Pertanika J. Sci. & Technol. 27 (2): 779 - 796 (2019)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Structural and Statistical Similarity Measure based Approach for Effective Eye Blink Recognition

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ABSTRACT

Eyeblinks are having the significance to analyze the attention, fatigue, behaviour and emotion of an individual. Eyeblink recognition is adopted by many medical and surveillance applications to identify the person's state. The eye blink recognition on videos requires tracking the eye region and to count the number of eye blinks. In this paper, a three-stage model is presented to detect the eye blinks accurately. In the first stage, the frame similarity analysis, background separation, positional and mathematical filters are applied collectively to identify the effective eye region on unique frames. In the second stage, the similarity analysis using wavelet decomposition and statistical filters are applied on the segmented eye region. The filtered evaluation is performed to identify the change on the eye region of continuous segmented frames. At the final stage, distance driven map on structural and statistical features is applied to remove the invalid frame changes and to obtain the accurate eye blink count. The proposed model is applied on real time, web-collected and the NRC-IIT dataset videos. These complex videos are associated to the indoor and outdoor environments. The news reading and other complex video sequences are analyzed in this research. The observations identified that the proposed model has reduced the possible generated errors and provided the accurate detection of eye blinks.

Keywords: Eyeblinks, statistical, structural, video sequences

ARTICLE INFO

Article history:
Received:7 July 2018
Accepted:7 February 2019
Published: 25 April 2019

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INTRODUCTION

The Eye and eye-blink tracking has gained its scope in various real-time applications in

ISSN: 0128-7680
e-ISSN: 2231-8526

recent time (Choi et al., 2011; Ryu et al, 2013; Junjea, 2015). The static eye has already proven as individual biometric or part of multi-model systems to recognize an individual. Eye direction, movement and blink are also recorded as the advancement to generate more interactive observations. The confidence or attention of a student or employee can be observed within the class or conference using these measures. The fatigue or doziness of a driver or athlete or worker can be recognized by characterizing the eye behaviour. The quality of these eye tracking systems depends on the continuous recording of face and eye-region. Earlier, the distance cameras were used to record the eye movement. Such cameras were not effective and sensitive to face movement, pose and occlusion. But in recent times, various wearable devices are available with specialized cameras to record each and minor movement clearly. The smart eye-glasses and head-movement sensitive cameras are available to acquire more focused and continuous tracking of eye-region (Rihana et al., 2012; Choi et al., 2011; Abe et al., 2014). This kind of tracking is able to resolve many of the real time deficiencies that can affect the accuracy of such predictive systems. Even, the distance camera based eye-tracking is also used through surveillance cameras to observe the group of people. The eye blink tracking and recognition are having several challenges and characteristics that are required to resolve and measure for improving the accuracy of the decision system. These characteristics and relative functional behaviour are provided in table 1.

Table 1
Characterization of eye-blink tracking

Feature	Role	Usage/Scope	User
Pupil	Position and direction of Pupil	Attention Recognition	Student, Employee
Blink	Frequency, transition duration	Doziness, Fatigue estimation	Driver, Athlete, Patient
Eye	Biometric Feature	Biometric and Multimodal Authentication	Online Users

The applications and the functional behaviour of eye blink are dependent on various physiological and environmental factors recognition (Chen et al., 2015; Bacivarov et al., 2008; Choi et al., 2011). The head position or the pose of the individual can obscure the acquired information or features. The geometric misalignment and out-of-focus situation can drop the recognition rate. The camera alignment and positioning can also be the reason of such kind of disruption. The environmental situation such as lighting, fog and camera quality can also affect the visualized features of the eye and iris. The real time eye tracking is affected by all such disruptions and can affect the quality of eye blink recognition.

In this paper, a statistical and mathematical filter based model is provided to recognize the eye blink count accurately. The model is defined to process on real time videos. The video frame processing, eye region processing and blink characterization are included as intermediate work stages of this model. The similarity measures are implied at each stage based on mathematical, structural or statistical filters. In this "INTRODUCTION" section, the characterization and scope of eye blink recognition are discussed. The applications and the behaviour of eye and eye-blink tracking are provided in this section. In "RELATED WORK" section, the algorithms and models adopted by the researchers for improving the eye-blink tracking are provided. In "RESEARCH METHODOLOGY" section, the proposed algorithmic framework is provided with the functional description of each inclusive stage. In section "RESULTS AND DISCUSSION", the results are generated for sample videos taken in different environments. The graphical evaluation is provided to verify the significance of the proposed model. In section "CONCLUSION", the conclusion of the proposed eye-blink recognition model is provided.

