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Eye Tracking Area of Interest in the Context of Working Memory Capacity Tasks

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***Abstract*—Adults diagnosed with Attention-Deficit / Hyperactivity Disorder (ADHD) have reduced working memory capacity, indicating attention control deficits. Such deficits affect the characteristic movements of human gaze, thus making it a potential avenue to investigate attention disorders. This paper presents a converging operations approach toward the objective detection of neurocognitive indices of ADHD symptomatology that is grounded in the cognitive neuroscience literature of ADHD. The development of these objective measures of ADHD will facilitate its diagnosis. We hypothesize that the characteristic movements of human gaze within specific areas of interests (AOIs) may be used to estimate psychometric measures and that distinct eye movement scan patterns can be used to better understand ADHD. The results of this feasibility study confirm the utility of a combination of fixation and saccade feature set captured within specific AOIs indexing Working Memory Capacity (WMC) as a predictor of a diagnosis of ADHD in adults. Tree-based classifiers performed best in-terms of predicting ADHD with 86% percent accuracy using physiological measures of sustained visual attention during a WMC task.**

***Keywords-component;* working memory capacity, eye movements, ADHD**

I. Introduction

With the release of the Diagnostic and Statistical Manual of Mental Disorders 5th edition (DSM-V), researchers have increasingly recognized that ADHD persists through adulthood, with prevalence estimated to increase from 6.1% in 1997 to 10.2% in 2016 in the U.S. [1]. Adults with ADHD have difficulty attending to important details, planning task completion, modulating responses, and processing auditory information [2], [3]. We also know that adults with ADHD have reduced working memory when compared to their peers [4]. Differences in working memory capacity (WMC) predict performance during a range of cognitively demanding tasks, such as complex learning, dichotic listening, and processing speech in noise [5], presumably because of differences in attention control. Attention control is the psychological construct responsible for regulating and allocating attention according to task demands, especially in the presence of distracting stimuli [6], and serves as the underlying resource for executive functions [7], [8] accounting for approximately 60% of the variance seen across people in measures of WMC [9]. Despite the understanding that ADHD deficits are associated with serious long-term negative academic and occupational outcomes, there is a paucity of data investigating and understanding how factors, like WMC and eye gaze characteristics, relate to ADHD diagnostic criteria.

The primary goal of this paper is to understand the utility of area of interest (AOI) in order to capture eye gaze metrics and predict ADHD in the context of a WMC task using machine learning algorithms. In addition, we are interested in investigating the differences between ADHD and non-ADHD participants by analyzing two main sequence relationships of saccade amplitude towards saccade duration and peak velocity.

II. Background

Eye movement behavior is a result of complex cognitive processes; therefore, eye gaze metrics can reveal objective and quantifiable information about the quality, predictability, and consistency of these covert processes [10]. Saccade is a rapid eye movement from one fixation point to another. Fixations require preceding saccades to help place the gaze on target stimuli to gather salient and relevant information.

At present, machine learning is being used for diagnostic prediction based on data extracted from wearable devices. Classification algorithms build a mathematical model by discovering the data patterns in the training dataset in order to classify the class accurately. The first study to use machine learning for ADHD classification is [11] and they have used support vector machine (SVM) algorithm with event related potential (ERP) dataset. In [12], authors have used SVM with EEG training dataset to predict ADHD. They has achieved an accuracy of 97% . In [13], authors have used extreme learning machine (ELM) algorithm to predict ADHD using structural MRI data and has achieved 90.18% accuracy.

In [14], authors have developed an ensemble classifiers for ADHD, Non-ADHD classification for both adult and children using MRI training dataset with accuracies 66% for adults and 67% for children.

The study [15] have used data from 5 channels of EEG during an attention network task as the training dataset for a Gaussian mixture model to classify ADHD and Non-ADHD. They have achieved an average of 92% accuracy classification of ADHD and Non-ADHD. Authors concluded that performance of ADHD detection depends on the type of task employed in the experiment.

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In [16], authors have used fMRI data to propose a bi-objective ADHD classification scheme based on SVM which facilitates to choose an efficient classifier to predict the diagnosis of ADHD. Similarly [17] have used a fMRI training dataset to figure out the features which discriminate ADHD and Non-ADHD the best. Using the discriminating features for ADHD as the training data, the authors have used a SVM classifier to classify ADHD subjects. They have achieved a highest accuracy of 86.7%.

