Abstract

Early screening, which can lead to early diagnosis and intervention of children with autism (ASD), can significantly improve the life quality of children with autism. The observational process of ASD diagnosis and lack of experts make the technology-based ASD screening methods more necessary. Early ASD screening based on behaviors is one of the most reliable methods that could be done by analyzing children's playing patterns. This paper presents an extension of the intelligent toy car functionalities by adding shaft encoders to detect attention details traits in children with ASD. Thus, the proposed approach uses two different modalities that improve screening accuracy by 10%.

Introduction

 Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder that causes social communication and interaction problems [1]. Unfortunately, ASD is becoming more prevalent in the last two decades [2]. On the other hand, studies show that early diagnosis resulting in early intervention can effectively reduce the disorder's impacts. Diagnosing autism requires experts to observe children and interview parents to determine the severity of the symptoms. Unfortunately, this is a time-consuming and challenging process. Furthermore, many cases remain undiagnosed due to the lack of widespread experts, especially in low and middle-income societies. Consequently, it becomes essential to develop technology-based screening methods to make screening services cheap and widely available to overcome these challenges.

Many technology-based methods are originated from the CHAT family[3] questionnaires, in paper-based format or mobile apps or web applications[4]. These methods employ machine learning algorithms to improve the screening accuracy [5]. Although these methods are proved effective, they rely on licensed clinicians and observers, making them time-consuming and exhausting [3, 6]. To overcome the shortcomings of the questionnaire-based systems, many researchers have focused on biological markers of ASD[7] using brain imaging techniques like fMRI[8] or EEG methods to find ASD symptoms[9].

Although these methods are proved effective, they require costly equipment. Furthermore, putting a child in an fMRI or putting on an EEG cap may cause many discomforts limiting the usage of these approaches. On the other hand, wearable devices like smart glasses or sensors are used for ASD screening [10, 11]. Despite the lower cost of these systems compared to fMRI and EEG, they still need to be conducted at dedicated centers. Intelligent observation of behaviors is a method to overcome the challenges of biometric and wearable methods. For instance, Moghaddas et al. developed a vision-based method to screen children with ASD based on the interaction between children with ASD and a parrot-like robot [12]. Although this approach reduces mentioned difficulties in wearable methods, but still depends on dedicated centers to conduct the screening.

That is why home-based IoT devices such as the intelligent toy car[13] were designed to perform screening in children's natural settings at a very low cost. Along with this trend, in this study, we improved our intelligent toy car by incorporating two shaft encoders on the wheels of our car to investigate if children with autism focus on the wheels instead of the whole car more than Typically Developed (TD) children. This new modality, combined with its initial modality, which was based on capturing the acceleration features in playing with the car, helped improve screening accuracy by 10%. In other words, our contribution is in incorporating two modalities to better screen ASD.

Related work

There have been several studies focused on using technology for ASD screening. These methods try to observe the ASD symptoms automatically using biomarkers or behavioral markers.

For example, William J. Bosl et al. focused on early screening of ASD by a data-driven method based on the EEG's data. They collected EEG measurements of 99 infants with an older sibling that received an ASD diagnosis and 89 low-risk controls. They screen ASD in children as early as three months of age with 95% sensitivity and PPV at some ages. They suggest EEG signals might be a valuable biomarker for ASD screening[9]. Also, MladenRakić et al. presented a method to improve ASD detection by combining structural and functional MRI data. They applied machine learning techniques on imaging data of 817 cases and successfully classified them with an accuracy of 85%[14]. Integrating biomarkers with other modalities has also proved effective; JiannanKang et al. identified ASD in children from 3 to 6 by inputting a combination of EEG and eye-tracking features collected with power spectrum analysis and areas of interest methods to an SVM classifier. They tested on a total number of 97 children and reached the maximum accuracy of 85%.[15].

Stereotypical Motor Movements (SMM) is one of the ASD symptoms that multiple methods have been developed to detect. Rad, N. M et al. proposed a Convolutional Neural Network that uses accelerometer sensor data worn on multiple body points to detect SMM. They applied feature learning and transfer learning approaches to improve their deep neural network performance[10].

Detecting and analyzing gaze is also a method in ASD screening; Anish Nag et al. compared the gaze data of 16 children with ASD, and 17 typically developed children were collected using google glass and gaze tracker. Although smart glasses perform promisingly, they do not outperform other automatic classifiers significantly[11]

Although wearable devices are a helpful method for ASD screening, it is always challenging to persuade a young toddler to wear such devices, especially children with special needs; besides, wearing such devices is usually a major distraction that affects the procedure. Robots are an excellent option for evaluating social interactions, but they are costly and usually require operators to handle the process.

