

Quantum Shift Based Gaze Pattern Recognition Using Recurrent Neural Machine Learning Technique

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ABSTRACT: Gaze pattern recognition is the technique for detecting what and where the human eyes are pointing in a predefined plane. It is important for predicting human attention and also used to recognize human activities along with interactive systems. Several techniques are introduced in the field of human vision identification with a number of patterns. These methods achieve fewer eyes tracking quality and it takes more time complexity (TC) for recognition. A new technique called Quantum Shift Based Recurrent Neural Machine Learning (QS-RNML) technique is developed for efficient gaze pattern recognition with minimum time. At first, the number of eye images is taken from the Dataset (DS). QS-RNML technique includes three processes namely preprocessing, gaze estimation and pattern recognition. The Adaptive median filter is employed in preprocessing of eye images for removing the noise artifacts from eye images. In gaze estimation process, Quantum Shift is applied to estimate the patterns by movement of the eyelid in gaze plane. After that, Recurrent Neural Machine Learning technique is used for recognizing the gaze patterns by matching the estimated patterns with the ground truth patterns. The proposed QS-RNML technique is simple and efficient for identifying the human visual attention, emotion, feelings and so on. Simulation results of proposed QS-RNML technique are carried out using Synthes eyes DS and MPII gaze DS. The results evident that QS-RNML technique improves gaze pattern recognition accuracy (GPRA), true positive rate (TPR) and lessens the TC as well as false positive rate(FPR).

Keywords: Gaze pattern estimation, Quantum Shift, gaze plane, Recurrent Neural Machine learning technique, Gaze pattern recognition,

1.INTRODUCTION

Eye gaze estimation is a process to locate the human eye point for recognizing a person's visual attention. It is a significant task in computer vision and has several applications such as human-computer interaction, human behavior analysis and so on. There are several techniques has been developed for eye gaze pattern estimation in gaze plane. Uncalibrated Gaze Pattern Recovery model was introduced in [I] for gaze estimation with different eye images of the person. This model was not efficient to perform gaze recognition with less complexity. An auto-calibrated gaze estimation method was designed in [II] through gaze patterns. The estimation method failed to perform eye image preprocessing for improving the image quality. A convolutional neural network (CNN) was introduced in [III, VII] based on pupil center detection approach for gaze estimation with infrared eye images. The CNN failed to perform pattern matching for gaze pattern recognition. Minimum redundancy maximum relevance (MRMR) and support vector machine was developed in [IV] for activity recognition through eye movement analysis. The method failed to improve the recognition accuracy.

Support Vector Machine-based recognition approach with discriminative action features was determined in [V] from recorded human gaze patterns. The approach has less recognition accuracy with more time consumption. A novel Gaze Analysis Technique (GANT) was developed in [VI] which contain fixation point series collected from the human eye movements. The GANT technique failed to perform the eye alignment for improving the recognition. In [VIII], a gazing point dependent eye gazing estimation technique was introduced to calculate the location of the gaze point. These gaze points were not aligned to perform accurate pattern matching. A Gabor Directional Binary Pattern (GDBP) image descriptor was developed in [IX] for efficient gaze assessment using Support Vector Regression (SVR). The descriptor achieves minimum eye tracking quality. An adaptive linear regression (ALR) technique was designed in [X] for individual gaze estimation from the eye appearance. The technique has high TC since it contains more training samples.

Appearance-based gaze estimation was introduced in [XI] with neighbor regression achieves efficient performance within subject and cross-subject gaze estimation. The neighbor selection method was not performed the

preprocessing before gaze pattern estimation. The certain issues are identified from the above said literatures such as lack of gaze recognition accuracy, high complexity, failure to improve image quality, lack of accurate pattern matching and so on. In order to address the problem of existing methods, a new technique called QS-RNML is developed.

The major contribution of the QS-RNML technique is described as follows

- ❖ The QS-RNML technique contains three major contributions. At first, the eye image preprocessing is done by using an adaptive median filter for removing the noisy pixel from the image to improve the image quality. Secondly, the phase shift of the eyelid is estimated using quantum approach with the help of qubits. This helps to reduce the TC in gaze pattern recognition.
- ❖ Finally, Recurrent Neural Machine Learning to recognize the gaze pattern with high accuracy. The estimated points are selected based on the activation function results to form a gaze pattern for pattern matching. The output unit performs pattern matching with the estimated patterns and ground truth patterns using SoftMax function. This helps to improve the gaze patterns recognition and reduce false positive rate.