From the literature, it is evident that machine learning algorithms could accurately predict ADHD with the use of various types of datasets. Though there are studies which uses machine learning approaches to predict ADHD, [18] is the only study to investigate the eye gaze metrics indexing working memory capacity as a feature set to predict a diagnosis of ADHD using six classifiers. The results of [18] indicated a combination of fixation, and saccade feature set could achieve a higher percentage of accuracy around with 91% with multiple classical classifier.

The studies [19] and [20] have considered AOIs of stimuli for statistical analysis of the eye tracking. The study [21] compared borderline personality disorder (BPD) patients to Cluster-C personality disorder (CC) patients and non-patients (NP) regarding emotion recognition in ambiguous faces and their visual attention allocation to the eyes which is the AOI. The authors have found BPD have a biased visual attention towards the eyes. In [22], authors have investigated the immediate effects of coloured overlays on reading performance of preschool children with ASD. The authors of the study have used eye tracking and concluded that coloured overlays may not be useful to improve reading and ocular performance in children with ASD in a single occasion.

According to the literature, AOIs have been used in multiple studies related to various attention tasks. Even though AOIs have been used, there is a paucity of using eye movement fixations and saccades occurred within the AOIs when completing a WMC measure for ADHD classification using machine learning approach.

In this paper, we look at the consistency and stability of eye movement fixations and saccades occurred within the AOIs of stimuli when completing a WMC measure [18]. This is an important line of inquiry because it investigates how relevance may be reflected in eye movements features for atypical and complex attentional systems, such as in the context of ADHD.

III. Methodology

A. Working Memory Capacity Task

WMC is measured using complex span tasks. Reading Span (RSPAN) is one of the complex span tasks which reflects the cognitive system's ability to maintain activated representations [9], [23]. During the RSPAN task, participants are asked to read 42 sentences which are presented in varying sets of 2-5 sentences with a letter printed at the end of the each sentence on a computer screen and remember the letter. In addition, participants are asked to judge sentence coherency by saying 'yes' or 'no' at the end of each sentence. After a 2-5 sentence set, participants need to recall all the letters they can remember from that set.

Based on the evidence that WMC is reduced in adults with ADHD [4], measurement of eye movements in the context of WMC will address the following research questions:

- Using only the eye movement feature values on all stimulus items during the RSPAN, are there significant differences in main sequence relationships for adults with and without ADHD?
- Do the eye movement feature values within AOIs based on scenes during the RSPAN predict classification of ADHD in adults?
- Do the eye movement feature values within AOIs based on sentences during the RSPAN predict classification of ADHD in adults?
- Using only the eye movement feature values within AOIs based on scenes during the RSPAN, are there significant differences in main sequence relationships for adults with and without ADHD?
- Using only the eye movement feature values within AOIs based on sentences during the RSPAN, are there significant differences in main sequence relationships for adults with and without ADHD?

B. Apparatus

We used Tobii Pro X2-60 computer screen-based eye tracker with Tobii Studio analysis software for recording and analyzing eye gaze metrics. Tobii I-VT fixation filter was used to pre-process eye gaze metrics within Tobii Studio analysis software. We used Tobii Studio analysis software's [24] Area of Interest tool to draw the boundaries around elements of the eye tracking stimulus. The three AOI groups include (see Fig. 1):

- AOI 1 - Stimulus (the whole sentence)
- AOI 2 - Critical word (critical word when determining the coherency of the sentence)
- AOI 3 - Determiner (the decision point with the letter to be remembered)

We then applied Tobii Studio analysis software to infer the eye gaze metrics within the boundary based on the classificaiton filter.

C. Participants

We recruited a total of 14 adult participants with and without a diagnosis of ADHD for this study. All of the participants fulfilled the following inclusion criteria:

- Between 18 and 65 years of age
- Spoke English as their first language
- Self-reported normal vision with or without corrective lenses
- No history of psychotic symptoms
- No comorbid cognitive impairments (e.g. documented learning disabilities, reading disabilities)

There were seven adults with a diagnosis of ADHD and seven adults without a diagnosis of ADHD as shown in the

Table I. The participants with a diagnosis of ADHD confirmed their diagnosis through verified documentation. In addition, each ADHD participant went through a verbal informational interview in order to confirm the diagnosis. We asked adult ADHD participants to avoid medication for 12 hours prior to our experiment. We informed them the risks of avoiding medication as well. Participants were allowed to take part in the study only upon providing their consent by signing forms approved by the University's Institutional Review Board (IRB) in accordance with the Helsinki Declaration. We gave a ten dollar Amazon or Chick-Fil-A gift card to the participants who completed the study.

