Asian Journal of Research in Computer Science

3(1): 1-14, 2019; Article no.AJRCOS.47899
ISSN: 2581-8260

Human Fatigue Characterization and Detection Using the Eyelid State and Kalman Filter

Dominic Asamoah[1], Emmanuel Ofori Oppong[1], Peter Amoako-Yirenkyi[2] and Stephen Opoku Oppong[3*]

[1]Department of Computer Science, KNUST, Ghana.
[2]Department of Mathematics, KNUST, Ghana.
[3]Faculty of Computing and Information Systems, GTUC, Ghana.

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/AJRCOS/2019/v3i130082
Editor(s):
(1) Dr. Omidiora, Elijah Olusayo, Professor, Department of Computer Science and Engineering, Faculty of Engineering and Technology, Ladoke Akintola University of Technology (LAUTECH), Nigeria.
Reviewers:
(1) Zlatin Zlatev, Trakia University, Bulgaria.
(2) Anthony Spiteri Staines, University of Malta, Malta.
Complete Peer review History: http://www.sdiarticle3.com/review-history/47899

Original Research Article

Received 25 December 2018
Accepted 05 March 2019
Published 15 March 2019

ABSTRACT

One of the most promising commercial applications of Human Computer Interface is the vision based Human fatigue detection systems. Most methods and algorithms currently rely heavily on movement of the head and the colorization of the eye ball. In this paper, a new algorithm for detecting human fatigue by relying primarily on eyelid movements as a facial feature is proposed. The features of the eye region and eyelid movement which are geometric in nature are processed alongside each other to determine the level of fatigue of a person. Haar classifiers are employed to detect the eye region and eyelid features. The eye region is, however processed to ascertain attributes of eyelid movement of each individual of interest. The eyelids are then detected as either opened, closed or in transition state. The movement or velocity of the eyelid is tracked using a Kalman filtered velocity function. This algorithm calculates a human blink cycle for each individual, and estimates the associated errors of the eye movement due to friction using the Kalman filter.

**Corresponding author: E-mail: sopokuoppong@yahoo.com;*

The study has established human blink cycle calculation as a new classifier to characterize human fatigue and the calculation of the movement of eyelid using the Kalman filter in determining the level of fatigue.

Keywords: Kalman filter; eyelid; blink cycle; human fatigue; Human Computer Interface.

1. INTRODUCTION

According to the 2010 accident statistics of the Ghana National Road Safety Organization of many of the accidents that occurred on the roads in Ghana were a direct result of driver fatigue [1]. Thus, driver fatigue has resulted in an un-estimated number of deaths and injuries. It is therefore paramount that an active surveillance system that could effectively detect fatigued drivers on the roads of Ghana would contribute to a large reduction in these fatal and injury causing accidents According to the Journal of Applied Physiology, “fatigue is a feeling of continuous tiredness or weakness and which can be either physical, mental or a combination of both”. At a point in life, most adults will experience fatigue but it can literally affect anyone.

A human fatigue state can be analyzed by the use of surveillance systems. The applications include image acquisition and the extraction of the important features through proper and appropriate segmentation methods. These features are subjected to extraction processes that extract important facial feature information from the original images, followed by classification processes that categorize the features. A certain activity is considered to be detected if the features fall in a corresponding category. Previous authors have identified several approaches to Fatigue and drowsiness monitoring systems with sensor-based techniques [2]. However, such have been known to possess some inherent disadvantages over vision-based techniques. For example, the sensor fusion based system by Sahayadhas et al. [3], [4] used multiple sensors to study drivers’ drowsiness and fatigue. The sensors were fixed to the upper quarter of the body of drivers and thus impeded their driving processes. Experiments conducted on them showed poor detection rates. Other researchers have devoted their work to developing fatigue detection systems using machine vision techniques [5]. Many early researches are only centered on the analysis of the pupil movements. These systems used infrared cameras based on the “red eye effect” to help track the pupils. Although an infrared camera can capture clear images in dark environments, it usually loses most of its features under sufficient lighting environments especially under very bright illumination [6]. This has affected and reduced the accuracy of the infrared approaches with enough illumination.

Classical facial expression detection systems consist of several stages: image acquisition, image preprocessing, face detection, facial feature detection, feature extraction and classification. A video camera is used to obtain the image in the image capturing stage. In the image preprocessing stage, the images which were captured are improved by removing and reducing the bulk of the data size to enable processing. The face segmentation stage primarily consists of two processes, the face detection process and a facial features location process. The face detection indicates the presence of a face in the image and the facial features location process indicates the position of the eyes and mouth of the face. The face segmentation stage is followed by the feature extraction stage, which is used to extract salient features from the face. Lastly, the classification stage categorizes these features into different groups of expressions.

Most researches have tried characterizing fatigue based on the eye using mainly the pupil and the iris although these method works but has got its own limitations. These features cannot be easily extracted without the full cooperation of the individual, where the individual needs to gaze directly into the camera. Computing information on the iris is also subjective if the prior information of the individual is not known as this depends on race [7]. These methods therefore tend to be impractical especially when the individual’s awareness is not needed.

The objective of this paper is to investigate, analyze, design and develop a prototype that detects fatigue based on the eyelid movement.

