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Design and Analysis of Improved Iris-Based Gaze Estimation Model

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Abstract
The detection accuracy of gaze direction mainly depends on the performance of features extracted from eye images. Limitations on the estimation of gaze direction include harmful infrared (IR) light, expensive devices, static thresholding, inappropriate and complex segmentation techniques, corneal reflections, etc. In this study, an efficient appearance cum feature-based detection model, namely, iris center-based gaze estimation (ICGE), has been proposed. The model is an extension of the earlier proposed glint-based gaze direction estimation (GDE) model and overcomes the above limitations. The ICGE model has been analyzed for GDE based on iris center coordinates using a local adaptive thresholding technique. An indigenous database using more than two hundred images of different subjects on a five quadrant map screen generates almost 90% accurate results for iris and gaze quadrant detection. The distinguishing features of the low cost, non-intrusive proposed model include a lack of IR and affordable ubiquitous H/W designing, large subject-camera distance and screen dimensions, no glint dependency, and many more. The proposed model also shows significantly better results in the lower periphery corners of the quadrant map than traditional models. In addition, aside from the comparison with the GDE model, the proposed model has also been compared with other existing techniques.

Category: Smart and Intelligent Computing

Keywords: Iris center based gaze estimation (ICGE) model; Adaptive thresholding; Iris center; Non-intrusive; Gaze quadrant detection; Glint

I. INTRODUCTION

Gaze-based systems requires the estimation and detection of gaze with high accuracy after segmenting the region of interest (ROI). This ROI can be glint, iris contours, iris, pupil, eye corners, etc. Gaze estimation is generally done in relation to the gaze direction of a user's eye position with specific eye movements after segmentation or extraction of local features like the eye outline, eye contours, edges of pupil, eye corners, center of the eye, iris, or pupil, or corneal reflections or glint, etc. [1-5]. There exist several image segmentation techniques which partition the image into various parts based on the different image features like pixel intensity value, color,

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texture, etc. These techniques can be categorized on the basis of the segmentation method used for extracting ROI [6].

Most of the research work in eye center detection methods can briefly be classified into two categories: pupil center and iris center detection. Pupil center detection along with glint detection is used mainly in intrusive systems. However, the use of infrared (IR) light makes the gaze detection limited to indoors. In addition, IR may be harmful to eyes due to ambient IR illumination. In the case of pupil center detection-based methods, the data quality of the captured images may depend on the size of the pupil [7-9]. In contrast, iris center detection is more evident, cheap, and widely used in non-intrusive systems. It often works under visible light. In addition, the iris is circular, darker than the sclera, constant in size, more stable, and is not affected by glare or glint formation in contrast to the case of pupil detection (Fig. 1).

Iris segmentation or localization requires accurate detection of the boundaries separating the iris from any other unwanted components or regions in the image. Iris recognition is independent of non-uniform illumination caused by the position of the light source [10]. As shown in Fig. 1, there may be multiple glints G_i within the sclera S_c region due to multiple sources of incident light on the pupil region. The relative position of the iris center (C_i) to the center of eye (C_e) can be used for further gaze-based processing [11]. Iris-based eye gaze identification and estimation systems are used in a lot of applications in various fields, including personal identification and automated border crossing. It has been reported in certain cases that iris-based gaze detection systems perform better than other identification methods like signatures or finger printing [12-14].

For the segmentation of the iris, different image-based segmentation methods have been applied on the basis of template, appearance, and features. These methods have been implemented using various techniques. These techniques include thresholding, ellipse fitting, edge detection, 2D Gabor wavelet filters, circular Hough transform (CHT), blob detection, eigenspace methods, adaptive thresholding, etc. [15-22]. The appearance-based method requires a photometric appearance of the eyes whereas the template-based uses a generic, predesigned eye model.

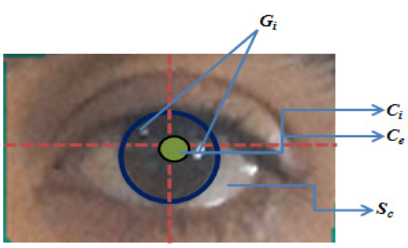

Fig. 1. Coordinates of eye C_e, iris C_i and multiple glints G_i within sclera region S_c (indigenous database).

The appearance-based method detects eyes based on their photometric appearance. In contrast, feature cum shape-based methods require the identification of certain eye characteristics for the detection of ROI. Appearance-based methods require large amounts of data for training classifiers in neural networks or support vector machines. Further, in the case of the template matching method, if there is a significant variation in size, scale, rotation, illumination or orientation of the input images, then the template and eigenspace based methods require further normalization. This may make the model less efficient and time-consuming [23].

All of the above-mentioned segmentation methods may be used to design the iris recognition and detection model using one of or a combination of the above techniques along with adaptive thresholding. The Hough transform method is often used for binary valley or edge maps but depends on the threshold values, leading to processing delays. CHT is used to detect the iris border precisely with both the center and radius estimated simultaneously. This may also lead to high memory requirements. However, CHT fails to localize the ROI, if a correct estimation is not provided. The CHT method may give good results when combined with some other segmentation methods [17, 23-25]. Another segmentation method, namely, blob detection, is also used for feature extraction. This method is based on the image gradients, eigenvalues, or templates. It requires clear background relation and pixel precision. Although blob analysis takes less time than edge detectors, it requires fixed thresholds like edge detectors. Edge detectors are used to segment the regions with high intensity variations with the help of the thresholding method. This is used to turn a gray scale image to a binary image based on a certain threshold value. However, the selection of thresholds may affect the outcomes significantly as edge detection is highly noise sensitive, crucial, and computationally expensive. This may be due to rapid changes in intensity values in an image which does not provide good information about edges. It has been observed that the quality of images depends upon the image distance and the color of both skin and iris, which may degrade the performance of iris segmentation. In addition, the presence of discontinuities in the surface orientation may further require applications of different morphological operations to connect the breaks or eliminate the holes [11, 24, 26, 27]. Further, it is very clear that segmentation methods may require variations of specific fixed global threshold values for all pixels in an image. The threshold works only in images with a strong illumination gradient and where the intensity histogram of the image contains distinct peaks. Further, more processing time is also required for these methods. Outcomes are dependent on certain input parameters and thresholds.

