Medical Technologies Journal, Volume: 3, Issue: 1, January-March 2019, Pages: 316-333. Doi : https://doi.org/10.26415/2572-004X-vol3iss1p316-333

On Assisted Living of Paralyzed Persons through Real-Time Eye Features Tracking and Classification using Support Vector Machines

Type of article: Original

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Abstract

Background: The eye features like eye-blink and eyeball movements can be used as a module in assisted living systems that allow a class of physically challenged people speaks – using their eyes. The objective of this work is to design a real-time customized keyboard to be used by a physically challenged person to speak to the outside world, for example, to enable a computer to read a story or a document, do gaming and exercise of nerves, etc., through eye features tracking

Method: In a paralyzed person environment, the right-left, up-down eyeball movements act like a scroll and eye blink as a nod. The eye features are tracked using Support Vector Machines (SVMs).

Results: A prototype keyboard is custom-designed to work with eye-blink detection and eyeball-movement tracking using Support Vector Machines (SVMs) and tested in a typical paralyzed person-environment under varied lighting conditions. Tests performed on male and female subjects of different ages showed results with a success rate of 92%.

Conclusions: Since the system needs about 2 seconds to process one command, real-time use is not required. The efficiency can be improved through the use of a depth sensor camera, faster processor environment, or motion estimation.

Keywords: Assisted living; Rehabilitation; Paralyzed persons; Eye-blink detection; Eyeball detection; Biomedical engineering; SVM; Machine learning; Image processing.

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Received: 26 January, 2019, Accepted: 28 Mars, 2019, English editing: 04 Mars, 2019,Published: 01 April, 2019.

1. Introduction

Human feature detection and tracking are gaining more importance each day due to a wide variety of applications that can be built. One application is constructing interactive ways to communicate with Internet-enabled devices linked to people with disabilities [1]. Commuting and communication are the main issues of these patients. One such class of people with Tetra/quadriplegia face even communication difficulties. Another class has rehabilitative disabilities (spinal cord injury, repetitive strain injury, etc.) and motor disabilities (autism, cerebral palsy, Lou Gehrig's, and so forth). Historically, techniques like Partner-Assisted Scanning (PAS) have been used to help these people communicate. In this technique, the nurse/caregiver presents a set of symbols (e.g., words, alphabets, pictures, letters) on a screen to the disabled patient, observes the patient’s eye on the screen, and then determines selection from among those symbols to express needs. Augmentative and Alternative Communication (AAC) is a very general term and is diversified into two types; aided and unaided systems [2]. In aided systems, a tool or device (low or high tech) is used to help communicate. The examples are pointing or touching letters/pictures etc. on a screen to speak for oneself. PAS is an example of this type of AAC. Some assistive technologies exist, for example, for children with autism to communicate, and for people with Lou Gehrig's disease to stay connected to family, friends, and fans. Nevertheless, the solutions are expensive, as it requires two extremely high-quality camera sensors to capture an image and build a 3D model of the user's eyes to figure out gaze point and eye location in space relative to track box (computer). In unaided systems, signs, facial expressions or body language are used to support communication. In some cases, combinations of both types are used to convey expression.

The advancement in the field of communication, electronics, and biomedical area have changed the use of eyes. Technology-assisted living using eye as a window to the world enables to communicate, gain independence through eyes, and control of the environment. The gesture recognition can also improve the brain functioning through exercise when such affected people want to stimulate their brain using eye-blink and eyeball movements. The right brain and eyes are profoundly connected. As an example, right-left, up-down eyeball movements each held for few seconds can help sense colors and light. Beginning from this, the right brain's senses begin to surface, and the person can start sensing warm feelings, odor and pain. Through this eye training, the sensory faculties of the right brain start to wake up. The researchers believe that brain exercise could offer hope in cases of spinal cord injuries, strokes and other conditions where doctors emphasize regain in strength, mobility, and independence. Solutions built until today are not satisfactory as they do not meet criteria of affordable cost together with technology-assisted mobility and communication of the physically challenged person in the absence of a nurse.

