IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 19, Issue 4, Ver. VI (Jul.-Aug. 2017), PP 64-74
www.iosrjournals.org

Eyelid Phase Shift and Difference Map Algorithm for Gaze Pattern Estimation

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Abstract: *Eye gaze provides a vital sign for vision-based intelligent systems to recognize the human visual attention, emotion, feelings and so on. A different gaze estimation method employs local or global features as eye. But it failed to work well under natural light and it is still hard to obtain accurate gaze pattern for human vision recognition. In order to improve the gaze pattern estimation, Eyelid Phase shift Momentum based Difference MapAlgorithm (EPSM-DMA) is introduced. The EPSM-DMA technique captures the various eye images from the dataset. Initially, the Eyelid Phase shift Momentum technique is applied in EPSM-DMA to measure the movement of the eyelid for detecting the gaze pattern. After that, Difference Mapalgorithm is used formappingthe point in Euclidean space to providefixed degree of the mapping. This helps to provide the accurate eye image alignment. Finally, the recovered gaze pattern is matched with the ground truth pattern by using Bayes' theorem to recognize the gaze pattern. Experimental results show that the proposed EPSM-DMA technique significantly achieves better performance in terms of Computational complexity, true positive rate and Pattern matching accuracy with number of eye images.*

Keywords: *Eye gaze estimation, eyelid phase shift momentum, Difference map algorithm, Euclidean space, Bayes' theorem, Pattern matching.*

Date of Submission: 08-08-2017 Date of acceptance: 26-08-2017

I. Introduction

Gaze estimation is the process of identifying at what and where the eyes are pointing. The number of application has been generated in field of human computer interaction which includes good graphical interface, advance eye tracking system and so on. Therefore, the eye gaze plays a significant role in understanding human attention, feeling, mind and so on. It is essential for many multimedia applications such as cognitive processes analysis and human- computer interaction. Human gaze pattern recognition is important for intelligent systemsto identify the user behavior and perform effective interactions. Hencethe human eye gaze is an essential for interacting with the outside world.The gaze estimation techniques are separated into two types such as feature-based and appearance-based. Generally, Feature- based techniques depends on pupil detection with the light sources' reflections on the cornea. This in turns achieve very high accuracy. An appearance-based technique handles the cropped eye image as a point illustration in high dimensional space and discovers the mapping relation from this point in aspecified feature space to monitor coordinates. Therefore, our proposed technique uses appearance based technique for Gaze pattern estimation. Appearance-Based Gaze Estimation using Uncalibrated Gaze Pattern Recovery model from separate eye images of the person and scene was designed in [1]. However, the performance of the appearance based approach was not improved.A Synthetic Iris Appearance Fitting (SIAF) technique was introduced in [2] to calculate 3D gaze direction from iris shape. However, the method needs training and it considered as a more time complexity.Person-independent appearance-based gaze estimation model was introduced in [3] for improving the accuracy of eye gaze prediction. However, the eyelid based gaze estimation was not performed. A new approach was designed in [4] to auto-calibrate gaze estimators in an uncalibrated system. But, the distance among the points were not measured to obtain the exact pattern alignment.

An appearance based gaze estimation approach was developed in [5] using saliency maps. But the gaze estimation accuracy was not improved effectively. In order to improve the gaze estimation, hybrid scheme was introduced in [6] to integrate head pose and eye location information. However, the mapping accuracy was not improved. An efficient method was introduced in [7] for a fast and perfect localization of Iris centre (IC) position in low-resolution grey-scale images. However, it has more computational complexity. A crowd-powered technique called Fauxvea was developed in [8] that estimates gaze locations through the investigation tasks with static information visualizations without considering eye tracker. But it failed to construct a robust computational approach of gaze for visualization tasks. An appearance-based gaze estimation technique was developed in [9]with deep feature representation and feature forest regression. However, it failed to implement the real-time driver gaze tracking. The recognition of the gaze direction was introduced in [10] from remote imaging. But it was not trained on poorly illuminated imageshenceit'sreduced the performance.

The issues observed in above reviews such as lack of gaze patternrecognition, more time complexity, failed to handle poorly illuminated images and lack of eyelid based gaze estimation. In order to overcome such kind of issues in existing methods, a hybrid approach called as Eyelid Phase shift Momentum and Difference Map Algorithm (EPSM-DMA) is introduced.

The major contribution of the paper is described as follows,

- Eyelid Phase shift Momentum and Difference Map Algorithm (EPSM-DMA) is introduced to improve the gaze pattern estimation. The different input images are taken from the gaze dataset in order to perform the estimation. These images are preprocessed for removing the noise present in the image. After the preprocessing, the Eyelid Phase shift Momentum technique is applied to detect the gaze patterns through the movement of eyelid. This helps to lessen the computational complexity.
- Secondly, Difference Map Algorithm (DMA) is applied to align the eye images with the set of gaze patterns. This alignment is used to form the gaze pattern. The DMA is used for solving the point intersection problem in Euclidean space. Then the closet distance points are considered to form a gaze pattern by using Euclidean distance measure thereby improving the true positive rate and avoid the misalignment.
- Finally, the gaze pattern matching is done with the help of the Bayesian probability. During the pattern matching, theBayes' theorem provides the probability results to match the recovered gaze pattern with ground truth patterns for recognize the gaze patterns. This helps to achieve the higher pattern matching accuracy.