In contrast to the above-mentioned methods, the local adaptive thresholding technique selects an individual threshold to separate the desirable foreground image objects from the background for each pixel in the image. This separation is based on the range of intensity values in the local neighborhood. Adaptive thresholding is applied only to those generated images for which the global intensity histogram doesn't contain distinctive peaks. The appropriate window sizes must be defined in order to extract maximum image information from the resultant binarized image. The adaptive thresholding system outperforms fixed thresholding because it adapts to the local image properties [18, 26, 28-31]. It is further observed from the literature review that an efficient iris-based system may not require IR light. In addition, the system should be simple, low cost, and non-intrusive utilizing affordable ubiquitous devices. The model should be able to detect the gaze of the subject at different positions on the screen placed in front.

In our earlier work [11], glint-based eye gaze detection has been analyzed using proposed gaze direction estimation (GDE) model which works on the position of the glint coordinates. The experiments have been conducted on 200 single eye images taken from 20 different subjects for detecting correct gaze quadrants at 122 cm distance in contrast to existing models working at a maximum distance of 70 cm. The criteria of the selection of the eyes, including clarity and formation of iris, image resolution, visibility, blurriness, etc., have also been investigated and analyzed. The feature-based shape method has been proposed for the comparative analysis of two selected standard edge detectors for estimating the position of the glint coordinates and subsequently, gaze quadrant detection, based on the different human eye images dataset. Glint formation varies on the basis of the incident light falling on the cornea of the eye, producing significant changes in the results. The limitations of the GDE model have been overcome by using adaptive thresholding and iris-based analysis in this proposed work. The proposed GDE model has been discussed in more detail in the following section.

In this research work, an appearance cum feature-based shape model named Iris Center-Based Gaze Estimation (ICGE) has been proposed. This model is based on the detection of the center coordinates of the segmented iris using adaptive thresholding technique without IR light for the estimation of the gaze direction based on the coordinates of the iris center. The image is binarized using an adaptive threshold technique along with the CHT to find out the circular shape of the iris along with the estimated iris center. The eye images of different subject are taken from an indigenously created database. Various images have been processed for the analysis of results. This model is an extension of the GDE model [11]. The GDE model is a feature-based shape model that primarily works on the detection of glints from the input eye images using two standard edge detectors, Canny and Sobel. The limitations of the GDE model include the formation of multiple glints, the absence of proper glint or no glint, dependency on light sources, etc. In comparison, the ICGE model is designed to estimate the gaze based on the position of the iris irrespective of glint formations. The following experiments are performed in an indoor laboratory. Eyes with spectacles and squint eyes have not been considered in this research work.

The rest of the paper is organized as follows. The literature review is presented in Section II. The working methodology of the proposed ICGE model and its comparison with the earlier proposed GDE model is explained in Section III. The results and discussion are described in Section IV. The conclusion and further research directions are presented in the last section of the paper.

II. RELATED WORK

Different methods are being used to estimate the direction and duration of eye gaze of a given subject. The significant part of any gaze-based controlled system is the precise identification of the direction, position, and duration of the eye gaze. ROI can be glint, iris, iris center, or any other related feature. Some of the significant algorithms and models for segmentation of ROI, iris localization and mapping presented by different researchers are discussed below.

The GDE model proposed by Sharma and Abrol [11] analyzed the resultant images for estimating the position of the glint coordinates as the ROI and subsequently the gaze direction in the eye images dataset using the two standard edge detectors, Canny and Sobel, by capturing facial images at a distance between the subject and the camera of 122 cm. However, there are certain limitations of the GDE model like dependency on the orientation of the light sources, image resolution, multiple glint formation, absence of proper glint or no glint, etc., leading to the generation of wrong results in determining the exact glint boundaries in the eye images. The model shows an 81% success rate in the detection of correct glint coordinates and correct gaze direction quadrants. In most cases, better results have been obtained by the canny edge detector than the Sobel operator.

Sigut and Sidha [8] have segmented the center of the iris without using IR light through the iris center corneal reflection (ICCR) method with visible light instead of PCCR. Images with resolution of 752×582 pixels of only 25 subjects at a maximum distance of only 70 cm feet have been used. However, the model is costly and time consuming. Yu et al. [14] propose a geometric relationship between the estimated rough iris center and the eye corners for only four states of the iris within the eye region of twenty subjects placed at a distance of 60 cm from the camera. However, the proposed model generates 94% result but can only deal with the left and right states and not the down states of the iris. The performance of the model also decreases due to dependency on the ambient light conditions. Abdullah et al. [30] propose Otsu's adaptive thresholding method which is used to separate the sclera in each eye image using gradient vector flow (GVF) active contour to achieve iris segmentation with visible and NIR lights. With the use of standard databases like CASIA, MMU, etc., the proposed iris model consists of two different methods for pupil and iris segmentation and requires additional methods to suppress glints, etc., from the eye images.