This paper is divided into seven sections. Section 2 surveys healthcare domain approaches to help physically challenged persons. Section 3 presents the development of a customized keyboard for rehabilitation and assisted living of the paralyzed person. Section 4 presents the technological components that work together with the keyboard. It includes camera calibration for eyeball tracking of the paralyzed person. For simplicity, the input device chosen is a webcam that captures pictures at a frame rate of 30 with resolution of 1.5 Megapixels. After eye-blink and eyeball tracking, the classification step is presented to map these eyeball movements to keyboard symbols. The simulation results conducted on test images taken from all ages and both genders are presented in Section 5, with a discussion in section six. The limitations of this research are highlighted in section 7, which are followed by conclusions.

2. Related work

2.1 Internet and Healthcare

The Internet of Things (loT), Internet of Nano Things, Internet of Medical Things (IOMT), and the Internet of Everything (loE) are ways to incorporate electrical or electronic devices connected via the Internet. Social relationships are established among objects, things, and people, and this is where social networking meets the IoT. As far as applications are concerned, IoT may be added with management features to link home environment, vehicle electronics, telephone lines, and domestic utility services to address concerns of the neighborhood to enable the realization of smart cities. In literature, as an example, [3] address these state-of-art technologies, possible future expansion, and even merger of IoT, IoNT, and IoE.
It was reported in 2013 that there were two Internet-connected devices for each person and predicted that by 2025, this number would exceed six [4]. In a health-IoT ecosystem, different distributed devices capture and share real-time medical information and then communicate to private, or open clouds, to enable big data analysis in several new forms in order to activate context dependent alarms, priorities of applications [5]. In another work [6], the authors develop and present an IoT based health monitoring system to manage emergencies, using a toolkit for dynamic and real-time multiuser submissions. Architecture is also proposed by [7] for tracking of patients, staff, and devices within hospitals - as a smart hospital system integrating Radio Frequency Identification (RFID), smartphone and Wireless Sensor Networks (WSN). The parameters sensed in this way are accessible by local as well as remote users via a customized web service. The work in [8] proposes an architecture of a healthcare system using personal healthcare devices to enhance interoperability and reduce data loss. In a study done by [9], a system is designed using Raspberry Pi to enable seamless monitoring of health parameters, update the data in a database and then display it on a website to be accessed only by an authorized person. The authors discuss that this way doctors can be alerted to any emergency.
The Internet in general and IoT platforms in particular face security problems and carry privacy concerns [1]. Work in [10] proposed different security levels and focused on the security challenges of the wearable devices within healthcare IoT sector. The security requirements for IoT healthcare environment have also been addressed in detail by [11], where authors present in-depth review and cost analysis of Elliptic Curve Cryptography (ECC)-based RFID authentication schemes. The authors argue that most of the approaches cannot satisfy all security requirements, whereas only a few recently proposed are suitable for the healthcare environment. Studies in [12] propose data accessing method for an IoT-based healthcare emergency medical service and present its architecture to demonstrate collection, integration, and interoperation IoT data from location-related resources such as task groups, vehicles, and medical records of patients [13].
There are inspiring applications of the IoT for healthcare to improve hospital workflow, optimize the use of resources, and provide cost savings. However, there is a need for real and scalable systems to overcome significant obstacles (like security, privacy, and trust) [14]. For example, [15] introduces a concept of an Internet of m-health Things (m-IoT). It discusses general architecture for body temperature measurement with an application example that matches future functionalities of IoT and m-health. Another work discusses building extensible ad-

hoc healthcare application and presents a prototype of a healthcare monitoring system for alerting doctors, patients, or patient-relatives [16]. Another prototype reported in [17] presents an infrastructure for healthcare and then build an Android-based smart healthcare application. [18] addresses another application related to Parkinson's disease (PD), where authors discuss existing wearable technologies and IoT with emphasis on systems assessment, diagnostics, and consecutive treatment options. [19] discusses a general framework for personal healthcare using RFID, where authors investigate RFID for personal healthcare by implementing a sensors network to track the quality of local environment and wellness of patients. Likewise, [20] proposed a secure modern IoT based healthcare system using a Body Sensor Network (BSN) to address security concerns efficiently.

In order to provide context awareness to make disabled patient's life easier and the clinical process more productive, [21] introduces IoT in medical environments to obtain connectivity with sensors, the patient, and its surroundings. Another work [22] presents an intelligent system for a class of disabled people to have access to computers using biometric detection to improve their interactivity, by using webcam and tracking head movement and iris. Similarly, [23] presents an IoT architecture stack for visually impaired and neurologically impaired people, and identifies relevant technologies and IoT standards for different layers of the architecture. As an application, another mobile healthcare system based on emerging IoT technologies for wheelchair users is presented by [24], where the focus is on the design of a wireless network of body sensors (e.g., electrocardiogram (ECG) and heart rate sensors), a cushion that detects pressure, sensors in home environment and control actuators, and so forth.