The structure of the paper is arranged as follows. In Section 2, brief explanation of Eyelid Phase shift Momentum and Difference Map Algorithm (EPSM-DMA) is presented for gaze pattern estimation with neat diagram. Section 3 presents the experimental settings and the results discussion are presented in section 4. Section 5 discusses the reviews related to the research works to show the performance of proposed work. Conclusion of the paper is presented in Section 6.

II. Eyelid Phase Shift Momentum And Difference Mapalgorithm For Gaze Pattern Estimation

The Eyelid Phase shift Momentum and Difference MapAlgorithm (EPSM-DMA) is developed for knowing the person's visual and possible actions being produced. The various eye gaze pattern estimation provides a chance to identify the appearance and hence for any recognition algorithm to work in practice. Initially, the eyelid phase shift momentum technique is applied for measuring the angle during the eyelid movement. With the help of the extracted angles, the difference map algorithmis used toidentify fixed degree of the mapping. Finally, matchingis performedwith obtained patternsand ground truth patterns to recognize the accurate gaze estimation from acquired input eye images. The flow processing diagram of the proposed EPSM-DMA is shown in figure 1.

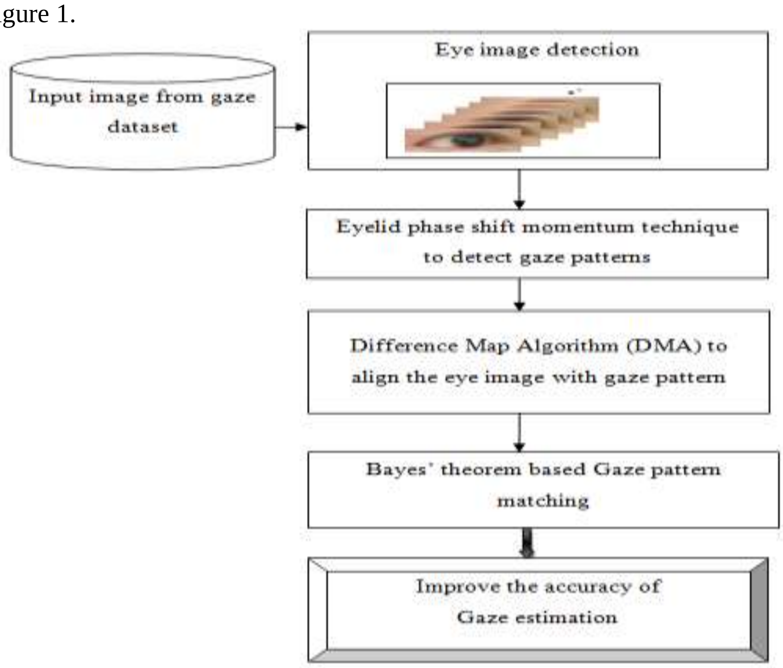

Figure 1 Flow Processing diagram of the Eyelid Phase shift Momentum and Difference Map Algorithm

Figure 1 clearly shows the flow processing diagram of the Eyelid Phase shift Momentum and Difference Map Algorithm (EPSM-DMA) to obtain the higher gaze pattern recognition accuracy with minimum complexity. The numbers of input images are taken from the gaze dataset. From the input images, the eye images are detected and cropped for gaze estimation. The original eye images are preprocessed in order to remove the noise and redundant artifacts present in the images. The main aim of pre-processing is an improvement of the original eye image data that removes the redundant distortions and enhances significant image features for further processing. Eye image detection is used to recognize the gaze pattern in digital images. Then Eyelid phase shift momentum technique is used to detect gaze patterns by the movement of the eyelid. Difference Map Algorithm is used for aligning the gaze pattern by using Euclidean distance measure and obtains the recovered pattern. Finally, gaze patternmatchingis carried outusing Bayes' theorem and it provides the method for successfully recover the gaze patterns. The brief explanation about the proposed EPSM-DMA is presented in next sections.

1.1 Eyelid phase shift momentum technique

The first step in the design of EPSM-DMA is the Eyelid phase shift momentum technique to detect the gaze pattern.When the eyeball is in motions, the eyelids move with it. Hence it is important for gaze estimation. Eyelidis a thin fold of skin which covers and provides theshields of human eye. The movement of eyelid is expressed as a rotation, but a different movement of the eyelid has differentrotational axes. Therefore, an Eyelid movement is the visual behaviors thatused to replicate a person's fatigue level. The primary purposeof eyelid movement is to detect the eye patternswith the help of thepoints.

Phase shift momentum is avector quantity that signifies the product of an Eyelid rotational inertia and rotational velocity about a particular axis. Phase shift momentum is also represented as the rotational regarding thelinear momentum. Linear momentum involves basics of the center after eyelid movement and displacement (i.e. velocity). Therefore the velocity of an eyelid is the rate of change of its position.