Ryan et al. [16] approach iris segmentation by adapting the starburst algorithm to locate pupillary and limbic feature pixels used to fit a pair of ellipses using IR LED's which may cause eye damage. The image database has low contrast between the pupil and iris leading to problems, along with the simple thresholding algorithm generating poorer fits. Moravcik [19] uses a binary edge map followed by a CHT algorithm for pupil and iris segmentation. However, the algorithm takes higher computational time and memory consumption. The range of an expected radius must be expanded due to the loss of circle configuration of the iris, compared with the center position. Memer Zedah and Harimi [26] propose CHT with adaptive thresholding for iris segmentation from the images taken from different mobile devices. Although CHT is a robust algorithm used in finding circles in an image, it suffers from computational complexity. As reported, the researchers observe that the size of the iris in the image depends on the distance from camera. The colors of both the skin and iris can degrade the performance of the iris segmentation algorithms. An additional process for the removal of sclera is required. Further, the model could not properly estimate the upper and lower iris boundaries occluded by eyelids. A robust fast feature light reflection-based detection method is proposed by Yoo and Chung [29]. It uses an ellipse-specific active contour to find the exact features and shows accurate results under large head motion. It requires extra hardware in the form of five LED light sources and two cameras. Different methods using adaptive thresholding based on complex algorithms like eigeniris, Euclidian distance, SVM classifier, etc., for iris center location have been proposed with the limitations of using a canny operator with fixed thresholds [32-35]. A novel adaptive thresholding method proposed by Shah and Ross [17] is to extract the limbic boundary of the iris as well as the contour of the eyelid using geometric measures of the iris image that has been found to have a 57% success rate. However, this method does not take into account the amount of edge detail and also fails to stop at the desired iris boundaries. At times, it generates wrong extraction due to the specular reflections in the iris or pupil images. Yonezawa et al. [36] propose a fast method of circular pattern matching iris center detection for a fixed head eye gaze system using a ring-shaped template for disabled as well as healthy users. The model includes a workstation for more efficient verification that also requires calibration. Wang and Sung use elliptical iris shape in an image using iris contour as the edge of an ellipse to find a circle with two cameras, and thus add extra cost and time to the system. Only one eye is processed for the estimation of eye gaze for higher accuracy with a canny edge detector and fixed thresholds [37-40]. A comparative analysis for the glint detection has been carried out on different single eye images with various parameters of distance and orientation by using the edge detectors for eye gaze-based systems using the GDE model. The proposed model improves the time of interactivity for enhancing the accuracy and performance by varying the number of processor affinities. The minimum execution time taken to find the glint coordinates and subsequently the gaze direction is estimated [41]. It is also observed that the number of training images in the gaze detection systems is directly proportional to the rate of success and the CPU speed [28].

As is evident from the literature review, different methods can be used for segmenting the boundary of the iris for detecting gaze direction. The precision of this gaze detection is very important in iris recognition methods. The limitations of the template matching, eigenspace like size and orientation of the face image, and variation in illuminations as discussed above, require further improvements. Requirements of specialized and expensive equipment add an extra cost to the iris-based models. The loss of iris circle configuration may lead to inaccurate detection and can be corrected by varying the range of the expected radius for the correct detection of the iris eye corner [15-17, 23]. Localization of the iris should be done properly by reducing the unwanted resultant noises like eyelashes, corneal reflections, pupils, eyelids, and occlusion that may lead to poor performance of iris-based eye detection algorithms [6, 33-34]. The higher image resolution, the greater the relative time is consumed by any algorithm [20]. The interactivity of time can be minimized by using a single eye for detection of gaze direction using uniform lighting conditions. Images with blurred and squint eye may affect the accuracy rates of iris detection models. Further, as observed from the literature review, the use of IR light for the gaze detection process may be hazardous to human eyes. A gaze detection model based on visible light may be preferred. Moreover, certain existing methods have used edge detectors for segmenting ROI. Edge detectors may require the manual setting of fixed thresholds. Edge operators like canny are highly sensitive to noise and may further increase the complexity by using horizontal and vertical gradients [30, 35, 42]. In addition, gaze detection at the down states, especially in the bottom left and bottom right periphery, appears to be difficult because of the factors like hidden iris edges and resulting in incomplete information on the iris edge points [14].

III. EXPERIMENTAL ANALYSIS

As mentioned above, an appearance cum feature-based shape ICGE model has been proposed for the detection of the center coordinates of a segmented iris using an adaptive thresholding technique for the estimation of the gaze direction. The proposed ICGE model is low cost, non-intrusive, simple, and doesn't require IR light or edge detectors. The adaptive threshold technique has been used in ICGE to overcome the limitations of edge detectors and fixed thresholds. The model has been analyzed for five different screen quadrants on the screen along with tuning parameters like pixel and radius range, window size, etc. ICGE does not require initialization of a search line radius nor any template for the gaze detection process. On the basis of the above discussion, the proposed research work has been divided into two subsections, 'the ICGE model - design and development' and 'the ICGE and GDE models - comparative analysis'. These have been discussed below in detail.

A. ICGE Model - Design and Development

A workflow for the detection of iris center coordinates has been shown in Fig. 2. The proposed iris localization method in the present research is adaptive thresholding [18, 28] along with CHT algorithm [25, 26] which is used to extract the iris circle in the feature cum appearance-based shape detection module. The single input eye image is converted into a binary image using the adaptive thresholding technique. The threshold value T at pixel location (x, y) in the image depends on the neighboring pixel intensities. In adaptive thresholding, the local mean of every region within the selected window size (35×35) is computed by iterating over each pixel to generate a local mean filtered image.