D. Procedure

The entire experiment lasted approximately for 45 minutes. Before starting the experiment, participants were briefed regarding the purpose of the study. Participants were entered to the testing area only upon providing their consent.

A Dell Computer with a 21-inch monitor was used for the test. In order to maintain the viewing angle of the monitor as 45 degrees, the distance and position of each participant were modified. Before starting the experimental task, each participant's eye gaze was calibrated. Then, they were presented with a presentation with several tasks, including the RSPAN task. RSPAN task consisted of 42 sentences presented in 2-5 sentences sets. Before starting the RSPAN task, participants were given three practice sentences to familiarize with the testing environment.

E. Eye Movement Features

Fixations, saccades, smooth pursuits, optokinetic reflex, vestibule-ocular reflex, and vergence [25] are the six main eye movement types. Eye-trackers provide the X and Y coordinates of participant's eye position along with other gaze related parameters such as gaze event type (fixation or saccade), gaze event duration, timestamp etc. In addition to these basic features, we derived other gaze related parameters required to analyze participant's' attention patterns such as saccade peak velocity.

ADHD causes reduced working memory capacity, resulting in attention control deficits in adults [4]. Such deficits affect the characteristic movements of the human gaze because there is substantial overlap in brain systems that are involved in oculomotor control and cognitive dysfunction in ADHD. Eye gaze metrics measured during a cognitively demanding task, especially saccade features could reliably reveal important differences of underlying cognitive functionality between adults with and without ADHD.

F. Main-Sequence Relationship

We investigated the main sequence relationship [26] (the duration, peak velocity and amplitude of saccadic eye movements) for both ADHD and Non-ADHD groups. Feature sets for the main sequence relationships are based on the following qualifiers: saccade amplitude measured in degrees, saccade duration measured in milliseconds, and saccade peak velocity measured in degrees per second. Saccade amplitude is the size of a saccade. Saccade peak velocity is the highest velocity reached during a saccade. Saccade duration is the time taken to complete the saccade.

Saccade peak velocity is calculated by (1) in degrees/second [27],

$$\dot{\theta}_{peak\_velocity} = \dot{\theta}_{MAX} \times (1 - e^{-\theta_{amplitude}/C}). \qquad (1)$$

where $\dot{\theta}_{peak\_velocity}$ is the saccade peak velocity, $\dot{\theta}_{MAX}$ is the asymptotic peak velocity (500 degree/second), $\theta_{amplitude}$ is the saccade amplitude (degrees) and C is the constant (14 for normal humans). Fig. 3(c) shows the relationship between saccade amplitude and saccade peak velocity for normal humans.

Saccade duration in milliseconds is calculated by (2) [28]. Fig. 4(c) shows the relationship between saccade amplitude and saccade duration for normal humans.

$$t_{duration} = (2.2 \times \theta_{amplitude} + 21). \qquad (2)$$

G. Area of Interests

In addition, we employed a number of fixation and saccade based features captured within three AOI groups in sentences presented in RSPAN task. We utilized a standard RSPAN task where participants are instructed to read a sentence and a letter displayed on a computer screen, judge the sentence's coherency, and memorize the letter at the end. We extracted their eye movement features based on three stimuli: 1) area of the sentence, 2) area of the critical word that determines the coherency of the sentence, and 3) the decision area with the letter to be remembered. Fig. 1 shows the three AOIs drawn on a single sentence using Tobii Analysis software. Note that the boundaries of AOIs are drawn manually (static AOIs).

We derived two feature sets for the investigation of fixations and saccades within AOIs based on the following qualifiers: number of fixations in AOI 1, 2 and 3, fixation duration in AOI 1, 2 and 3, average fixation duration in AOI 2, fixation standard deviation in AOI 2, pupil diameter of both eyes in AOI 2 and 3, maximum and minimum saccade amplitude in AOI 1, 2 and 3, average saccade amplitude in AOI 1, 2 and 3, and standard deviation of saccade amplitude in AOI 1, 2 and 3, respectively.

- *Scene-based*: Feature set including the above qualifiers within the AOIs of sets of 2-5 sentences.
- *Sentence-based*: Feature set including the above qualifiers within the AOIs of all the sentences.

