Oculomotor Plant Feature Extraction from Human Saccadic Eye Movements

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Abstract

Abstract—Eye movements can be used as a source to predict the user interest behavior in human computer interaction system. Oculomotor Plant Feature (OPF) values are the anatomical components of extra ocular muscles which are responsible for the eye movements. This paper is focusing on extracting the optimized oculomotor plant feature values from the saccadic trajectories generated by the two-Dimensional Oculomotor Plant Mathematical Model (2DOPMM) and selecting the best optimization algorithm to extract the optimized OPF values. The root mean squared error is used to minimize the error between simulated and classified saccadic trajectories and the existing algorithms such as Neldermead, levenberg-marquardt and trust-region reflective algorithms are compared to analyze the processing time for the optimization. This project concludes by analyzing results of optimized OPF values and the optimization algorithms used.

Keywords- oculomotor plant; feature extraction; saccadic eye movements

I INTRODUCTION

This paper presents a methodology for extracting the anatomical characteristics of the human eye during saccadic movement and involves in finding the optimization framework to extract the features in terms of processing time and feature analysis. The eye movements can be used in user interest modeling systems to accurately predict the personalized information delivery. But, in such systems by considering the gazes will not give the accurate model. Because, we cannot treat focus activity equally when using gaze information for user interest modeling. Anatomical characteristic of eye can be used to aid personalization in user interest modeling techniques.

Human oculomotor plant (OP) consists of eye globe and six extraocular muscles (EOM) such as medial, lateral, superior, inferior recti and superior and inferior oblique. Each of these EOM can be classified as either agonist or antagonist muscle. Also, eye can move in eight directions; right, left, up, down, right upward, left upward, right downward, left downward. There are six primary eye movements. Among that fixation is used to maintain the visual gaze on a single location and saccade is used for reading or scanning a scene [3]. These movements are controlled by neuronal control signals generated by different areas of the brain. And the movement patterns are unique to

individuals which can be affected differently by fatigue, drugs, and diseases.

Two-dimensional oculomotor plant mathematical model (2DOPMM) can simulate normal human saccades on a two-dimensional plane; horizontal and vertical trajectories during saccadic eye movements. This mathematical model is a twelve-order system created by a set of linear mathematical components representing major anatomical properties of EOM and the eye globe and it is driven by a simplified pulse-step neuronal control signal which is sent by brain to muscles to perform the eye movement task.

A. Oculomotor Plant Feature Values

Each extra ocular muscle is represented by the complex anatomical structures and these anatomical structures consists of anatomical components [1]. For the detailed computation of extra ocular muscle forces requires accurate modeling of each anatomical component inside of an extraocular muscle. These anatomical components are referred as oculomotor plant feature values such as series elasticity, passive elasticity, length tension relationship, force velocity relationship, passive viscosity, muscle tension and etc. Default OPF values from Collins and Bahill model are used in 2DOPMM to generate the simulated saccade trajectories [5]. Some of these parameter values were previously estimated from a record of just one subject. Some parameters such as length tension and series elasticity were derived by manual data fitting and hand drawn straight line approximations [2].

II. RELATED WORK

The study of [4] presents the importance of oculomotor plant feature in user interest modeling. This paper argues that though gaze time is the primary feature to be incorporated in user interest modeling, oculomotor plant feature during user's interaction with applications will give better interpreting user gaze data. In 2010, V. Komogortsev et al [12] extracted some of the oculomotor parametric values using Nelder-mead and Trust-region reflective algorithm in two strategies. In [13], the features are extracted from fixations and saccades based on backward selection framework. They trained Gaussian RBF networks using the features form fixations and saccades separately. In the detection phase, scores obtained from both RBF networks are used to get the subject's identity.