RELATED WORK

Eyes are considered as an effective biometric feature to recognize the individual. But in the recent years, the application and phenomenon of eye processing are extended. Now, eye movement, eye blink, iris region is processed separately or collectively to identify disease, fatigue, attention-level and behaviour of an individual. The camera position, quality and application increase the complexities to eye processing. The researchers have provided the methods to handle these real time challenges as well as to improve the processing behaviour of each integrated stage. In this section, the contribution of researchers in terms of stage, challenge and application specific methods is discussed.

The eye tracking and blink detection are challenging in real environment because of scene, head movement and low-resolution cameras. Effective segmentation methods are required to track the eyes and to count the eye-blink. Pauly and Sankar (2015b) processed the HOG (Histogram of Oriented Gradients) features with SVM (Support Vector Machine) classifier to detect the eye blink accurately and gained the accuracy over 92%. A wavelet transformation adaptive Neuro-fuzzy system was provided to count the fast eye-blinking accurately (Azar & Akhbardeh, 2007). Author improved the performance of eye-blink detection while handling the overlapped eye-blink problem. The template matching with similarity measure was proposed to reduce the false detection of eye-blink in the changing background scene (Awais et al., 2013). The correlation score evaluation based eye blink detection method achieved the higher accuracy for different experimental conditions. The Eigen-eye approach was employed to recognize the close-eyes with smart glasses (Le et al., 2013). Author combined the non-maximum suppression algorithm with Gradient Boosting algorithm to improve the robustness and accuracy of eye-blink recognition. The RBF (Radial Basis Function) classifier was applied on acquired statistical features to classify the eye-blink (Rihana et al., 2012). The color information surrounding eye-region was analyzed to predict the eyelid movement (Panning et al., 2011). The adaboost learning and grouping method provided by Choi et al. (2011) to provide outlier robust detection of eye and eye-blink (Bacivarov et al., 2008) used the statistical features to encode the variations caused by blinking. The model was also robust to head-pose and gaze variations. SIFT (Scale-Invariant Feature Transform) feature processing with affine transformation was proposed to achieve pose robust eye-blink tracking (Lalonde et al., 2007). The constraint adaptive blob region was trained to determine the eye-blink length and sequence. The lighting, reflection and illumination challenges were dealt by Chen et al. (2015) for robust iris detection. Author used the polynomial interpolation and inter-class similarity for eye, gaze and eye-blink detection. Ryu et al. (2013) had proposed the Local ternary pattern and SVM (Support Vector Machine) based composite algorithm for real time eye blink detection and integrated it to the smart devices. The composition of peak detection algorithm and ICA (Independent Component Analysis) algorithm was provided to detect the eye-blink (Gao et al., 2010).

The accuracy and effectiveness of eye-blink recognition depends on the quality and mechanism of video capturing. Various devices, camera types, camera-integrations and sensors integrated devices are designed by the researchers to getting more informative and robust eye-blink recognition. Smart glasses camera was used with low-energy imaging and effective computation capabilities to improve the accuracy of eye-blink detection (Le et al., 2013). The Doppler sensors were used by Kim (2015) for noise and pose robust eye and eye-blink tracking. A camera based integrated system was designed to monitor the head, eye and eye-blinks (Pullano et al., 2016). The ultrasonic transmitter integrated network was designed to validate the system reliability in the real environment.

The eye-blink processing and analysis is having its effect in various real-time applications including attention identification, fatigue determination and driver drowsiness has evaluated the level of attentiveness of a person to determine the fatigue of person (Haq & Hasan, 2016). The addressed application can be employed in vehicles to warn the driver by observing the fatigue and the number of accidents can be reduced. The vigilance driving was detected using iris processing to improve the road safety (Nacer et al., 2014). The doze state of an individual was observed using Blink burst and isolated-blink detection (Naito et al., 2012). The consciousness level cases for fatigue, lack of sleep and repetition of task were identified by the author. Involuntary and voluntary blinks were isolated by to monitor the Human's fatigue (Kurylyak et al., 2012). Pander et al. (2008) also designed a fatigue indicator by observing the spontaneous eye blink action. An evaluation on drowsiness condition of driver was observed to reduce the car crashes (Cristiani et al., 2010). The algorithm observed the face and eye under drowsiness constraints. The HOG features integrated SVM classifier was applied by Pauly and Sankar (2015a) to detect the drowsiness of drivers. A multi-featured probabilistic model was provided to identify the driving disability of an individual because of fatigue or drowsiness (Junjea, 2015).