2. LITERATURE REVIEW

2.1 Introduction

Smart surveillance systems are required to provide timely behavior-detection by investigating online videos or enhancing certain incidents on already captured surveillance videos to present a smaller quantity of data for investigation. The advantages of this system far outweigh those of the traditional video surveillance systems. This traditional system combines an investigative stage and a preventive stage with the preventive stage serving as a follow up to the investigative stage [8]. This system is used mainly to achieve timely alerts.

The techniques used in this system can effectively reduce data redundancy through content-based video recording [9,10].

Smart surveillance systems have the capability to detect and simulate human behaviors and the ability to react to changes in such human behaviors. Current video surveillance systems only capture, store, and distribute images. They do not extract nor analyze features of the images. These are left for human operators. However, this human monitoring operation can be extremely labor-intensive. Furthermore, the capacity to hold attention and to respond to seldom occurring events can prove very challenging and also susceptible to errors due to gaps in attention. Studies have shown that, manual detection of events in surveillance systems is not effective [11].

2.2 Face Detection

The initial stage of the concept of face recognition-systems is face detection obviously because a face is needed to be identified. An image can be given to a face detection system and be required to discover all available faces in that image and pinpoint their specific positions and sizes. This concept always occurs in two (2) phases [12]:

1. Examining a whole image to find regions that are identified as “faces”.
2. Localizing a more precise estimate of the specific position and size of the face.

2.3 Image Segmentation

Image segmentation has also seen some improvements and is used with image processing. In image analysis, image segmentation is usually the initial step [13]. Image segmentation is used to separate an image into a number of segments so that the image representation will be easier to analyze. [13] in their work, describe image segmentation as a process of partitioning an image into multiple segments so as to enable the illustration to be more significant and simpler to analyze, Segments can be intensity or texture in an image or a set of pixels in a region.

2.4 Noise Filtering

In 2008, [14] studied noise reduction methods in stripped images and they stated that noise filtering is a vital factor that impacts the quality of the image. Noise filtering can be applied during the process of image acquisition and transmission. The main purpose of reducing noise in image processing is that it helps to restore the detail of the original image as much as possible [15]. Noise filtering is thus necessary in image processing and image interpretation. The research [14] also reported that noise removal or filtering relies on the form of noise which corrupted the image.

2.5 Feature Extraction

Feature extraction is an essential stage in image classification and it is used to perfectly represent image content. Feature extraction methods can be classified into Color Feature Extraction which is a pivotal feature in classification and retrieval of images and the commonest method used in color feature extraction is color-histogram; Texture Feature Extraction which is a technique need for large images which contain repetition regions. The texture is a group of pixels that have certain characteristics and Shape Feature Extraction which focuses on shapes that are seen logically similar by the human, which also have the exact characteristics different from the others.

2.6 Eye Tracking Method

One important area in computer vision is object tracking. The tracking process can be hindered by different movement conditions and occlusions [16]. The solution is therefore to apply recursive linear Kalman filtering algorithms that can update the state of the input data after each recursive application.

According to Duchowski [17], analysis of movement of the eye is an essential element research in eye tracking especially in real-time settings.

Eye movement prediction is practically required for the enhancement of sensor lag. Binary classifications of the eye movements is a broadly studied area relating to works and approaches [18]. Although effective and simple, it causes confusion to the classification of the smooth pursuit. However, using Kalman filters helps to alleviate this confusion. This Kalman filters scheme with its inherent prediction method and correction framework allows for first order movement extrapolation that which are exported to minimize lags. Kalman filters have been effectively used in a variety of applications for prediction and state determination of systems.

3. METHODOLOGY

3.1 Introduction

The design of the proposed system has been presented as a series of procedures and algorithms. The underlying rationale, concepts and theories that were employed to perform various process of the characterization system have also been discussed.

3.2 Conceptual Framework

The conceptual framework of this study is captured in Fig. 1. This shows the main concepts and methods used in this study.

The steps taken to achieve the main objective of this study i.e. to detect fatigue are outlined below:

1. Sample videos are collected under different intensities and illuminations over a specified time interval
2. The acquired video stream is then split into individual frames for use in face and eye detection using The Haar Cascade classifier.
3. Histogram Equalization is performed on the grayscale image which redistributes the gray values uniformly by stretching their contrast.
4. The extracted eye images are binarized (digitized) after thresholding using Otsu method.
5. The maximum or highest intensity values of each binarized eye image is computed and stored in a buffer.
6. Gaussian filters are then applied to produce smoothening of the data to determine whether the eye is close or open.
7. The establishment of a blink cycle between the open and closed eye states is performed by using the sample data from the dataset which forms the basis of judging the fatigue level of the individual.
8. The state of the eyes (whether opened, closed or transition) is decided by the distance between the first two intensity changes stored in the buffer. When there are a number (say 5) of consecutive frames that find the eye closed, the previous state before the closure of the eye begins to constitute a cycle.
9. Tracking the eyelid is done using the Kalman Filter. The pixel positions of the moving eyelid from the initial stage to the final stage of tracking are used in calculating the distance covered by the eyelid.
10. The eyelid's state is estimated using the Kalman filter. The value of the current state is determined by the prediction state equations of the Kalman Filter determine using values from the previous state.
11. After the analysis of the captured data representing the velocity of the eyelid movement using Kalman filter, it can be confirmed that a person is in the active state if it has most of the peaks below the Kalman line (update). However, the situation where most of the peaks of the velocity (current) from the graph fall above the Kalman line indicates that the person is in fatigue stage. On the other hand, if the current velocity at any given time is the same as the estimated velocity at the same time, then the person is in normal state.

