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Automated Classification of Complex Oculomotor Behavior

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Abstract

Complex oculomotor behavior in response to a simple step stimulus can include a variety of different types of saccadic patterns including combinations of normal saccades, simple/corrected/multi-corrected overshoots/undershoots, express, dynamic overshoots, and compound saccades depending on the state of the oculomotor plant and the neuronal control signal supplied by the brain. This paper presents an algorithmic framework that allows automated classification of such behavior. Automated classification results were compared to manually classified data used as a reference baseline. In addition, this work investigates the impact of various filtering methods and basic eye movement classification algorithms on the accuracy of classification of complex oculomotor behavior. The proposed framework can be used in clinical examination of normal and abnormal visual systems.

Keywords: classification, algorithm, saccade, oculomotor behavior

INTRODUCTION

The assessment of oculomotor behavior is fundamental to clinical examination and research of the visual system (R. J. Leigh & Kennard, 2004). Two primary eye movements, fixations and saccades, have proven valuable in characterizing normal eye function along with impaired function related to several psychological, degenerative and neurological disorders (Hernandez, Levitan, Banks, & Schor, 2008). By definition, a state of fixation involves maintenance of a visual target on the fovea while a ballistic reset of the eye to change focus to a new target of interest is called a saccade. For instance, normal saccadic eye behavior is commonly used to reset the eyes to accurately view new targets of interest or focus during every day activity i.e. reading signs while driving or watching a tennis match. The visual system typically responds to a changed target position with a delay of 200ms with great accuracy (only 0.5% error). However, saccadic behavior can be impaired in patients diagnosed with Alzheimer's disease (Bylsma et al., 1995), schizophrenia (Karoumi, Ventre-Dominey, Vighetto, Dalery, & d'Amato, 1998), macular degeneration (McMahon, Hansen, & Viana, 1991; Radvay, Duhoux, Koenig-Supiot, & Vital-Durand, 2007), attention deficit disorders (Armstrong & Munoz, 2003), or persons suffering from vestibular-related pathologies such as Meniere's Disease (Isotalo, Heikki, & Ilmari, 2009). Atypical eye behavior can interfere with postural control and balance (Monzani et al., 2005). Tracking changes in eye movement control can provide information about patient responses to medical treatment or improvements in functional tasks during activities of daily living such as balance during gait or reading (Radvay et al., 2007).

Frequently, manual classification of eye behavior has been typically used to separate fixations and saccades within the raw eye movement trace (Mosimann et al., 2005). However, during recent years, automated classification algorithms have been increasingly used in the study of oculomotor behavior to our understanding of normal eye function control in response to external stimuli or due to pathology or aging (Di Fabio, Zampieri, & Greany, 2003; Munoz, Armstrong, Hampton, & Moore, 2003; Van Beuzekom & Van Gisbergen, 2002).

There are existing eye movement classification algorithms available to detect *basic oculomotor behavior* (BOB) defined as individual fixations and saccades including properties such as onset, offset, duration and amplitude (O. V. Komogortsev, Gobert, Jayarathna, Koh, & Gowda, 2010; Salvucci & Goldberg, 2000). Even detection of BOB is a challenging task by researchers reporting a substantial amount of variability among the algorithms and thresholds (Blignaut, 2009; O. V. Komogortsev et al., 2010; Nystrom & Holmqvist, 2010; Shic, Chawarska, & Scassellati, 2008). However, there are no algorithms, to the best of our knowledge, that are able to reliably detect various *complex oculomotor behavior* (COB) which may include different combinations of simple/corrected/multi-corrected overshoots/undershoots, dynamic overshoots, express and compound saccades. For example, recent studies indicate that normal eye function for children may include such atypical patterns up to ages 10 – 12 years when they finally develop adult-like function (Yang, Bucci, & Kapoula, 2002). In addition, training of the saccadic system to decrease response delay has been associated with an increase in express saccades from 7% to 14% (Bibi & Edelman, 2009). The ability to perform COB classifications would potentially aid in testing normal and abnormal eye function. Especially in persons with neurological deficits due to central lesions of cerebellar fastigial nucleus, cerebellar dorsal vermis, collicular function and various visual system pathologies (R. John Leigh & Zee, 2006).

The goal of the proposed framework is to detect COB in cases when a step stimulus is presented. To establish a very thorough performance baseline the framework's performance was evaluated using a step stimulus of fixed magnitude. This chosen fixed condition was imperative to set standardized assumptions and decrease performance variability. The performance baseline was established for the recording equipment with various characteristics such as accuracy and sampling rate. The impact of the 1) eye position signal filtering and 2) BOB classification methods on the resulting COB classification accuracy is established to provide additional reference points for the future investigation of automated COB classification.

COMPLEX OCULOMOTOR BEHAVIOR DURING SACCADES

Figure 1 illustrates several examples of COB events or saccadic eye behavior in response to a simple step stimulus (e.g., jumping dot of light) with formal classification definitions provided below. The definitions assume that there is no calibration error present in the eye tracking equipment.

Normal: the offset position of the stimulus-induced saccade falls within a certain distance threshold (<0.5°, this and subsequent numbers in brackets represent empirically selected thresholds employed in this work) from the target. Moreover, there are no additional saccades (excluding micro-saccades) present prior to the next target's jump.

Simple undershoot/overshoot: the offset position of the stimulus-induced saccade below/above a certain threshold (>0.5°) from the target's position. Moreover, there are no additional or corrective saccades present until the next target's jump (R. John Leigh & Zee, 2006).