   One of the major symptoms of ASD is repetitive and stereotypical behaviors that are considered an essential indication in ASD's diagnosing.[16] In recent years, many technology-based screening systems have been developed, many methods focused on vision-based approaches, behavioral analysis methods that use machine vision to detect and recognize movements and motor function patterns. R. Oberleitner et al.[17] developed a recognition system for detecting abnormal behaviors that can be used in screening, assessment, or rehabilitation. Rasool Taban et al. [18] record walking patterns by Kinect and then analyze them using central pattern generator parameters as their classifier features. They accurately distinguished between tip-toe walking and regular walking pattern. Guillermo Sapiro and et al. [19] developed a low-cost mobile app that uses machine learning and machine vision methods to detect movement patterns and assess eye tracking patterns.

Vision-based methods also used for studying the subject attention; Kathleen Campbell and et al. [20] developed an app that record and analyze the reaction of the toddlers to video stimuli that designed to engage child's attention; their algorithm classifies by automatically detecting and tracking multiple facial landmarks and analyzing their patterns.

One of the best ways to study the behavior in children is through their play with toys and pet animals. Since children spend a considerable amount of time playing with toys at a young age, the repetitive patterns could easily be recognized. Studying playing patterns does not have challenges like the discomforting feeling of brain imaging or EEG analyzing methods, and unlike wearable devices, they do not affect child attention and are considerably more cost-effective than robots.

Sensorized toys are valuable tools in ASD screening, embed different sensors inside toys to capture playing patterns, and are classified based on proven effective, i.e., Lanini M. and et al. combined accelerometer, gyroscope, and magnetometers data.[21] Also, Moradi et al. introduced a platform for autism screening based on acceleration data of a toy car that, in their first version, a Wii remote controller perform as a sensor hub and a Matlab program developed to interact with the system to collect accelerometer data of x, y, and z axes to investigate distinctive playing patterns and implement an SVM classifier with 85% accuracy[13]

In this research, the intelligent toy car 2.0 is introduced. It extends the previous version functionality by adding shaft encoders to the wheels, introducing new features, and optimizing the feature selection method. It enables us to study the ASD symptoms with a multi modalities approach and simultaneously analyze the repetitive behaviors and the obsessive attention to the details.

System design

The intelligent toy car is designed to capture the signs of two major symptoms in children with ASD, i.e., obsessive attention to detail and repetitive behaviors. i.e., Thus, in the first design Intelligent Toy Car 1.0, a Wii Mute handle which includes an accelerometer, was placed in the car. Our new design, the intelligent toy car 2.0 (Fig. 1(a)), has had multiple upgrades with respect to its first design. The new system has an inexpensive IoT board ESP8266 NodeMCU[[1]](#footnote-1) to read sensor data and send them wirelessly through Wi-Fi via UDP protocol to ensure maximum data collection rate. Also, the cheap MEMS accelerometer ADXL345 is placed inside the car, and two magnetic shaft encoders are installed on the front and back axles of the car. The whole system runs on a battery, and all electronic parts are embedded inside the car deliberately to avoid any distraction. The diagram of the system is shown in Fig. 1(b).

The intelligent toy car firmware is based on the Arduino ecosystem to make future R&D more effortless. Also, an ROS (Robotic Operating System) package is developed for interfacing with the system. It makes integrating the intelligent toy car in other systems more straightforward.

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| --- | --- |
|  | Diagram  Description automatically generated |
| (**a**) | (**b**) |

Figure 1. (a) the intelligent toy car and (b) the schematic of the system

Experiments

The data collection process took place in the Dosste-Autism center (Autism friends center) in Tehran, Iran. The intelligent toy car was tested on 50 children ranging from 3 to 6 years old in three groups children with ASD, TD children, and other (CP and fragile X syndrome) shown in Table 1. Since it has been shown that the play complexity and toy engagement of children with ASD in both genders for the car-like toys are almost similar [17][18], we did not normalize the number of cases based on their gender. The subjects played with the intelligent toy car for about 3 to 5 minutes in a 3x4 meters room. The children could play in the test room alone or with their parents or therapists. The recorded data from each participant consists of time, acceleration in 3 dimensions, front and back wheel rotation counts saved in a database. A unique id in the database only identified each participant, and to preserve user anonymity and privacy, no personal data was recorded during the procedure. Furthermore, the parents' consent was taken for all the participants.