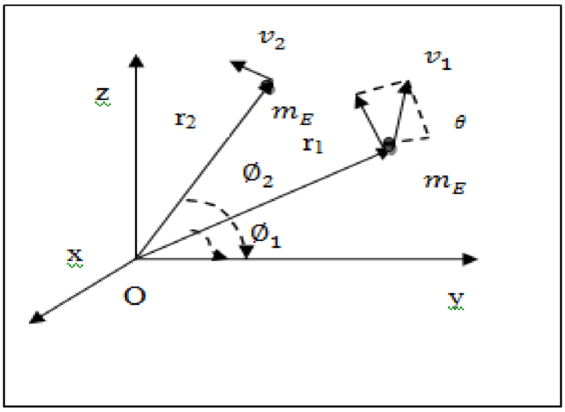

Figure 2 phmomentum
Figure 2 phaseshiftmomentum

Figure 2 shows the phase shift momentumtechnique to identify the movement of the eyelid.By using phase shift momentum technique, the gaze patterns are identified. From the figure, three gaze direction are presented x, y, z. $\emptyset_1$ and $\emptyset_2$ are the two angles for measuring the position after moving the eyelid. The Velocity of the eyelid considers the origin 'O'which is measured into components parallel and perpendicular to the radius vector *r*. Therefore, the phase shift momentumis proportional to the perpendicular component of the velocity. The linear phase shift momentum is measured with the product of the center point after eyelid movement (m_E) and velocity (i.e. displacement). The linear phase shift momentum is defined as follows,

$$L = m_E * v \quad (1)$$

From (1), L denotes a linear phase shift momentum. Then the phase shift momentum is also proportional to moment of inertia (I) and angular speed (ω). The momentum of the inertia is defined as the ratio of the phase shift momentum (L) and angular speed (ω). It is defined as,

$$I = \frac{\text{phase shift momentum (L)}}{\text{angular speed } (\omega)} \quad (2)$$

Hence, the phase shift momentum (L) is measured as,

$$L = I * \omega \quad (3)$$

From (3), L is referred as the phase shift momentum relative to that center of origin 'O'. For a single eyelid movement, the momentum of inertia is $I = r^2 m_E$ and the angular speed $\omega = \left(\frac{v}{r}\right)$, the phase shift momentum (L) is described as follows,

$$L = r^2 m_E * \left(\frac{v}{r}\right)(4)$$

Hence the phase shift momentum of the eyelid is obtained as,

$$L = r * m_E * v \quad (5)$$

From (5), 'r' is the position vector of the eyelid in relation to the center of origin and v is the velocity of the movement of eyelid relative with the origin and m_E center point after eyelid movement. This helps to create strong specular highlights around the boundary of the eyelids. The phase shift of eyelid movement is measured as follows.

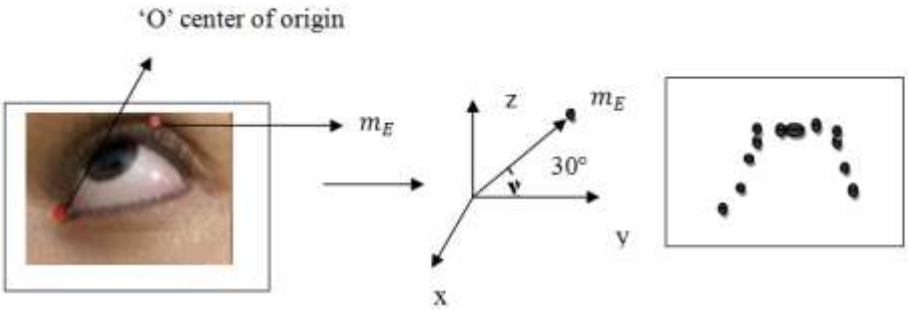

Figure3 eyelid phase shift momentum

Figure 3 shows the Eyelid phase shift momentum to obtain the set of boundary points used to form a gaze pattern. Therefore, the result of the phase shift momentum is also called as moment of momentum of the eyelidagainst that the eyelid center point. From the phase shift momentum results, the points are marked to estimate gaze patterns.This helps to reduce the time complexity during the gaze pattern estimation.

1.2 Difference MapAlgorithm

Once gaze patterns are detectedto align the eye according to the shape of the gaze pattern. This is performed by using difference-map algorithm. The results aredetermined as fixed points of the mapping.Dense gaze points are detected using Eyelid phase shift momentum technique. More points are detected but few of them are not matched with the gaze patterns accurately. But some of the points are closet to match the gaze patterns. These points are more feasible to be used as significant gaze patterns in real scenarios. Therefore, the Difference Map Algorithm (DMA) is generally designed to discover the global optimal point for gaze pattern estimation.