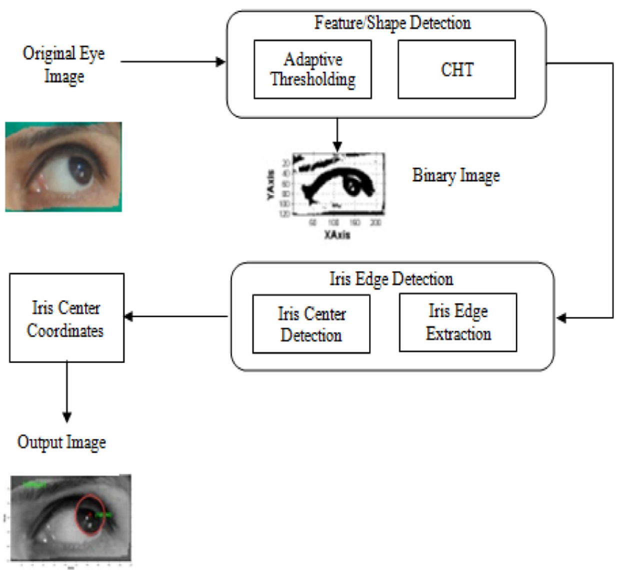

Fig. 2. Work flow of the iris center detection ICGE model.

The threshold value $T(x, y)$ is normalized and computed using a parameter C_n ranging from 0.0143 to 0.0543 iteratively for every single pixel in the image. The threshold value obtained is applied to the entire image area for the generation of a binary image. The CHT algorithm is then applied to the binary image to find the boundary of the iris in the image. Further, the extracted iris image is used for iris edge extraction and the estimation of iris center coordinates in the iris edge detection module.

The eye images are taken from an indigenous database (DB) consisting of eye images of different subjects. The experimental setup has been created using gaze estimation quadrant map M as shown in Fig. 3. All the images have been captured using a SONY NEX-5 ultra-compact digital camera with a resolution of 4592×3056 pixels. The facial image of each subject is captured, cropped, and normalized to a resolution of 220×120 pixels to select the better images of the two eyes. The criteria of the selection of the eyes include clarity, formation of iris, image resolution, visibility, blurriness, etc. The eye image I_i for each region has been captured for each subject for the creation of a comprehensive DB. More than 220 images have been obtained from 45 different subjects. The subjects consist of both males and females (specifically, in a 27:18 ratio) without spectacles within an age range of 20–40 years. The focal point of view rather than the peripheral view is taken into consideration in the working of the model. The quadrant map M, placed at a distance of 122 cm (4 feet) from the subject has been divided into five specific regions, namely, TopLeft (TL), TopRight (TR), BottomLeft (BL), BottomRight (BR), and Center (C).

Each subject has been instructed to gaze at five above regions of M in the sequence C→TL→TR→BR→BL respectively as shown in Fig. 4.

The central quadrant C with center $N(x, y)$ has a pixel range of ±10. An input image I_i is taken from the DB for further processing. Superimposition of the extracted iris

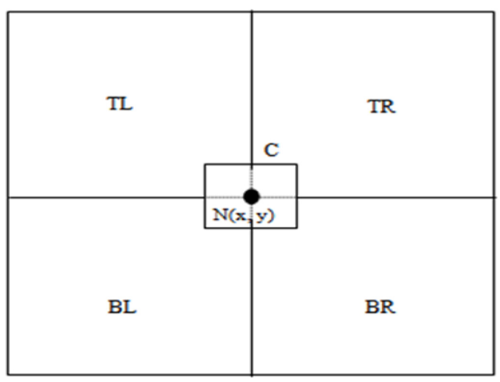

Fig. 3. Gaze estimation quadrant map M. C is center quadrant with $N(x, y)$ for varying pixel range ±10.

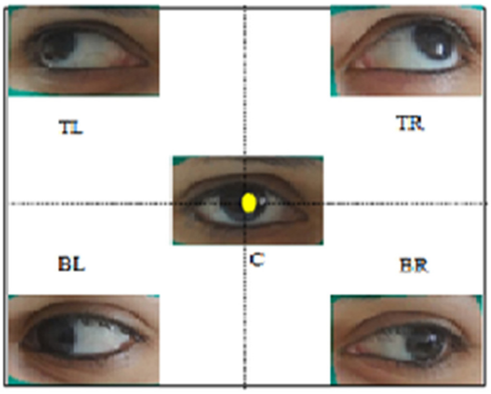

Fig. 4. Gaze estimation quadrant map *M*. Examples of eye images gazing at different quadrants.

region over the input image I_i results in position detection of the iris center coordinates $I(x, y)$. Different output cases of detection have been categorized and explained in Table 1.

The ICGE model has been applied to each image I_i of *DB* for classifying the results in the above mentioned three categories.

The interface for ICGE model has been developed using MATLAB R2013a environment in a Dell Optiplex-990 model with Windows 7 professional 64-bit operating system, Intel core i5-2500 CPU, 3.10 GHz and 2 GB RAM. The analysis of the results has been presented in the next section.

B. ICGE and GDE Models – Comparative Analysis

As explained above, the GDE model analyzes the glint coordinates in the eye images in order to ascertain the gaze-based quadrant detection, and it is evident from the literature review that the glint-based detection is an important method for gaze detection. The direction of the gaze is generally estimated by mapping reference point of the glint vector and the center of the pupil but the accuracy of glint detection in eye gaze-based system depends on several factors like the formation of proper glint and control parameters. Different eye features like glint, pupil, iris, etc. can be extracted using the edge detection operators. Edge detectors also facilitate the extraction of morphological outlines from the digitized image. The GDE model has been tested by creating an image database using a hundred images taken from 20 different subjects for five different quadrants in the experimental setup. The output glint coordinates and estimated gaze direction of the user are compared with the actual user gaze to test the efficiency and accuracy of the model. Varying values of threshold T and α factor value along with other parameters are used to obtain suitable results. The main features of the GDE method include cost effectiveness, its use of ubiquitous hardware and software, and simplified image capturing procedure. However, the GDE model suffers limitations because of the high dependency of the analysis on the glint formation.