The rest of the papers are arranged in the following manner. Section 2 discusses the related works. Section 3 provides the brief description of the QS-RNML technique with neat diagram. Experimental evaluation of proposed and existing state-of-art methods are described in section 4. Section 5 provides the results and discussion of certain parameters with table and graphical representation. Finally, the conclusion of the research work is described in Section 6.

2. RELATED WORKS

A low-computational technique for gaze pattern assessment was developed in [XII] with the help of eye touch system. The complexity of the gaze patterns estimation remained unaddressed. A hybrid technique was introduced in [XIII] to incorporate the location knowledge of head pose and eye position for improving the gaze estimation. The technique failed to perform the pattern matching. An active Shape Models (ASM) and Active Appearance Models (AAM) were developed in [XIV] to segment the facial features for gaze estimation. The models were not effectively aligned the eye image patterns for human vision recognition. In [XV], an accurate gaze estimation approach was introduced with slight head movements. The approach failed to achieve high precision in gaze estimation. The Bayesian multinomial logistic regression was introduced in [XVI] to create a gaze mapping function for eye-gaze estimation under the slight movement of the head. The method failed to enhance the depth estimation of eye gaze.

An implicit calibration approach for 3D model-based gaze estimation was introduced in [XVII] with high estimation accuracy. The calibration approach attains high gaze estimation error during eye tracking. An effective cascade regression scheme was developed in [XVIII] for localizing the eye and eye state estimation. The regression scheme was not focused the eye tracking and gaze estimation. A weighted least squareregression-based approach was designed in [XIX] for achieving high gaze estimation accuracy with less user attempts. The approach failed to perform eye tracking against the different illuminations. A Layered Hidden Markov Models (LHMM) was developed in [XX] for human activity recognition through the movement of eye gaze. The LHMM model was not obtaining high recognition accuracy. A novel probabilistic eye gaze tracking system was introduced in [XXI] without any individual calibration. The TC was remained unsolved during gaze pattern estimation. The issues and challenges are overcome by the above-said methods, the QS-RNML technique is presented in next sections.

3. QUANTUM SHIFT BASED RECURRENT NEURAL MACHINE LEARNING TECHNIQUE FOR GAZE PATTERN ESTIMATION AND RECOGNITION

The human visual attention is identified through eye gaze that plays a vital indication for vision-based intelligent systems. In order to improve the eye gaze pattern estimation and recognition, an efficient technique called QS-RNML is developed. The movement of the eyelid is pointed out to measure the various angle in gaze plane. By applying a quantum approach, the phase shift of the eyelid is measured for estimating the various gaze patterns. Followed by, the estimated gaze patterns are recognized. The block diagram of QS-RNML technique is shown in Figure 1.

Figure 1 shows the block diagram of QS-RNML technique. The proposed technique divided into three stages [XXII] such as preprocessing, gaze pattern estimation and gaze patterns recognition. Input eye images are taken from image DS to perform gaze estimation. At first, the preprocessing is carried out to remove the noise and unnecessary distortions present in an image for further processing. This is done by applying the adaptive median filtering

technique. Secondly, the gaze estimation is done using quantum shift through the movement of the eyelid in gaze plane. Finally, the gaze patterns are recognized by performing the pattern matching. These three different processes are explained in the following subsections.