During the alignment of the points, the intersection problem is arises hence this problem is solved in Euclidean space. In order to discover the points 'x' in the intersection of points 'a' and 'b' and the projection of intersectionis denoted as PR_a and PR_b. A point in the constraint set 'a' or 'b'that the nearest to the point 'x'. Therefore the difference map algorithm is defined as follows,

$$x \to D(x) = x + \alpha[PR_a(f_b(x) - PR_b(f_a(x))] \quad (6)$$

Where,

$$f_a(x) = PR_a(x) - \frac{1}{\alpha}\,(PR_a(x) - x)(7)$$

$$f_b(x) = PR_b(x) + \frac{1}{\alpha}\,(PR_b(x) - x) \qquad (8)$$

From (6), (7) and (8), $D(x)$ is the mapping of point 'x', $f_a(x)$ and $f_b(x)$is the mapping function of the point 'a' and 'b' respectively. The real parameter α is not equal to zero ($\alpha \neq 0$). But it has the value of $\alpha = 1$ thereby reducing the number of projections. The equation (7) and (8) are substituted in equation (6) to get mapping results.

$$D(x) = x + (2PR_b(x) - x) - PR_b(x) \quad (9)$$

Therefore, a point 'x' is fixed point of the map $x \to D(x)$ accurately when the following condition is satisfied.

$$P_a\left(f_b(x)\right) = P_b(f_a(x)) \quad (10)$$

As a result, theDifference map algorithm is observed by the difference between the two projections. These differences are described as follows,

$$\Delta= \left|P_a\left(f_b(x)\right) - P_b(f_a(x))\right| \quad (11)$$

From (11), Δ represents the difference function. This helps to avoid the problem of the intersectionduring the eye alignment. After that, closet points of the gaze patterns are aligned based on the Euclidean distance (d). Let us consider the two points 'a' and 'b' in the gaze pattern evaluation. Therefore the distance between the two points are measured as follows,

$$d(a,b) = \sqrt{\sum_{i=1}^{n}(a_i - b_i)^2} \quad (12)$$

From (12)$d(a,b)$ is the Euclidean distance between the points. The distance is compared with the specified threshold value for selecting the point to form a gaze patterns. Therefore, the comparison results (Y) provides more significant result to select the exact points for gaze patterns formation.

$$Y = \begin{cases} d(a,b) < \delta & ; selected \\ d(a,b) > \delta & ; not\ selected \end{cases} \quad (13)$$

From (13), δrepresents the threshold. If the distance between the two points is less than the threshold value (δ) then the point is selected to form a gaze pattern. If the distance between the two points is greater than the threshold valueδ, then the point is not selected to form a shape of the pattern.

Input : Number of gaze points
Output: Improve true positive rate
Step 1: Begin
Step 2: For each point
Step 3: Intersection of the point is identified and solved using (6)
Step 4: Difference map function is formularized using (11)
Step 5: Closet points are selected based on the Euclidean distance between the two pints using (12)
Step 6: **if** ($D(a,b) < \delta$) **then**
Step 7: Select the point to form a pattern
Step 8: Else
Step 9: Point is not selected
Step 10: end if
Step 11: End For
Step 12: End

Algorithm 1 Difference MapAlgorithm

Algorithm 1 describes the Difference Map Algorithm to identify the intersection point and closet distance between the points. The intersection of the point problem is solved using Difference MapAlgorithm. Then the closet points are selected according to the shape of the gaze patterns. If the distances between the two points are less than the threshold value, then the point is selected to form a gaze pattern. Otherwise, the point is not selected. This helps to align the eye image and reduce the misaligned eye image thereby improving the true positive rate.

1.3 Gaze pattern matching

After the eye image alignment with gaze pattern, matching of the recovered gaze pattern with ground truth pattern is performed. Pattern matching is the process of verifying the recovered patternswith the ground truth pattern. The seven ground truth patterns [1] are considered to perform the matching process.

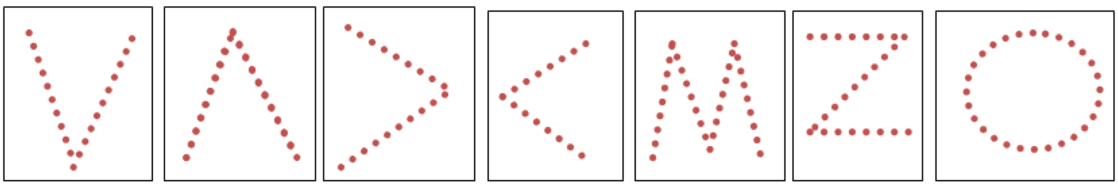

Figure 4 Seven ground truths gaze patterns

As shown in figure 4, there are seven ground truth gaze patterns are considered to perform pattern matching. Then the recovery using only captured test eye images is matched with the ground truth gaze patterns to recognize the human vision. For each eye image, gaze patterns and testing sample to find eye cornerregion by matching its appearance to the template.

The EPSM-DMA performs pattern matching by using Bayes'theorem. Let us consider the ground truth gaze patterns (f_1) and gaze patterns with recovery result (f_2), then the Bayesian probability is explained as follows,

$$P\ (f_1/f_2) = \frac{P(f_2/f_1)P(f_1)}{P(f_2)} \quad (14)$$

From the equation (14), $P(f_1)$and $P(f_2)$ are the probabilities of matching between the two patterns. Here, $P\ (f_1/f_2)$represents the probability ofground truth patterns is matched whereas $P(f_2/f_1)$ denotes the probability of recovered gaze patterns is matched with recovered patterns. This helps to recognize the gaze pattern accurately. Therefore, the probability is described as follows,

$$P\ (f_1/f_2) = \begin{cases} 1 & Patters\ matched \\ 0 & patterns\ not\ matched \end{cases} \quad (15)$$