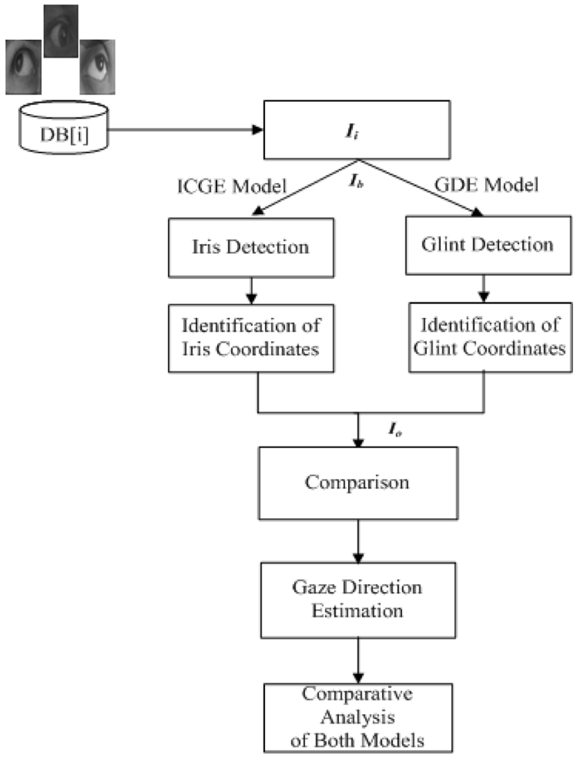

Fig. 5. Comparative analysis of ICGE and GDE models.

To achieve the second objective, i.e., comparative analysis of ICGE and GDE models, the same set of test images of all 45 subjects for both the models have been analyzed. A workflow of this comparative analysis is presented in Fig. 5.

The input in both models is the same eye image from the DB. The comparison has been done for the coordinates detection (iris/glint) and corresponding iris or glint

Table 1. Classification of outputs in different categories

Symbol	Meaning	Remark
C_IC_G	Correct iris & correct gaze	Successful quadrant detection
C_IW_G	Correct iris & wrong gaze	Gaze quadrant could not be correctly detected in spite of correct iris detection
W_IW_G	Wrong iris & wrong gaze	Unsuccessful quadrant detection

detection for each subject. The glint coordinates and the corresponding quadrant have been estimated in case of GDE model. In the GDE model, two edge detectors have been selected from the standard edge detectors like Sobel, Canny, Prewitt, Roberts, Zerocross, etc., in order to detect edges and their orientations for extracting glint from the eye images, and to be used for producing reasonable results. The Sobel is sensitive to noise and generates inaccurate results at times. The Canny edge detector, however, is the optimal and more efficient edge detector. It uses a Gaussian filter and is better, especially in noise conditions, than the Sobel detector. Different morphological image processing functions like erosion, dilation, etc. have also been used in the GDE model for removing unwanted regions or boundaries for the location of exact glint coordinates. However canny edge detection generates more accurate results than Sobel in the GDE model.

The ICGE model is compared to the GDE model for the analysis of correct gaze quadrant in same image gazing at the TR quadrant, as shown in Fig. 6. The results thus obtained from both the models have been compared and analyzed.

Finally, as for the differences and similarities of the features, the design and methodology of the proposed ICGE model with other existing models are also discussed in the next section.

The iris coordinates generated by the ICGE model are also compared with those of the GDE model for performance analysis of the detection of correct gaze quadrant. For the same subject, the position of iris coordinates and corresponding quadrant on the map M have been estimated. The result for all 45 subjects has been obtained for each of the five quadrants. Unlike ICGE, the GDE model initially detects the glint in the eye images and subsequently the glint coordinates $G(x, y)$.

A more detailed and diagrammatic representation of the comparative analysis along with intermediate representations has been shown in Fig. 6. The rate of correct quadrant detection for both models has also been compared. The comparison of both the GDE and ICGE models has been presented in the next section.

IV. RESULTS AND DISCUSSION

As explained above, an appearance cum feature based ICGE model with adaptive thresholding has been proposed for gaze detection. On the basis of the objectives of the proposed research work and the workflow presented in the above section, the results have been divided into following three subsections: analysis of ICGE model; ICGE and GDE models; and comparison with other methods.

A. Analysis of ICGE Model

In order to evaluate the performance of the proposed ICGE model, a series of eye images of different subjects on the five-region quadrant map M have been tested as explained in the previous section. The results of five different subjects selected for five different map regions are presented in Fig. 7. The second column I_i is the input image from the database DB. I_o represents the output image with segmented iris region and center coordinates $I(x, y)$. $I(x, y)$ is generated for each instance of image on the basis of the position of the iris within the eye. In the case of I_1, since both x and y coordinates are below $C(x, y)$, the generated region of gaze is correctly detected as TL and the output is C_IC_G. However, in the case of I_5, even though the subject is gazing at the central region, the ICGE-generated output shows TL with the outcome as C_IW_G. This may be attributed to the selected specific pixel range as mentioned above. A change in the region coordinates may affect the outcome of such cases. It has been observed that out of the 225 images, the ICGE