3.3 Thresholding

Thresholding is a process used to convert a gray scale image to a binary image so that objects of interest are segregated from the background. For thresholding to be effective in object-background separation, it is necessary that the objects and background have sufficient contrast with known intensity levels of either the objects or the background.

In a fixed thresholding scheme, the characteristics of the intensity are used to determine threshold value. Assuming that a binary image D[i,j] is the equal to a threshold gray image $M_T[i, j]$ which is achieved using a threshold T for the original gray image M[i, j] [19], then

$$D[i,j] = M_T[i,j] \quad [1]$$

For a darker object on a lighter background

$$M_T[i,j] = \begin{cases} 1 & if\ M[i,j] \leq T \\ 0 & otherwise. \end{cases} \quad [2]$$

If it is known that the object intensity values are a range [T_1, T_2], then we may use

$$M_T[i,j] = \begin{cases} 1 & if\ T_1\ \leq, M[i,j] \leq T_2 \\ 0 & otherwise. \end{cases} \quad [3]$$

Where intensity levels for an object come from several disjoint intervals, a general threshold scheme may be represented as

$$M_T[i,j] = \begin{cases} 1 & if\ \ M[i,j] \in Z \\ 0 & otherwise. \end{cases} \quad [4]$$

where Z is a set of intensity values for object components.

3.4 The Mathematics behind the Otsu Method

Let $\mathbf{r_1}$ and $\mathbf{r_2}$ represent the estimate of class probabilities [20], $\sigma_1^2(t)$ and $\sigma_2^2(t)$ be the individual class variances, the class means are $\mu_1(t)$ and $\mu_2(t)$ and ***S*** the image histogram. The problem of minimizing within class variances can be written as a maximization problem of the between class variances. This can be given as a difference of total variances and within class variances:

$$\sigma_b^2 = \sigma^2 - \sigma_w^2(t) = r_1(t)[1 - r_1(t)][\mu_1(t) - \mu_2(t)]^2 \quad [5]$$

This expression can then be safely maximized and the solution is t that is maximizing $\sigma_b^2(t)$. To get the binary threshold, a call is made to Otsu's methods, and the threshold value is used to create a new Buffered Image object exhibiting the same attributes as the original image. Because it is gray scaled, only the first pixel value is checked after going through all the pixels of the image. A binarized image is created by setting the pixel value that exceeds the threshold to 255, otherwise 0.

3.5 Histogram Equalization

Histogram Equalization is performed on the binarized image. Locating images in which every intensity value fall within a small range is very common if the images have unevenly distributed gray values. Histogram equalization redistributes the gray values uniformly by stretching their contrast. This makes the selection process of threshold more efficient. Generally, histogram equalization improves an image's quality subjectively and is beneficial for an observer who will view it. The maximum or highest intensity values of each binarized eye image is computed and stored in a buffer.

3.6 Gaussian Filters

Gaussian filters belong to a family of linear smoothing with filters weights selected in relation to the shape of the Gaussian function. By applying the Gaussian smoothing filter, it provides a convenient way of removing noise inherent in a normal distribution.

In one dimension, the Gaussian function with mean zero k(x) is represented as [19]:

$$k(x) = e^{-\frac{x^2}{2\sigma^2}} \quad [6]$$

where $\boldsymbol{\sigma}$ is the Gaussian spread parameter. This defines the width of the Gaussian function.

The discrete Gaussian function with mean zero in two dimensions k[i,j] is used in image processing as a smoothing filter [19].

$$k[i,j] = e^{-\frac{(i^2+j^2)}{2\sigma^2}} \quad [7]$$

3.7 The Kalman Filter

The Kalman Filter has for a long time been viewed as the ideal solution to many tracking and data prediction problems. It has been well and frequently documented by many researchers in the analysis of visual motion [21]. The Kalman Filter has been used positively in a variety of predictions and state determination application systems.

The Kalman filter is usually derived by using vector algebra as a minimum mean squared estimator. The Kalman filter is obtained from first principles by manipulating a key property of the Gaussian distribution which states that the multiplication of two Gaussian distributions gives another Gaussian distribution.

