Multimodal Fusion for Cognitive Load Measurement in an Adaptive Virtual Reality Driving Task for Autism Intervention

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Abstract. A virtual reality driving system was designed to improve driving skills in individuals with autism spectrum disorder (ASD). An appropriate level of cognitive load during training can help improve a participant's long-term performance. This paper studied cognitive load measurement with multimodal information fusion techniques. Features were extracted from peripheral physiological signals, Electroencephalogram (EEG) signals, eye gaze information and participants' performance data. Multiple classification methods and features from different modalities were used to evaluate participant's cognitive load. We verified classifications' result with perceived tasks' difficulty level, which induced different cognitive load. We fused multimodal information in three levels: feature level, decision level and hybrid level. The best accuracy for cognitive load measurement was 84.66%, which was achieved with the hybrid level fusion.

Keywords: autism, virtual reality, multimodal fusion, cognitive load measurement

1 Introduction

Autism spectrum disorder (ASD) is a common disorder that impacts 1 in 68 children in the US [1]. Although at present there is no single accepted intervention, treatment, or known cure for ASD, there is a growing consensus that appropriately targeted individualized behavioral and educational intervention programs have the potential to positively impact the lives of individuals with ASD and their families [2, 3]. However the availability of trained autism clinicians is limited and the cost associated with traditional therapies is enormous. As a result, the development of economical and effective assistive therapeutic tools for autism intervention is urgent.

A growing number of studies have investigated the application of technology, specifically computer and virtual reality (VR) systems, to autism intervention. There are

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numerous reasons why incorporating VR technology into intervention may be particularly relevant for children and adolescents with ASD. The VR-based intervention platform is characterized by malleability, controllability, modifiable sensor stimulation, individualized approach, safety, and the potential to reduce problematic aspects of complex adaptive life skills [4]. These systems could not only help children with ASD generalizing learned skills to the real world, but also provide more control over how the basic skills are taught.

At present, most VR-based platforms have been designed to improve social skill deficits in ASD population [5, 6]. However, other activities of daily life that are important for functional independence for individuals with ASD have not received similar attention. In this work, we focus on VR-based driving since independent driving is often seen as a proxy measure for functional independence and quality of life for adults across a variety of disability and non-disability groups. It is noted that many individuals with ASD fail to obtain driving independence [7]. In addition, an emerging literature suggests that individuals with ASD display processing differences in driving environments that may be linked to unsafe driving behaviors. Despite its importance, to our knowledge, only two studies have investigated driving interventions for teenagers with ASD [8, 9].

Previous work has investigated the use of technological interventions for driving skills in people with ASD, but no studies have developed a closed-loop individualized system to the best of our knowledge. Reimer and colleagues (2013) and Classen and colleagues (2013) presented participants with a set of driving scenarios using a driving simulator paradigm within a real vehicle that was converted into a simulation tool [8, 9]. Classen and colleagues found a higher error in driving performance for teens with ASD or Attention Deficit-Hyperactivity Disorder (ADHD) compared with typically developing (TD) group [9]. Reimer and colleagues found different gaze patterns and physiological signals, such as heart rate and skin conductance level (SCL), between the TD control group and individuals with autism [8]. They also found the variation of heart rate in TD group under different cognitive condition. These related research work highlighted the need for deeper research in individualized driving system for autism intervention.

We plan to develop an individualized intervention system that can maximize a participant's long-term performance by adapting the difficulty level of a driving task. Task difficulty directly affects a participant's cognitive load [10]. A lot of studies modulated cognitive loads using different task difficulties [11, 12]. An appropriate cognitive load could maximize individual's long-term performance [13]. An individualized system, which can measure the user's current cognitive load and modulate the cognitive load to its optimal level by adjusting the task difficulty, has the ability to effectively improve the user's performance.

This paper measured cognitive load from multimodal signals, including performance data and three classes of psycho-physiological signals: peripheral physiological signals (heart rate, SCL etc), EEG signals, and eye gaze signals. Performance-based measure was traditional way for cognitive load measurement [14]. Performance features, including reaction time, accuracy and error rate, indicated a participant's cognitive load [11]. Psycho-physiological measurement have been shown to provide real time information about cognitive load [15-17], which in turn can be used to our individualized difficulty level adjustment. For example, eye gaze offers rich physiological information, such as blink rate and pupil diameter, to reflect a user's cognitive state [18, 19]. EEG are sensitive and reliable data for memory load measurement [20, 21]. Peripheral physiological signals, such as electrocardiogram (ECG), photoplethysmogram (PPG), electromyogram (EMG), respiration (Resp.) and skin temperature (SKT), can reflect the variation of cognitive load [22, 23] as well as affective states [24, 25].