All fixation features and saccade features were calculated using Pandas [29], a Python data analysis library. Prior studies [30] suggested that diagnostic criteria for ADHD should be adjusted to gender differences. We find that including gender in the feature set slightly increases the performance across all our classifiers.

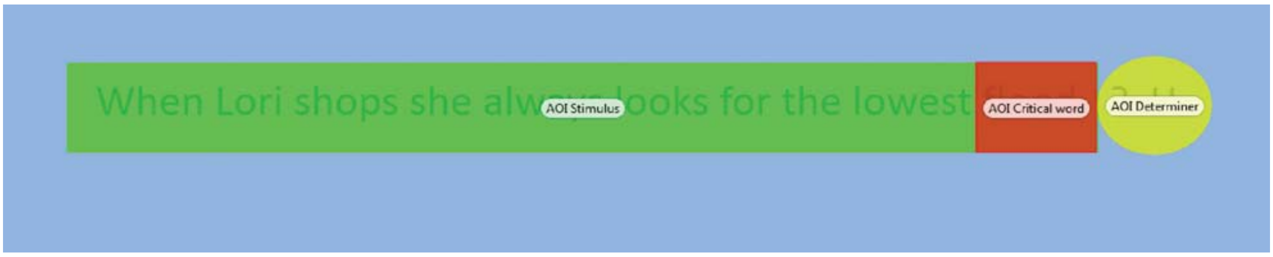


Figure 1. AOIs During WMC Task from a Sentence generated using Tobii Studio Analysis Software.

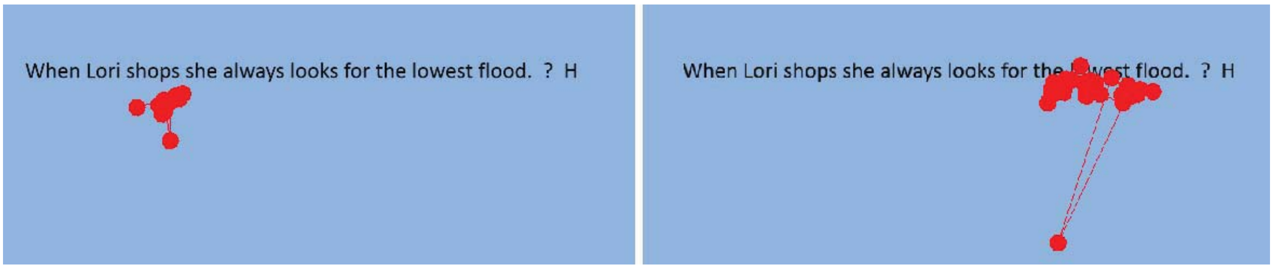
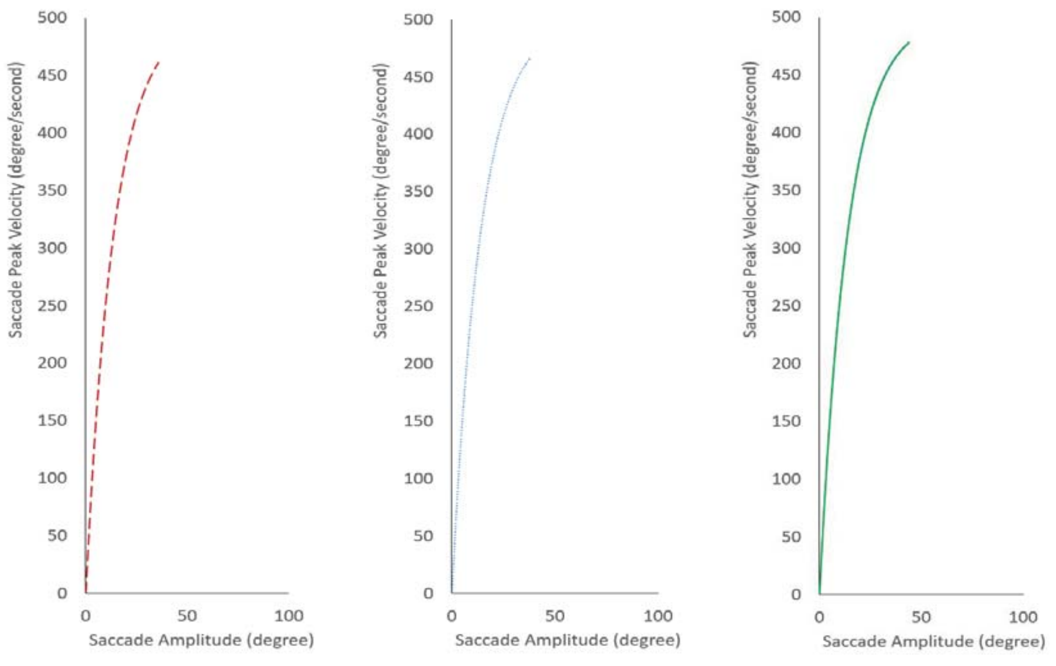


