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 smart 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. For diagnosing autism, experts should observe children and interview parents to determine the severity of the symptoms. Unfortunately, it 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 prove effective, licensed clinicians and observers should do them, 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][7, 10].

[9]Although these methods are proven 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 biometric and wearable methods. For instance, Moghaddas et al. screen children with ASD based on the[12]. Although this approach reduces mentioned difficulties in wearable methods, but still depends on dedicated centers to conduct the screening. [11][13]

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 smart toy car by incorporating two shaft encoders on the wheels of our car to see 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].

(SMM) is one of the ASD symptoms 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]

help

   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 smart 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 smart toy car 2.0 (Fig. 1(a)) has received multiple upgrades regarding its previous version; the new system has an inexpensive IoT board ESPRESSIF 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, a cheap MEMS accelerometer ADXL345 and two magnetic shaft encoders are installed on forward and backward axles. The whole system runs on a battery power supply, and all electronic parts are embedded inside the car deliberately to avoid any distraction. The diagram of the system is available in Fig. 1(b).

The smart toy car firmware is based on the Arduino ecosystem to make future R&D more effortless. Also, for interfacing with the system, a ROS (Robotic Operating System)[[2]](#footnote-2) package is developed. It makes integrating the smart toy car in other systems more straightforward.

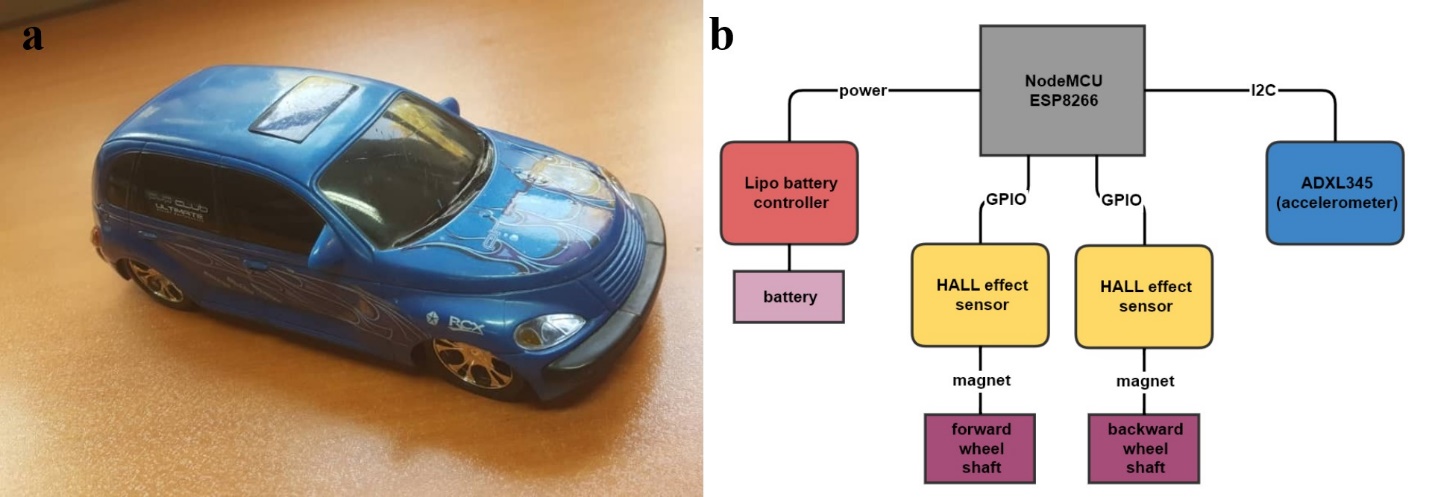


Figure 1. (a) the smart toy car and (b) the schematic of the system

Tests

The data collection process took place in the DOOSTEAUTISM autism center, and the smart toy car was tested on 50 children from 3 to 6 years old, from three groups autistic, non-autistic and other, the details of participants are available in table 1. Since Clare Harrop et al.[22] are shown that the play complexity and toy engagement of children with ASD in both genders for the car like toys are almost similar, and no difference in genders was observed in the previous research on the smart toy car[13], we do not normalize the number of cases based on their gender. The test cases play with the smart toy car for about 3 to 5 minutes in a 3x4 meters room; that child could go to the test room alone or with his/her parents to comfort any stress. The recorded data from each participant consists of time, acceleration in 3 dimensions, forward and backward wheel rotation values 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.

From the total number of test cases, 28 were autistic, and 18 were non-autistic; four children in the other group had CP and fragile X syndrome that tested for better system evaluation. From the 28 autistic cases, 5 of them did not seem interested in playing with the smart toy car and neglected it.