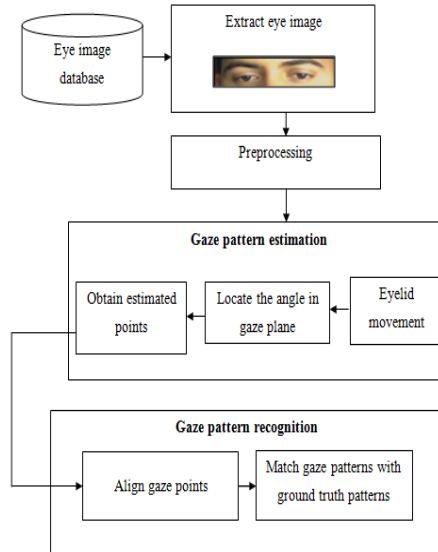


Figure 1 Block diagram of QS-RNML technique

3.1 Adaptive Median Filtering Based Image Preprocessing

Preprocessing of eye images involves in removing the noise in the image and normalizing the intensity of the individual eye images taken from the DS before gaze estimation process. The QS-RNML technique removes the noisy pixel in an eye image using adaptive median filtering approach. The adaptive median filter changes each entry with the center value of its neighboring pixel. Neighboring pixel patterns are also known as windows. Let us consider the number of input eye images $I_i = I_1, I_2, \dots, I_n$, taken from the DS. The adaptive median filter contains each pixel in an eye image and its neighboring pixels. Then the median values of these pixels is estimated by arranging the pixels in ascending order and take the median value for changing the center pixel. If any two neighborhood pixels in the order, then the average value of these two pixels is considered as center value. The mathematical formula for adaptive median filters are explained as follows,

$$y = M \{a_{ij}\} \quad (1)$$

From above equation (1) y' denotes an output of the adaptive median filter and M denotes a median filter, a_{ij} denotes a row and columns value of the 3x3 window. The 3x3 window is show in figure 2.

a_0	a_1	a_2
a_3	a_{ij}	a_5
a_6	a_7	a_8

Figure 2 3x3 window

As shown in the figure, the central pixel value of 3x3 windows a_{ij} is replaced with the median values of all the pixel value $a_1, a_2, a_3, \dots, a_8$. The median process is applied in the entire pixel to recognize the level of noise and accordingly the median value changes the noisy pixels in the window. This helps to the proposed QS-RNML technique for improving the image quality for further processing.

3.2 Quantum Shift Based Eye Gaze Pattern Estimation

After image preprocessing, the different gaze patterns are estimated using quantum phase shift. The eyelid covers the eye when it closed. The upper eyelid moves freely, but the lower eyelid has less freedom to move around the gaze plane. The movements of the eyelids are used to points the angle in gaze plane. The Quantum approach is used for locating the angle by the movement of the eyelid in the form of quantum states, or qubits. The qubit is also known as basis states. Generally, two types of qubits are presented in quantum approach namely vertical polarization and horizontal polarization which is denoted as $|0\rangle$ and $|1\rangle$. Therefore, a qubit is represented as a linear

combination of $|0\rangle$ and $|1\rangle$. Eyelid rotational along a particular axis is measured using these quantum bits (i.e. qubits).

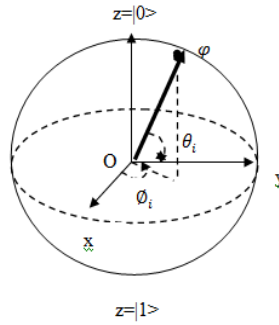


Figure 3 spherical representations of qubits

Figure 3 shows the spherical representations of qubits $|0\rangle$ and $|1\rangle$ with three different gaze directions x , y and z . ‘O’ denotes an origin and ‘ φ ’ is the point which is referred to as a phase shift from an origin. This phase shift is identified after the movement of eyelid in gaze plane. The gaze position is obtained through the known point on the gaze plane. φ_i and θ_i denotes two different angles used for measuring the linear combination of the qubits. The linear combination of the qubits is represented as follows,

$$\varphi = a|0\rangle + b|1\rangle \quad (2)$$

From (2), a and b denotes a probability amplitude which is expressed in the trigonometric functions as follows,

$$a = \cos \cos\left(\frac{\theta_i}{2}\right) \quad (3)$$

$$b = e^{i\varphi_i} \sin \sin\left(\frac{\theta_i}{2}\right) \quad (4)$$

Based on the above equations (3) (4), the different angles of the eyelid is identified through the eyelid phase shift from the zero phases. Figure 4 shows the estimation of gaze patterns using quantum phase shift. By using quantum shift, the position of the eyelid from the zero phase is identified. Similarly, all the points are marked in a gaze plane. As a result, the different points are arrived based on the movement of the eyelid. This helps to recognize the gaze patterns with minimum time.