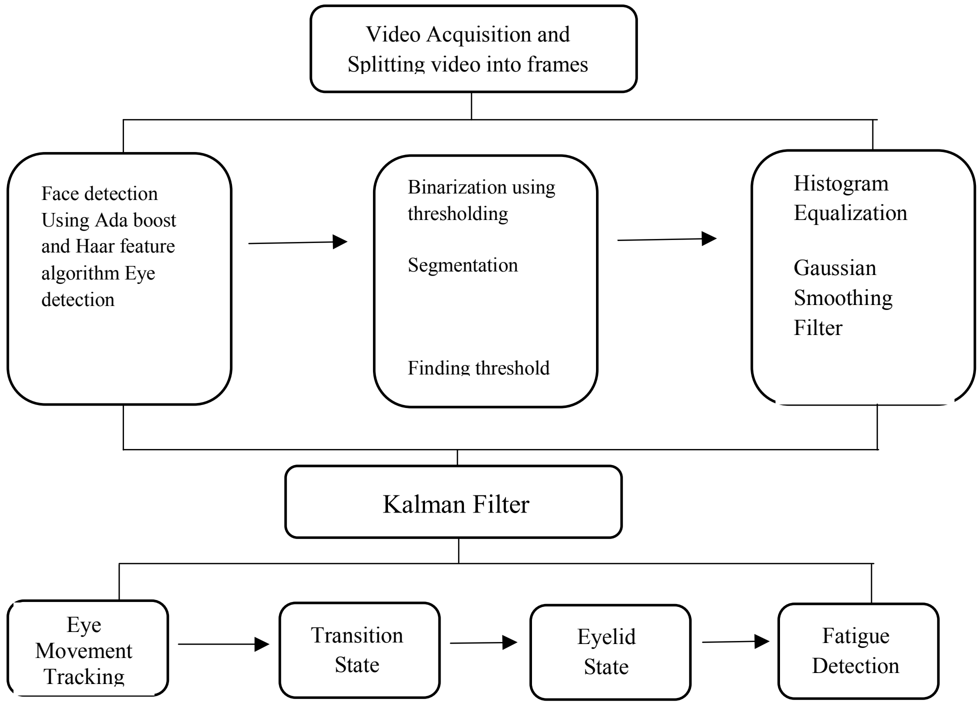


Fig. 1. Conceptual framework

It is assumed in the Kalman filter model that the state of a system at time $\boldsymbol{t}$ evolved from the prior state at time $\boldsymbol{t}$**-1** according to the equation [22]:

$$X_t = W_t + F_t X_{t-1} + B_t U_t \quad [8]$$

Where;

$\boldsymbol{U_t}$ = vector containing any control inputs (steering angle, throttle setting, braking force)
$\boldsymbol{X_t}$ = state vector containing the terms of interest for the system (e.g., position, velocity, and heading) at time *t.*
$\boldsymbol{F_t}$ = the state transition matrix which applies the effect of each system state parameter at time t-1 on the system state at time t (e.g., the position and velocity at time t-1 both affect the position at time t).
$\boldsymbol{W_t}$ = the vector containing the process noise terms for each parameter in the state vector. The process noise is assumed to be drawn from a zero mean multivariate normal distribution with covariance given by the covariance matrix **Q***t.*
$\boldsymbol{B_t}$ = the control input matrix which applies the effect of each control input parameter in the vector $\boldsymbol{U_t}$ on the state vector (e.g., applies the effect of the throttle setting on the system velocity and position)

The measurement of the system is also performed using the given model below;

$$Z_t = V_t + H_t X_t \quad [9]$$

Where

$\boldsymbol{Z_t}$ = vector of measurements.
$\boldsymbol{H_t}$ = transformation matrix which maps the state vector parameters into the measurement domain.
$\boldsymbol{V_t}$ = vector containing the measurement noise terms for each observation in the measurement vector.

The measurement noise is assumed to be zero for mean Gaussian white noise with covariance R*t* just like the process noise.

The Kalman filter is analysed in the environment of multi-modal eye detection and eyelid movement using data from captured videos or image sequences. The Kalman filter is shown to be suitable for real-time non-stationary classifier fusion. The available sequential uni-modal and multi-modal decisions combined does not only also bring about a consistent continuous stream of decisions, but also leads to substantial improvements when compared to the input decision performance.

The focal point in the research field of human-machine interaction and computer vision in recent years has been on eye tracking due to the fact that it plays significant role in many applications. Eye tracking becomes difficult due to many factors including lighting, gesture and covering objects. There are a number of computational methods that can be used to solve tracking parameters according to [23].

The Kalman filtering process has the following advantages;

- It is recursive in nature, computationally efficient and does not need large amount of storage for the past samples.
- The information about the system and measurement noise is stored in its model,
- It deals with time varying signals effectively.
- The current states are estimated by the results of the previous step
- The estimation's accuracy can be ascertained by observing the error covariance.

4. ANALYSIS AND RESULTS

4.1 Introduction

This session discusses the experiments performed with respect to face detection, facial feature extraction, eye detection, image segmentation, Kalman Filter and blink cycle classification and fatigue characterization to accomplish the functionality of the proposed system. The results of each experiment are analysed.

4.2 Video Acquisition

Twenty video clips were acquired and processed. A sample image from each video clip is presented in Fig. 2.

In the video acquisition experiments, frames were extracted from each video sequence. These frames constitute the basis of the analysis. The extracted images were analysed by identifying whether faces can be detected in them or not. The computer technology in this study identifies both the human face location and size in any given digital images and also identifies only features of the face and disregards anything other thing, such as buildings, tress, cars and others. This makes it a specific case of an object-class detection system.

The results of the analysis is represented in Table 1.

- **Time**
  The time captured for the acquisition of the individual videos is measured in seconds. Thirty (30) frames per seconds were recorded for each video capture.