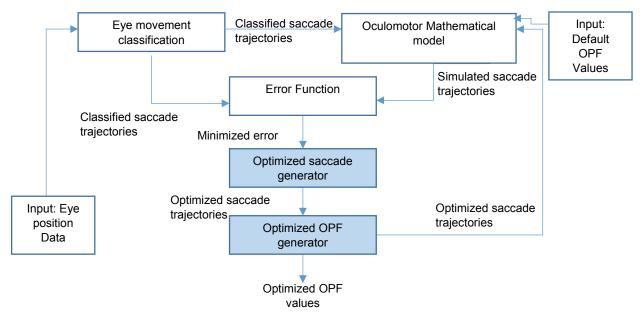


Figure 1: Model to generate optimized OPF values

Gradient based optimizers are efficient at finding local minima for high-dimensional, nonlinearly-constrained and convex problems. But, this algorithm approaches the best fit very slowly. Gradient free methods are not necessarily guaranteed to find the true global optimal solutions. Genetic algorithms can handle mixed continuous, integer and discrete design variables and less likely to reach in local minima. But, this algorithm is expensive compared to gradient methods, especially for larger number of design variables.

A simplex method or Nelder Mead algorithm does not need the derivatives to be computed and does not require the objective function to be smoothed. But, this is not very efficient for problems with more than about 10 design variables. Levenberg-marquardt algorithm combines the advantages of gradient descent and gauss newton steps based on adaptive rules. This algorithm is very efficient for finding minima and performs well on most test functions. The performance of this algorithm depends greatly on initial guess. Trust-region reflective algorithm when negative curvatures are encountered though both are Newton step-based algorithms. But, the complexity of trust-region reflective algorithm is higher compared to levenberg-marquardt algorithm.

III. DATASET

The dataset for this framework is used from the previous works of [9, 13, 14], which is publicly available. For this study 22 subjects (9 males, 13 females) were selected. These data were recorded using Tobii x120 eye tracker with accuracy 0.50, spatial resolution 0.20 and sampling frequency 120 Hz. These participants have normal or corrected to normal vision. Saccadic data were differentiated from fixation by applying the Velocity Threshold algorithm

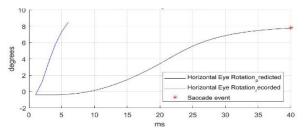
to the collected data.

IV. METHODOLOGY

Eye movement classification classifies the data from the eye tracker as fixation and saccade using the Velocity-Threshold algorithm. Then, the classified saccade trajectories which are represented by the onset and offset coordinates of the eye position and amplitude of the saccade are used to generate the simulated saccade trajectories based on the default OPF values. Optimized saccade trajectories were generated by comparing each individual classified saccade with the simulated saccades by minimizing error between each pair. Optimized OPF generator produces the corresponding optimized OPF values from the optimized saccade trajectories as shown in Figure 1. Error function used in this procedure is root mean square error (RMSE). RMSE measures the error between simulated and classified trajectories.

To extract the optimized OPF values from these optimized saccade trajectories algorithm such as Neldermead algorithm, Levenberg-marquardt algorithm, trustregion reflective algorithm is considered. For all these algorithms, the default values of OPF are considered as the initial value set.

The optimization algorithms are used to improve the default OPF values by minimizing the error between classified and simulated trajectories. In this paper, we have considered three optimization algorithms to determine the optimized OPF values. The Nelder-Mead (NM) algorithm [6] is the best-known algorithm for the multidimensional unconstrained optimization without derivatives. In this algorithm, a simplex is a structure in n-dimensional space formed by n+1 points that are not in the same plane. It starts with the simplex of n+1 points and then modifies the simplex



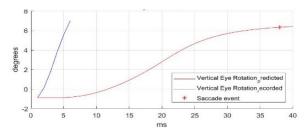
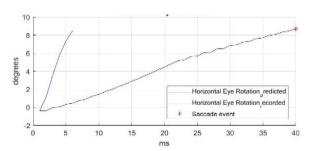