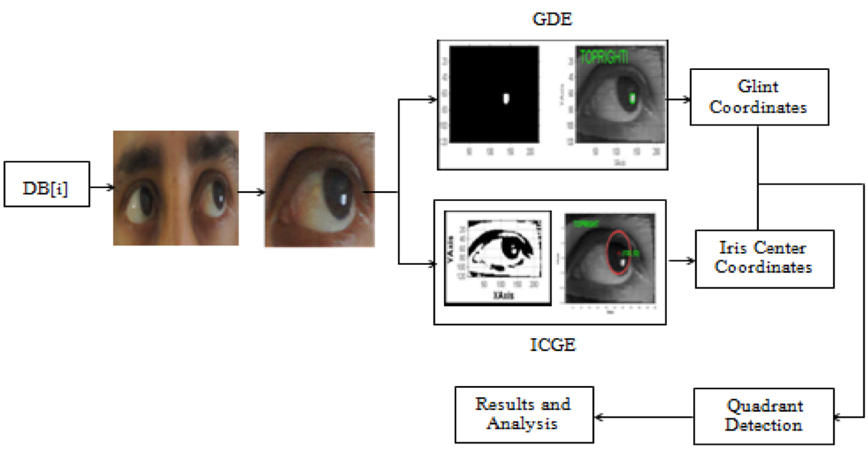

Fig. 6. Comparative analysis of GDE and ICGE models for gaze quadrant detection.

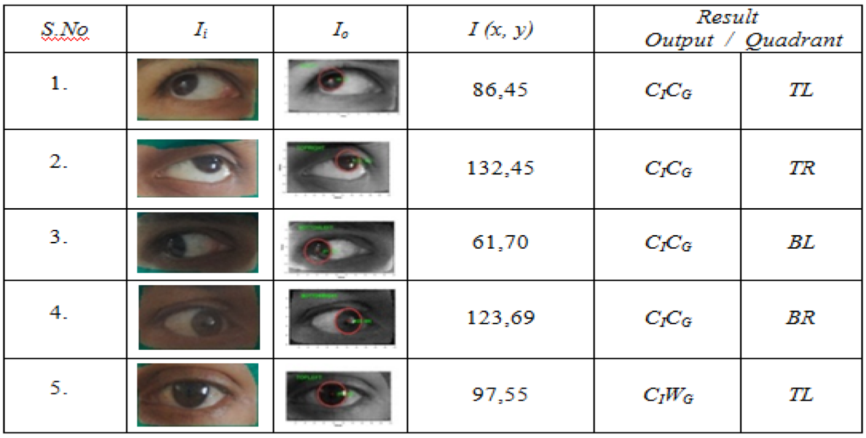

Fig. 7. Resultant five gaze quadrants for selected subjects.

Table 2. Quadrant wise results

Quadrant (Q_i)	Subjects (n = 45)	CQD (%)
TL	45	100
TR	42	93
BL	40	89
BR	38	85
C	43	96

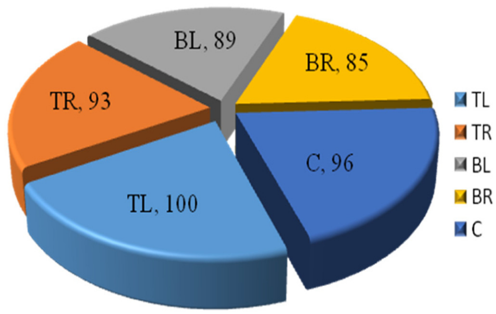

Fig. 8. Quadrant-wise detection rates for 45 subjects.

model correctly identifies the iris and subsequently the gaze quadrant (C_IC_G) for 202 images, showing a success rate of approximately 90%. C_IW_G category (approximately 10%) is generated for the remaining images.

Further, in all such cases of C_IW_G, the system correctly identifies the iris coordinates, but fails to detect the gaze quadrant of the subject correctly. In a few cases, the output produced is W_IW_G (0.44%). This occurs due to incorrect detection of the center coordinates, leading to incorrect gaze quadrant detection. The reason for incorrect detection of iris coordinates may be improper iris formation or image blurriness.

Further, incorrect region mapping by the ICGE in spite of the correct detection of iris coordinates may be attributed to the selected specific pixel range as mentioned above. A change in the region coordinates may affect the outcome of such cases. The quadrant wise detection of the correct gaze of all the images has been shown in Table 2. The percentage of the correct quadrant detection (CQD) for each of the five quadrants has been shown for each of the five selected quadrants using 45.

The quadrant-wise detection rate for all 45 subjects has been pictorially represented in Fig. 8. As evident from the graph, the best gaze detection rate is at the TL and C quadrants. The TR also shows above 90% correct detection. The BL and BR quadrants are showing comparatively less but still significant detection rates (above 85%) at the lower periphery of the screen quadrant map. This is very significant as compared to other existing models in which gaze detection at down states was not significant and thus not considered.

B. ICGE and GDE Models

In order to further investigate the performance of the ICGE model, a comparative analysis of ICGE model has been done with the earlier proposed GDE model. The comparative results for single subject gazing at all the five different regions (TL, TR, BR, BL, and C) of the gaze map M detected by the ICGE model have been compared with those of the GDE models as shown in Fig. 9.

LE and RE indicate the selected left or right eye image that is applied to both models for each instance. The iris coordinates $I(x, y)$ generated by the ICGE and glint coordinates $G(x, y)$ computed by the GDE model have been shown for each case along with the quadrant detected by each model. As evident, the variations in the coordinates are due to the formation of glints at any place within the iris or pupil region. In Fig. 9, I_o is the corresponding output image generated by both models for each input image I_i.