RESEARCH METHODOLOGY

Eyeblinks can be monitored and considered as a decisive phenomenon to identify the drowsiness and fatigue of individuals. The accurate estimation eyeblink count improves its significance in various medical and surveillance applications. This paper provides a mathematical, structural and statistical aspect based model to identify the eyeblink count accurately. The model has accepts the real-time facial video as input and extracts the effective frames and eye-region in the earlier stage. At the earlier stage, the mathematical filters are applied to identify the effective frames by observing the frame dissimilarity. The identified effective frames are analyzed under positional and mathematical filters to segment the eye region. The redial filter is applied on the eye region to segment the continuous frames. This extracted eye region is now acquired for significant individual frames to generate the effective features. A wavelet decomposition based block map is applied to acquire the low pass features. The content feature evaluation is implied on these block regions to describe the effective eye region. In the final stage, a distance driven map is applied of generated features to the open and close eye feature datasets. The maximum match based decision is considered to identify the eyeblink. The proposed structural and statistical feature based eyeblink detection model is provided in figure 1.

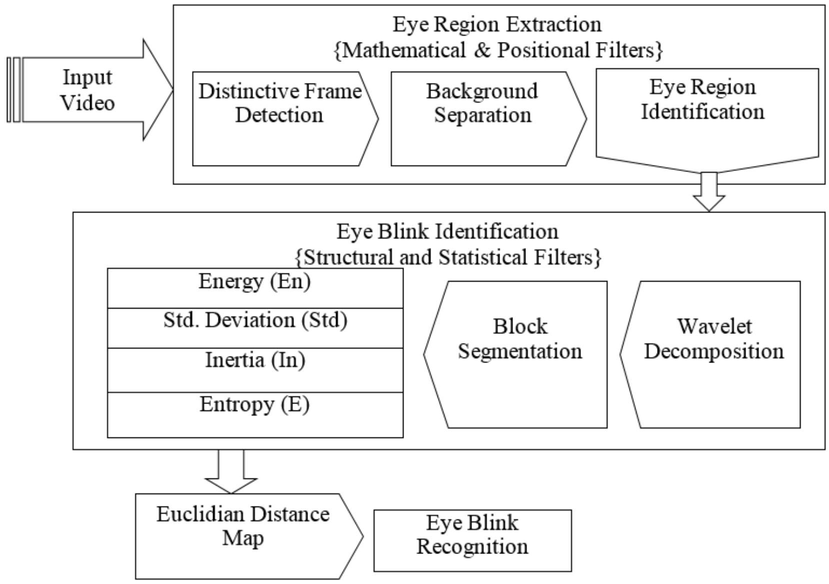

Figure 1. Structural and Statistical Feature adaptive Model

The proposed eyeblink model shown in Figure 1 is divided into three functional stages. In the first stage, the mathematical and positional filters are applied to identify the qualified frames and eye-region. The distinctive frames were identified by applying the frame-similarity evaluation. The identified frames were processed by mathematical morphological operators to separate the background and to identify the eye region. The positional estimation is also combined to identify the relevant and decisive eye region. To acquire the features, the low pass filtration is applied on effective eye region using wavelet decomposition. The block segmentation is applied on low featured region. The statistical and structural features are extracted on each block featured segment. This structural and statistical featured mapped eye is compared with open and close eye-image dataset using the Euclidian distance measure. The proposed model is defined as a generic model can be later applied for medical application, fatigue estimation, attention identification and driver drowsiness identification. The model is implemented on the larger face focused video sets with complex and diverse scenes. The implementation results are provided and discussed in "RESULTS AND DISCUSSION" section.

Effective Eye Region Extraction

The face-focused video is taken from diverse scene is accepted as the input to the eye-region extraction stage. The mathematical and position based evaluation is performed to identify the contributing frames and the eye region. The Distinctive frame detection, background separation and eye-region identification have defined the functional description of eye-region extraction.

Distinct frame Extraction

The video file is transformed to frame-images by applying the Matlab tool. The frame-rate and file format are defined while extracting the frames. The distance-based analysis is performed between the consecutive frames. The n-dimensional transition and feature vector generation is done in terms of energy (En) and mean coefficient (MC) evaluation. The distance estimation between these two vectors is done on consecutive frames as $dist(frame_i, frame_{i+1})$. Where each frame is described by $frame_i=(En,MC)$. The distance evaluation is done based on Euclidean distance (Ed) estimation. The formulations of feature vector and distance estimator are provided below:

$$En = \frac{1}{N^2}\sum_{i=1}^{N} Frame(i)^2 \quad (1)$$

Where, N is the length of vector, i is the block index of vector.