Corrected undershoot/overshoot: the offset position of the initial stimulus-induced saccade falls below/above a certain threshold from the target's position. This initial position is followed by a corrective saccade resulting in a new fixation, which is closer to the target's location. Subsequently, there are no saccadic events prior to the next target's jump (R. John Leigh & Zee, 2006).

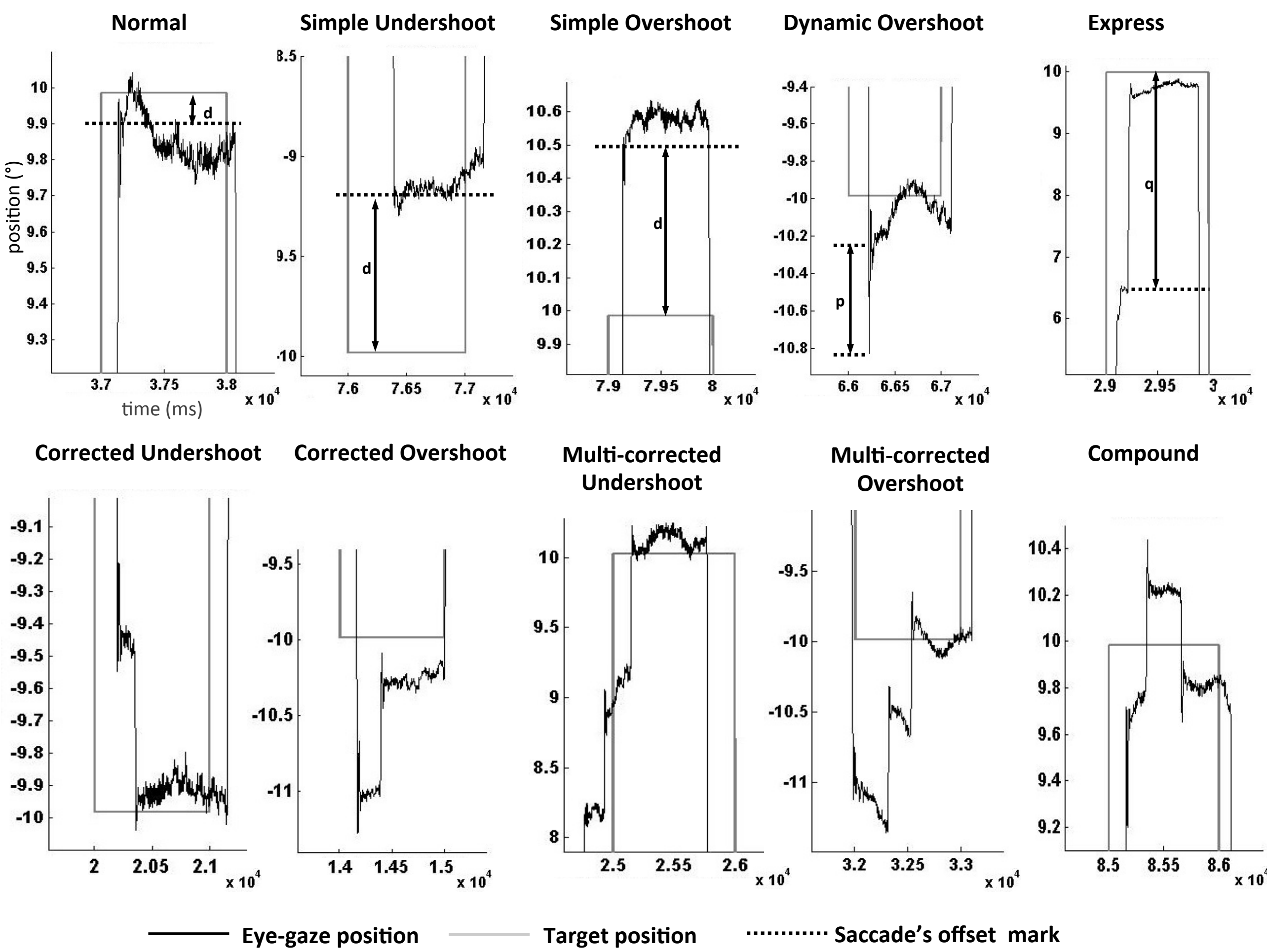

Figure 1. COB events. x-axis represents the time measured in milliseconds, y-axis represents the position of the target and the recorded eye movement signal expressed in degrees of the visual angle. Variable *d* represents the distance employed to perform a check to define each basic saccade as normal/undershoot/overshoot. Variables *p* and *q* represent the thresholds that are checked during dynamic overshoot and express saccade classification.

Multi-corrected undershoot/overshoot: is similar in definition to the corrected undershoot/overshoot saccade however there are additional series of corrective saccades that bring the resulting fixation position closer to the target.

Dynamic overshoot: is the oppositely directed post-saccadic eye movement in the form of backward jerk at the offset of a saccade. The amplitude of such movement usually appears in the range of 0.25-0.5°(R. John Leigh & Zee, 2006).

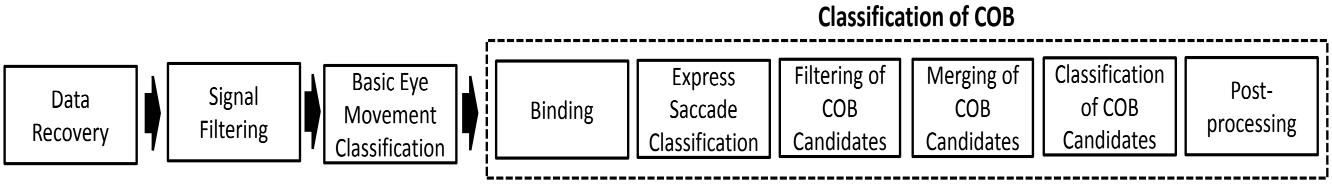

Figure 2. Framework for the automated classification of the COB.