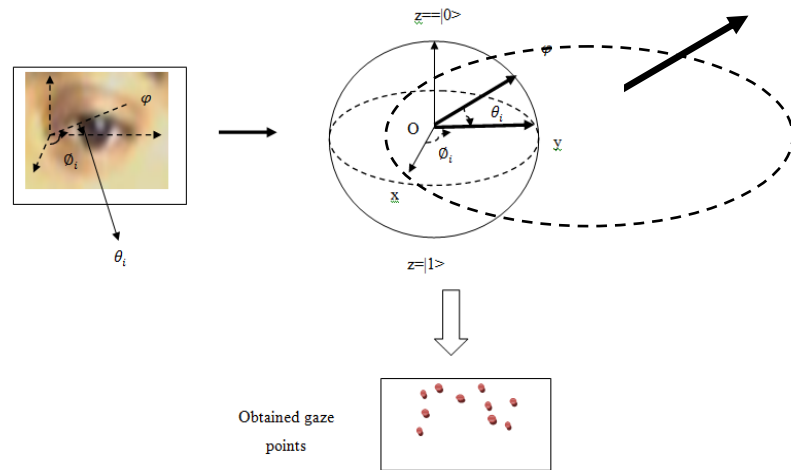


Figure 4 Quantum shift based gaze pattern estimation

3.3 Recurrent Neural Machine Learning Based Gaze Pattern Recognition

After estimating the gaze points using quantum shift, then these points are arranged in a gaze plane to recognize the gaze patterns. The gaze pattern recognition is carried out using Recurrent Neural Machine Learning (RNML) technique. In RNML technique, the neurons like nodes are interconnected with another layer to form a network. If the link between two nodes is strong, the RNML provides efficient result in gaze pattern recognition. The RNML

technique contains three different units namely input, hidden and output unit. The input unit receives the estimated gaze points. The hidden unit processing the gaze points recurrently from the input unit and output unit attains the processing results. Hence, the name is called as Recurrent Neural Machine Learning. The output unit is used for displaying the gaze pattern recognition results. The process of RNML technique is shown in figure 5.

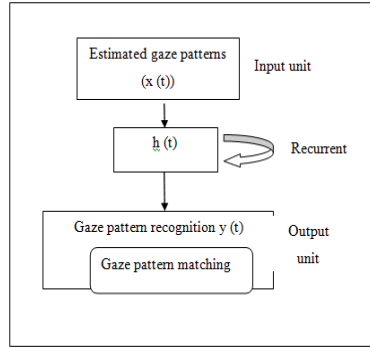


Figure 5 Process of recurrent neural machine learning technique

Figure 5 shows the process of recurrent neural machine learning technique which includes three units. The RNML technique includes the number of estimated gaze patterns in input units. In the hidden unit, the input estimated points are aligned and perform the matching process. The input estimated patterns have set of points $p_1, p_2, p_3 \dots, p_n$ to form a gaze patterns. As shown in figure 5, h_i denotes a hidden state at the time 't'. At each time stamp, the recurrent process in the hidden unit is measured as follows, $h(t) = \alpha (w_{ih} x(t) + w_r h(t-1))$ (5)

From (5), $h(t)$ denotes an output of the hidden state at the time stamp 't' and previous hidden state $h(t-1)$. ' α ' represent activation function that provides the outcomes depending on input. $x(t)$ denotes a estimated gaze patterns (i.e. input). w_{ih} represents a weight between input unit and hidden unit. w_r denotes a recurrent weight between the hidden layers at adjacent time stamps. In RNML technique, the activation function (α) is used as a tanh function which is normalized from -1 to 1. Hence, the above equation (5) is modified as follows,

$$h(t) = \tanh (w_{ih} * x(t) + w_r * h(t-1)) \quad (6)$$

Based on the activation result, the points which are close to the eye patterns are selected from the estimated gaze patterns. This process is continually carried out to select the point for recognizing the gaze patterns.

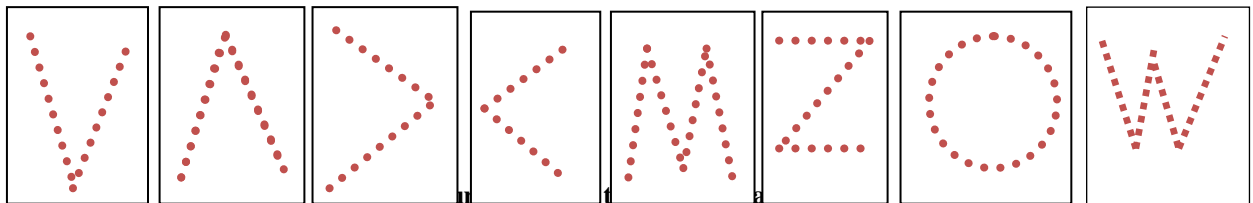
$$\alpha = \{+1, \text{ point selected } -1, \text{ point not selected } \} \quad (7)$$