2.2 Challenges faced by Paralyzed People

The state of paralyzed people suffering varies as paralysis exists in four different forms: *a*: Monoplegia, with one limb paralyzed; *b*: Hemiplegia, with the leg and arm of one side paralyzed; *c*: Paraplegia, with legs paralyzed or sometimes the lower body and the pelvis; and *d*: Tetraplegia/Quadriplegia, with both the legs and arms paralyzed. Quadriplegia (or tetraplegia) is caused by damage to the cervical spinal cord segments and may result in function loss in arms and the legs. People suffering from Monoplegia, Hemiplegia, and Paraplegia can get support to move around and be functional at home using assistive technology tools, like Home Automation Assistive Technology, Accessible Video Gaming, and Computing, whereas the condition of people with quadriplegia needs continuous attention and monitoring. These people with quadriplegia face many challenges and difficulties even when performing simple daily activities like communication, and in some cases cannot even move their body muscles. For such cases, several techniques help those people communicate through PAS. In this approach, the selection of symbols or characters can be triggered by eye blinking, which depends on the challenged person's abilities [25].

2.3 Current Solutions

The applications that use gesture recognition exist in various disciplines including healthcare. Current technological developments in gesture recognition have introduced newer ways to interface with machines for vital sign monitoring, virtual reality, gaming, among others; however, the corresponding tools cannot help a paralyzed person as the tools are developed for normal people.

Recent literature contains real-life applications in different fields using eye features detection and tracking. For example, in [26], there is a real-time eye tracking method to detect eyelid movement (for open or close) to work under realistic lighting conditions for drowsy driver assistance. Effectively, the authors have developed a hardware interface involving infrared illuminator together with a software solution to avoid accidents. For the same objective, [27] investigates visual indicators that reflect the driver's condition such as yawn, eye behavior, and lateral and frontal assent of the head in developing a drowsy driver algorithm and display interface. In another research [28], the authors develop eye tracker attached to a head-mounted display for virtual reality to support learning.

Similarly, the work in [29] also develops a hardware-based eye tracking and calibration system involving infrared sensor/emitter installed on a pair of glasses to detect eye gaze. Eye movements for biometric applications and address such behavior modality for human recognition are examined in [30]. The relevant acquisition aspects of eye movements are also discussed. In another work, a hybrid approach based on neural networks and imperialist competitive algorithm to work in RGB space is proposed by [31] for skin classification issues in face detection and tracking.

In terms of approaches or methods for gesture recognition, researchers have used approaches based on facial features, a priori knowledge, and appearance to name a few. For example, the work in [32] detects the face and then the eyes. The authors from [33] investigate gaze estimation with Scale Invariant Feature Transform (SIFT), the homography model and Random Sample Consensus (RANSAC). In other works, classifiers are applied for extraction of facial features [34] and skin color segmentation along with Hough transform [35].

The challenge in eye-blink and eyeball movement detection of the paralyzed person is due to the low frame rate of the camera. Once the paralyzed person blinks, this generates only a few (~ 25-30) frames.

3. Designing Scanning Keyboard

The different eye movements like a blink (bat an eyelid) or eyeball rotation can be mapped to various keys on the keyboard. In the proposed design, the purpose is to make keyboard layout simpler (with needed functions only) and compatible with the PAS technique. As per proposed design, PAS could display alphabets, signs, objects, or web links as shown in Figure 1 to help assisted living (such as communication, mobility, entertainment, and service) and support rehabilitation. The displayed keyboard has five activity categories and can be modified to support additional categories.

In Figure 1, the outer five circles (A, B, C, D, and E) represent the start of each activity. The one in the middle represents the system start or standby position. Blinking enables the selection of the activity (shown as shaded 'A' in Figure 1), whereas no blinking takes to the next activity in the clockwise direction after pausing two seconds (set tentatively). If there is no selection after two rounds in the clockwise direction, the system goes to standby position.