Compound: is a saccade that is followed by two or more oppositely directed saccades of small amplitude that move the eye-gaze back and forth from the target position.

Express: is a sequence of saccades directed toward the target where the offset distance of the initial saccade is located greater than a threshold (2°) from the target. The subsequent saccade leading to the final fixation position has an extremely short latency of less than a threshold (<60ms) (R. John Leigh & Zee, 2006).

Invalid: represents an event case when classification of a COB for a given target's jump is not possible.

AUTOMATED CLASSIFICATION OF COB EVENTS

Definitions provided in the previous section above seem to be theoretically simple and straightforward behaviors to classify. However, practical challenges include substantial between-person variability, noise in the recorded signal, data loss, and imperfect positional accuracy.

The proposed framework addresses these challenges by employing a series of logical modules to ensure reliable classification of the COB events. This framework detects a sequence of COB events, which are exhibited in response to the target's positional change. The frequency of occurrence of various COB events, given the number of target's jumps defines a set of quantitative metrics that can be employed for the assessment of subject's performance.

Figure 2 presents the diagram. The detailed description of each module is provided next.

Data Recovery

The first module is responsible to ensure preliminary eye trajectory signal recovery despite circumstances when the eye position signal is lost due to equipment failures, or eye related issues such as blinks, increased moisture, and squinting. Though solutions to these problems can be potentially found in the replacement of the corrupted signal in one eye by the signal from the other eye, linear interpolation, or substitution by a simulated signal from a mathematical model of the eye (more details can be found in (O. Komogortsev, V. & Khan, 2008)), the actual data recovery is beyond the scope of this work. The proposed framework is designed to provide the COB classification even when the “Data Recovery” module is inactive.

Signal Filtering

Signal filtering is extremely important to the eye movement classification process because it can make certain signal features more pronounced or/and can reduce the amount of noise in the signal potentially leading to a more accurate classification of the COB.

Two signal filtering algorithms were investigated in our work – a two state *Kalman filter* (KF) (O. V. Komogortsev & Khan, 2007) and the local regression algorithm using a weighted linear least squares with a second-degree polynomial model (LOESS) (Cleveland & Devlin, 1988). Both the KF and LOESS provide noise reduction and signal smoothing capabilities. The KF is capable of accepting the estimate of the measurement and system (eye globe) noises to provide a more accurate estimate of the actual signal. The LOESS assumes that the signal can be approximated as a second degree polynomial on a relatively small time interval, therefore reducing the effect of outliers produced by noise.

Classification of Basic Oculomotor Behavior (BOB)

The BOB classification module extracts a sequence of basic eye fixations and saccades together with their properties such as onset, offset coordinates, duration and amplitude from the recorded eye position trace.

To investigate the impact of the BOB classification module on the performance of the COB classification, four algorithms were considered: Velocity Threshold Identification (I-VT), Hidden Markov Model Identification (I-HMM), Dispersion Threshold Identification (I-DT), and Kalman Filter Identification (I-KF). The details of each method including possible classification thresholds for each method are described elsewhere (O. V. Komogortsev et al., 2010).

Classification of COB

Classification of COB is presented by six modules wrapped by a dashed line of Figure 2. As it is possible to see from Figure 1, COB events consist of a sequence of saccades/fixations and are defined by their spatial and temporal characteristics. The goal of these six modules is to group appropriate saccades that have the potential to create COB events, disregard cases when the automated classification is impossible, and finally, map sequences of saccades into COB events.

For the simplicity of presentation we define the notion of the *stimulus-saccade* which represents the instantaneous target's jump from one location to the next. The amplitude of the stimulus-saccade marked as A_T is measured as the Euclidian distance between the initial and subsequent target's location (Figure 4). Also, *stimulus-fixation* is defined by the coordinates and the duration (D_F) of the target stimulus (Figure 4).

The outcome of the automated classification is represented by the stimulus-saccade and the associated COB event/s that is/are triggered by it. Such data structure allows easier collection of statistics about behavior in response to a step stimulus.

If in case it is impossible to classify a COB event resulting from a given stimulus-saccade, it is marked as “invalid”.

Detailed description of each module in the presented framework is provided in the following subsections.

Binding.

For the purpose of the automated classification, each stimulus-saccade is associated with a single COB event. Exceptions to this rule are dynamic and express saccades that can co-exist with other COB events.

Each exhibited saccade must be bound to the corresponding stimulus-saccade (target’s positional signal change) to allow subsequent classification of the COB events. The binding must occur in a meaningful temporal window (Figure 4) around each stimulus-saccade to be able to include all eye behavior associated with the target’s position change. The lower and upper boundaries of this temporal window are searched between the half of the stimulus-fixation duration prior to the stimulus-saccade (to include possible anticipatory saccades) and the offset of the stimulus-fixation following the stimulus-saccade (to consider all possible saccades that might occur during the stimulus-fixation).

The *lower boundary* of the temporal window is represented by the first saccade that satisfies the following two conditions that select the occurrence of a meaningful saccade (appearing in response to the target’s jump) as the lower boundary for the temporal window: 1) its direction coincides with the stimulus-saccade 2) its amplitude is greater than a threshold

($A_T/6$). The choice of the threshold value that is proportional to the amplitude of the stimulus-saccade allows the framework to work with step-stimulus that contains target jumps of various amplitudes and effectively filters out various COB events that are exhibited in response to the previous stimulus-saccade and not related to the current stimulus-saccade.