From (15), If the result of$P\ (f_1/f_2) = 1$, then the two gaze patterns are matched accurately. If the probability result is zero, the gaze patterns are not matched. This helps to improve the accuracy of the gaze pattern matching. The pattern matching algorithm is described as follows,

Input: Eye images $\{I_i = I_1, I_2, .., I_n\}$, number of gaze patterns, Test sample , ground truth patterns
Output: Improve pattern matching accuracy
Step 1: Begin
Step 2: For each eye image
Step 3: For each gaze patterns
Step 4: Bayes's probability is measuredusing (14)
Step 5: if $(P\ (f_1/f_2) = 1)$ then
Step 6: Matched the gaze patterns
Step 7: else
Step 8: Patterns are not matched
Step 9: End if
Step 10: End for
Step 11: End for
Step 12: End

Algorithm 2 Gaze pattern matching algorithm

Algorithm 2 describes the Gaze pattern matching algorithm to perform efficient gaze pattern estimation. For each image and patterns estimated from the analysis, the Bayes' probability result is used for matching the resultant patterns with the ground truth patterns. If the probability value 1 indicates the patterns are accurately matched. Then the probability value 0 indicates the patterns are not matched. This in turn achieves higher pattern matching accuracy.

III. Experimental Evaluation

An efficient Eyelid Phase shift Momentum and Difference MapAlgorithm (EPSM-DMA) is experimented using MATLAB with two different dataset namely syntheseyes dataset and MPII gaze dataset. The syntheseyes dataset consists of 11,382 synthesized close-up images of eyes. The dataset contains ten directories andindividual for each robust eye region model in the collection. Each eye image has related data stored on the pickle file. The picklefile maintains tracked objects and it has beenpreviously serialized, hence that the later references to the similar object cannot be serialized another time.

The MPII gaze dataset consists of 213,659 images from 15 participants. The more eye imagesgathered by each participant varied from 34,745 to 1,498. The eye images collected samples across different factorscomprises the percentage of moreimages having different mean grey-scale intensities within the face region (top left), having horizontally different mean grey-scale intensities from the left to right half of the face region (to right), collected at different times over the day (bottom left), and collected by each participants. Performance analysis is conducted with certain parameters such as computational complexity, true positive rate and pattern matching accuracy, with respect to number of eye images.

IV. Results And Discussion

The result and discussion of Eyelid Phase shift Momentum and Difference MapAlgorithm (EPSM-DMA) is performed with existing Uncalibrated gaze pattern recovery model [1] and Synthetic Iris Appearance Fitting (SIAF) technique [2]. Experimental evaluation is performed with the various metrics such as computational complexity, true positive rate and pattern matching accuracy compared to the state-of-the-art methods. Performance analysis is carried out based on following metrics with the help of tables and graph values.

4.1 Impact of computational complexity

Computational complexity is defined as the product of number of eye images collected from the different user and the time required for detecting the gaze patterns. The mathematical formula for computational complexity is measured as,

$$CC = No.of\ eye\ images * time\ (gaze\ pattern\ detection) \quad (16)$$

From (16), the computational complexity (CC) is measured with respect to the number of eye images given as input for gaze pattern detection. It is measured in terms of milliseconds (ms). Lower the computational complexity, more efficient the method is said to be.

Table 1 Tabulation for Computational complexity

No. of eye images	Computational complexity (ms)					
	Syntheseyes dataset			MPII gaze dataset		
	EPSM-DMA	Uncalibrated gaze pattern recovery model	SIAF	EPSM-DMA	Uncalibrated gaze pattern recovery model	SIAF
5	0.25	0.38	0.5	0.28	0.45	0.52
10	0.32	0.42	0.53	0.36	0.46	0.56
15	0.38	0.46	0.57	0.40	0.50	0.60
20	0.44	0.52	0.60	0.47	0.55	0.65
25	0.48	0.63	0.68	0.53	0.65	0.70
30	0.53	0.68	0.75	0.58	0.70	0.78
35	0.59	0.70	0.79	0.63	0.72	0.83
40	0.65	0.76	0.82	0.68	0.80	0.86
45	0.71	0.80	0.88	0.74	0.82	0.92
50	0.73	0.82	0.91	0.76	0.84	0.95

Table 1 describes the analysis of computational complexity with respect to two different data sets namely Syntheseyes dataset and MPII gaze dataset. The computational complexity is measured with respect to number of input images is varied from 5 to 50. While varying the number of eye images, the computational complexity is reduced using proposed EPSM-DMA than the existing methods Uncalibrated gaze pattern recovery model [1] and SIAF technique [2].