Figure 2: Horizontal & vertical simulated trajectories



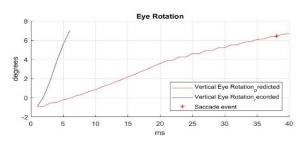


Figure 3: Horizontal & vertical optimized trajectories

TABLE I. TASK CONFIGURATION FEATURE MINIMIZATION USING NELDER-MEAD

		Subject Number														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Simulated Trajectories	Avg. RMSE HR	5.47	5.04	6.66	6.17	6.9	10.9	5.65	7.46	7.28	5.58	8.7	5.86	10.2	6.55	5.65
	Avg. RMSE VR	6.26	5.27	5.79	5.11	7.28	8.38	6.68	7.75	7.46	6.39	8.94	6.59	6.8	7.36	6.79
Optimized Trajectories	Avg. RMSE HR	1.93	1.48	1.13	0.86	1.18	3.06	1.78	1.80	1.20	1.01	1.29	2.16	0.95	2.44	1.32
	Avg. RMSE VR	2.30	2.26	1.04	1.90	1.49	3.19	3.53	1.50	1.51	3.11	1.69	1.31	1.5	1.89	1.78
% Error Reduced	HR	64.8	70.7	83.0	86.0	82.9	71.9	68.6	75.8	83.5	81.9	85.2	63.1	90.7	62.7	76.6
	VR	63.2	57.2	82.1	62.9	79.5	61.9	47.1	80.7	79.7	51.3	81.1	80.1	78.0	74.3	73.7

at each iteration using four simple operations (reflection, expansion, outside contraction, inside contraction and shrinking). The sequence of operations to be performed is chosen based on the relative values of the objective function at each of the points.

Trust-region-reflective uses the trusted region around the initial parameter values to search the better value. The size of the trusted region is increased if the algorithm finds a better value. Otherwise, the trusted region is reduced. Levenberg-marquardt algorithm takes the default parameter values as initial values and then the new estimate of parameter is calculated by its linearization.

V. RESULTS

The result shown below in Table 1 is based on Neldermead algorithm. Other two algorithms Levenberg-Marquardt algorithm and trust-region reflective algorithm resulted in local minimum when reducing the root mean squared error and these algorithms are not capable enough to reach the global minimum points of saccades. But, these algorithms are performing well in terms of processing time compared to Nelder-mead to reach the same initial local minimum points..

Figures 2 and Figure 3 shows the horizontal and vertical simulated trajectories and optimized trajectories respectively for the random saccade of a random subject. Using Neldermead, the error is reduced between recorded and predicted results as shown in Table 1 by more than 50%. From the results, we can infer that the algorithm performs very well in terms of the optimization but suffers in processing time.

Statistical analysis is used to determine if the oculomotor feature values are significantly different between subjects and within the subjects using one-way ANOVA test. The Table 2 provides the summary of one-way ANOVA test. From Table 2, it is evident that the P value for K_{LT} , B_P and J are less than the 0.05 significant level.

VI. CONCLUSTION AND FUTURE WORK

In this paper, we present a methodology to extract the oculomotor feature values from 2DOPMM which simulates normal human eye in horizontal and vertical trajectories. RMSE is used to minimize the error between classified and

simulated trajectories and feature values are obtained using Nelder-mead algorithm when the error is minimum.

TABLE II. SUMMARY OF STATISTICAL ANALYSIS OF FEATURES

Oculomotor Feature	P value
Kse	0.3231
K _{LT}	0.0009
ВР	0.0011
Bag	0.1467
BANT	0.222
J	0.0274
C _{AG1}	0.2089
C _{AG2}	0.9367
Cant1	0.963
Cant2	0.9998
КР	0.642

Using this approach, oculomotor parametric feature values such as length tension, passive viscosity and eye globe inertia shows the unique properties that can be applied towards user modeling and other human computer interactions processes. Testing this approach in more data set will provide more accurate result. Also, the Levenberg-

marquardt and trust-region reflective algorithm didn't support to extract the features as they cannot reach the global minimum points. As the Nelder-mead takes longer to time to optimize, using this algorithm in real time applications is still questionable. In the future we are interested in studying more efficient algorithm to improve the processing time so that we can extract the features in real time.

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