The *upper boundary* is selected as a result of the following two conditions: 1) its direction is opposite to the stimulus-saccade 2) same as for the lower boundary or the distance between the target's position and the position of saccade's onset coordinate is greater than a threshold. The second part of the condition (2) allows correct processing of the cases where the initial part of the saccade is absent due to the missing signal.

All saccades that occur within the boundaries of the temporal window are bound to the corresponding stimulus-saccade for subsequent COB classification.

Express saccade classification.

Express saccades occur prior to any other COB event, therefore providing an opportunity for their separate classification. The module detects express saccades and marks the corresponding stimulus-saccade as having "express" property.

The first step of the express saccade classification is to process each stimulus-saccade with a corresponding group of detected saccades supplied by the previous module and look for the candidates to create a valid express saccade pattern according to the detected number of saccades.

<u>Single saccade present:</u> If the distance between the initial saccade's offset and the target's position is greater than a threshold ($0.4A_T$) the corresponding saccade is marked as a candidate to be an express saccade. This condition allows for the correct classification of the express saccades

even in cases when saccades following an express saccade are lost due to equipment noise or blinks.

Multiple saccades present: If among saccades there is a one, whose offset does not reach the target's position by more than a threshold (2º) with subsequent saccades progressing toward the target, then all saccades prior to this are marked as express saccade candidates. This condition allows effective separation of express saccades from the other COB events.

No saccades present: This condition results in no express saccades detected for the corresponding stimulus-saccade.

Saccades that pass the above-mentioned conditions are inserted in the *express candidate list*. Remaining saccades are inserted in the *COB candidate list*, which is subsequently employed in the classification of the remaining COB events.

The second step of the express saccade classification is an additional validation procedure with a purpose of removing the saccades whose corrupted signal prevents reliable classification. Specifically, three trajectory corruption checks are administered for each saccade in the express candidate list:

Initial: If the initial part of the first candidate's trajectory is missing and the length of the missing part exceeds a threshold ($A_T/6$), all saccades are removed from the express candidate list. This condition represents a case where there is an insufficient amount of information to determine if the express saccade exists for this stimulus-saccade or not.

Intermediate: If the sequence of the express saccade candidates contains intermediate saccades in which part of the trajectory is corrupted by noise/blinks, it would represent a probable case where a very short fixation between subsequent saccades is missing. Such situation makes it impossible to determine if the express saccade exists for this stimulus-saccade or not.

Final: If the ending part of the last saccade's trajectory in the express candidate list is missing, the COB type of the corresponding stimulus-saccade remains unknown indicating that the express saccade candidates will be revisited after the remaining COB events are classified. This condition allows correctly processing cases where the missing part of the trajectory does not allow making an immediate detection of an express saccade if it is followed by a corrected or multi-corrected undershoot. Therefore, if corrected or multi-corrected undershoot is effectively detected, by a Deterministic Finite Automata mechanism described below, saccades preceding the classified COB would go through an additional check that would allow to identify the express saccades.

The saccades on the express saccade candidate list go through a final check where the duration of a fixation following a saccade is checked against a threshold (value of 60ms is used in our work as suggested by Leigh & Zee (2006)). For cases where such fixation duration is below the threshold, an express saccade is detected and the COB type corresponding with the stimulus-saccade is marked as "express".

Filtering of COB candidates.

The COB candidates that prevent reliable classification of the COB events due to missing signal data are removed at this stage. The removal occurs based on the number of saccades in the COB candidate list and the properties of the missing signal.

Single saccade present: If at least 10ms of the eye movement signal is missing after the offset of the initial saccade, the corresponding stimulus-saccade condition is marked as invalid, simplifying the detection heuristic. The condition tracks the case where the presence of dynamic overshoot is possible, but the missing data does not allow performing its classification.

Multiple saccades present: If the distance between the initial saccade and the following saccade exceeds a threshold (0.5º) and a time interval exists between these two saccades where the positional signal is missing for longer than a temporal threshold (≥30ms) then an *invalid* COB event is detected. This condition represents the case where it is not possible to determine such COB events as multi-corrected overshoot/undershoot or compound saccade due to the missing signal.

Merging of COB candidates.

Dynamic overshoots.

Two possible scenarios exist for the dynamic overshoot classification. In the first scenario, the initial saccade to the target and the oppositely directed saccade are detected as a part of a single saccade. The classification occurs via detection of the movement direction change in the saccade's trajectory. The second scenario presents a case where a dynamic overshoot is represented by two temporally close, oppositely directed saccades. The temporal proximity threshold was empirically selected to be 60ms, allowing the threshold to be substantially less than 100ms at which oppositely directed saccades would represent a corrected overshoot. Both saccades creating a logical dynamic overshoot are merged together into a single saccade to allow further detection of the COB candidates. Dynamic overshoots classified as a result of the both scenarios undergo a spatial check in which the amplitude of the dynamic overshoot exceeds a threshold (value of 1.25° is employed to detect exaggerated dynamic overshoots), the corresponding stimulus-saccade is marked as having dynamic overshoot property.

Corrective saccades.

Corrective saccadic movements that are parts of the corrected and multi-corrected overshoot/undershoots might occur as a series of micro saccades that are temporally close to each other. To simplify the task of classifying the COB events, these small corrective saccades are merged together if they are not more than 80ms apart from each other.

Pre-classification of COB candidates.

Each saccade on the COB candidate list is pre-classified as normal, undershoot, or overshoot to allow subsequent classification of the COB events. The classification occurs based on the spatial criteria, where the offset of the saccade is checked against intended target's location. In case the absolute difference does not exceed a specified threshold (<0.5°), the saccade is marked as normal (saccade.normal=true). If the difference above the threshold with saccade's offset does not reach the target's position, the corresponding saccade is marked as undershoot (saccade.undershoot=true) and otherwise it is marked as overshoot (saccade.overshoot=true).