ASD group has 28 children that five of them did not seem interested in playing with the intelligent toy car and neglected it. All TD children were very interested in playing with the intelligent toy car, and children with fragile X syndrome and CP also played with the intelligent toy car but with less enthusiasm. Generally, the TD children playing was more energic, and they moved the car in the greater area than other groups.

Table 1. Details of participants

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| --- | --- | --- | --- |
|  | autistic | TD | other |
| number | 28 | 18 | 4 |
| mean age | 4.63 | 4.61 | 5.5 |
| median age | 4.0 | 4.0 | 5.5 |

# Feature extraction

As mentioned earlier, the intelligent toy car is designed to capture the repetitive behavior and focus on details symptoms of children with ASD. In our previous study, we used movement patterns extracted from acceleration data for classification [13]. In this research, the same patterns are extracted, and the encoder's data are integrated into the model to enhance the accuracy of the classification. Also, new features are added.

To capture the repetitive patterns and focus on details symptoms, three steps are taken: extraction of features representing the pattern of the car movement, extraction of features representing focusing on details, i.e. wheels rotation, feature selection to reduce the complexity of the model, and classification of the data based on machine learning methods

To use the data collected from the intelligent toy car, the following preprocessing step is performed. Since even small changes in the signals may considerably affect the result, a simple wavelet filter[22] is used to remove the acceleration sensor noises in all three axes. In the next step, 46 features from the acceleration signals were extracted and was clustered in 6 groups: 1) the mean and the variance in each coordinate axis, 2) the highest frequencies in each direction and their relative amplitude, 3) the total energy of the signal in each direction, 4) the correlation of acceleration signals between every two axes, 5) the number of jolts extracted from acceleration in the y-axis, which is the direction of the car movement, and 6) the time of the play. Two new features, compared to the features presented in [17], representing roll tilt and pitch tilt in the movement were added to increase the model's accuracy. These two features are extracted using Short Term Fourier Transform[23] with different window samplings. Since the jolt extracted from acceleration in the y-direction is a compelling feature in the data set, it is expected that the roll and pitch in the z and x-direction would enhance the model in the same way.

Eight features were extracted from shaft encoders. The first feature is the total number of wheels turns during the play per time.~~number of spikes in encoders' derivation per time, representing the total number of wheelwheels turns during the play (number of times wheels change from stationary to rotating)~~. ~~Other features of the encoders are extracted by convolving acceleration signals and the summation of two encoders signals.~~ Other features are extracted by convolving encoders signals and acceleration signals.

To combine the features, analyzing the states of playing with the car is useful. The whole children's playtime with the intelligent toy car can be divided into four states: 1) no playing, 2) playing only with wheels, 3) playing on the ground, and 4) playing in the air. In the not playing section, the intelligent toy car is almost stationary and has no movements, and both encoders and acceleration signals are almost zero. The playing only with wheels section is when the intelligent toy car is almost motionless while rotating its wheels. In such a case, the shaft encoders show changes while there is no significant change in the acceleration. In the playing on the ground section describes those portions of playing that the intelligent toy car is moved which creates changes in both acceleration and shaft encoder signals. Finally, the playing inn air section is when the intelligent toy car is moved in the air, and the acceleration is changing, and its wheels are not rotating. Thus, the encoders signals show zero rotation.

Integrating the jerk of the summed acceleration signals with the variation of the encoders' data separates these four mentioned sections from each other. If the jerk is almost zero, then the car is almost stationary and depending on the shaft encoders' signal variation, the car can be in the No Playing state or in the playing only with wheels state. If the jerk was non-zero, then the car is moving and based on its encoders data it could be in the playing on the ground or playing in the air states. The percentage of every state in the play time of a subject is considered a feature. By defining an active duration for the intelligent car that consists of total time minus not playing section, the absolute interaction period of the test case is calculated. The ratio of each state to the length of the absolute interaction period is also a feature.

## Classification Structure

To train classifiers, the collection of 45 subjects' data was divided into two groups: the training set with 80% of samples and the test set with 20% of remaining samples. The training set is used to train the classifier, and the test set is used to measure the classifier's performance. The K-fold cross-validation method[24] separates test and training sets in k=5 different ways to generalize the result and make it more reliable. The average of the accuracy, sensitivity, and specificity of the trainings are reported. In this research, a Support Vector Machine (SVM)[24] is a suitable machine learning method that can effectively classify this kind of data. By testing three kinds of SVM, SVM with a linear kernel is selected for its considerably better performance.