- **Accuracy**
  The accuracy of the images retrieved from the sample video sequences is given by the ratio of the number of detected face images to the extracted images. This is expressed as a percentage.

$$\text{Accuracy} = \frac{Number\ of\ detected\ face\ images}{Number\ of\ extracted\ \ images} \times 100 \qquad [10]$$

- **Redundancy Factor (RF)**

  The Redundancy Factor (RF) is a measure that provides the extent of undetected face images upon completion of the experimental process for the face detection. The RF is expressed as:

$$\text{RF} = \frac{(Total\ of\ images\ retrieved) - (Total\ \ of\ detected\ face\ images)}{Total\ of\ detected\ face\ images} \qquad [11]$$

4.2 Eye Detection Analysis

The Haar cascade classifier is used to detect the facial features such as the mouth, eyes, and nose. The classifier is trained using the Ada Boost algorithm and Haar feature algorithms. The results of the eye detection process is shown in Table 2.

4.3 Binarized Image

Sample image used for binarization and equalization is shown in Fig. 3.

Table 3 shows the highest intensity values of the segmented eye images extracted from a sample video in Fig. 1. These maximum intensity values become the main data for analysis. Gaussian filters are then applied to produce smoothening of the data to determine whether the eye is close or open.

4.4 Eyelid Movement Analysis (Based on Open and Closure)

The eye movement analysis is based on how often the eyelid state change from being open to close and the vice versa. A cycle is defined as moving from the open state to the closed state to the open state. Each Individual has its maximum blink value. Beyond this indicates a fatigue state. A person is said to be in the normal state if it has a blink rate that is equal to the threshold of the maximum blink as shown in Table 4 below. However, because of differences in the eyelid feature, eye ball and eye blink rate, there is the need to establish a blink cycle and its relative velocity.