Classification of COB candidates.

The COB candidate list with pre-classified saccades serves as input to this module. The output from the module presents the results of the final COB classification where each stimulus-saccade is associated with identified COB events.

Sequence of pre-processed saccades and their temporal and spatial characteristics provide an opportunity to utilize the concept of Deterministic Finite Automata (DFA) (Ric, 2008; Sipser,

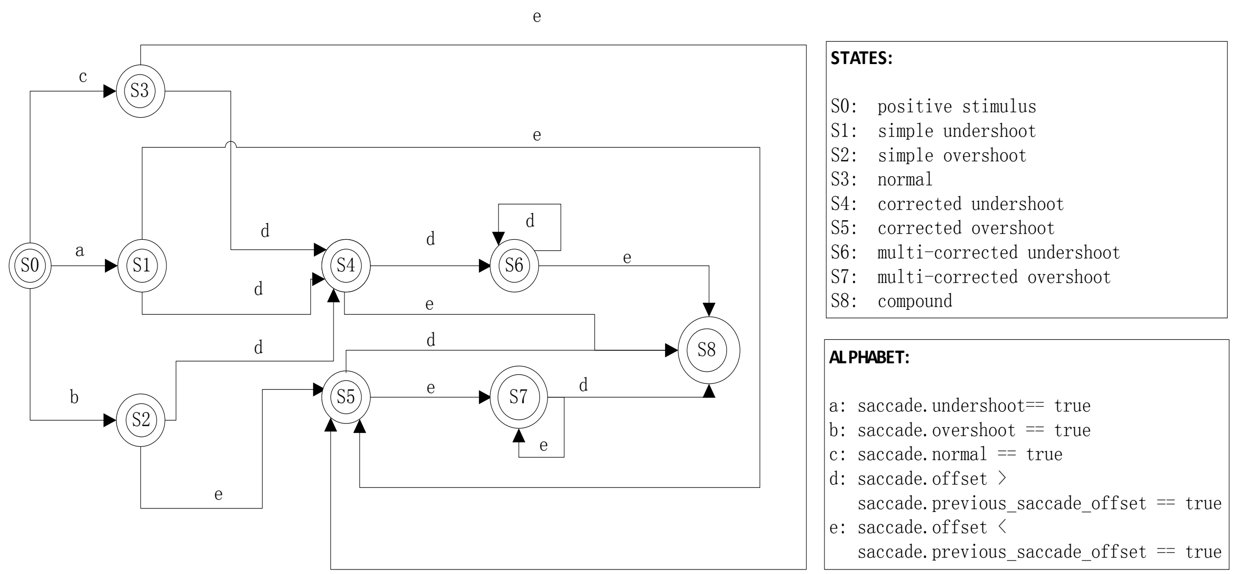

Figure 3. Deterministic finite automata for COB classification.

1997) which allows mapping of a string of symbols (events with certain properties) to a finite state of states that represent actual meaning behind the input string.

The proposed DFA is illustrated by Figure 3 and defined as $M = (K, \Sigma, \delta, q_0, A)$, where: K is a set of states (COB events), Σ is an alphabet (sequence of saccades with their characteristics), q_0=S0 is the initial state, $A \subseteq K$ is the set of accepting states (defined as double circles in Figure 3), and δ is the transition function from $(K \times \Sigma)$ to K visually represented by transition arrows in Figure 3.

Each logical structure presented by the suggested DFA is especially useful in cases of the eye tracker's low positional accuracy. This disrupts the spatial relationship between the eye position and stimulus signal possibly leading to misclassification of the COB events when only spatial classification criteria is employed. The DFA approach considers a sequence of saccades and their relative spatial relationship to each other in addition to the spatial relationship of the stimulus. Therefore, it provides a higher tolerance of COB classification to degradation of accuracy of the eye tracking equipment.

EXPERIMENTAL METHODOLOGY

Two data sets recorded by two different hardware setups were used to assess classification capabilities of the proposed framework.

120Hz Data Set

Apparatus.

The experiments were conducted with a Tobii x120 eye tracker (Tobii, 2010) at 120Hz sampling frequency and connected to a 24-inch flat panel screen with a resolution of 1980x1200pix. A chin rest with forehead support was employed to provide higher accuracy and stability of the eye positional data. Subjects were seated approximately 710mm from the screen.

Saccade target sequence.

The step stimulus was presented as a ‘jumping point’ with vertical coordinates fixed to the middle of the screen (Figure 4). The first point was presented at the middle of the screen while subsequent points moved horizontally to the left or right of the screen’s center with a spatial amplitude of 20°. The jumping sequence consisted of 15 points including the original center point plus 14 additional stimulus-saccades for each test trial. After each jump, the point remained stationary for 1.5s before the next jump was initiated. The size of the point was approximately 1° of the visual angle with the center marked as a black dot. Each point consisted of white pixels (except for the central black dot) on a black screen background.

Participants & positional data quality.

The test data was collected from 26 student volunteers (8 males/ 18 females) with an average age of 21.8 (± 3.23). All were with normal or corrected-to-normal vision. None of the participants had prior experience with eye tracking. An advanced accuracy test procedure was used to monitor the quality of the collected data [Koh et al. 2009]. The average calibration error was 0.89º (±0.7°) and the average data loss was 2.84% (±5%).

1000Hz Data Set

Apparatus.