The energy is the high pass information vector that that generates the derivation ratio based absolute value. The content driven analysis is provided by this energy vector. The mean-coefficient evaluation is provided in equation (2). It computes the average intensity of each frame block.

$$\text{MC} = \frac{1}{N}\sum_{i=1}^{N} Frame(i) \quad (2)$$

The Energy (En) and Mean-Coefficient (MC) vector based frames were compared on consecutive frames using Euclidean distance measure shown in equation (3). The similar frames are neglected and the non-similar frames are considered as an effective frame to take the decision on eye-blink.

$$\text{EDist}(\text{Frame}_i, \text{Frame}_{i+1}) = \sqrt{\sum_{i=1}^{N} (Frame_i - Frame_{i+1})^2} \quad (3)$$

Background Separation

The eyeblink detection is focused on the facial and eye region (Choi et al., 2011; Kim, 2015). The background separation is applied to avoid the scene complexity and to process only the relevant region. The skin region adaptive mean filter evaluation is performed on YUV (Luminance (Y), blue–luminance (U), red–luminance (V)) converted frames. This color model is more robust to noise and illumination change. The RGB (Red-Green-Blue) to YUV color model transition is shown in equation (4)

$$\begin{pmatrix} Y \\ U \\ V \end{pmatrix} = \begin{pmatrix} +0.0247 & +0.504 & +0.098 \\ -0.148 & -0.291 & +0.439 \\ +0.0439 & -0.368 & -0.071 \end{pmatrix} . \begin{pmatrix} R \\ G \\ B \end{pmatrix} \begin{pmatrix} 16 \\ 128 \\ 128 \end{pmatrix} \quad (4)$$

The threshold adaptive morphological operators are applied on color transited image to identify the effective region. The log transition function adopted for region extraction is provided in equation (5)

$$ERegion(x, y) = a + \frac{\log(EFrame(x, y) + 1)}{b * \log(c)} \quad (5)$$

Where, EFrame is the effective frame; a, b and c are the illumination controlled constraints.

The threshold limits are applied through a, b and c values to identify the effective region (ERegion) using this log transformation. The morphological and convolutional filters are also applied respective to mean pixel value to clean the smaller chunks and to identify the effective skin region over the image. The stage has removed the background and the non-relevant region from the effective frames and identified the effective region (ERegion).

Eye-Region Detection

The effective facial region (ERegion) is processed using positional parameters to identify the eye region (Nacer et al., 2014). The ratio adaptive geometric analysis is performed to identify the eye region. Once the face region is captured, the facial components can be identified by applying the geometric ratio evaluation. The horizontal and vertical analysis can be applied for different facial components. The estimation on eye position, distance between eye-nose and between-eyes is done to extract the eye region. The work is successful implementation of facial component extraction. Same work is applied to extract the effective eye region in this work.

Eye-Blink Detection

In the second stage of this model, the eye blink detection process is accomplished by applying the structural and statistical feature evaluation. It is a composite process in which, the extracted eye region is first decomposed using the low-pass filtration. This filtration stage has identified the relevant content information from the image. Now the block segmentation is applied on this extracted featured region. For each block, the structural and statistical features are extracted to represent the eye region as processing feature set. In this Eye-Blink Detection stage, each of the integrated process stage is described.

Wavelet Decomposition

Haar wavelet transformation method is applied in this research for low-pass filtration and to reduce the dimension of processing information. In this filter, the average of two adjacent pixels is taken to take the decision on the low-pass filtration. Two-level wavelet decomposition is applied independently on eye-region columns and then rows. The sub-bands are generated at each level of this decomposition. The low frequency subband is processed to acquire the adaptive and reduced resolution features. The extracted features are adaptive to the energy so that the information contents are extracted using this decomposition stage. The approximation coefficient is taken at each level of this decomposition. This decomposed energy features are processed by block adaptive feature generation stage to generate the processing featureset.