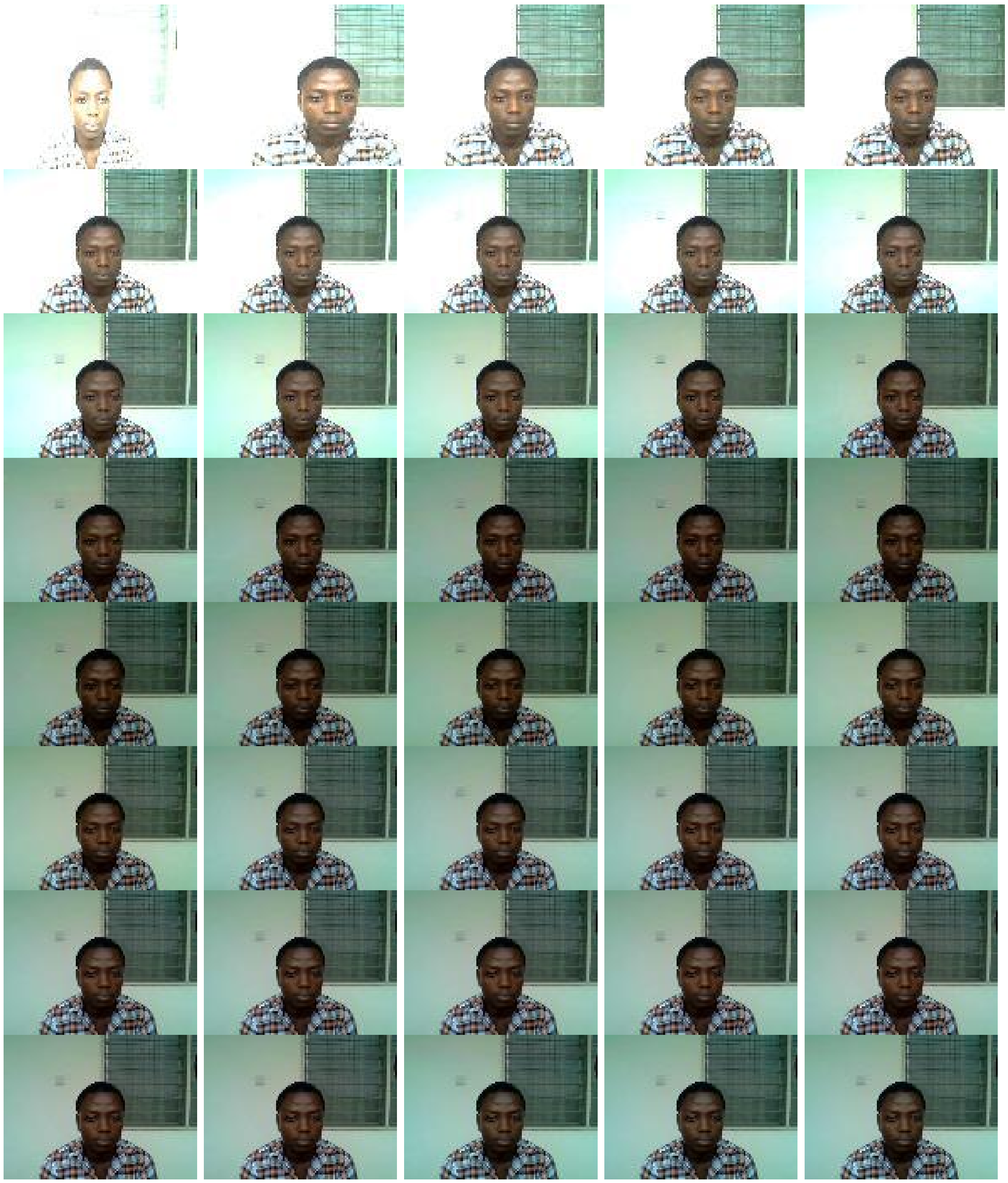


Fig. 2. Sample image

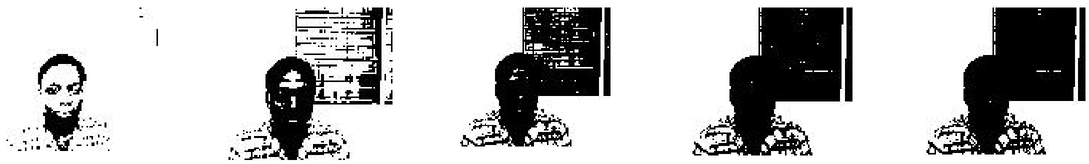


Fig. 3. Sample Binarized face images

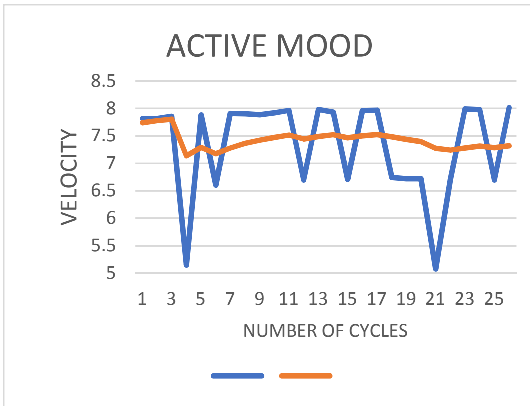


Fig. 4a. Active mood state prediction

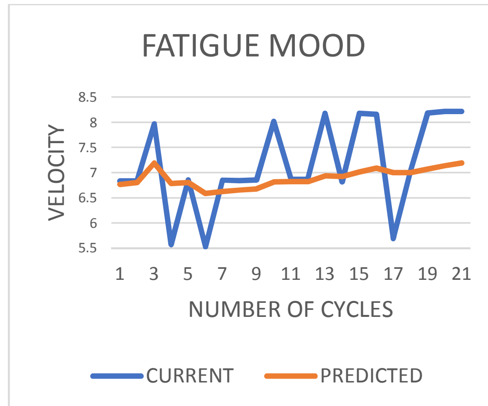


Fig. 4b. Fatigue mood state prediction

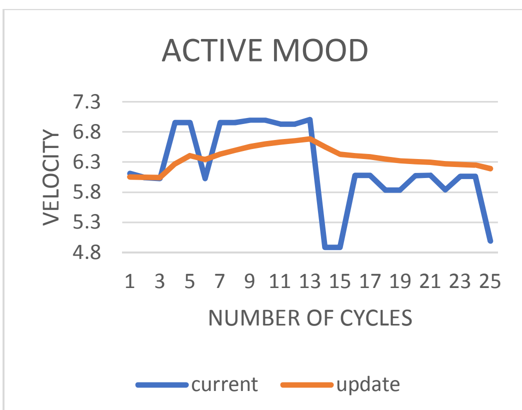


Fig. 5a. Active Mood Prediction (Sample II)

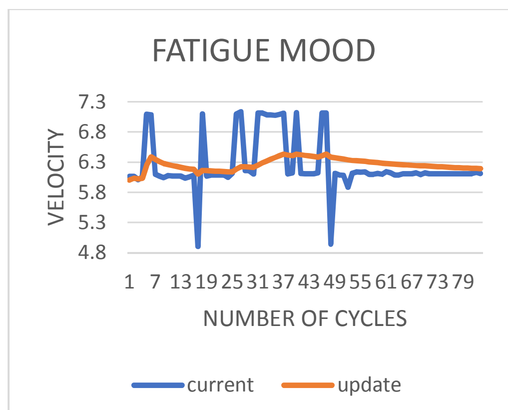


Fig. 5b. Fatigue Mood Prediction (Sample II)

Rate: The rate, as used in the eyelid movement analysis, is calculated based on the number of closed eye frames found within ten consecutive frames. The rate is given by

$$Rate = \frac{Closed\ Eyes}{maximum\ blinks} \qquad [12]$$

W = Widely Awake.
N = normal
F = Fatigue

4.5 Eyelid Tracking Using Kalman Filter

The eyelid is tracked using the Kalman Filter. This is done by first extracting frames from the sample videos. From the individual frames, the object of interest is selected for tracking by setting the position of the mask in the initial frame. This position of the object is then used for tracking in subsequent frames. The object's distance is determined by using the centroid position of the mask. The pixel positions of the moving object from the initial stage to the final stage of tracking is used in calculating the distance covered by the said object. The velocity of the moving objects is calculated by the distance it travelled with respect to time. Table 5 shows the velocity of the moving eyelid for the twenty (20) sample videos taken for the analysis.