Figure 2. Comparison of Eye Fixations for ADHD (Left) and Non-ADHD (Right) Participant During WMC Task from a Temporal Point as Generated during the Replay Mode of the Tobii Studio Analysis Software.



(a) Amplitude vs. Peak Velocity of ADHD

(b) Amplitude vs. Peak Velocity of Non-ADHD

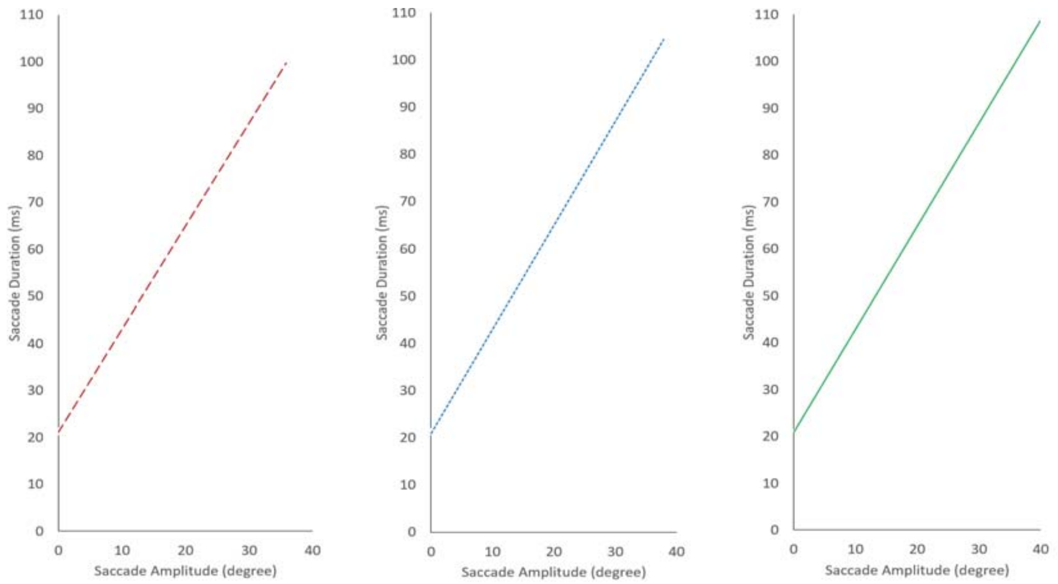
(c) Amplitude vs. Peak Velocity of Normal

Figure 3. Main Sequence Relationships (a) the relationship between saccade amplitude (degree) and saccade peak velocity (degrees/second) of ADHD subjects, (b) the relationship between saccade amplitude (degree) and saccade peak velocity (degrees/second) of Non-ADHD subjects, and (c) the relationship between saccade amplitude (degree) and saccade peak velocity (degrees/second) of Normal humans.

IV. RESULTS

A. Analysis of Main Sequence Relationships

In general, saccades are stereotyped: The relationships between saccade amplitude, saccade peak velocity, and saccade duration are relatively fixed for normal human beings, and are referred to as main sequence relationships. The two main sequence relationships are: 1) the relationship between saccade



(a) Amplitude vs. Duration of ADHD (b) Amplitude vs. Duration of non-ADHD (c) Amplitude vs. Duration of Normal

Figure 4. Main Sequence Relationships, (a) the relationship between saccade amplitude (degree) and duration (ms) of ADHD subjects, (b) the relationship between saccade amplitude (degree) and duration (ms) of Non-ADHD subjects, and (c) the relationship between saccade amplitude (degree) and duration (ms) of Normal humans.

amplitude (degree) and duration (ms), and 2) the relationship between saccade amplitude (degree) and saccade peak velocity (degree/second). We hypothesize that any differences encountered in main sequence relationships could lead to the conclusion that the saccade is not normal.