Block Segment based Feature Extraction

After extracting the relevant content driven eye region, the block segmentation is applied to generate the information and region adaptive featureset. The rectangular blocks of 4x4 are generated over the segmented region. On each block, the statistical and structural features such as Energy (En), Inertia (In), Standard Deviation (SD), Entropy (E) parameters. These are the content-driven parameters which are able to identify the intensity and variation driven analysis within the block (Blk). Each of the block pixels is processed for these features to generate the content adaptive wider feature set. These equations are these content features are provided:

$$\mathrm{En} = \frac{1}{N^2}\sum_{i=1}^{N} Blk(i)^2 \qquad (6)$$

Energy (En) identifies the derivation adaptive content information to represent the eye-region effectively. Equation (6) represents the energy feature evaluation based on content specific ratio value. Another content driven evaluation is performed by Inertia (In) parameter described through equation (7). It identifies the intensity level distribution within the block. In these equations, N is the size the length of block and w, h are the weight and height of block.

$$In = \sum_{x=1}^{w}\sum_{y=1}^{h}(x-y)^2 Blk(x,y) \qquad (7)$$

The intensity and content driven variation exist within the block is evaluated using Standard Deviation (sD) and Entropy (E) features provided in equation (8) and (9). The variations exist within the block and the degree of heterogeneity based on pixel intensity is evaluated by these features.

$$sD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} Blk(i)^2} \qquad (8)$$

$$E = -\sum_{i=1}^{N} Blk(i).\log Blk(i) \qquad (9)$$

These structural and content based features are generated for each block over the effective eye-region. The wider feature set of eye-region is compared with feature transformed open and close eyes. The maximum matched eye-status is considered as the status of that particular eye-frame. The distance-based comparison is done using Euclidean distance measure described in the "RESULTS AND DISCUSSION" section.

Euclidean Distance Matching

Once the eye-region of input video-frames and the eye images of training datasets are transformed to statistical and structural features, the Euclidean distance based match is applied to identify the eye status. The feature adaptive vector set is analyzed using the Euclidean distance (EuD) based pattern measure shown in equation (10).

$$\mathrm{EuD} = \sqrt{\sum_{i=1}^{M} |InputEye_i - TrainngEye_i|^2} \qquad (10)$$

Where, M is the length of feature vector.

The feature vector of extracted eye region is compared with open-eye and close-eye training set images separately. The identified eye image with maximum match is considered as the status of the eye. Once the eye statuses are identified, the sequence of change of eye status from open-to-close and close-to-open are identified to estimate the eye-blink count. The proposed eye-blink detection model is implemented on self captured and the videos collected through random web sources. The implementation results and the description of dataset are provided in the next section.

RESULTS AND DISCUSSION

In this paper, the mathematical and statistical filters are applied at different levels to count the eye blinks. The proposed model has acquired the eye region effectively from complex scenes of video frames. The mathematical filters are applied to recognize the contributing frames and the eye-region. The statistical measures such as Energy (En), Inertia (In), Standard Deviation (sD) and Entropy (E) are applied on block segmented region of each selected-frame to represent the decisive features. These features are compared to the open and close eye datasets using Euclidean distance measure to recognize the frame class. The frame sequence is finally mapped respective to eye status to identify the blink-count. In this section, the comparative evaluation of the proposed structural and statistical measure adaptive model is applied on multiple video collected randomly from Google search (Youtube.com, 2018), self-captured real time videos and the videos taken from NRC-IIT (Videorecognition.com, 2018) dataset of facial videos. The description of these videosets used in this research is provided in Table 2.

Table 2

Characterization of eye-blink tracking

	Real Time Videos	External Web Sources (Youtube.com, 2018)	NRC-IIT Dataset (Videorecognition.com, 2018)
Number of Videos	30	20	22
Type	Color	Color	Color
Category	Indoor, Outdoor Driving	Indoor, Outdoor Driving, Drunken Videos	Indoor Office Video
Format	3gp	AVI	AVI
Resolution	176x144	Multiple	160x120
Environment	Indoor, Outdoor	Indoor, Outdoor	Indoor

These videos are categorized as new reader videos, drunken driver videos, person real-time videos and outdoor scene based videos. These all videos are collected in versatile environments with individual focusing with different camera distances. The personal real time videos are self collected videos in indoor and outdoor environment as family video dataset. These videos are collected in different formats such as AVI, WMV, MP4 and converted to standard AVI format. The evaluation is performed by identifying the actual eyeblinks identified by monitoring the video file manually and the number of eyeblinks identified by the model. To verify the significance of the proposed model, the implementation of existing-threshold based, dynamic-threshold based approaches is also provided. Junjea (2015) is the work already done by me to identify the eye-blink count for driver disability evaluation. These three existing and proposed statistical measure adaptive method are implemented in the matlab environment on more than 50 videos of diverse lengths and environment which are taken from various sources shown in Table 2. The detailed evaluation of nine videos is provided in Table 3. These videos are taken randomly from the video pool of different lengths and categories. The table contains the actual number of eye-blinks in each video and the eyeblinks identified by each of existing and proposed approach.