Integrating such psycho-physiological signals with performance data has the potential to increase the robustness and accuracy for cognitive load measurement [26]. Son and colleagues integrated performance with physiological data to estimate a driver's cognitive workload and got the best result with selected performance features and physiological features [27]. Koenig and colleagues have quantified the cognitive load of stroke patients with both psycho-physiological and performance data and applied in a closed-loop system[12]. Although other work has studied applications of cognitive load in individualized intelligent systems with multimodal information fusion techniques, this has not yet been done for individuals with ASD to the best of our knowledge.

The multimodal information fusion techniques could be presented in three levels: feature level, decision level and hybrid level [28]. The feature level fusion was an easily accomplished approach because it required only one learning phase on the combined feature vector [29]. However, the synchronization from multimodal information was found to be more challenging [30]. Decision level fusion combined the sub-decisions of each modality to arrive at a more robust decision[31]. However, it was not good at reflecting the correlation between features of different modalities [32]. Hybrid level fusion methods seek to combine the advantages of feature level fusion and decision level fusion [28].

In our previous work [33, 34], we presented a novel VR driving environment with the ultimate aim of developing an intervention platform capable of enhanced teaching of driving skills to teenagers with ASD. In this paper, we present our current work in fusing multimodal information to assess one's cognitive load during driving. We evaluated multiple classification methods for multimodal fusion and compared three levels of fusion in this paper. The long term goal is to close the loop in such a way that the driving task can be autonomously adapted to one's cognitive load to optimize performance, which is beyond the scope of this current paper.

2 Methods

2.1 Experimental setup

The virtual driving system was designed with three components: a driving simulator, a data acquisition module and a therapist rating module, shown in **Fig. 1**. Participants used the driving simulator to engage in driving tasks. The data acquisition module acquired their psycho-physiological information and performance data in real time. One therapist observed and rated participants' emotional state and cognitive state from another room. All the data collected were synchronized by time stamped events from the driving simulator via a local area network (LAN).

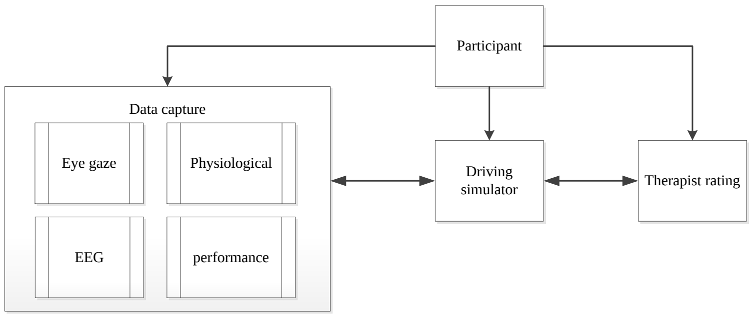


Fig. 1. The framework of the VR-based driving system

The driving simulator was composed of a virtual environment and a Logitech G27 steering wheel controller, shown in **Fig. 2**. The models in the virtual environment (e.g., the city, the car, and pedestrians) were realized with the modeling tools ESRI CityEngine (www.esri.com/cityengine) and Autodesk Maya (www.autodesk.com/maya). The game engine Unity3D (www.unity3d.com) was used to manipulate the logic of the system. The system was composed of six different levels of difficulty to invoke different cognitive loads. Each level included three driving assignments. Each assignment included a series of eight driving tasks in order to train the specified driving behaviors, such as stopping properly at a stop sign, yielding to pedestrians, merging lanes, and turning left.

Fig. 2. The driving simulator and environment

Participants controlled a vehicle in the virtual environment using the controller. Their driving behaviors and task performance were logged within the system. In addition to recording performance data, the data acquisition system recorded psycho-physiological data with psycho-physiological sensors shown in **Fig. 3**. A Tobii X120 remote eye tracker (www.tobii.com/) was used to track the participant's eye gaze. Biopac MP150 (www.biopac.com) sensors recorded ECG, EMG, Resp., SKT, PPG, and galvanic skin response (GSR)signals wirelessly [35, 36]. The GSR and PPG sensors were attached on the participant's toes instead of fingers to reduce the motion artifact from driving [37]. An Emotiv EEG headset (www.emotiv.com) recorded 14 channels of EEG signals.