The EyeLink II eye tracker (EyeLink, 2010) was employed, which consisted of a custom designed high-speed camera connected to a dedicated host computer running a real-time operating system. The eye tracker has the following characteristics: accuracy 0.5°, spatial resolution 0.01º, drift 0.3°, and eye position sampling frequency of 1000Hz. A chin rest was used again for higher accuracy and head stability. The stimulus was presented on a 21 inch CRT monitor with a screen resolution of 1024x768pix. Subjects were seated approximately 710mm from the screen.

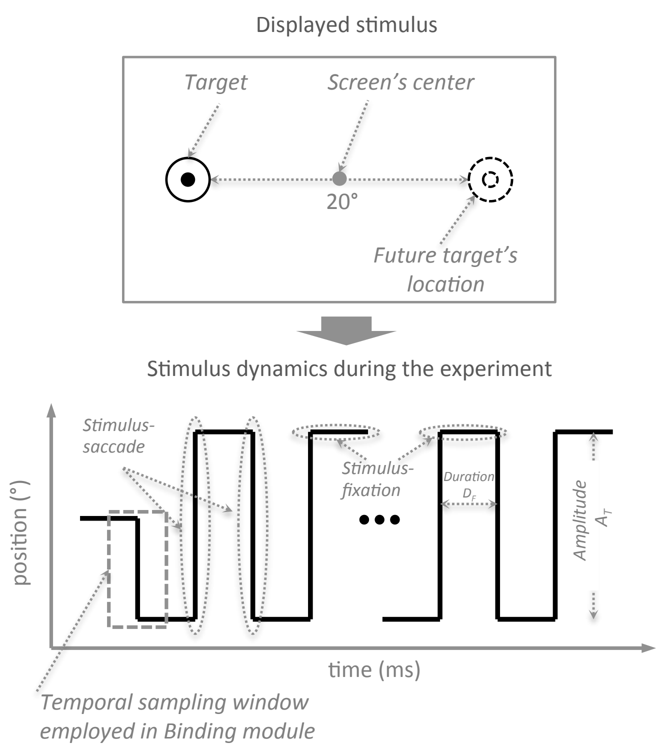

Figure 4. Stimulus properties.

Saccade target sequence.

The same saccade target sequence was used as with the 120Hz setup, except the number of stimulus-saccades was increased to 99. This was done to ensure the robustness of the automated COB signal classification during prolonged recording sessions despite subject fatigue which can result in various signal artifacts or frequent anticipatory saccades.

Participants & positional data quality.

The test data were collected from 9 student volunteers (7 males/ 2 females) with an average age of 23.8 (±4). All were with normal or corrected-to-normal vision. None of the participants had prior experience with the eye tracking protocol. The average calibration error was 0.53º (±0.46) and the average data loss was 2.44% (±11%).

Manual Classification of COB

A research assistant, who was trained by an oculomotor rehabilitation specialist, manually classified the COB events for all recordings in the 120Hz and 1000Hz datasets following the definitions provided in Section "Complex Oculomotor Behavior During Saccades". In cases of low spatial accuracy of an eye-tracker for a given target's position, e.g., signal with a shape of corrected undershoot located above the target's position, manual classification was performed based on the shape of the signal instead of the spatial relationship between the signal and stimulus, similarly to the DFA classification.

Performance Metrics

Two types of performance metrics were employed in our research. First, *individual performance metric* (IPM) reports the percentage of correct classification for each individual COB event.

$$IPM_i = 100\frac{AC_i}{MC_i} \tag{1}$$

where MC_i is the amount of manually classified COB events of the type i, and AC_i is the amount of automatically classified COB events that correspond to MC_i.

Second, is an *aggregate performance metric* (APM) that intakes the information from each individual performance metric and weights this information depending on the amount of manually classified COB events for this category.

$$AMP = \sum_{j=1}^{N} w_j \cdot IPM_j \tag{2}$$

where $w_j = \frac{MC_j}{\sum_{i=1}^{N} MC_i}$ is the weight for COB event j. The resulting AMP presents overall classification accuracy of the proposed framework.

RESULTS

The results outlined in this section represent the case of the maximum classification accuracy (defined by the maximum achievable AMP) that is obtained by varying a classification threshold of each algorithm employed for classification of BOB.

120Hz Data Set

Impact of basic oculomotor classification.

Table I presents the results. The automated classification framework performed best when the I-VT algorithm was utilized for the classification of the basic oculomotor behavior as indicated by the highest AMP of 66%. The I-VT algorithm helped to achieve the best accuracy in 7 out of 9 possible COB events. Among the remaining algorithms for the basic oculomotor behavior the I-DT allowed to achieve the highest accuracy for the simple undershoot (85%) and dynamic overshoot (100%). The difference between the I-VT and the I-DT method was substantial in part due to the fact that the I-VT did not allow the framework to detect any dynamic overshoots.

Impact of signal filtering techniques.

Among signal filtering methods the LOESS allowed improvement of the detection of corrected undershoots (75% vs. 73%), express saccades (52% vs. 49%), dynamic overshoots (17% vs. 0%), and invalid events (76% vs. 59%). However, the accuracy of the classification performance for the remaining COB events remained either on the same level or lower, resulting in the essentially same AMP value. Signal filtering performed by the KF did not yield an increase in the accuracy of the performance for any COB events.

1000Hz Data Set

Impact of basic oculomotor classification.

Table II presents the results. The I-VT algorithm achieved the highest accuracy for normal (81%), corrected overshoot (54%), and express saccades (69%). Overall the I-VT provided the most accurate performance as indicated by the AMP metric (69%). The I-HMM algorithm achieved the highest accuracy for the simple overshoot (60%), corrected undershoot (81%), multi-corrected undershoot (50%). Overall performance of the I-HMM algorithm was next best with the AMP of 68%. The I-KF allowed identifying the highest number of the “invalid” events (63%). The I-DT allowed to achieve the most successful detection of the simple undershoots (72%) and dynamic overshoots (61%).