Table 3

Analysis results on eye blink identification on sample videos

Video Files	Total Eye Blinks	Threshold based Approach	Dynamic Threshold	(Junjea, 2015)	Proposed
Video1.avi	18	11	14	15	18
Video2.avi	24	16	19	21	23
Video3.avi	9	5	7	9	9
Video4.avi	14	9	11	12	14
Video5.avi	7	5	7	7	7
Video6.avi	19	12	15	15	17
Video7.avi	31	24	27	28	29
Video8.avi	27	19	22	24	25
Video9.avi	11	7	8	11	11

The analytical observations collected for a random set of videos is provided in Table 3. The video files names with actual eye blink count are listed in the table. The existing threshold based method has considered the single static value for taking the decision on eyeblink detection. As the method performed the lesser dynamic computation, the detected eyeblink count is very less in this method. The dynamic threshold based method has performed the intensity and region density specific evaluation to identify the eyeblinks. The geometric and color model analysis was performed by Junjea (2015) for eye region extraction. The probabilistic estimation on correlation and content similarity analysis was performed for identification of eye status. This method also provided the comparatively better results than threshold and dynamic threshold based method. The proposed structural and statistical measure based evaluation method has used multiple measures to take the concrete decision to track the eye status. The results identified that the proposed model

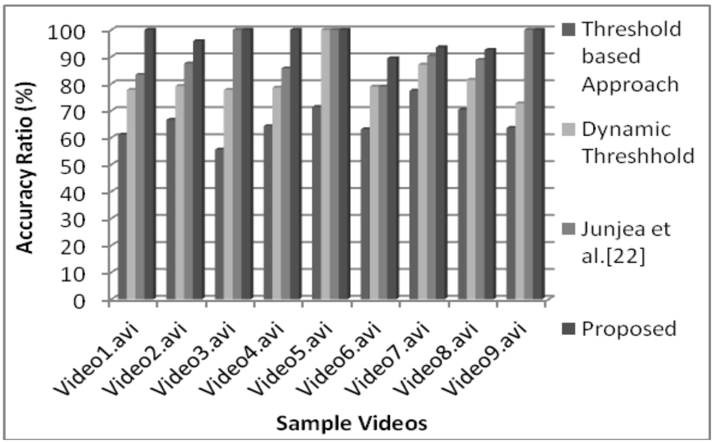

Figure 2. Accuracy ratio analysis of eyeblinks (sample videos)

has identified the eyeblinks effectively for variant scenes. All the eyeblinks are identified in many of the sample videos by this proposed model. The accuracy based evaluation estimated from the statistics of this table is depicted in Figure 2.

The accuracy ratio of eye blink detection on each sample video is provided in this figure for existing and proposed methods. The bar of threshold-based approach observed the minimum accuracy of 61.11% and maximum of 77.42% for eyeblink detection. The Dynamic threshold taken the decision based on the scene strength by setting up the dynamic decisive values. In this method, the minimum accuracy obtained is 72.73%, whereas all other videos achieved the accuracy over 75%. The maximum accuracy achieved for this method is 100% for video5.avi. Junjea (2015) defined the probabilistic estimation based on structural and content specific evaluation. In this method, on an average 90% accuracy rate is achieved. The maximum accuracy achieved for this method is 100% for 3 videos. The proposed structural and statistical feature based evaluation method achieved the significant gain in accuracy of eyeblink detection. In this method, all the videos achieved the accuracy over 90% and on an average 96.8% accuracy is achieved. Out of nine videos, the eyeblink detection on five videos is done with 100% accuracy rate.

The robustness of the proposed structural and statistical feature evaluation model is verified by applying it on the larger set of videos. These videos are captured personally through mobile camera or collected from video sites through Google search. All these videos are categorized based on the scene or the environment in which the video is captured.

The collected videos are divided in four categories named News reader videos, drunken driver videos, Personal videos and outdoor videos. Each of the video categories is defined with the different number of video instances. The evaluation provided in figure 3 is having 12 instances of New-reader categories, 8 videos for drunken drivers, 14 videos of random outdoor scenes and 18 personal videos. Each of the video in the sample set is processed manually and by using each of existing and proposed method. The comparative evaluation of accuracy rate of eye-blink detection methods is provided in Figure 3.

