in Table 3.

The prediction models created by three machine learning classifiers, had been done independently with ten-fold cross-validation method. This method was repeated using all sub-sets and means obtained by this process calculated for Receiver Operating Characteristic curves with Area under Curve. Algorithms modified with their primary settings and left the minor tuning con-

Table 2. Sociodemographic and clinical variables of the study group

Study parameters		Groups Specific learning disorder Mean±SD (n=20)	Healthy control Mean±SD (n=20)	Test statistics	p
Age (years)		9.3±1.4	9.3±1.4	χ^2=0.00	1.00
Gender		80.0% male	80.0% male	χ^2=0.00	1.00
Mother education (years)		11.0±2.7	12.0±2.5	t=1.70	0.10
Father education (years)		12.5±2.1	14.0±2.0	t=2.21	**0.03**
IQ points	Verbal	96.9±5.6	105.1±6.1	t=4.10	**0.01**
	Performance	100.4±3.2	103.4±8.4	t=1.10	0.32
Subtype of SLD	Reading disorder	100.0%	-	-	-
	Written expression	85.0%	-	-	-
	Mathematics	25.0%	-	-	-
Comorbid diagnosis	ADHD	55.0%	-	-	-
	Anxiety disorder	10.0%	-	-	-
	Language disorder	5.0%	-	-	-

SLD: Specific learning disorder; HC: Healthy control

Table 3. Action unit intensity scores for each clip

Action unit	Video 1 SLD	HC	u	p	Video 2 SLD	HC	u	p	Video 3 SLD	HC	u	p
AU2	16.00	25.00	110	**0.02**	15.60	25.40	102	**0.01**	14.10	26.20	86	**0.02**
AU4	18.80	22.20	158	0.26	18.20	22.80	128	0.21	18.80	22.20	82	**0.01**
AU12	19.30	21.70	176	0.35	17.20	23.80	134	0.08	16.60	26.40	166	0.32
AU25	16.90	21.10	128	0.52	16.90	24.10	158	0.26	14.80	26.20	82	**0.02**

Table 4. Results of cross-validation for each classifiers

Classifier	AUC (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
Support vector machine	0.76	82.4	72.1	96.0
Naive bayes	0.71	70.3	67.0	90.0
Logistic regression	0.61	70.1	62.0	86.0

AUC: Area under curve

Table 5. Weights for support vector machine (AUC=79%, Accuracy=82.4%)

AU2	0.45
AU12	0.32
AU4	0.20
AU25	0.18

stant default values to prevent overfitting issues. After progress, we chose automatically optimized Support Vector Machine (SVM) method for the highest AUC (0.76) value (Table 4). AU2 had the highest weight for the SVM model. Each weight of AUs in the SVM model shown in Table 5.

CONCLUSIONS

In the psychiatric examination, an individual's nonverbal skills have an important role. We examined the affective reaction to emotional scenes via facial behavior with state-of-art computational methods in SLD and HC groups. The present analysis aims to develop classifier models with machine learning methods to differentiate between children with SLD and HC based patterns on facial behavior.

Our study showed HC group had significantly high intensity in particular AU while video 1, 2, and 3. In video 3 (Bambi’s sad scene), AU25 (lip corner depressor) which shows unpleasant mental states, were significantly higher in the HC group. AU12 (Lip corner puller), which indicating smiling was shown more elevated activity in video 2 (Tom and Jerry). AU2 (Outer brow raiser) were used more by the HC group in video 1, 2 and 3, HC group raise their brows more. In total, the HC group showed more facial AU activity and, this may represent children in SLD group had lesser understanding, processing, and reflecting emotions through watching these scenes. This deficit in these processes may fail to understand verbal and visual messages in scenes, and that causes lowered affect and facial expression to these emotional moments. Recent studies showed children with SLD evidence of deficits in theory of mind, which negatively affects the understanding of mental states, emotions, and thoughts of the others.[20] Individually, children with autism spectrum disorder (ASD) having difficulties judge other people's expressions and emotional states and respond with appropriate gestures.[21] Also SLD and ASD are shown to share genes which can contribute this neurobehavioral trait.[22]

Our machine learning model for all videos able to distinguish HC and SLD groups with a reliable performance (AUC: 79%, accuracy: 82.4%, sensitivity: 71.1%, specificity: 96.0%), based on AU activities during watching sessions. Also, we identified the importance of AU units weights to contribute the model, AU2 (outer brow raiser) intensity in upper facial muscles which indicates mostly ‘surprise’,[23] were a most discriminative feature in the model. AU12 indicator of smiling behavior which was higher intensity in the HC group was the second discriminative feature in the model. In the context of this emotional stimulus, facial behavior descriptors are being extracted are helpful for building models and visual information.

We demonstrated recognition of Facial Action Units with computerized methods could be used to differentiate HC and SLD groups. Computational identification of facial behavior in children a promising beginning for the technologies to aid psychiatrists in the evaluation of learning and other neurodevelopmental disorders. Quantitative assessment of facial expression in neurodevelopmental disorders are both beneficial and informative and in future may be used as an addition to traditional methods of psychiatric examination.

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