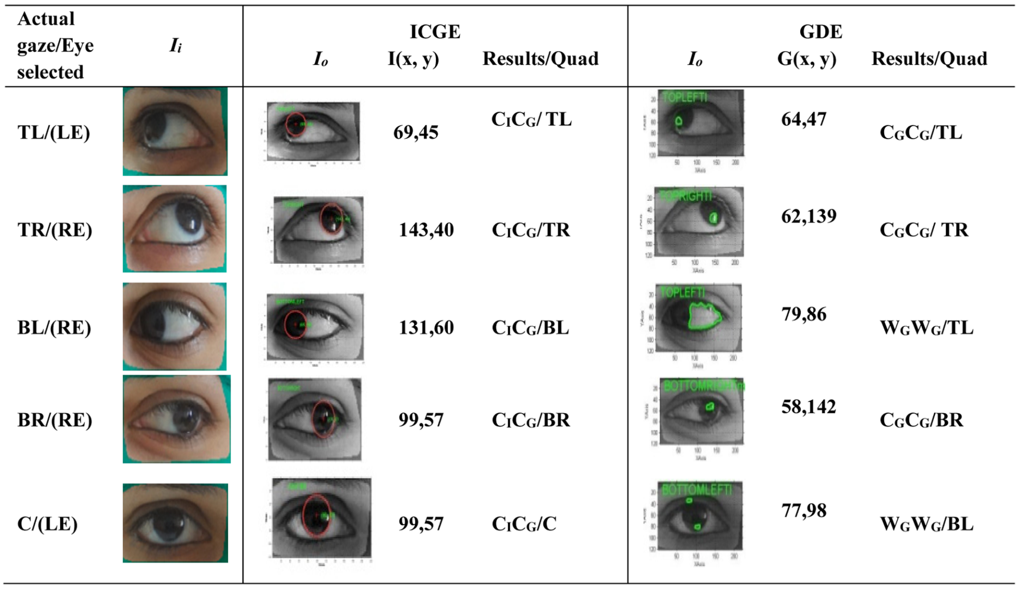

Fig. 9. Comparison of GDE and ICGE coordinates for a selected subject.

Table 3. Success rates

Model	Category	Success rate (%)
ICGE	$C_I C_G$	89.77
	$C_I W_G$	09.77
	$W_I W_G$	00.44
GDE	$C_G C_G$	63.56
	$C_G W_G$	13.33
	$W_G C_G$	07.55
	N_G	08.89
	$W_G W_G$	06.66

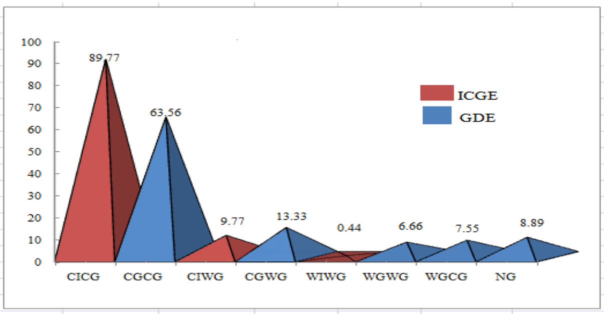

Fig. 10. Success rate for ICGE and GDE.

The GDE model detects the correct glint and subsequently estimates the correct gaze whereas the ICGE model detects the correct iris and the correct gaze. Further, the actual gaze of the subject is correctly detected by the ICGE model but not by the GDE model. In the cases of I_1, I_2, and I_4 images, the gaze of the subject is correctly detected at the quadrants TL, TR, and BR respectively. In the cases of I_3 and I_5 images, the ICGE model correctly identifies the gaze quadrant (BL and C) after the identification of the iris coordinates. However, the GDE model for these cases fails due to incorrect glint detection. Similar results have been obtained for the rest of the 215 images of the remaining 44 subjects in this study. The comparative category wise success rates of the implementation of both the models on the entire database *DB* has been presented in Table 3 along with a graphical representation in Fig. 9. It is observed from the table that the GDE model fails to detect either the correct glint or the corresponding gaze in 22% of the cases.

This also includes a few cases in which no glint (N_G) has been detected. The reason for N_G may include variations in the glint formation, multiple glints, absence of glint, etc. This also includes a few cases in which no glint (N_G) has been detected.

The reason for N_G may include variations in the glint formation, multiple glints, absence of glint, etc.

Further, in 13% of the cases, even though the GDE model detects correct glint, it fails to identify the correct gaze quadrant on the map *M*. This may be attributed to its high dependency on the light sources. The ICGE model fails to detect the gaze correctly in approximately 10% of the cases. A significant observation of the comparative analysis is that in the case of ICGE, the incorrect detection of iris coordinates is almost negligible compared to the wrong glint detection in GDE (21%). The improved factors and techniques used in the ICGE model, like adaptive thresholding with CHT and wider area of ROI, have increased the correct gaze detections as shown in Fig. 10 with the help of cluster pyramids. The performance of the ICGE model is approximately 90%, compared to the 64% of the earlier GDE model. These results indicate that the ICGE model which is based on the segmentation of iris center detection shows better performance than the earlier proposed glint-based GDE model for different gaze quadrants for various subjects.

C. Comparison with Other Methods

Comparative analysis of ICGE with other existing techniques with various distinguishing factors like IR, lower periphery corner accuracy, screen dimensions, subject camera distance, segmentation techniques, etc. has been presented in Table 4. In addition, the type of databases used with glint dependency, light source dependency, and accuracy of the results has also been discussed.