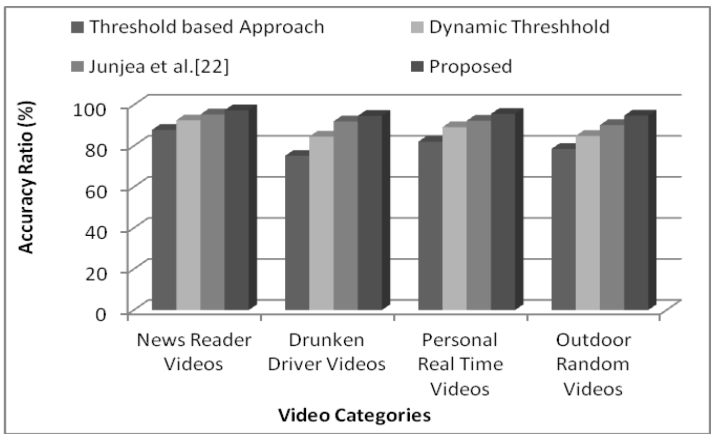

Figure 3. Accuracy analysis of eyeblink detection (video categories)

Figure 3 has provided the comparative evaluation in terms of existing and proposed methods for each video category. The results show that the threshold has achieved the minimum accuracy rate and the proposed method achieved the maximum accuracy rate for each video category. The new-reader videos are more face-focused with stable camera position so that the maximum accuracy is achieved for these videos respective to each eyeblink detection method. The minimum accuracy rate achieved for new-reader videos is 87.8% by using the threshold based method and the maximum accuracy rate achieved is 97.39% for proposed method. The drunken videos are generally captured in the night through mobile cameras. The minimum accuracy rate achieved for these videos is 75.17% and the maximum accuracy rate is 94.63%. The outdoor and personalized videos provided the mixed results based on the camera and video quality.

Other than the real time and web-collected videos, the NRC-IIT (avi) dataset. The eye blink analysis was conducted on five random videos of videos taken from same dataset and captured from the real environment. These videos were also used by Juneja (2015). The analysis was conducted in terms number of eyeblinks and eye movement count against the actual number of eyeblinks and eye-movement exist in the videos.

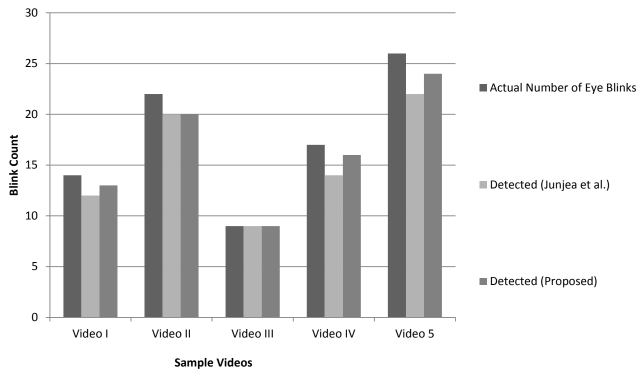

Figure 4. Actual Vs. computed eyeblinks analysis (RealTime DB)

Figure 4 provids the comparative analysis on eyeblinks count against the number of actual eyeblinks and the eyeblinks detected by (Junjea, 2015). The figure shows that the number of eyeblinks detected by this proposed method are higher than for video I, Video III and video IV (Junjea, 2015). It shows that the proposed approach has performed effectively well then existing Junjea (2015) approach.

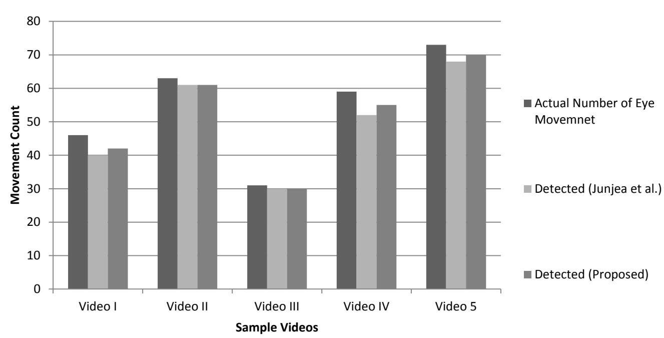

Figure 5. Actual Vs. computed eyemovement analysis (RealTime DB)

The evaluation on eye-movement detection for real-time videos is provided in Figure 5. The comparative results show that the proposed approach has performed better than Junjea (2015) approach. In case of Junjea (2015) method the minimum eye-movement detection rate achieved was 86.96%, whereas, in proposed approach the minimum accuracy detected for eye-movement recognition is 91.3%. The average accuracy of eye-movement detection in Junjea (2015) and proposed approaches are 92.4% and 94.80% respectively. These results verify a significant gain is achieved for these real-time videos using proposed approach.