The top activity represents brain exercise, where the user's up/down/left/right eyeball movement pushes the shaded ball in the corresponding direction. After two seconds, the ball comes to the center. Activity B represents communication with the nurse or any other person. Again, eyeball movement selects the desired message. Similarly, activity C represents the service needed by the user like a blanket, changing clothes, brushing teeth, and access to the toilet. The activity D is for entertainment like watching TV, listening to the radio, accessing sports website(s), for example. Activity E supports mobility and seating positioning. Effectively, within each activity, the desired selection is based on eyeball movement. Once the desired selection is completed and no more selection is desired, the system takes to the next activity after pausing for two seconds. The pause speed may be modified to conciliate the user pace with system sampling intervals. It is clear from keyboard design that eye-blink and eyeball movements are used all the time during rehabilitation and assisted living activities.

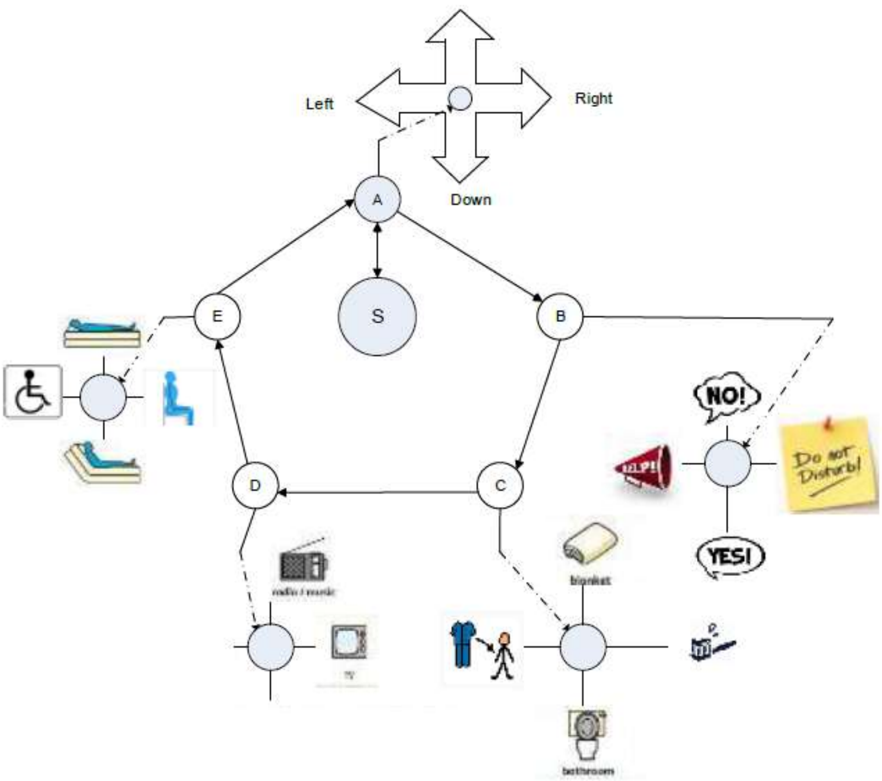

Figure 1: Proposed eye-tracking based keyboard

4. Eye tracking

Here, eye facial features and eye tracking captured by a system go through several consecutive stages. The first stage is camera calibration, which is needed to be done once, as the user is paralyzed, and the person alone may not use the device (Figure 2 depicts the complete algorithm). The first step logically is to start the system, which includes the camera in front of the user. Once the image is captured, then the face is detected. There are many methods to calibrate, but a software solution based on SVMs was investigated for better accuracy. A set of sequential equations involving dot product of data points x_i and weights w, and variable b as bias are used to implement SVMs. The classified output y (as ±1) is determined using the best hyperplane that satisfies [36]:

$y_i (\langle w, x_i \rangle + b) \geq 1$ given that $\langle w, x \rangle + b = 0$ is a separating classifier line (1)

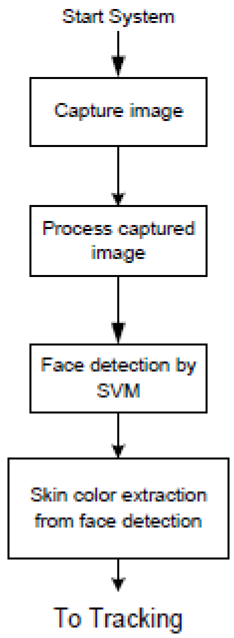

Figure 2: Steps for Camera Calibration

For simplicity and maximum margin, Lagrange multipliers α_i are selected to lie between 0 and C, where C variable is a constraint to keep α_i within a limited range. For computational efficiency, kernels are often applied such that a function transforms data x from complex space to linear [36]:

$K(x, y) = \langle \varphi(x), \varphi(y) \rangle$ (2)

where $\varphi(x)$ and $\varphi(y)$ mean transformed support vector values x, and y respectively; $\langle \varphi(x), \varphi(y) \rangle$ means dot product of these transformed values; and $K(x, y)$ means equivalent kernel function that replaces these dot products. The kernel concept is used in training an SVM to detect face during calibration. The training uses a polynomial kernel of order three as follows:

$K(x, y) = (x^T y + 1)^3$

with constraints of higher training and validation accuracy resulting in minimum error rate and maximum correct rate. The number of support vectors and execution time for training, however, was not considered as a constraint. Based on a dataset that had favorable samples for the experiment, a subset of 68 image samples was chosen to be divided into two file sets and termed as positive and negative respectively. The first positive (set) contained face image samples, while the second negative (set) contained non-face image samples. Out of these total 68 image samples, half taken from each file set served for training SVM, with the remaining images for validation. During training, values of α_i were generated using twenty-five support vectors and resulted in a high accuracy (for the given set of subjects and the experiments performed) and weight matrix as [36]:

$$w = \sum_i \alpha_i \, y_i \, x_i \tag{3}$$

where α_i are multipliers, x_i and y_i are support vectors, and w are the resulting weights. During training, it was found out that C=0.00000001 was good enough for training SVM in the calibration stage to match weight matrix w to face since larger values of C failed in the corresponding match. While camera calibration approaches are different, better features for using SVM approach were noted as (i) no iterations needed, (ii) no hardware requirement, (iii) only-once training, and (iv) extremely high accuracy for testing results.

4.1 Eye-blink Detection

For eye-blink detection, skin color approach was used in differentiating between open and closed areas of the eye. The skin color approach uses histogram back projection, where the histogram represents the user's skin color. A higher value in a back-projected image denotes the more likely object location. Thus, within the eye region, a higher percentage of skin color pixels means closed eyes, otherwise open.

After the user's face is detected, a rectangle around the eyes marks a Region of Interest (ROI). Then, these ROI region colors are enhanced to offset makeup, lighting, or shadow effects. Effectively, the color intensities are replaced by the brightness of the same colors using the power of gamma (γ), where:

$$\gamma = \begin{Bmatrix} 1-\beta, & \beta > 0 \\ \frac{1}{1+\beta}, & \beta \leq 0 \end{Bmatrix}, \tag{4}$$

where $0 < \beta < 1$ is a user-defined value. Once γ is chosen, the image pixels are enhanced by multiplying the ROI pixels with this value. Next, the enhanced image pixels are converted to grayscale to retrieve luminance value. Then, the gray scale pixels are enhanced and the contrast increased to convert it to black and white. In this step, dark areas such as eye boundaries, pupils, eyelashes, etc., in the grayscale convert to black color and all light areas, such as skin color convert to white. Effectively, the procedure maps pixels with a luminance above 0.25 to 1 and 0 otherwise.

In order to determine whether the eyes are open or closed, the skin color percentage is used. In the case of open eyes, the white area percentage will be less than that of closed eyes. For this purpose, each '0' pixel adds to the black area, and each '1' pixel adds to the white area. The following formula calculates the skin area percentage:

$$Skin\ Percentage = \frac{White\ Area}{Total\ Image\ Area}\ X\ 100\ . \qquad (5)$$

An eye-blink corresponds to a frame with a higher skin area percentage in the ROI. With trial and error method, it was determined that the skin area percentage exceeds 90% when eyes close. The value less than that corresponds to open eyes. In order to determine the accuracy of the approach, twenty trials were run in different lighting conditions, and it was found that out of 20 trials, there was only one false result, which amounts to 95% success rate. The reason behind the false result was poor lighting condition used in that trial, which resulted in the change of luminance. The success rate of 95% is higher than the ones reported by [37, 38].

4.2 Eyeball Tracking

In this section, feature extraction such as skin color and facial measurements are discussed followed by tracking. Though different methods can be used as reported by [39], an SVM-based method was adopted to test and check performance efficiency experimentally.

The algorithm used for this part of the work accomplishes tracking by a trained SVM. Once the user is seated with no head tilt, the center of the eyes is tracked by two methods. One uses a trained SVM, while the other uses the black pupil detection method. If both methods detect the left and right eyes in the same region, it is considered a success for eyeball tracking.