Table I. COB classification performance for 120Hz data set. Manual classification row presents the amount of manually classified COB events. The percentages in the light grey area present IMP for each COB event and the final AMP value. Bold numbers indicate the best performer among various basic eye movement classification methods. "Signal Filtering Added" section presents the accuracy of the best performer as indicated by AMP when it is supported by a specific filtering algorithm described in "Signal Filtering" section. Bold numbers in this section highlight the accuracy of a COB event if it is higher than the original method with no added filtering.

120Hz dataset, manual/automated classification results and performance metrics	normal	simple undershoot	simple overshoot	corrected undershoot	corrected overshoot	multi-corrected undershoot	multi-corrected overshoot	compound	express	dynamic overshoot	invalid	AMP
manual class. (amount)	71	59	34	133	17	2	1	6	75	6	41	N/A
I-VT (threshold 29°/s)	**62%**	66%	**76%**	**73%**	**53%**	0%	**100%**	**33%**	**49%**	0%	59%	**66%**
I-HMM (threshold 18°/s)	51%	75%	76%	42%	24%	0%	0%	17%	37%	33%	41%	51%
I-KF (threshold 10)	51%	68%	65%	20%	6%	0%	0%	0%	25%	33%	**76%**	43%
I-DT (threshold 0.36)	42%	**85%**	50%	28%	24%	0%	0%	0%	29%	**100%**	27%	41%
Signal Filtering Added												
LOESS + I-VT	58%	66%	59%	**75%**	47%	0%	100%	33%	**52%**	17%	76%	66%
KF + I-VT	58%	63%	47%	60%	35%	0%	0%	17%	44%	33%	88%	60%

Table II. COB classification performance for 1000Hz data set.

1000Hz dataset, manual/automated classification results and performance metrics	normal	simple undershoot	simple overshoot	corrected undershoot	corrected overshoot	multi-corrected undershoot	multi-corrected overshoot	compound	express	dynamic overshoot	invalid	AMP
manual class. (amount)	202	81	47	325	95	2	5	22	180	120	112	N/A
I-VT (threshold 9°/s)	**81%**	64%	53%	78%	**54%**	0%	20%	18%	**69%**	49%	61%	**69%**
I-HMM (threshold 23°/s)	79%	58%	**60%**	**81%**	48%	**50%**	20%	18%	69%	43%	56%	68%
I-KF (threshold 7)	59%	54%	55%	46%	33%	0%	20%	9%	51%	50%	**63%**	50%
I-DT (threshold 0.3)	71%	**72%**	57%	53%	27%	0%	20%	18%	56%	**61%**	53%	55%
Signal Filtering Added												
LOESS + I-VT	**81%**	**65%**	51%	**85%**	**61%**	0%	**40%**	5%	**72%**	40%	61%	**72%**
KF + I-VT	81%	64%	53%	78%	54%	0%	20%	18%	69%	49%	61%	69%

Table III. Detailed COB classification performance for 1000Hz data set. Diagonal row with bolded numbers presents accurate classification results, while numbers in the remaining cells indicate misclassification amount in each category.

1000Hz dataset, manual & automated classification Results, I-VT, threshold=9°/s	normal	simple undershoot	simple overshoot	corrected undershoot	corrected overshoot	multi-corrected undershoot	multi-corrected overshoot	compound	invalid
manual class. (amount)	202	81	47	325	95	2	5	22	112
normal	**80%**	4%	5%	8%	1%	0%	0%	0%	1%
simple undershoot	20%	**64%**	1%	11%	2%	0%	0%	0%	1%
simple overshoot	26%	2%	**55%**	9%	9%	0%	0%	0%	0%
corrected undershoot	10%	7%	2%	**79%**	1%	0%	0%	0%	1%
corrected overshoot	23%	1%	16%	9%	**51%**	0%	0%	0%	0%
multi-corrected undershoot	0%	50%	0%	50%	0%	**0%**	0%	0%	0%
multi-corrected overshoot	20%	0%	20%	0%	40%	0%	**20%**	0%	0%
compound	9%	9%	0%	45%	5%	0%	9%	**23%**	0%
invalid	10%	8%	5%	8%	4%	3%	0%	1%	**61%**

Impact of signal filtering techniques.

Among signal filtering methods, the LOESS improved the accuracy of the best performer among the basic eye movement classification methods (I-VT) achieving the AMP of 72%. Specifically, the LOESS improved the detection of the normal saccades (81.2% vs. 80.7%), simple undershoots (65% vs. 64%), corrected undershoots (85% vs. 78%), corrected overshoots (61% vs. 54%), multi-corrected overshoots (40% vs. 20%), express saccades (72% vs. 69%). However, the accuracy of the detection performance for the remaining COB events remained either on the same level or lower, resulting in the essentially same AMP value. The employment of the KF did not change classification accuracy of the I-VT method.

Summary 120Hz vs. 1000Hz dataset

The higher sampling rate of the eye positional signal coupled together with a slightly higher positional accuracy achieved better classification results. Overall best performance as indicated by the AMP was higher (72% vs. 66%). The 1000Hz dataset yielded better performance for most common COB events such as normal, corrected undershoots/overshoots and express saccades. The difference between the best performances between the two data sets varied between 8% and 60%.

Impact of basic oculomotor classification.

The I-VT achieved the best overall classification accuracy for both data sets. The I-KF improved classification of the "invalid" events in both dataset while the I-DT improved the classification accuracy of simple undershoots and dynamic overshoots.