From (7), α indicates an activation function, the estimated points are form a shape of gaze patterns with the two results such as +1 and -1. The result '+1' represents the point is chosen. Or else the point is not chosen to outline the structure of gaze patterns. Then a result of the hidden units is transformed into output units. The output processing unit at time stamp 't' is measured to match the patterns with the already stored ground truth patterns. The output unit performs the matching process of recovered gaze pattern with already stored patterns. The output of the recurrent neural machine learning technique is expressed as follows,

$$y(t) = \sigma \{h(t) * w_{oh}\} \quad (8)$$

From (8), $y(t)$ denotes an output of recurrent neural machine learning technique, σ denotes softmax function used in the final units, w_{oh} denotes a weight between hidden and output units. In RNML technique, a softmax function is a normalized exponential function that is used for pattern matching. softmax function matches the estimated gaze patterns with different class of truth patterns which is available in [1]. The matching process using softmax function is defined as follows,

$$\sigma \rightarrow P(y(t) = t_j | p_i) = \frac{\exp(\exp(p_i))}{\sum_{j=1}^k \exp(\exp(p_j))} \quad (9)$$



From (9), softmax function compute the probability that this estimated gaze patterns in hidden units p_i is belongs to the class of ground truth pattern t_j . The various truth gaze patterns are shown in Figure 6. Figure 6 shows the ground truth patterns. With the help of the quantum shift, the newly estimated patterns are shown at last to perform the matching process. The estimated gaze patterns with the ground truth patterns are matched based on the probability outcomes. The patterns are matched, when the probability outcome is 1. Or else, the patterns are not matched. The matched patterns are employed to recognize the human vision. This process is repeated for all the input eye images. The algorithmic process of QS-RNML is described as follows,