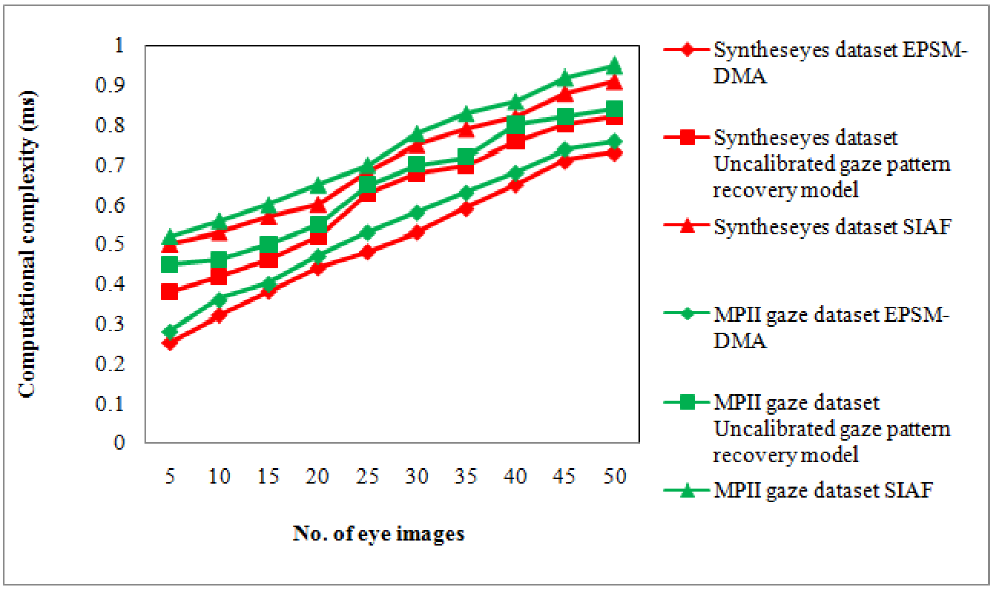

Figure 5 Measure of computational complexity

As shown in figure 5, the computational complexity is measured with respect to number of input eye images with two different dataset namely Syntheseyes dataset and MPII gaze dataset. From the figure, the red color line indicates the computational complexity of the Syntheseyes dataset whereas green color line indicates the computational complexity of the MPII gaze dataset. With the two dataset, the computational complexity is significantly reduced using EPSM-DMA than the existing methods. This is because, Eyelid Phase shift momentum technique is applied in EPSM-DMA. The phase shift angle is measured through the linear phase shift momentum with the product of the center point after eyelid movement and displacement of the eyelid from the origin. Therefore the movement of the eyelid is marked as a point in order to form a gaze pattern. In addition, the eye images are preprocessed for removing the noise and detect the gaze pattern accurately. As a result, the computational complexityduring the gaze pattern detection is reduced. By using the Syntheseyes dataset, computational complexity is significantly reduced by 19% and 29% when compared to existing Uncalibrated gaze pattern recovery model [1] and SIAF technique [2]. The computational complexity is also reduced by 18% and 28% using MPII gaze dataset when compared to existing methods [1] [2] respectively.

4.2Impact of true positive rate

True positive rate is defined as the ratio of the number of eye images are correctly aligned with gaze patterns to the number of eye images. The formula for true positive rate is measured as follows,

$$TPR = \frac{No.of\ Eye\ images\ correctly\ aligned\ with\ gaze\ patterns}{No.of\ eye\ images} * 100 \quad (17)$$

From (17),TPR represents True Positive Rate (TPR). It is measured in terms of percentage (%).

Table 2 Tabulation for true positive rate

No. of eye images	True positive rate (%)					
	Syntheseyes dataset			MPII gaze dataset		
	EPSM-DMA	Uncalibrated gaze pattern recovery model	SIAF	EPSM-DMA	Uncalibrated gaze pattern recovery model	SIAF
5	82.36	63.45	43.21	80.12	61.20	41.10
10	85.10	65.32	46.25	82.45	63.12	43.25
15	86.32	68.47	48.10	84.36	65.47	45.36
20	87.10	71.20	52.36	85.42	68.55	48.69
25	88.13	73.64	55.41	87.15	70.68	50.12
30	90.12	75.95	58.47	88.36	73.12	52.47
35	91.36	78.10	60.12	89.1	75.41	56.78
40	92.75	81.36	65.45	90.23	78.52	62.36
45	93.47	83.25	68.98	92.10	80.14	65.13
50	94.75	85.75	73.21	93.65	83.10	70.46

Table 2 describes the analysis of true positive rate with respect to number of eye images with two different dataset. The number of eye images is varied from 5 to 50 for performing the experiment in order to obtain the exact gaze pattern. The true positive rate of the proposed EPSM-DMA is higher when compared to existing Uncalibrated gaze pattern recovery model [1] and SIAF technique [2].