Table 1. Facial detection analysis

Video index	No. of images extracted	No. of detected face images	Time(s)	Accuracy	RF
1	891	887	60	99.55	0
2	888	888	60	100	0
3	889	888	60	99.89	0
4	890	890	60	100	0
5	891	891	60	100	0
6	888	888	60	100	0
7	888	887	60	99.89	0
8	888	888	60	100	0
9	889	889	60	100	0
10	891	891	60	100	0
11	891	891	60	100	0
12	890	887	60	99.66	0
13	891	891	60	100	0
14	890	890	60	100	0
15	888	888	60	100	0
16	889	888	60	99.89	0
17	889	889	60	100	0
18	890	890	60	100	0
19	888	888	60	100	0
20	888	887	60	99.89	0

Table 2. Eye detection analysis

Video index	No. of images extracted	No. of detected face images	no. of detected eye images	Time(s)	Accuracy	RF
1	891	887	887	60	100	0
2	888	888	887	60	99.89	0.0011274
3	889	888	888	60	100	0
4	890	890	890	60	100	0
5	891	891	890	60	99.89	0.0011236
6	888	888	888	60	100	0
7	888	887	887	60	100	0
8	888	888	888	60	100	0
9	889	889	889	60	100	0
10	891	891	889	60	99.78	0.00224972
11	891	891	889	60	99.78	0.00224972
12	890	887	887	60	100	0
13	891	891	890	60	99.89	0.0011236
14	890	890	890	60	100	0
15	888	888	888	60	100	0
16	889	888	887	60	99.89	0.0011274
17	889	889	889	60	100	0
18	890	890	889	60	99.89	0.00112486
19	888	888	888	60	100	0
20	888	887	887	60	100	0

4.6 Eyelid State Prediction Analysis Using Kalman Filter

The eyelid's state is estimate using the Kalman filter which is useful in smoothing out noisy data and giving estimations of parameters of interest. The value of the current state is determined by the prediction state equations of the Kalman Filter determine using values from the previous state. Using the velocity data gathered from the previous section as inputs to the Kalman Filter, the state of the eyelid can be determined at any given time. Data gathered from two different people captured under the two main conditions are used (fatigue and active conditions). The Kalman Filter is applied on the relative velocities of the video samples as shown in Fig. 4 and Fig. 5. Video index 19 which shows the active mood and Video Index 20 showing the fatigue mood are used in Fig. 5 (Sample I) and Fig. 5 (Sample II) respectively.

After the analysis of the captured data representing the velocity of the eyelid movement using Kalman filter, it can be confirmed that a graph representing the person in the active state has most of the peaks below the Kalman line (update). However, the situation where most of the peaks of the velocity (current) from the graph fall above the Kalman line indicates that the person is in fatigue stage.

On the other hand, if the current velocity at any given time is the same as the estimated velocity at the same time, then the person is in normal state.

From the above analysis, the following three states of fatigue characterization, which is defined by the frequent blinking and long durations of eye closure, are presented in Table 6.

Table 3. Segmented eye intensity values

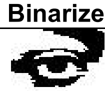
S/N	Binarized image	Intensity values
1		0.377358490566037
2		0.415637860082304
3		0.375786163522012
4		0.329729729729729
5		0.322911051212938

Table 4. Eye movement analysis

Video index	Continuous detection		No. of cycles	Freq	Rate	Fatigue
	Open eye(OE)	Closed eye(CE)				
1	300	150	40	10	15	F
2	390	200	36	10	20	F
3	400	80	14	10	8	W
4	502	70	20	10	7	W
5	470	140	30	10	14	F
6	444	150	41	10	15	F
7	510	56	8	10	5.6	W
8	325	100	25	10	10	N
9	333	84	32	10	8.4	W
10	412	40	26	10	4	W
11	152	250	30	10	25	F
12	253	120	32	10	12	F
13	300	150	25	10	15	F
14	240	88	28	10	8.8	W
15	222	90	19	10	9	W
16	248	110	27	10	11	F
17	333	46	32	10	4.6	W
18	361	88	22	10	8.8	W
19	400	62	25	10	6.2	W
20	400	200	82	10	20	F

Table 5. Moving eyelid velocity

Sample	Velocity
1	1.213351648213
2	1.130019665512
3	1.410476672776
4	1.410476672776
5	1.280733296896
6	1.110055053690
7	1.114051664471
8	2.929753006240
9	1.013354564541
10	1.054092553389
11	1.174260996921
12	1.050132266802
13	2.989332887303
14	1.314555269114
15	1.056855924166
16	1.257532857976
17	1.251221625275
18	1.409984239471
19	1.511621645783
20	1.562211404446

Table 6. Fatigue characterisation

Characterization	Description
Active	If greater proportion of current velocity is less than the estimated velocity at a specific time range. It means that most of the cycles detected are below the Kalman line.
Normal	If the current velocity and the estimated velocity at the same time t are the equal.
Fatigue	If greater proportion of current velocity is greater than the estimated velocity at a specific time range.

5. CONCLUSION AND RECOMMENDATIONS

This paper has outlined and demonstrated a generic approach to machine vision based on using the Kalman filter for the characterisation and detection of fatigue. These improvements have included the use of several techniques and methods such as feature extraction, segmentation and object identification in textual images. Methods to identify the rate at which the eye blinks within a cycle and predicting the state of the eyelid using the Kalman Filter have also been explored extensively. The proposed system has also been applied successfully in determining fatigue levels in people using Java programming language and Open Computer Vision Library.