Fig. 3 presents the relationships between saccade amplitude and saccade peak velocity in representative ADHD and Non-ADHD adults during the entire session of WMC task. The data in Fig. 3(a) and Fig. 3(b) show a similar relationship between saccade amplitude and the saccade peak velocity with trend line as well for normal humans (see Fig. 3(c)). These results are consistent with the study [31] which describes the main sequence relationship indexing the test of variables of attention.

The data in Fig. 4 show a similar relationship between saccade amplitude and the saccade duration for ADHD and Non-ADHD adults during the entire WMC task. In addition, it shows similar trend line with normal humans as well (see Fig. 4(a), Fig. 4(b), and Fig. 4(c)).

B. Machine Learning on Feature Set

We chose standard information retrieval evaluation measures precision, recall, f1 and accuracy for the evaluation of our work. Precision measures the correctly predicted number of labels out of all predicted data instances. Recall measures the correctly predicted number of labels out of all labeled data instances for a specific a category label. F1 measures the balance between precision and recall. Accuracy indicates the percentage of correctly classified instances.

We obtained all performance metrics using WEKA [32] by executing the selected classifier with a 10-fold cross validation using the both feature sets we developed for the investigation of fixations and saccades within AOIs. The reason for using WEKA is that, it facilitates users to execute machine learning algorithms out-of-the-box and visualize how different algorithms perform for the same data set.

TABLE I
CLASSIFICATION OF THE PARTCIPANS.

Participant	Age	Gender	Classification
3	18	F	Non-ADHD
7	35	M	Non-ADHD
9	19	F	Non-ADHD
17	23	M	Non-ADHD
20	21	F	Non-ADHD
25	32	M	Non-ADHD
26	20	F	Non-ADHD
30	21	F	ADHD
34	19	M	ADHD
35	26	F	ADHD
36	29	F	ADHD
37	21	F	ADHD
38	21	F	ADHD
47	23	F	ADHD

Table I shows the classification of the participants in the current study. Fig. 2 presents images of eye gaze patterns from two adults participants, one with and one without ADHD. According to the Fig. 2, the adult with ADHD is fixating primarily below the AOIs of stimulus items in sentence including: the words, the decision point, and the item to be remembered (see Fig. 1). The adult without ADHD has a larger number of fixations which are in-line with AOIs.

In [18], authors showed that a combination of fixation, and saccade feature set could achieve a higher percentage of accuracy around with 91% when using the RandomForest classifier indicating that the combination of fixation and saccade feature set classifies a diagnosis of ADHD with greater than 90 percent accuracy. We selected the six top performing classifiers listed in [18] for our study. We utilize our feature sets which primarily consist of fixation and saccade features within AOIs to train the six classifiers.

Table II lists the classification results of the scene-based feature set. The RandomForest classifier yielded the highest percent accuracy of with 83.33% indicating that the scene-based feature set alone classifies a diagnosis of ADHD with greater than 80% accuracy. The Kstar classifier yielded the lowest percent accuracy at 63.04% for the scene-based feature set.

Table III lists the results of the sentence-based feature set. The RandomForest classifier yielded the highest percent accuracy of with 86.20% indicating that the sentence-based feature set classifies a diagnosis of ADHD with greater than 85% accuracy. For sentence-based feature set, K star classifier yielded the lowest percent accuracy at 71.83%.

Since any differences encountered in main sequence relationships could lead to the conclusion that the saccade is not normal, we plot Fig. 5 and Fig. 6 to analyze the main sequence relationships of the two feature sets we generated using AOIs. Fig. 5(c) presents the relationship between saccade amplitude and the saccade peak velocity in representative ADHD adults and 5(d) presents the relationship between saccade amplitude and the saccade peak velocity in representative Non-ADHD adults when using the scene-based feature set during the entire WMC task. The data in Fig. 5(c) and Fig. 5(d) show a similar relationship between saccade amplitude vs. the saccade peak velocity and similar saccade amplitude range for both ADHD and Non-ADHD subject groups. The data in Fig. 5(a) and Fig. 5(b) show a similar relationship between saccade amplitude and the saccade duration for ADHD and Non-ADHD adults when using the scene-based feature set during the entire WMC task. The results indicate when considering AOIs of scence-based sentences, ADHD and Non-ADHD adults display similarities in main sequence relationships which are similar to normal humans as well.