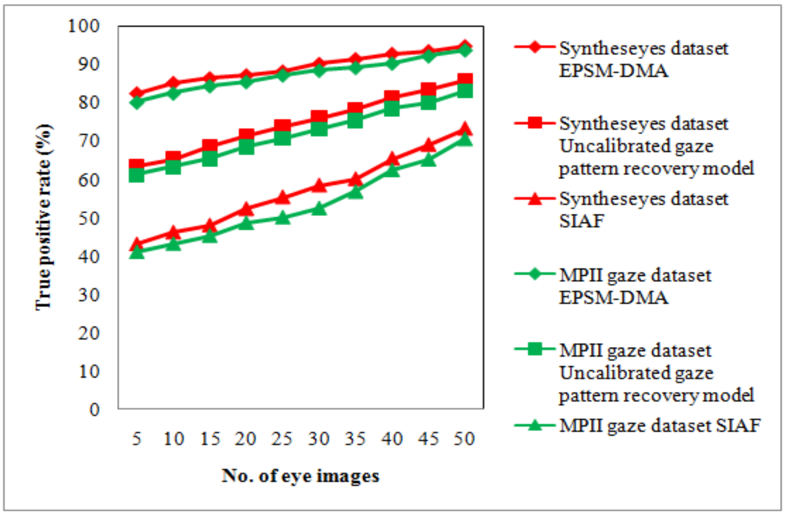

Figure 6 Measure of True positive rate

Figure 6 depicts the true positive rate measurement with respect to number of eye images. The true positive rate is measured with two dataset namely Syntheseyes dataset and MPII gaze dataset. As shown in figure, it is observed that the proposed EPSM-DMA obtains higher true positive rate than the existing methods. The results reported here it confirms that the number of eye images are increased, the true positive rate also increased and comparatively observed to be higher in proposed EPSM-DMA. This is because; Difference Map Algorithm (DMA) is applied in EPSM-DMA to align the eye along with the nature of the gaze pattern. This algorithm is used to discover the global optimal point for gaze pattern matching. The intersection problem in the alignment process is also solved by using Difference Map Algorithm. In addition, the closet distances between nearest points are selected to align the eye images based on the Euclidean distance. If the distances between the points are less than the threshold value, then the points are selected to form a gaze pattern. Otherwise, the points are not selected for gaze pattern estimation. Finally, the eye images are aligned correctly with the estimated gaze patterns. Therefore, this helps to increase the true positive rate. The true positive rate of EPSM-DMA using syntheseyes dataset is increased by 20% and 59% compared to existing Uncalibrated gaze pattern recovery model [1] and SIAF technique [2]. By using MPII gaze dataset, the true positive rate is considerably improved by 22% and 67% when compared to existing methods [1] and [2] respectively.

4.3 Impact of pattern matching accuracy

Pattern matching accuracy is defined as the ratio of the number of (no. of) gaze patterns in eye images are correctly matched with the ground truth patterns to the total number of eye images. The Pattern matching accuracy is defined as follows,

$$PMA = \frac{No.of\ patterns\ \ in\ eye\ images\ \ are\ Correctly\ \ matc\,hed}{No.of\ \ eye\ \ images} *100 \qquad (18)$$

From (18),PMA represents a Pattern matching accuracy and it is measured in terms of percentage (%). Let us Consider 5 input eye images. The number of gaze patterns in those images is correctly matched with ground truth patterns.

Table 3 Tabulation for pattern matching accuracy

No. of eye images	Pattern matching accuracy(%)					
	Syntheseyes dataset			MPII gaze dataset		
	EPSM-DMA	Uncalibrated gaze pattern recovery model	SIAF	EPSM-DMA	Uncalibrated gaze pattern recovery model	SIAF
5	84.12	65.68	45.12	83.12	63.47	43.12
10	86.32	68.12	47.54	85.46	65.36	45.85
15	87.36	70.12	52.65	86.47	68.97	50.12
20	88.12	72.36	58.69	87.36	70.47	56.74
25	89.45	74.52	62.35	88.43	72.48	60.1
30	90.16	76.46	65.47	89.35	74.76	62.89
35	92.36	80.12	69.78	90.12	76.17	65.79
40	94.78	82.1	73.2	92.45	80.64	70.12
45	95.64	83.47	75.98	94.65	81.69	72.48
50	97.54	85.69	80.1	95.47	82.48	77.55

Table 3 clearly shows that the pattern matching accuracy with respect to number of eye images taken from the two different dataset. The recovered gaze patterns are correctly matched with the ground truth patterns in order to obtain the higher accuracy. The proposed EPSM-DMA improves the pattern matching accuracy when compared to existing methods Uncalibrated gaze pattern recovery model [1] and SIAF technique [2].