Table 1. Details of participants

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

# Purposed method

The research aims to classify the data collected from children into two groups: autistic and non-autistic. The smart toy car is designed to detect the signs of two major symptoms in children with ASD, obsessive attention to detail and showing repetitive behaviors. These symptoms can be extracted from data obtained from the smart toy car. The previous studies 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. Based on similar studies on movement patterns, three necessary steps should be taken in this approach: extraction of features representing the pattern of the car movement, feature selection to reduce the complexity of the model, and classification of the data based on machine learning methods.[13]

## Feature Vector Extraction

To use the data collected from the smart car, preprocessing is necessary. Since even small changes in the signals may considerably affect the result, a simple wavelet filter[23] removes the acceleration sensor noises in all three axes. In the next step, 46 features for the acceleration signals are extracted and is 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.[13] two new features 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[24] 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. Also, Encoder's features can represent another important indication of ASD: a child's obsessive attention to detail. Eight features are extracted from encoders. The first feature is the number of spikes in encoders' derivation per time, representing the total number of wheel 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. The whole children's playtime with the smart toy car can be divided into four sections: not playing, playing only with wheels, playing on the ground, and playing in the air. In the not playing section, the smart toy car is almost stationary and has no movements, and both encoders and acceleration signals are almost constant. The playing only with wheels section is when the test case holds the smart car almost motionless while rotating its wheels. The playing on ground section describes those portions of playing that the test case is only moving the smart car on the ground, and both acceleration and encoders change continuously, and the playing on air section is when the smart toy car is moved in the air, and the acceleration is changing, and its wheels are not rotating and, the encoders data is almost constant. Integrating the jerk of summed acceleration signals with the variation of the Encoder's data separates those four mentioned sections from each other. If the jerk is almost zero, then the car is almost stationary and depends on the encoders variation; the smart car could be in the not playing or the playing only with wheels section, and if the jerk was non-zero, then the car is moving and based on its encoders data it could be moved on the ground or in the air, The percentage of every part to the whole signal is a feature. By defining an active duration for the smart car that consists of playing only with wheels, playing on the ground, and playing in the air sections, the absolute interaction period of the test case is calculated. The ratio of each section to the length of the absolute interaction period is also a feature.

## Classification Structure

It is possible to differentiate between children with autism and others by applying machine learning methods. In this regard, the collection of 45 samples is 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[25] separates test and training sets in k=5 different ways to generalize the result and make it more reliable. K=5 times the classification algorithm is implemented, and the accuracy, sensitivity, and specificity are investigated each time. The average of these factors is calculated and considered a benchmark for measuring the classifier's effectiveness. In this research, a Support Vector Machine (SVM)[25] 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 reducing the number of features, their Correlation is examined. Only one feature from every group with high Correlation is selected while the others are removed. Forward selection and backward elimination[25] select the most compelling feature from high correlated groups.[26] The remained features are 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 claimed 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%. Adding merely new acceleration features can increase the accuracy from 72% to 76%.

Moreover, by adding both encoder features and the new acceleration features, the accuracy reaches 86%. [Fig3] Based on the optimized feature selection method used in this study, the most effective encoder 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 X direction, roll tilt in the Y direction, the energy of the signal in the Y direction, Correlation of the acceleration signals between X and Y directions.

Figure 3. The best accuracy, sensitivity, and specificity gained by adding new features to the baseline classification. a) Baseline classifier based on [17], b) Encoder features are added to the baseline classifier, c) Only a new extracted acceleration feature is added to the baseline classifier. e) The accuracy in each classifier shows that adding encoder features increases the accuracy of the model effectively

# Discussion

# In the previous study, the accuracy was 85% based on six groups of acceleration features mentioned earlier[13]. In this study, the accuracy decreased to 72% using the same features. It is due to the differences between the two systems. In the previous system, the Wii remote acted as a sensor hub. Typically, the quality of its sensors is better than cheap MEMS accelerometers that yield cleaner sensor data; also, the Wii remote has multiple preprocessing stages that significantly improve 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. In order to solve this issue, children's playtime is divided into four sections by an innovative approach. 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

This research introduced the smart toy car 2.0; adding encoders and optimizing the feature selection strategy increases system accuracy by multi-modal analyzing ASD symptoms. We like to mention that this system is more like an early warning solution than a screening or diagnosing method for ASD; its primary application is to give a warning for referral to an expert.

The smart toy car 2.0 design strategy was developing a cost-effective device, and this approach yielded to choosing inexpensive off-the-shelf sensors. However, we differentiate between autistic and non-autistic groups accurately with more noisy sensors by fusing multi-sensor data. Intrinsically better sensors enhance the final results.

The smart toy car could be used as a screening device integrated with other screening devices in a future comprehensive autism screening system that analyzes ASD symptoms with more modalities to ensure more reliable results.

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2. www.ros.org [↑](#footnote-ref-2)