The data in Fig. 6(c) and Fig. 6(d) show a similar relationship between saccade amplitude vs. the saccade peak velocity for both ADHD and Non-ADHD subject groups when using the sentence-based feature set during the entire WMC task. The data in Fig. 6(a) and Fig. 6(b) also show a similar relationship between saccade amplitude and the saccade duration for ADHD and Non-ADHD adults. These relationships are similar to the relationships obtained from the scene-based feature set (see Fig. 5).

TABLE II
CLASSIFICATION OF EYE FIXATION AND SACCADE FEATURES WITHIN AOIS OF SCENCE-BASED DURING WMC

Classifier	Precision	Recall	F1	Accuracy
J48	0.75	0.75	0.75	75.36
LMT	0.79	0.79	0.79	**79.71**
RandomForest	0.83	0.83	0.83	**83.33**
REPTree	0.70	0.70	0.69	70.29
K*	0.63	0.63	0.63	63.04
Bagging	0.80	0.79	0.79	**79.71**

TABLE III
CLASSIFICATION OF EYE FIXATION AND SACCADE FEATURES WITHIN AOIS OF SENTENCE-BASED DURING WMC

Classifier	Precision	Recall	F1	Accuracy
J48	0.79	0.79	0.79	79.39
LMT	0.82	0.82	0.82	**82.61**
RandomForest	0.86	0.86	0.86	**86.20**
REPTree	0.82	0.82	0.82	82.04
K*	0.72	0.71	0.71	71.83
Bagging	0.84	0.83	0.83	**83.93**

V. DISCUSSION

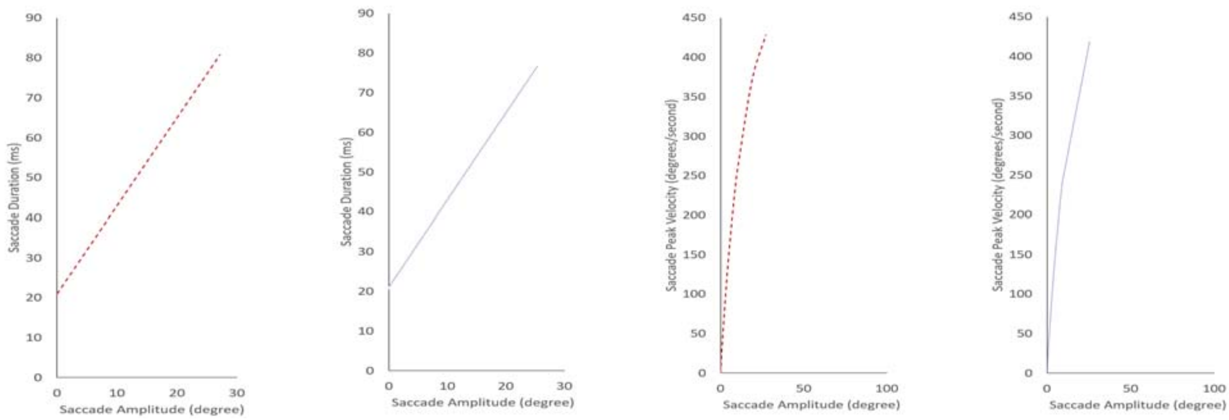
Since participants are presented with varying sets of 2-5 sentences, we developed one feature set considering the AOIs in the first sentence of all the sentence sets (scene-based feature set) and the other feature set considering the AOIs of all the 42 sentences in the RSPAN task (sentence-based feature set). We used common AOIs among all the participants, thus they are static shapes and would not change from one subject to another. In the case of static AOIs, the granularity of the sentence-based feature set is increased when compared to the granularity of the scene-based feature set. As a result, we observe better accuracy in each classifier(See Table III).

Consideration of fixation as well as saccade features set according to stimulus AOIs, lead us to classify a diagnosis of ADHD with greater than 80% accuracy. Our results confirm the utility of eye movement feature set generated according to stimulus AOIs indexing WMC as a predictor of a diagnosis of ADHD in adults. RandomForest classifiers performed best in-terms of predicting a classification of ADHD with 86.20% percent accuracy by using sentence-based feature set representing a physiological measure of visual attention during a WMC task.

Since we are utilizing the eye gaze metrics calculated by Tobii Studio analysis software within the manually marked static AOI boundaries for the development of our feature sets, there might be instances where we have less data points. The static AOIs may not be enough in terms of the area boundary to capture eye gaze metrics of some of the participants. We did not consider device error or human error when creating the AOI boundaries. In the future, we are interested in identifying AOIs dynamically for each participant in each sentence.