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Input: Number of eye images  $I_1, I_2, I_3, \dots, I_n$ 
Output: Recognize the gaze patterns
Begin
1. for each eye image  $I_i \in D$ 
2.   Remove noise in an  $I_i$  by applying  $y = M \{a_{ij}\}$ 
3.   Estimate eyelid phase shift ' $\varphi$ ' from origin 'O'
4.   Hidden state at the time stamp ' $t$ '  $\rightarrow h(t)$ 
5.   if  $(\alpha = +1)$  then
6.     point is selected
7.   else
8.     point is not selected
9.   end if
10.  for each gaze patterns  $p_i$ 
11.    Compute the probability  $P(y(t) = t_j | p_i)$ 
12.    if  $P(y(t) = t_j | p_i) = 1$  then
13.       $p_i$  matched to truth patterns  $t_j$ 
14.    else
15.       $p_i$  not matched to truth patterns  $t_j$ 
16.    end if
17.  end for
18. end for

```

Algorithm 1 Quantum Shift Based Recurrent Neural Machine Learning

Algorithm 1 describes the QS-RNML to recognize the gaze pattern with minimum time. For each input eye image, the preprocessing is done with the help of adaptive median filter to remove the noise pixels in an image. After that, the eyelid movement is measured in terms of an angle using quantum phase shift. As a result, the phase shift of the eyelid from the origin is measured and obtained the patterns. These estimated patterns are given the input of the recurrent neural machine learning technique. The input unit has a set of points in the form of gaze patterns. Then these points are transformed into a hidden unit for aligning the eye image points to form patterns. Based on the activation function results in hidden unit, the points are selected to form a gaze patterns. With the obtained gaze patterns is given to output unit for pattern matching. In output unit, the softmax function is employed to match the estimated gaze patterns with the ground truth patterns based on probability results. This helps to improve the gaze patterns recognition.

4. EXPERIMENTAL EVALUATION

The performance of QS-RNML technique is evaluated with the experimental setup and the data. Experimental evaluation of QS-RNML technique is implemented using MATLAB with two different eye image DSs namely syntheses Eyes DS and MPII gaze DS. The SynthesEyesDS(<https://www.cl.cam.ac.uk/research/rainbow/projects/syntheseeyes/>) consists of 11,382 synthesized close-up images of eyes. For the experimental consideration, totally 50 eye images are taken as input for gaze pattern estimation and recognition. The other DS is MPII gaze dataset which is taken from(<https://www.mpi-inf.mpg.de/de/abteilungen/computer-vision-and-multimodal-computing/research/gaze-based-human-computer-interaction/appearance-based-gaze-estimation-in-the-wild-mpiigaze/>). This DS contains 213,659 images taken from 15 different participants. The number of eye images is gathered and ranges from 34,745 to 1,498. Eye images include dissimilar mean grey-scale intensities within face region gathered for every participant. Result analysis is conducted with TPR, GPRA, TC, FPR with respect to a number of eye images.

5. RESULTS AND DISCUSSIONS

Results and discussion of three different methods are QS-RNML technique and existing Uncalibrated gaze pattern recovery model [I] and Auto-Calibrated Gaze Estimation method [II] are clearly described in this section. The various parameters are used such as TPR, GPRA, TC and FPR with two different DSs namely syntheses eyes DS and MPII gaze DS for measuring the performance of three different methods. Performance analysis is carried out using above said metrics to show the effectiveness of the proposed QS-RNML technique than the existing methods.

5.1 Impact of True Positive Rate

TPR is measured as the ratio of number of eye images are correctly aligned with estimated gaze patterns to number of eye images. TPR is expressed as below,

$$TPR = \frac{\text{No.of eye images are correctly aligned with estimated gaze patterns}}{n} * 100 \quad (10)$$

From (10), TPR represents True Positive Rate (TPR) and 'n' denotes a number of eye images. It is measured in terms of percentage (%).

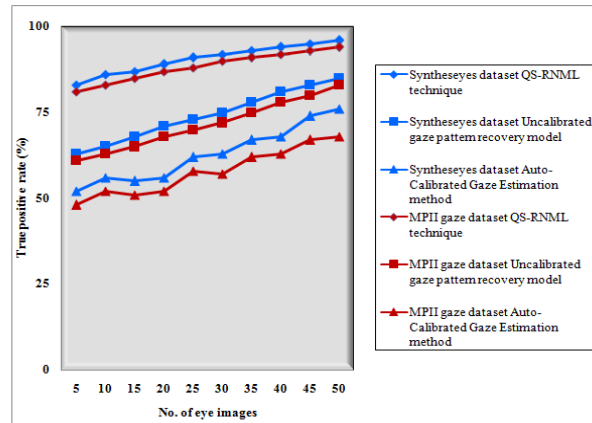


Figure 7 Performance results of true positive rate

Figure 7 illustrates performance results of TPR versus a number of input eye images. As shown in figure 7, the number of images is taken as input in 'x' direction whereas the output of TPR in 'y' direction. For the experimental consideration, the numbers of eye images taken from 5 to 50. The two colors indicate the TPR of two different DSs. The blue color curve indicates the performance of TPR using syntheses eyes DS and brown color curve indicates the performance of TPR using MPII gaze DS. By using two different DSs, the above graphical results clearly illustrates that the true positive results of proposed QS-RNML technique is improved than the existing uncalibrated gaze pattern recovery model [I] and auto-calibrated gaze estimation method [II]. This is because, the proposed QS-RNML technique effectively uses recurrent neural machine learning technique in which the gaze points are aligned to form a gaze patterns. The input unit in RNML technique has a set of estimated points. The hidden unit has an activation function which repeatedly verifies the estimated gaze points a different time interval. An activation function provides two different outcomes. Based on the activation function results, the eye images are correctly aligned. This helps to perform efficient pattern matching.