This work can be used to reinforce the development of smart surveillance systems which can be used on our roads by the national road safety commission in Ghana to curb down fatigue related accidents. Furthermore, it can also be used in the development of other hyper-vigilance systems and security related systems in industrial and other social work areas.

The reduction of faulty detection is necessary in this research. To reduce these faults, future works should investigate the differences between fatigue and other similar behaviours from the psychological point of view. These similar behaviours include laughing, orientation of the head and speaking with the mouth widely opened. A more accurate fatigue detection that contains other facial features would be necessary to reduce faulty detection.

From the experiment, the Kalman filter would be a strong thresholding application that can be used in tracking and predicting the blinking rate of the eyelid. The speed or the velocity of the eyelid movement can therefore be used to determine when an eye is opened or closed since the Kalman filter mimics the same behavioral pattern of the eyelid movement. And finally it can be used in smoothing the noisy data for estimation or prediction of the various fatigue levels.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Hinneh S. Fighting fatigue driving In Ghana. National Road Safety Commision Annual Conference; 2014.
   Available:www.newsghana.com.gh
   (Accessed 28th October, 2015)
2. Bergasa LM, Nuevo J, Sotelo MA, Barea R, Lopez ME. Real-time system for monitoring driver vigilance. Intelligent Transportation Systems. IEEE Transactions. 2006;7(1):63-77.
3. Sahayadhas A, Sundaraj K, Murugappan M. Detecting driver drowsiness based on sensors: A review. Sensors. 2012; 12(12):16937-53.
4. Elena A, Philiastide A, Van M, Majid E. Driver drowsiness detection using multimodal sensor fusion. Multisensor Multisource Information Fusion: Architecture, Algorithms and Applications. 2004;380-390.
5. Edenborough N, Hammoud R, Harbach A, Kisacanim B, Malawe P, Newman. Driver State Monitor from DELH, 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. 2005;1206-1207.
6. Zhou, Xiang S, Thomas S. Huang. Relevance feedback in image retrieval: A comprehensive review. Multimedia Systems. 2003;8(6):536-544.
7. Galbally J, Ortiz-Lopez J, Ortega-Garcia. Iris liveness detection based on quality related features. in Proc. ICB, New Delhi, India, pp. 271-276.
8. Chang Chi, Zhang Ji-Xian, Zheng-Jun. Study on Methods of Noise Reduction in Stripped Image. 2003;6(4):279-284.
9. Hosur PI, Carrasco RA. Enhanced frame-based video coding to support content-based functionalities. ICCIMA 2005. Proceedings of the 6th International Conference on Computational Intelligence and Multimedia Applications. 2005;266-271.
10. Abdel K, Chellapp MF, Zheng Q. Integrated motion detection and tracking for visual surveillance. Proceedings of the. 4th IEEE, International Conference on Computer Vision Systems (1CVS). 2006;28-34.
11. Jordan K, Hoofar J, Francis B, Raffaello PE. Food chain integrity: A holistic approach to food traceable, safety, quality and authenticity. Elsevier; 2011.
12. Takaaki S, Park HS, Sigal L, Sheikh Y, Hodgins JK. Motion capture from body-mounted cameras. ACM Transactions on Graphics (TOG). 2011;30(4).
13. Rajeshwar D. Priyanka, Swapna Devi. Image Segmentation Techniques. IJECT 2012;3.
14. Chi FL, Morgan P, Moschetti, Michael HR. Surface wave tomography of the western United States from Ambient Seismic Noise: Rayleigh and Love Wave Phase Velocity Maps. Geophysical Journal International. 2008;173(1):281-298.
15. Priyanka K, Versha R. A brief study of various noise model and filtering Techniques. 2013;4(4).
16. Cuevas E, Zaldivar D, Rojas R. Kalman Filter for Vision Tracking. Technical Report B 05-12, Takustr. 9, D-14195, Germany; 2005.
17. Duchowski AT. Eye tracking methodology: Theory and practice. Springer-Verlag New York, Inc; 2007.
18. Yao KP, Lin WH, Fang CY, Wang JM, Chang SL, Chen SW. Real time vision-based driver drowsiness/fatigue detection system. Proc. IEEE 71st Vehicular Technology Conference, Tapei, Taiwan. 2010;1-5.
19. Ramesh J, Rangachar K, Brian GS. Machine vision, McGraw-Hill, Inc; 1995. ISBN 0-07-032018-7
20. Gonzales RC, Woods RE. Digital Image Processing“, 2nd Ed. Beijing; Publishing House of Electronics Industry; 2007.

21. Julier SJA, Uhlmann. Unscented Filtering And Nonlinear Estimation. Proc. IEEE. 2004;92(3):401-422.
22. Welch G, Bishop G. An introduction to the Kalman filter. University of North Carolina at Chapel Hill Department of Computer Science; 2001.
23. Xu W, Lee E. A novel multi-view face detection method based on improved real adaboost algorithm. KSII Transactions on Internet Information Systems. 2013;7(11).

Peer-review history:
The peer review history for this paper can be accessed here:
http://www.sdiarticle3.com/review-history/47899