Most of the existing models use fixed thresholding and edge detection for the iris segmentation, which require extra morphological operators and manual thresholding to find out the iris edges along with another limitation of occlusion of either eyelids or eye lashes, etc. The proposed ICGE model uses CHT along with dynamic thresholding to overcome the problem of removal of specular reflections and occlusions in the images. Moreover, instances of non-circular irises have been corrected by selecting specific tuning parameters ($C_{n,}$ window size ws, and radius range r_i) for CHT in the proposed model. For better performance, smaller optimal values of these parameters have been used. The automatic iris localization technique using adaptive thresholding with CHT for 60 images taken from ten different subjects as proposed in

Table 4. Comparison of the proposed ICGE model with other iris recognition techniques

Dynamic thresholding with CHT	IR, ubiquitous H/W	Screen size, subject-camera distance (cm)	Map used, number of quadrants	Indigenous DB, glint dependency	Lower periphery corners accuracy	Features	Ref.
Yes	No, Yes	*	*	Yes, No	NA	Only for mobiles devices, 10 subjects with glasses, only 60 colour eye images; removal of sclera required.	[26]
Yes	Yes, Yes	*	*	No, Yes	NA	Pupil and iris based, colour and grayscale images; removal of sclera and eyelashes.	[30]
Yes	Yes, *	*	*	No, Yes	NA	Pupil and iris based; preprocessing required; additional methods to suppress glint.	[31]
No	No, Yes	100×60, 60	Yes, 4	Yes, No	Low	Iris based, grayscale eye images.	[14]
No	No, Yes	304×122, 122	Yes, 5	Yes, Yes	Medium	Digital camera with 14.2 MP; binary image; accuracy 81%.	[11]
No	No, Yes	NA, 70	Yes, 2	Yes, Yes	NA	Personal calibration required; require binary masks; accuracy 94%.	[8]
Only CHT	*, Yes	*	*	No, *	NA	Iris and eye corners based, 105 subjects, upper half image. Cropped, global threshold for removing skin pixels, center and radius of iris estimated.	[41]
No	Yes, No	*, *	NA	No, Yes	NA	Pupil and iris based; median filter and threshold; require glint removal, many iterations; results into over segmentation for wrong iris edge details.	[17]
Only dynamic thresholding	Yes, No	*, *	*, *	No, *	NA	Gaussian smoothing filter.	[42]
Yes	No, Yes	304×122, 122cm	Yes, 5	Yes, No	High	Digital camera with 14.2 MP; larger distance; accuracy 90%; center of iris estimated.	Proposed ICGE model

*: not relevant or not known, NA: not applicable.

[26] concludes that the quality of the iris image depends upon the imaging distance. Gaze direction methods proposed in [8, 14] have taken the images of the subjects from maximum distances of 70 cm and 60 cm, respectively. The ICGE model, however, is experimentally evaluated for 220 eye images taken from 45 different subjects at a distance of at least 122 cm (4 feet) from the camera with a 90% success rate in detecting the correct gaze quadrants. It has been also observed from the literature review that CHT is intolerant to broken contours of the objects. This limitation has been overcome by using adaptive thresholding along with CHT in the proposed work. In contrast to standard databases with constraints of visible and IR light used by [17, 30, 31, 42] a non-IR, simple, low cost, and ubiquitous hardware based non-intrusive indigenous database has been created for the experimental evaluation of the proposed ICGE model.

A two-quadrant map has been used for analysis by the authors in [8]. In model [14], the authors report that the results are not very encouraging for this map, either for the lower periphery of the four-quadrant map or for the analysis of the gaze direction. In contrast, the ICGE model generates good results on a five quadrant-map *M* with better accuracy, even in the lower periphery of the BL and BR corners. A comparison of the techniques and other features including databases used in the proposed ICGE model with the other existing models and techniques has been presented in Table 4.

V. CONCLUSION

In this research work, a design and analysis of appearance cum feature-based shape model named the ICGE model has been proposed. The model is used for the estimation of the gaze direction based on the position of estimated iris center coordinates using adaptive threshold technique with CHT. The proposed method is an improvement over the existing models used for iris recognition. ICGE model is experimentally evaluated using an indigenous, non-IR, simple, low cost, and ubiquitous hardware-based, non-intrusive database. The database comprises 220 eye images taken from 45 different subjects at a distance of at least 122 cm (4 feet) from the camera on a five-quadrant map with a large screen size of 304 cm × 122 cm for the detection of gaze direction. The proposed model generates better results without the use of edge detectors and static thresholding, specular reflections, template-based methods, etc., unlike other existing iris recognition methods. The result shows more than 85% correct gaze quadrant detection by the ICGE model for all the five quadrants of the map. The model detects the gaze correctly even in the lower periphery of the BL and BR corners with better accuracy using certain selected tuning parameters for optimal performance. The instances of wrong gaze detection observed during the analysis may be attributed to factors like resultant noises, off-axis iris, incomplete iris circle, specific pixel range, iris on the move, etc. Comparative analysis of the proposed ICGE model with GDE shows a 26% higher success rate of correct quadrant detection on eye images using the same image dataset overcomes the limitations of earlier GDE model. In addition, the distinctive features of ICGE have also been compared aside from with the GDE model with other existing techniques. The features that differentiate the proposed ICGE model from other models include the use of dynamic thresholding with CHT, ubiquity, hardware design, non-IR, comparatively large subject camera distance and screen dimensions, single eye image processing, non-glint dependency, etc. Further, unlike many other existing models, removal of sclera and glint is not required in the ICGE model. This work may be further extended for online images with modified quadrant map for enhanced precision.

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