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Classification Algorithm for Saccadic Oculomotor Behavior

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Abstract

This paper presents a detection algorithm that allows automatic classification of hypermetric and hypometric oculomotor plant behavior in cases when saccadic behavior of the oculomotor plant is assessed during the course of the step stimulus. Such behavior can be classified with a number of oculomotor plant metrics represented by the number of overshoots, undershoots, corrected undershoots/overshoots, multi-corrected overshoots/undershoots. The algorithm presented in this paper allows for the automated classification of nine oculomotor plant metrics including dynamic overshoots and express saccades. Data from sixty-five human subjects were used to support this experimental study. The performance of the proposed algorithm was tested and compared to manual classification methods resulting in a detection accuracy of up to 72% for several of the oculomotor plant metrics.

CR Categories: I.6.4 [Simulation and Modeling]: Model Validation and Analysis; J.7 [Computers in Other Systems]: Process control, Real time.

Keywords: classification, algorithm, saccade, oculomotor behavior.

1 Introduction

The assessment of oculomotor behavior is fundamental to clinical examination of visual system pathology. Two primary eye movements, fixation and saccadic function, have proven valuable in the diagnosis of several psychological, degenerative and neurological disorders. For instance, abnormal saccadic eye behavior is common in patients diagnosed with Alzheimer's disease [1], schizophrenia [2], macular degeneration [3-4], attentional deficit disorders [5], and persons suffering from vestibular-related pathologies like Meniere's Disease [6]. Tracking changes in eye movement control can provide information about patient responses to medication or improvements in functional tasks during activities of daily living such as reading [4]. During recent years, eye movement classification algorithms have been increasingly used in the oculomotor field to aid our understanding of normal eye function control in response to external stimuli or due to pathology or aging [7]. However, to the best of our knowledge an automated classification algorithm for the assessment of oculomotor behavior during saccades does not exist. In this paper we describe development of such an algorithm and report the performance of the algorithm versus manually classified data.

2 Oculomotor Behavior During Saccades

The oculomotor behavior during saccades can be accessed via the amount and magnitude of hypometria (undershoot)/hypermetria (overshoot), number of express saccades and dynamic overshoots [8]. A practical look at the hypometric and hypermetric behavior of the oculomotor plant allows assessment of such behavior through a number of simplified cases such as simple undershoot, simple overshoot, corrected undershoot, corrected overshoot, multi corrected undershoot, multi corrected overshoot, and compound saccade. Figure 1 presents eight specific examples with descriptions of each case provided in the text below. Stimulus saccade is defined as a step in the stimulus positional signal.

<u>Simple Undershoot/Overshoot:</u> the offset position of the stimulus induced saccade or eye movement falls below/above a certain threshold (>0.5° in our work) from stimulus fixation position.

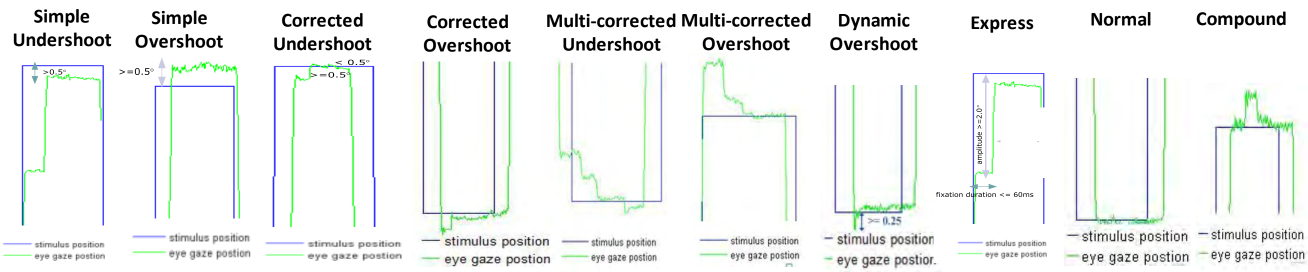


Figure 1. Examples of Oculomotor Plant metrics with eye positional accuracy better than 0.5°.

Additionally, there is no additional or corrective saccade present until the next stimulus evoked saccade.

<u>Corrected Undershoot/Overshoot:</u> the offset position of the stimulus induced saccade falls below/above a certain threshold (>0.5° in our work) from stimulus fixation position. The corrective saccade following the initial undershoot/overshoot results in an eye fixation position within a certain threshold of the fixation stimulus (<0.5° in our work). This metric assumes that there is no saccadic behavior prior to the next stimulus saccade.

<u>Multi-corrected Undershoot/Overshoot:</u> is similar in definition to corrected undershoot/overshoot however there are additional series of corrective saccades to bring the resulting fixation position within a specified distance (<0.5° in our work) to the fixation stimulus.

<u>Express Saccade:</u> a stimulus induced saccadic behavior where the offset location of the initial stimulus induced saccade is located at the large distance (>2° in our work). The subsequent saccade has an extremely short latency of less than 60ms [8]. With oculomotor plant behavior during saccades resembling the behavior during fixation.