Fig. 3. The psycho-physiological sensors [37]

In the therapist rating module, a therapist observed and rated the participant's affective state and the apparent difficulty of the assignment using a 0-9 Likert scale. The rating categories included difficulty level, engagement, enjoyment, boredom, and frustration. The module electronically recorded the rating in two ways: (1) the observer continuously rating affect and difficulty level during assignments, and (2) the observer providing an overall rating as a summary at the end of each assignment.

A total of 10 teenagers with ASD, with ages from 13 to 17 years, were involved in the experiment. We recruited teenagers with ASD through an existing university clinical research registry. The participants had a clinical diagnosis of ASD with scores at or above clinical cutoff on the Autism Diagnostic Observation Schedule [38]. Their cognitive functioning was measured using either the Differential Ability Scales [39] or the Wechsler Intelligence Scale for Children [40].

Each participant completed six visits on different days. The duration of each visit was approximately one hour including device setup, baseline measurement, driving practice, and the main task completion. As part of each visit, three researchers organized the sensors and carried out eye tracker calibration. After a three-minute period used for recording baseline physiological and EEG data, participants practiced driving for three minutes in a free-form practice mode. Finally, participants completed three driving assignments, which were unique except for the first and the last visit.

2.2 Feature extraction

Eye gaze features.

Eye gaze data was tracked by the eye tracker with a frequency of 120 Hz. The eye tracker had an average accuracy of 1cm for gaze position tracking when the participants sat approximately 70 cm away from the monitor. In addition to gaze position, the eye tracker also measured the pupil diameter and blink.

The eye gaze data was preprocessed by reducing the noise with the median value method [41]. The blink rate and pupil diameter were calculated from the preprocessed eye tracker data. For the blink rate, the closure duration used a range from 75 to 400 milliseconds [42]. The eye gaze features included mean and standard deviation of blink rate, pupil diameter, and fixation duration.

Physiological features.

The physiological signals were recorded with a 1000 Hz sample rate. The physiological features were preprocessed as shown in **Fig. 4**. First, we removed the outliers of physiological signals. Then, we removed signal noise with different high/low pass filters and notch filters[35, 36].

Fig. 4. Physiological signal analysis process

Sixty physiological features were calculated including sympathetic power, parasympathetic power, very low-frequency power and ratio of powers of ECG, Mean Interbeat Interval of ECG, mean and standard deviation of the amplitude and peak values of PPG. The details of the physiological features can be found in [37].

EEG features.

The Emotiv EEG headset recorded signals from 14 channels from positions AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4, defined by the 10-20 system of electrode placement [43]. There were two additional reference electrodes at locations P3 and P4. The bandwidth of the EEG headset was from 0.2 Hz to 45 Hz and the recorded sampling rate was 128 Hz.

After removing outliers, EEG signals were first filtered between 0.2 Hz and 45 Hz. We then removed eye blink, eye movement, and muscle movement artifacts by applying EOG-EMG artifact correction algorithm provided by EEGLab [44]. After this preprocessing, spectral features - averaged power of each channel on alpha (8-13Hz), beta (13-30Hz), and gamma (30-45Hz) bands-were then extracted from the clean signals [20]. A total of forty-two EEG features were extracted.

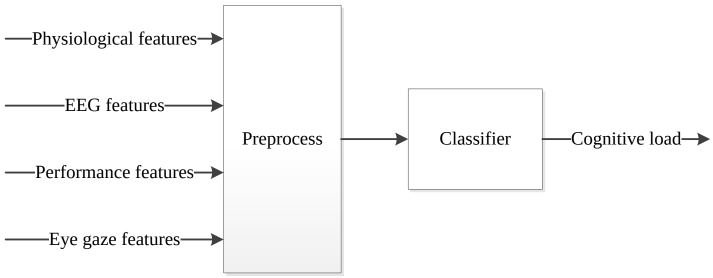
Performance features.

Performance features were extracted from the driving behavior data and task performance data. Performance features included the number of failure during one assignment, the score achieved during one assignment, the levels of accelerating acceleration and braking, and the average speed.