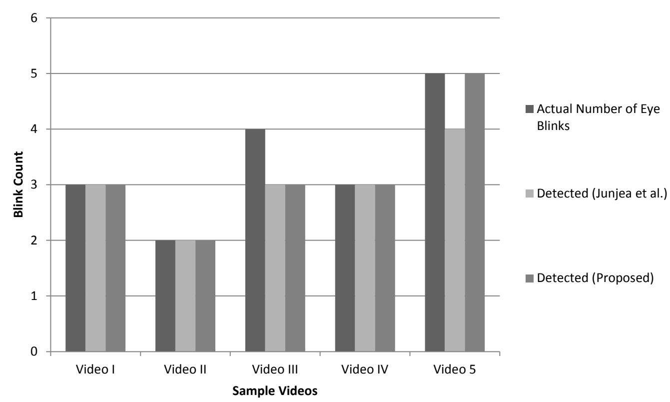

Figure 6. Actual Vs. computed eyeblinks analysis(NRC-IIT DB)

Figure 6 provids the analysis results of eye blink detection on five sample videos taken from NRC-IIT DB dataset. The comparative evaluation was conducted respective to the number of actual eyeblinks existed in the videos. The analysis was conducted against Junjea (2015) approach. The comparative results show all the eye blinks are detected for Video I, Video II and Video IV using proposed and Junjea (2015) approaches. The Junjea (2015) method also provided the significant results except Video 5. The proposed approach has detected all the eyeblinks even for this video. It shows that the proposed approach has performed effectively well for videos taken from NRC-IIT DB videos.

The eye-movement detection was another evaluation performed on NRC-IIT dataset to verify the significance of proposed work. The analysis was performed on five sample videos taken from the dataset. The comparative results against the number of eye-movements are provided in Figure 7. The bar graph clearly identifies that the proposed approach has improved the accuracy of eye-movement detection over Junjea (2015) approach. The average rate of eye-movement recognition in Junjea (2015) approach is 82.3%, whereas, in proposed approach the average accuracy of eye-movement detection is 89.67%. It shows that the proposed approach has significantly improved the accuracy of eye-movement recognition.

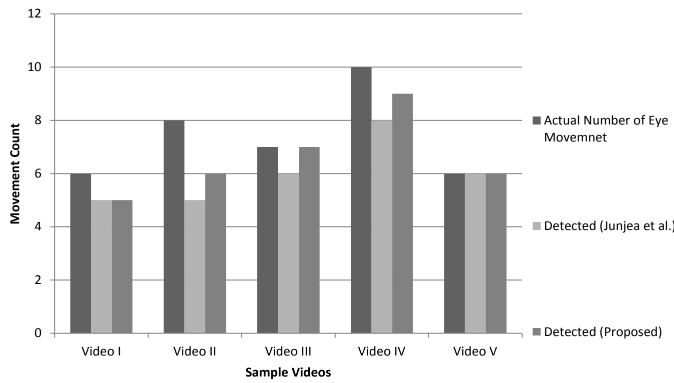

Figure 7. Actual Vs. computed eyemovement analysis(NRC-IIT DB)

CONCLUSION

In this paper, the structural and statistical feature adaptive model is provided for eye-blink detection for real time complex videos. The normalized AVI video frames are taken as input to the model. In the earlier stage, the statistical evaluation on consecutive frames is done using Energy (En) and Mean Coefficient (MC) parameters. The effective frames identified in first stage are processed under color adaptive mathematical and convolutional filter to identify the effective face region. The positional and geometric evaluation is performed on face region to extract the eye region. These extracted eye regions are gone through the next stage to transform the frame to effective features. The two-level wavelet decomposition is applied to identify the content features. Now to transform the eye region to adaptive structural and content based feature vector, the block segmentation is applied. The energy, pixel deviation and content specific features are generated for input and training set eye regions. In the final stage, the generated feature vectors of input eye-regions are compared on training set images to identify the eye status. The proposed model is applied on complex scene based videos captured in real time or collected through google search and NRC-IIT datasets. The evaluation is conducted for detection of eye-blinks and eye-movements in the videos. The comparative results are generated against threshold based, dynamic threshold based and Junjea (2015) methods. The results identify the significant improvement of 2% to 5% in accuracy rate for videos taken in different environments.

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