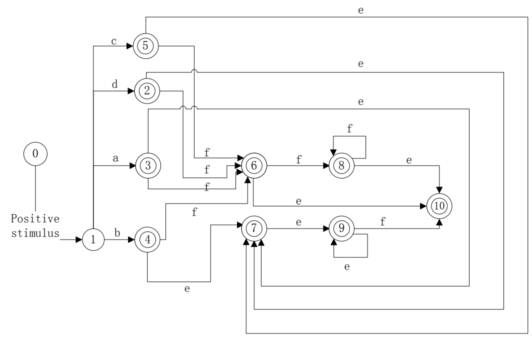
<u>Dynamic Overshoot:</u> is the movement of the eye that occurs after the offset of the stimulus induced saccade directed in the opposite direction from the previous saccade movement [8]. The amplitude of such movement usually appears in the range of 0.25-0.5°[8].

<u>Normal:</u> the offset position of the stimulus induced saccade falls within a certain threshold (<0.5° in our work) from stimulus fixation position. There is no corrective saccadic behavior prior to the next stimulus saccade related events.

<u>Compound:</u> normal that is broken by two or more small amplitude saccades (>0.5° but <1° in our work) that essentially bring the positional signal to the original offset position of the stimulus induced saccade.

3 Automated Classification of Oculomotor Behavior

Definitions provided in the section above seem to be theoretically simple and straightforward behaviors to classify. The practical challenges come from the fact that the eye position signal is noisy, prone to data loss, and interspersed with imperfect positional accuracy. Low positional accuracy disrupts the spatial relationship between the eye position and stimulus signal leading to a high risk of error when the stimulus based classifications described in the previous section are employed. The automated classification algorithm that we propose addresses the accuracy challenge by looking at the spatial behavior of the positional signal and considers the amplitudes and directions of the saccades following the initial stimulus induced saccade. Such saccadic sequence generated by the Oculomotor Plant can be characterized by a sequence of states represented by the Deterministic Finite Automation (DFA) model. Figure 2 presents an example of a DFA sequence generated for the positive amplitude stimulus. The resulting automated classification algorithm is presented by Figure 3. The stimulus_saccade_list data structure provided as an input to the algorithm contains a sequence of entries, where each entry is represented by a sequence of saccades recorded in response to each corresponding stimulus saccade. The stimulus_saccade_classifie_list represents the data structure where all saccades are classified according to the FDA states.



State 0: starting point
State 1: positive stimulus starting point
State 2: dynamic overshoot
State 3: simple undershoot
State 4: simple overshoot
State 5: normal
State 6: corrected undershoot
State 7: corrected overshoot
State 8: muti-corrected undershoot
State 9: muti-corrected overshoot
State 10: compound

Note:
single circle marks states where State Change is incomplete and State Change Condition must follow.
double circle marks final states

State Change Condition(SCC)

SCC a: undershoot
SCC b: overshoot
SCC c: normal shoot
SCC d: dynamic shoot
SCC e:
saccade.offset_position_deg < last_saccade.offset_position_deg
SCC f:
saccade.offset_position_deg > last_saccade.offset_position_deg

Note: SCC e and SCC f are sign sensitive

Figure 2. Deterministic Finite Automation of Saccadic Oculomotor Behavior

```
Algorithm: Oculomotor Automated Classification
Input: stimulus_saccade_list
Output: stimulus_saccade_classified_list

for each entry in the stimulus_saccade_list
 for each saccade present in the entry
  if sequential saccade's number is 1
   if (saccade is normal)
     assign type as normal
   else if (saccade is undershoot)
     assign type as undershoot
   else if (saccade is overshoot)
     assign type as overshoot
   else if (saccade is dynamic overshoot)
     assign type as dynamic overshoot
   else
     assign type as unknown

  if sequential saccade's number is 2
   if (SCC followed is e)
     assign type as corrected overshoot
   else if (SCC followed is f)
     assign type as corrected undershoot
   else
     assign type as unknown

  if sequential saccade's number is 3 or greater
    Start classification from the 2nd saccade in the list
    if (SCC followed are all e)
      assign type as multi corrected overshoot
    else if (SCC followed are all f)
      assign type as multi corrected undershoot
    else
      assign type as unknown

return stimulus_saccade_classified_list
```

Figure 3. Pseudocode for Oculomotor Automated Classification Algorithm

In addition, the nature of automated classification requires the definition of an "invalid" saccade which represents saccades that are exhibited in response to the stimulus however are directed in an opposite direction, or amplitude with less than 1/3 of the stimulus amplitude or out of working range. The most frequent reason for an invalid saccadic occurrence was data loss during the positional eye tracking signal. Saccade's classification to "invalid" state occurs prior to the classification of FDA states.