## Feature Selection

## Since the size of the training set is small compared to the size of the feature vector, feature reduction is necessary before applying machine learning methods. In the first step to reduce the number of features, their correlation was examined. Only one feature from every group with high more than 85% correlation was selected while the others were eliminated. In the ordinary algorithms there is no differentiation between features in a high correlated group, hence one of them is selected randomly. In this study, F forward selection and backward elimination [24] is used to select the most compelling feature from each highly correlated groups [25]. This method effectively reduces the number of feature vector by about 30%. The remained features were divided into acceleration features and encoder features. Feature selection methods, including Forward-selection algorithm, backward-elimination algorithm, and genetic algorithm, are implemented on each group of features individually to investigate the most important features. Lastly, different acceleration and encoder feature combinations are examined to reach the best result with higher accuracy, sensitivity, and specificity. As seen in [fig2], the best result is obtained by integrating five acceleration features and two encoder features.

Figure 2. The best accuracy, sensitivity, and specificity gained through three different combinations of acceleration features and encoder features.

# Results

Classification result based on previous studies is used as a baseline to examine the performance of adding encoder features in the model. The same SVM method is performed on the selected acceleration features presented in [13] to classify the new data. The best accuracy based on these acceleration features is 72%, as shown in Fig3. By adding encoder features, the accuracy is increased to 80%. By adding the new acceleration feature, the accuracy was increased from 72% to 76%.

Moreover, by adding both encoders' features and the new acceleration feature, the accuracy reaches 86% (Fig3 d). Based on the optimized feature selection method used in this study, the most effective shaft encoders' features are playing only with wheels, not playing, and the total number of wheels turns per time. The most effective acceleration features are the jolt in the Y direction, tilt about Y axis, the energy of the signal in the Y direction, Correlation of the acceleration signals between X and Y directions.

Table 2. The best accuracy, sensitivity, and specificity gained by adding new features to the baseline classification. The results show the advantage of adding both shaft encoders’ encoders' features and the new acceleration feature for classification. Also, it is obvious that encoders are more effective than the new  acceleration feature.

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| **Classifier** | **Accuracy** | **Sensitivity** | **Specificity** |
| Baseline | 71.11 | 67.14 | 80 |
| Baseline and encoder features | 80 | 79 | 78 |
| Baseline and new acceleration feature | 76 | 74 | 75 |
| Baseline, encoder features and new acceleration feature | 85.56 | 81.67 | 87.67 |

# Discussion

# As shown in Table xx, the accuracy of the new proposed multi-modal approach is better than the previously suggested single modal approach. Furthermore, adding the extra acceleration feature, i.e., …, in the feature set improved the classification accuracy.

# It should be noted that the accuracy reported in [13], i.e., 85% accuracy, is higher than what we got in this study, i.e., 72%, which may be due to the following reasons. First, the data sets were different in that ay created different results. Second, the first version of the car was different and used a set of lights to attract children with ASD. Finally, the system in [17] used high-quality accelerometers implemented in Wii mote with multiple preprocessing stages that significantly improved the status of the collected signals.

# The novelty of this research is its multi-modality structure resulting in the examination of ASD through a wider variety of symptoms. In order to reach this purpose, encoders are added to the system, which causes some new challenges. Encoders are simple signals which extraction of features from them is not straightforward. Children's playtime is divided into four sections by an innovative approach to solving this issue. This new idea provides useful encoder features to separate children with autism from others. Also, adding encoder features to extracted acceleration features makes the feature selection process more problematic. Applying feature selection algorithms on the entire set of features is not effective enough; therefore, the features are clustered in two groups, and feature selection algorithms are applied on each of them separately. In this regard, using more effective feature selection methods is also essential. The enhanced Correlation-based feature selection and examination of every feature in high-correlated feature groups to find the most suitable features can considerably improve the system's accuracy.

# Conclusion

In this paper, we introduced the intelligent toy car 2.0 which uses multi-modal ASD screening. The new design incorporates shaft encoders to capture the tendency of children with ASD into details and rotating items. Furthermore, we improved the feature selection strategy to increase the system accuracy by multi-modal analyzing ASD symptoms. The advantage of this system over other screening methods is in its low cost and limited need for expertise. It can be used at homes, daycares, or clinics for initial screening.

For the future work, we have to test the system on a wider population and test it on a variety of cognitive deficits to see if it can differentiate between different cognitive deficits or not. Consequently, at this stage, it can be used as a warning system to alarm the parents and care givers to perform further evaluation through experts.

Finally, the intelligent toy car can be used beside other screening devices to increase the accuracy by considering other modalities of children with ASD. We expect that having more modalities observed can help to better screening.

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