Let us consider the number of input eye images is 5 from syntheses eyes DS, the TPR of the proposed QS-RNML technique is 83% whereas the TPR of existing uncalibrated gaze pattern recovery model [I] and auto-calibrated gaze estimation method [II] is 63% and 52%. Similarly, nine different runs are carried out and calculate the average comparison results of proposed and existing methods. The average results of TPR are 23% and 45% when compared to uncalibrated gaze pattern recovery model [I] and auto-calibrated gaze estimation method [II]. By applying MPII gaze DS and the number of input eye images are 5, then the TPR of proposed QS-RNML technique is 81% and 61% and 48% using uncalibrated gaze pattern recovery model [I] and auto-calibrated gaze estimation method [II]. After performing the remaining nine runs, the comparison between proposed and existing are carried out. The comparison results show that the proposed QS-RNML technique is considerably increased the performance of TPR by 24% and 54% than the state-of-the-art methods.

5.2 Impact of Gaze Pattern Recognition Accuracy

GPRA is defined as the number of gaze patterns are recognized by performing the pattern matching with the ground truth patterns. The GPRA is measured as follows,

$$GPRA = \frac{\text{No.of gaze patterns of eye images are recognized}}{n} * 100 \quad (11)$$

From (11), *GPRA* denotes Gaze pattern recognition accuracy and it is measured in terms of percentage (%). The performances of GPRA with respect to number of eye images are shown in Table 1.

Table 1 describes the performance results of GPRA with respect to a number of eye images. These eye images are taken from two different DSs. By using two different DSs, the performance result of GPRA of proposed QS-RNML technique is increased than the two existing methods. The above table clearly illustrates the various runs of GPRA results. This improvement of proposed QS-RNML technique is obtained by performing two different processes namely pattern estimation and recognition. The gaze points are estimated by applying quantum shift. The shifting position of the eyelid from the origin is measured in the form of points. These points are fed into the input of the recurrent neural machine learning technique.

Table 1 Tabulation for Gaze pattern recognition accuracy

No. of eye images	Gaze pattern recognition accuracy (%)					
	Syntheseyes dataset			MPII gaze dataset		
	QS-RNML technique	Uncalibrated gaze pattern recovery model	Auto-Calibrated Gaze Estimation method	QS-RNML technique	Uncalibrated gaze pattern recovery model	Auto-Calibrated Gaze Estimation method
5	82	63	45	80	60	41
10	84	64	48	82	61	43
15	87	68	52	85	63	48
20	89	69	53	87	64	49
25	90	73	54	88	69	50
30	93	74	57	91	70	53
35	94	78	62	92	72	54
40	95	81	63	93	73	58
45	96	83	68	94	78	63
50	98	85	73	96	80	69

The hidden unit performs the eye alignment with the estimated gaze points based on activation function. The estimated patterns are transformed into output unit of RNML technique. The output unit has softmax function to match the estimated gaze patterns with already stored ground truth patterns. The matching probability results improve the GPRA. Let us consider the syntheseyes DS with a number of eye images is 5, the GPRA is significantly improved by 82% using QS-RNML technique. GPRA is enhanced by 63% and 45% using existing [I] and [II]. Followed by, the nine different runs are carried out with different input images. After performing the ten runs, the performance result of the proposed method is compared with existing methods. Finally, the GPRA using QS-RNML technique is increased by 24% and 60% as compared to existing [I] and [II].

Let us consider the MPII gaze DS and number of images is 5, GPRA of QS-RNML technique is 80% whereas GPRA of existing [I] and [II] are 60% and 41%. The GPRA of QS-RNML technique is enhanced by 29% and 71% as compared to existing [I] and [II].

5.3 Impact of Time Complexity

TC is measured as the amount of time consumed to recognize gaze patterns with number of input eye images. The TC is calculated using following mathematical formula,

$$TC = n * T \text{ (gaze pattern recognition)} \tag{12}$$