4 EXPERIMENTAL METHODOLOGY

Apparatus: The experiments were conducted with a Tobii x120 eye tracker [9] at 120Hz sampling frequency and connected to a 24-inch flat panel screen with resolution of 1980x1200 pix. Chin rest was employed to provide higher accuracy and stability of eye positional data.

Saccade Invocation Task: The stimulus was presented as a 'jumping point' with vertical coordinates fixed to the middle of the screen. The first point was presented at the middle of the screen while subsequent points moved horizontally to the left and right of the screen's center with a spatial amplitude of 20°. The jumping sequence consisted of 15 points including the original center point, yielding 14 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 65 student volunteers (24 males/ 44 females) with an average age of 21.22 (± 3.23). All were with normal or corrected-to-normal vision. None of the participants had prior experience with eye tracking. Advanced accuracy test procedure was employed to monitor the quality of the corrected data [10]. The average calibration error was 1.53º (±1.08°) and average data loss was 15% (±18%).

Eye movement classification algorithm: Specific values of the oculomotor plant metrics depends on the choice of the eye movement classification algorithm. In our work we have employed the Velocity Threshold Identification (I-VT) algorithm (Salvucci and Goldberg 2000) with a velocity threshold of 10º/s.

Data pre-processing: 1) The eye position trace was interspersed with missing coordinates of the positional samples due to eye tracking failures. Prior to classification of an eye movement, the data recovery was employed where in case of one missing samples, the coordinates of the sample were linearly interpolated. 2) Due to the predictable nature of the saccade's invocation task some subjects exhibited anticipatory saccades prior to the actual jump of the stimulus dot. Addressing such cases, the Oculomotor Automated Classification algorithm was employed 0.75s prior to the onset of stimulus saccade. This number thus defined the working range for each classification. 3) Dynamic overshoot behavior was sometimes broken into an initial large amplitude saccade followed by very short fixation like behavior (<60ms),

Manual & Automated Classification Results	normal	simple undershoot	simple overshoot	dynamic overshoot	corrected undershoot	corrected overshoot	multi-corrected undershoot	multi-corrected overshoot	express	compound	invalid
manual class. (amount)	*127*	*92*	*63*	*55*	*302*	*48*	*7*	*1*	159	1	*78*
normal	**63%**	6%	0%	3%	7%	2%	4%	4%	0%	0%	12%
simple undershoot	7%	**72%**	2%	4%	1%	2%	1%	2%	0%	0%	9%
simple overshoot	6%	2%	**65%**	8%	0%	6%	2%	3%	0%	0%	8%
dynamic overshoot	18%	9%	25%	**31%**	0%	7%	2%	4%	0%	0%	4%
corrected undershoot	6%	27%	0%	3%	**41%**	2%	8%	2%	0%	0%	11%
corrected overshoot	13%	2%	18%	13%	0%	**25%**	4%	8%	0%	0%	17%
multi-corrected undershoot	0%	57%	0%	0%	29%	0%	**14%**	0%	0%	0%	0%
multi-corrected overshoot	0%	100%	0%	0%	0%	0%	0%	**0%**	0%	0%	0%
express	0%	0%	0%	0%	33%	0%	0%	0%	**67%**	0%	0%
compound	0%	0%	100%	0%	0%	0%	0%	0%	0%	**0%**	0%
invalid	3%	10%	4%	3%	5%	0%	4%	1%	0%	0%	**71%**

Table 1. Manual and automated oculomotor metric classification results.

and then another corrective saccade. In these situations, the three movements were merged into a single complex signal logical saccade.

Manual Classification: a trained research assistant manually classified all oculomotor data tracings for participants described in Section 2 under the guidance of an oculomotor rehabilitation specialist.

5 Results

Classification results for the Oculomotor Automated Classification algorithm are reported vs. manual classification. Table 1 presents the results. The numbers in italics represent the results of the manual classification done by a human. Grey color represents automated detection accuracy. Highlighted percentages in bold represent the amount of correctly identified oculomotor plant metrics. Other percentages represent the amount of oculomotor plant metrics misclassified in a specific category. The best result was achieved for simple undershoots (72%) and express saccades (67%). The worst result of 0% was achieved for multi-corrected undershoot and compound saccades. This can be explained by the fact that just one actual saccade was presented in each category.

6 Discussion, Conclusions and Further Work

Our preliminary results are promising in that we have been able to demonstrate a useful automatic classification system to address nine (8) oculomotor behaviors in humans. Although we are encouraged by the algorithm's performance level, there are several challenging areas which deserve continued work as follows: 1) It was difficult to identify saccade properties in the midst of ocular drift. We expect that if information about surrounding fixations is added it would improve classification accuracy. 2) the question of what to consider an "invalid" saccade is quite challenging. Further research is needed to improve the definition provided in Section 2. 3) Robust eye position recovery algorithms are needed to improve the accuracy of classification.

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 accurately diagnose and track treatment response in many patient populations. Further work will continue to optimize the algorithm to develop a practical yet accurate assessment tool for clinical applications.

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