VI. CONCLUSION

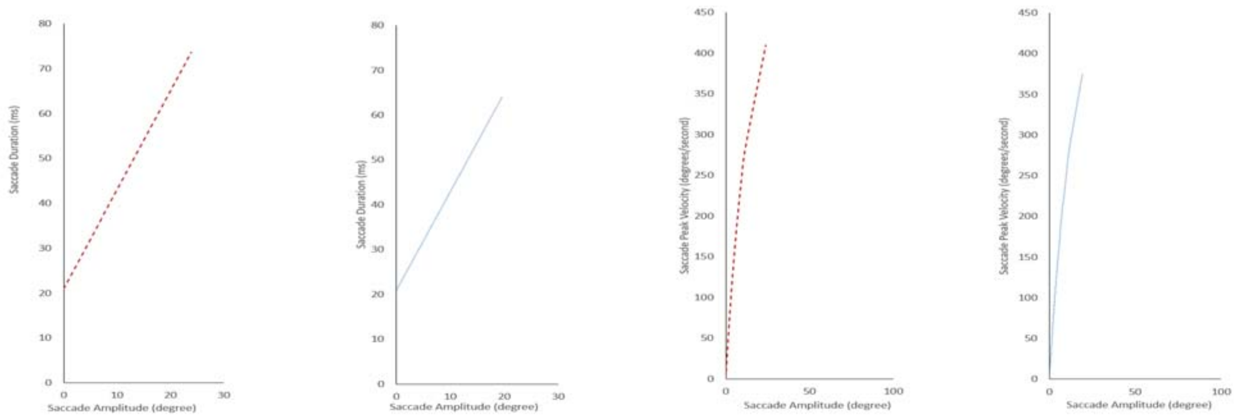
A WMC measure, like the RSPAN task, is a validated and reliable reflection of a person's ability to maintain attention on a target task while ignoring irrelevant information, making it an interesting measure for ADHD because disinhibition has been suggested to be a distinguishing diagnostic criterion. This



(a) ADHD (b) Non-ADHD (c) ADHD (d) Non-ADHD

Amplitude vs. Duration Amplitude vs. Peak Velocity

Figure 5. Main Sequence relationships obtained from the Scene-based Feature set including eye gaze metrics within the AOIs; (a) Saccade Amplitude vs. Saccade Duration relationship of ADHD participants, (b) Saccade Amplitude vs. Saccade Duration relationship of Non-ADHD participants, (c) Saccade Amplitude vs. Saccade Peak Velocity relationship of ADHD participants, and (d) Saccade Amplitude vs. Saccade Peak Velocity relationship of Non-ADHD participants



(a) ADHD (b) Non-ADHD (c) ADHD (d) Non-ADHD

Amplitude vs. Duration Amplitude vs. Peak Velocity

Figure 6. Main Sequence relationships obtained from the Sentence-based Feature set including eye gaze metrics within the AOIs ; (a) Saccade Amplitude vs. Saccade Duration relationship of ADHD participants, (b) Saccade Amplitude vs. Saccade Duration relationship of Non-ADHD participants, (c) Saccade Amplitude vs. Saccade Peak Velocity relationship of ADHD participants, and (d) Saccade Amplitude vs. Saccade Peak Velocity relationship of Non-ADHD participants

feasibility study generates a better understanding of the physiological underpinnings of an important cognitive construct which can inform the ”how” of the working memory system and has potential as a predictor of a diagnosis of ADHD. The results of this feasibility study confirmed the utility of a combination of fixation, and saccade feature set generated within AOIs while completing RSPAN tasks as a predictor of a diagnosis of ADHD in adults. Tree-based classifiers performed best in-terms of predicting a classification of ADHD with 86% percent accuracy using physiological measures of sustained visual attention within AOIs during a WMC task. This project is a necessary first step in delineating a feature set of eye gaze metrics captured within AOIs which represent physiological diagnostic criteria, including executive attention in adult ADHD.

In the future, we will expand the experimental studies to further analyze eye gaze metrics according to dynamically changing stimulus AOIs with respect to the participants using a larger sample size. Specifically, creating a boundary for the AOIs; the sentence, the word which determine sentence accuracy, the visual point of decision, and the item to be remembered. Identifying these AOIs dynamically for each participant will enable us to generate a detailed feature set which could be utilized to classify a diagnosis of ADHD with a greater percentage of accuracy than of this study.

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