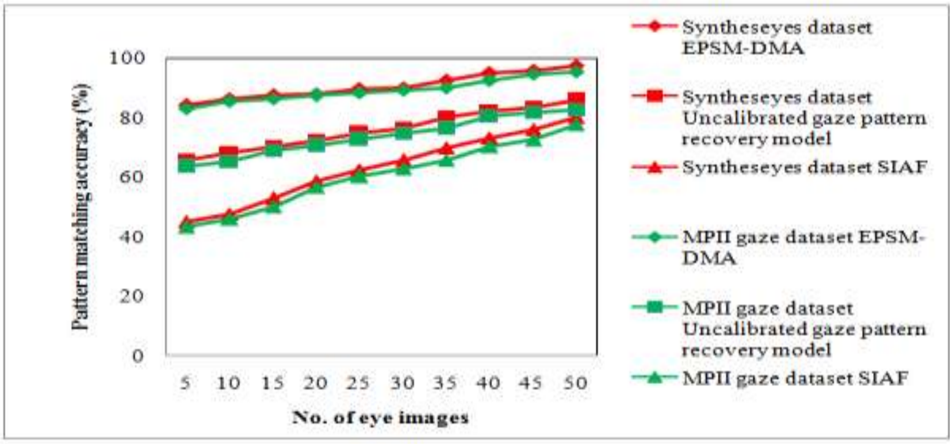

Figure 7 Measure of Pattern matching accuracy

Figure 7 depicts the pattern matching accuracy based on the number of eye images taken from two dataset namely Syntheseyes dataset and MPII gaze dataset. While increasing the number of input eye images, the pattern matching accuracy gets increased in all the methods with two different datasets. But comparatively, the EPSM-DMA increases the accuracy of the pattern matching with the help of Bayes' theorem measured. It provides the two probability results to perform efficient gaze pattern estimation. For each recovered patterns from the gaze pattern analysis, the Bayes' theorem is used for matching the resultant patterns with the ground truth patterns. Then it provides the probability value is 1 then the patterns are accurately matched otherwise the patterns are not matched with the ground truth pattern. Therefore, the EPSM-DMA improves the pattern matching accuracy. The accuracy of pattern matching is increased by 20% and 47% compared to existing Uncalibrated gaze pattern recovery model [1] and SIAF technique [2] respectively using Syntheseyes dataset. By applying MPII gaze dataset, pattern matching accuracy is increased by 22% and 52% compared to existing methods [1] [2].

V. Related Works

A real-time gaze estimation system was introduced in [11] using a webcam but it failed to focus on gaze estimation with large head pose dissimilarity. The proposed EPSM-DMA improves the accuracy of gaze estimation with different pose images through the pattern matching process.

A Bayesian filtering method was introduced in [12] using the information from camera-based driver monitoring systems for determining the possibility that the driver gaze in the different zones. However, the mappings in gaze estimation were used in limited set of data. The EPSM-DMA performs efficient mapping through the difference map algorithm with large set of data.

An eye-model-based approach was developed in [13] for gaze estimation using color information about the eyeball and iris centers. But it failed to use an appearance-based approach. The EPSM-DMA uses appearance based approach to improve the gaze pattern estimation.

An appearance-based gaze estimation technique was presented in [14] for digital signage and also achieved correct focus-point gaze estimation. But it failed to perform eye image alignment during the gaze estimation. The proposed EPSM-DMA performs efficient alignment using Difference Map Algorithm.

A novel gaze-tracking technique was developed in [15] for archiving higher performance of a gaze-tracking system using a large screen at a distance. However, the technique was not used in different environments like gaze detection. The proposed EPSM-DMA performs efficient gaze estimation through the analysis of the gaze pattern detection using eyelid phase shift momentum technique.

Gazing point dependent eye gazing estimation method was introduced in [16] but it more difficult to find the correlation between the pupil center and the real plane. The EPSM-DMA performs efficient gaze estimation through the eyelid phase shift momentum.

A gaze tracking system was designed in [17] with near-infrared (NIR) camera using fuzzy system in accordance with the user calibration information. However, estimation of gaze patterns was not performed. The EPSM-DMA obtains higher gaze pattern estimation accuracy by performing the pattern matching.

In [18], a Gaze Analysis Technique, namely GANT was introduced using graph-based illustration of fixation points attained by an eye tracker during human computer interaction. However, it does not use multiple features like iris and face, using a multi-view camera for acquisition. Therefore, the EPSM-DMA effectively performs gaze pattern through the eyelid movement.

Agaze-based Relevance Feedback(RF) method was designed in [19] for region-based image retrieval. But, the matching was not performed for recognizing the gaze patterns. The proposed EPSM-DMA obtains higher pattern matching accuracy for gaze pattern estimation.

An integration of head pose tracking and eye gaze tracking was introduced in [20] for obtaining the large collection of tracking. However, it failed to providegaze estimation results with very high accuracy and it was not sufficient for visual performance. The EPSM-DMA gaze pattern estimation improves the visual performance result through higher pattern matching accuracy.

As a result, the proposed Eyelid Phase shift Momentum based Difference Mapping Algorithm (EPSM-DMA) improves the gaze pattern estimation through less computational complexity, higher matching accuracy and true positive rate.

VI. Conclusion

An efficient Eyelid Phase shift Momentum based Difference Map Algorithm (EPSM-DMA) is developed to perform gaze pattern estimation. The input eye images are taken from dataset to perform gaze estimation. The EPSM-DMAtechnique consists of three processing steps. Initially, eyelid phase shift momentum technique is applied to detect the gaze pattern by the movement of the eyelid. After that, the eye images are aligned based on the detected point using Difference Map algorithm. This algorithm also used to avoid the point intersection problem in Euclidean space. Then the Euclidean distance is measured between the two closet points toalign a gaze patterns. Finally, the obtained gaze patterns are matched with the ground truth patterns using Bayes'theorem. It provides the probability result for pattern matching to identify the human visual attention. Experimental evaluation is performed with two different dataset namely Syntheseyes dataset and MPII gaze dataset. The performance result shows that the proposed EPSM-DMA considerably improves the pattern matching accuracy, true positive rate and also reduces the computational complexity than the state-of-the-art methods.

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IOSR Journal of Computer Engineering (IOSR-JCE) is UGC approved Journal with Sl. No. 5019, Journal no. 49102.

K. Rathi. " Eyelid Phase Shift and Difference Map Algorithmfor Gaze Pattern Estimation." IOSR Journal of Computer Engineering (IOSR-JCE), vol. 19, no. 4, 2017, pp. 64–74.