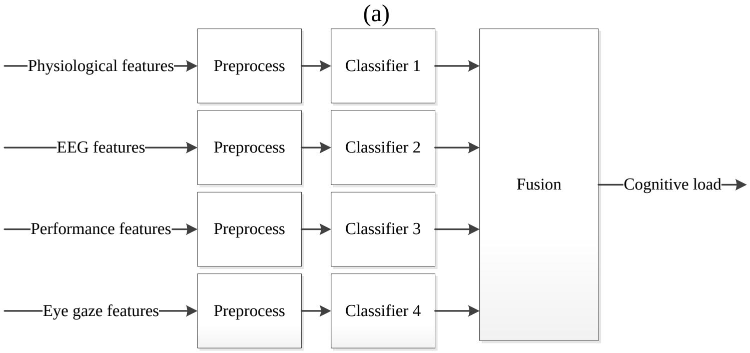
2.3 Data fusion methods

In order to evaluate cognitive load, features from different modalities were input into classifiers The classifiers in Matlab (http://www.mathworks.com/) and Machine Learning Toolbox (MLT) (http://mirlab.org/jang/matlab/toolbox/machineLearning/) were used, including Support Vector Machine (SVM), Naïve Bayes (NB), Gaussian Mixture Models (GMM), K-Nearest Neighbors with (KNN), Quadratic Classifier (QCL), Decision Tree (DT), and Linear Classifier (LCL).

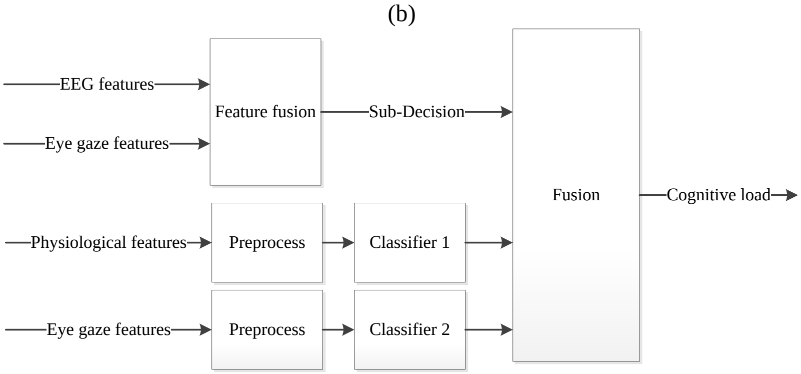
The therapist's overall rating of difficulty level was used as the ground truth for cognitive load classification methods. The 0-9 Likert scaled difficulty level rating was grouped and relabeled as low (difficulty level less than five) and high (difficulty level larger than five) to reflect a binary-level cognitive load. In brief, we hypothesized based on prior published research [12] that a participant in a high difficulty level task had high cognitive load; while a participant in a low difficulty level task had low cognitive load.



(a)



(b)



(c)

Fig. 5. (a) Feature fusion framework; (b) decision fusion framework; and (c) hybrid fusion framework

Three level fusion approaches were implemented to fuse multimodal information: feature fusion, decision fusion and hybrid fusion. **Fig. 5** (a) showed the feature level fusion. All features were input into the preprocess module, which normalized features and reduced their dimension with principal component analysis. The cognitive load was evaluated with the preprocessed features.

Fig. 5 (b) showed decision level fusion. We preprocessed the features from each modality separately and then input them into different classifiers. Each classifier output a cognitive load as a sub-decision. The fusion part summed all sub-decisions (D_1, D_2, D_3, D_4) with weights for the final cognitive load (D_{final}) as shown in equation (1).

$$D_{final} = w_1 D_1 + w_2 D_2 + w_3 D_3 + w_4 D_4 \quad (1)$$

Fig. 5 (c) gave one example of hybrid level fusion. Hybrid level fusion combined the feature level fusion and decision level fusion. Features from more than one modality (EEG and eye gaze) were preprocessed to make one sub-decision; while other modalities features (physiological and performance) were preprocessed separately to assess other sub-decisions. The final decision summed all sub-decisions with weights.