From (12), *TC* represents time complexity and 'n' denotes the number of eye images, T denotes a time. TC is calculated in milliseconds (ms). The performance results of TC with three different methods are clearly illustrated in Figure 8. Figure 8 depicts the performance results of TC with respect to a number of eye images. For the experimental purposes, the number of eye images taken from the two DS is varied from 5 to 50. The performance results of TC using syntheseyes DS indicate in blue color curve. The TC results of three different methods using MPII gaze DS indicate a brown color curve. With the application of two different DS, the TC of proposed QS-RNML technique is considerably reduced in gaze pattern recognition. The input eye images are taken from the image DS and perform the preprocessing using adaptive median filtering technique to improve image quality. After performing the preprocessing, the gaze patterns are estimated by movement of the eyelid in gaze plane. The eyelid phase shift is measured in terms of different angles. As a result, the various patterns are obtained.

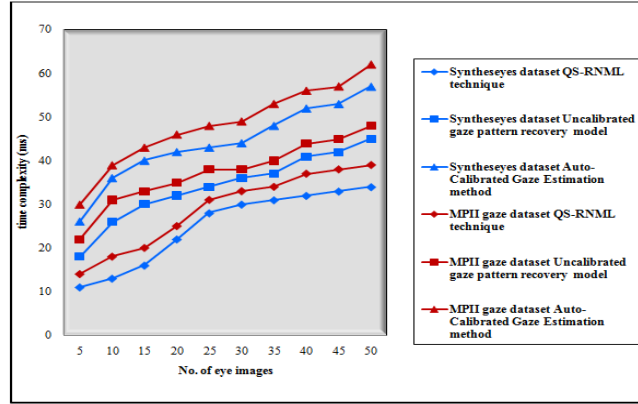


Figure 8 Performance results of time complexity

The RNML technique receives the estimated points in the form of patterns and removes the certain points to form a gaze patterns. The estimated gaze patterns are matched in the output unit to obtain the recognition results with minimum time. Let us consider the number of input eye images is 5, the TC of proposed QS-RNML technique is 11ms and 18ms, 26ms using existing uncalibrated gaze pattern recovery model [I] and auto-calibrated gaze estimation method [II]. Therefore, the comparison results of QS-RNML technique are considerably reduced by 29% and 45% using syntheseyes DS when compared to two existing methods. While considering the MPII gaze DS, the TC of proposed QS-RNML technique is 14ms and 22ms, 30ms is obtained by using two existing methods. The QS-RNML technique lessens the TC by 24% and 41% as compared to existing [I] and [II].

5.4 Impact of False Positive Rate

FPR is measured as the ratio of number of gaze patterns of eye images are inaccurately matched with ground truth patterns to total number of eye images. FPR is calculated as below,

$$FPR = \frac{\text{Number of gaze patterns of eye images are incorrectly matched}}{n} * 100 \quad (13)$$

From (13), FPR denotes a false positive rate and ‘n’ denotes the number of eye images taken for experimental evaluations. It is measured in terms of percentage (%).

Table 2 Tabulation for false positive rate

No. of eye images	False positive rate (%)					
	Syntheseyes dataset			MPII gaze dataset		
	QS-RNML technique	Uncalibrated gaze pattern recovery model	Auto-Calibrated Gaze Estimation method	QS-RNML technique	Uncalibrated gaze pattern recovery model	Auto-Calibrated Gaze Estimation method
5	21	39	58	24	42	60
10	23	42	59	25	45	63
15	24	43	62	28	46	65
20	28	47	63	31	53	66
25	33	51	65	36	54	68
30	35	53	69	38	58	71
35	36	54	70	39	59	73
40	39	57	72	42	61	74
45	40	58	73	43	63	75
50	43	61	75	46	65	78

Table 2 illustrates the FPR with number of eye images in the range of 5 to 50 taken from two DS. Let us consider the number of eye images as 5, the five different gaze patterns are obtained. Table 2 clearly evident that FPR of QS-RNML technique is minimized with the help of Syntheseyes DS and MPII gaze DS as compared to existing [I] and [II]. The FPR is the number of estimated patterns is incorrectly matched with the ground truth patterns. By applying the RNML technique, the pattern matching is carried out in the output unit. This is because of the estimated patterns from the hidden unit are matched with the available patterns to improve recognition accuracy. The pattern matching is done by applying the softmax function which results probability outcomes. The probability outcomes ‘1’ provides the estimated patterns are correctly matched with ground truth patterns. This in turn minimizes the incorrect pattern matching. With Syntheseyes DS, the FPR of QS-RNML technique is reduced by 37% and 52% as compared to existing [I] and [II] . In addition, the performance of FPR of QS-RNML technique using MPII gaze DS is reduced by 36% and 50% when compared to two state-of-the-art methods.

The above discussion results clearly illustrate that the proposed QS-RNML technique perform both gaze pattern estimation and recognition with less time complexity.

6. CONCLUSION

An efficient technique called QS-RNML is developed to improve GPRA with less time complexity. The QS-RNML technique initially performs preprocessing to remove the noise artifices from the input eye images. The preprocessing of eye images is done with the help of adaptive median filtering technique. After that, the gaze assessment is carried out to measure the phase shift of the eyelid from the initial location. Then the estimated gaze points are transformed into the recurrent neural machine learning technique. It performs the gaze point alignment repeatedly in the hidden unit for pattern matching. Finally, the estimated gaze patterns are matched with already stored ground truth patterns. The matched results provide high recognition accuracy of gaze patterns. Experimental evaluation of QS-RNML technique is performed with two eye image DS with certain parameters such as true positive rate, GPRA, TC and FPR based on a number of eye images. The results analysis shows that QS-RNML technique enhances GPRA, TPR with minimal TC and FPR than the conventional methods.

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