Impact of signal filtering techniques.

The LOESS filter improved the accuracy of several COB events in both datasets. It can be noted that the LOESS also had a higher positive impact on the 1000Hz dataset. However, use of the KF did not improve the classification accuracy for either of the databases.

DISCUSSION

Challenges of Manual Classification

It is possible to hypothesize that some errors in the automated misclassification might have occurred as a result of human errors during the manual classification process. Manual classification is very time consuming and an extremely tedious process - research assistant spent approximately 45 hours manually classifying the data for both datasets. The detection of an offset point of a saccade plays a significant role in the classification method. The following conditions make this detection especially challenging which increase the probability of misclassification: 1) post-saccadic events such as signal oscillations (visible in Figure 1, Normal) and drifts, 2) general "noisiness" of the signal during a saccade as created by tremor, drifts, micro saccades that occur during fixations and the noise introduced by the recording equipment. In the most difficult cases (though the percentage of such cases was small), the process of manual classification had to rely on the BOB automated classification algorithm to identify the offset point for a specific saccade.

Challenges of Automated Classification

The results of the automated misclassification are presented by the Table III. In general, the BOB automated classification process (which in itself can be a subject of significant variability (O. V. Komogortsev et al., 2010)) provided a substantial impact on the classification of COB behavior. A normal event might have been misclassified as undershoot/overshoot and the other way around depending on selection of the saccade's offset point. In addition, small saccades can be merged into a single fixation by the BOB classifier. Therefore corrected/multi-corrected undershoot/overshoots and compound saccades could be misclassified as simplified events such as normal/undershoot/overshoot or corrected undershoot/overshoot.

Stimulus & Applications

The proposed classification methods are not limited to the fixed step stimulus employed for data recording and can be applied primarily to a step stimulus of varying amplitude. However, in this work it was important to establish a thorough baseline for a fixed stimulus with the results that can be immediately applied to research related to the assessment of oculomotor function in people mild Traumatic Brain Injuries (mTBI) (Gobert & O. V. Komogortsev, 2010) and oculomotor dysfunction in people with drinking habits (Ceballos & Komogortsev, 2010).

Future applications of the proposed framework that involve free head movements will need to carefully synchronize head and eye rotation data and select the classification thresholds that would provide acceptable classification accuracy.

Equipment's Positional Accuracy Impact on Classification Results

Positional accuracy as defined by the eye tracking calibration errors will impact the performance of the proposed framework when such COB events such as normal, simple overshoot/undershoot patterns are identified. In cases when the proposed framework is employed for clinical diagnostics, the data recording facilitator should ensure that positional error is smaller than the thresholds suggested in this work. An alternative solution would be to adjust the corresponding thresholds to compensate for the calibration errors to ensure accurate classification of normal, simple overshoot/undershoot events.

When more sophisticated COB events are considered the DFA will assign correct COB states following the logic depicted by Figure 3. For example, if two saccades in response to the stimulus-saccade are classified as simple overshoot (i.e. both will have the property saccade.overshoot=true) due to the calibration error for this screen's region and the positioning of these saccades would be such that the second saccade is above the first one (i.e. condition saccade.offset > saccade.previous_saccade_offset) the DFA will identify the correct COB and will mark it as undershoot.

CONCLUSION & FUTURE WORK

This paper presented a framework for the detection of complex oculomotor behavior to aid the research of visual system pathologies. The results are promising in that the framework enables detection of nine (9) oculomotor behaviors in humans in response to a simple step stimulus task. The framework was developed using the concept of deterministic finite automata aided by mechanisms responsible for the reduction of noise and processing partially missing data. The framework was investigated with the help of four of the most common automated algorithms for classification of basic eye movement behavior such as fixations and saccades.

Two different hardware setups were employed to ensure the robustness of the framework on different eye tracking equipment. The results indicate that the proposed framework aided by velocity-based algorithms for classification of basic eye fixations and saccades provided the highest average accuracy of 69%. The employment of signal filtering improved the result to 72%. Among the nine oculomotor behaviors, the highest accuracy of detection was achieved for normal/undershoot and corrected undershoot. The lowest accuracy of detection was achieved for multi-corrected overshoot/undershoot and compound saccades; however the frequency of occurrence of such events in the eye movement trace is extremely low.

Although we are encouraged by the framework's performance level, there are several challenging areas which deserve continued work as follows: 1) Current framework employs saccade's offset coordinates as a foundation for classification. It is important to investigate possible impact of using positional information of fixations instead or in addition to saccade's offset information. The use of fixations might bring the improvement of classification accuracy for some COB events, e.g., normal, undershoot, overshoot, but might reduce the accuracy for more multifarious events such as multi-corrected undershoot/overshoot and compound saccades. 2) The question of what to consider as an "invalid" event when the classification of a valid COB event occurs, needs to be investigated further. 3) The impact of the robust eye movement recovery algorithms on the accuracy of the COB classification needs to be assessed in the future. 4) Automated threshold selection during classification of fixations and saccades needs to be investigated for the purpose of maximizing COB classification accuracy performance of complex oculomotor behavior. Possibly, this can be achieved with a help of quantitative and qualitative behavior scores (O. V. Komogortsev et al., 2010) or employment of adaptive thresholds (Nystrom & Holmqvist, 2010).

Despite the above challenges, our results still present an automated system to sufficiently classify nine possible oculomotor saccadic behaviors which can be of great value to better diagnose and track treatment outcomes for many patient populations. Further work will continue to optimize proposed algorithms to develop a practical yet accurate assessment tool for clinical applications.

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