3 Results

Each assignment yielded one data sample. A total of 180 data samples were extracted from ten participants. However, thirty-nine data samples were unusable due to factors largely unrelated to the task, such as participants' eye gaze moving out of eye tracker detection range, some electrodes of the EEG sensor were displaced during their experiments, or one instance of the Biopac physiological sensors stopped working.

3.1 The feature level fusion results

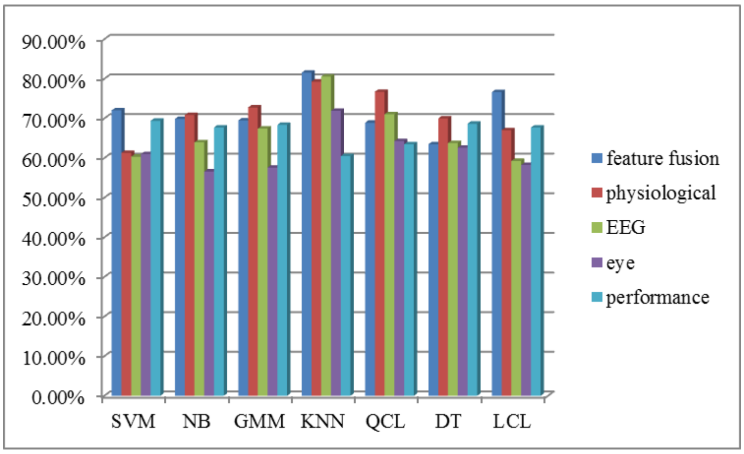


Fig. 6. The accuracies of different classifiers

The accuracies of different classifiers with features from each modality as well as all the modalities combined are shown in **Fig. 6**, with numerical values presented in

Table 1. The best results of three psycho-physiological modalities-- eye gaze, EEG and physiological features - were from the KNN method. For the performance, the best result was from the SVM method. KNN method also achieved the highest accuracy, 81.57%, for feature fusion. The feature fusion outperformed all individual modality classification.

Table 1. Accuracies of each modality and all modalities with different methods

	feature fusion	*physiological*	*EEG*	*eye*	*performance*
SVM	72.03%	61.32%	60.35%	60.99%	**69.41%**
NB	69.90%	70.86%	63.97%	56.62%	67.71%
GMM	69.51%	72.77%	67.44%	57.60%	68.38%
KNN	**81.57%**	**79.29%**	**80.58%**	**71.92%**	60.49%
QCL	68.92%	76.73%	71.07%	64.28%	63.48%
DT	63.50%	69.99%	63.79%	62.62%	68.67%
LCL	76.65%	67.03%	59.29%	58.24%	67.71%

3.2 The decision level fusion and hybrid level fusion result

For the decision level fusion, we tested all classifiers for every modality to get the sub-decision. We then tested various combinations of weights for every sub-decision. The best accuracy was achieved when using SVM for performance modality features and KNN for all three psycho-physiological modalities features. The weight for a sub-decision of one modality was proportional to the best accuracy of the modality. The results indicated that for one modality, the best method for decision fusion was consistent with the best method for its individual classification. The best decision fusion accuracy was 80.95%, which was similar to the best accuracy of the feature fusion.

Hybrid level fusion outperformed the feature level and decision level fusion with a best accuracy of 84.66%. The best accuracy was achieved when eye gaze and EEG features were combined for one sub-decision with KNN method and weight w_1, physiological features for one sub-decision with KNN method and weight w_2, and SVM method and weight w_3 for performance features ($0.5 > w_1 > w_2 > w_3$ and $w_1 + w_2 + w_3 = 1$).

4 Conclusions

This paper focused on multimodal fusion for cognitive load measurement during driving intervention for individuals with ASD. The signals for the cognitive load measurement were composed of physiological signals, EEG signal, eye gaze, and performance data.

Seven machine learning methods were explored to classify individual modality features and multimodal fusion. The KNN method yielded the best results for all the psycho-physiological related features, features from physiological signal, EEG data, and eye gaze. The SVM method yielded the highest accuracy for performance features.

This paper compared three levels multimodal information fusion approaches, feature level fusion, decision level fusion and hybrid level fusion, for cognitive load measurement. The multimodal fusion approaches outperformed individual modalities in cognitive load measurement. Hybrid fusion had the best result of 84.66% compared to other fusion methods.

The results will be used to choose an optimal game difficulty level for individuals with ASD to provide a more challenging yet fruitful skill development opportunity in the future.

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