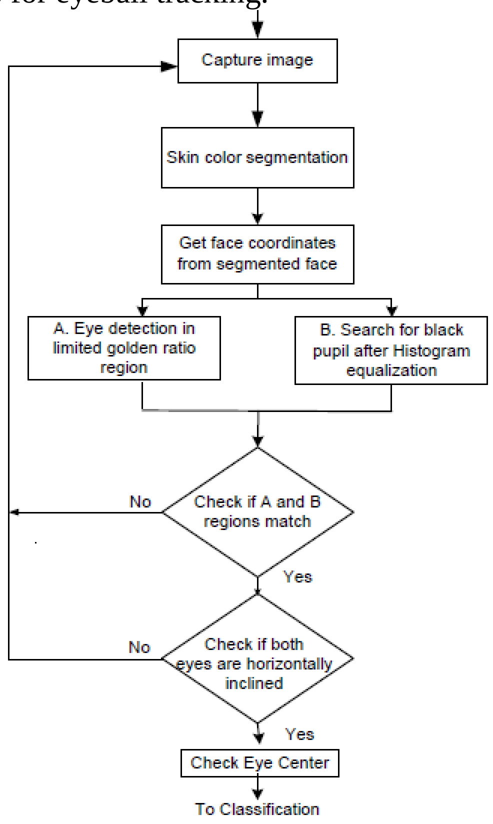

Figure 3: Eyeball Detection Steps

The first step is to train an SVM classifier for eye samples to get acceptable performance. The SVM parameters were varied, and it was trained with 100 image samples with each sample cut to size 35×65 include face region only. The purpose of the dimension was to know, how much of the image area needs to be cut to fit as a training sample, and later to match the size of the window used after training. Other dimensions were also tried such as 35×75 and 45×75, but 35×65 turned out to be optimum. Out of hundred 100 samples, 38 were used as support vectors. The confidence level of each point was computed by equation (1), using the bias and the weight matrix.

The eye search in the face center (per face golden ratio reported in [39]) used a moving fixed-sized window similar to the facial feature extraction method implemented by [40]. For this, the image is sub-divided into sizes larger than 35×65. The original image was of size 35×625, thus a maximum of nine (9) sub-images could be obtained for eye search. This number depends on the original image obtained after cropping the captured image. The position of the window is extracted once eyes are detected based upon a calculation of weight matrix of trained SVM and its comparison to a threshold. This threshold was set based on trial and error method and found to be 50%, which means that if confidence level increases 0.5, then the eye is detected by SVM.

Tracking results were satisfactory, with both eyes tracked with all 15 people (both genders aged 11 to 52 - male 6, female 9). To guarantee the accuracy, it examines to see that eyes are aligned either vertically (up or down) or horizontally (left or right). As discussed in Section 3, this up, down, left or right movement of the eyeball is used to map to mouse movement for rehabilitation and gaming applications. Briefly, the eyeball-detection steps are shown in Figure 3.

4.3. Classification

As discussed in Section 3, keyboard maps five eyeball movements: right, left, up, down and center. To classify the eyeball position, the method of dark pixel detection was used together with the trained SVM. In order to locate the black pupil, the histogram equalization was applied along with known facts in every person as:

$Eye\ width = \frac{1}{4th}$ of face width and (6)

$Eye\ height = 0.6\ \times$ Eye width. (7)

Using the ratio of black to white pixels, this results in the detection of eye pupil position, as shown in Figure 4. The center, right, left, up, or down positions of the eyeballs are used to map to four possible choices on the keyboard to enable the corresponding function to be executed in the system. As an example, the center indicates that no function is to be executed (refer to Figure 5). Figure 6 displays the classification flowchart 6.

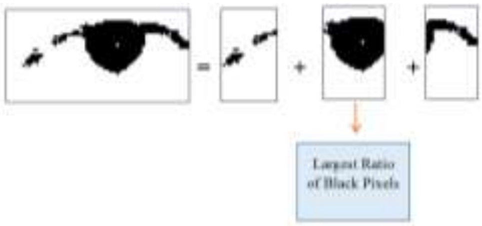

Figure 4: Detection of eyeball during classification stage

Figure 5: Center eyeball - nothing to be executed; Right eyeball - function to be executed.

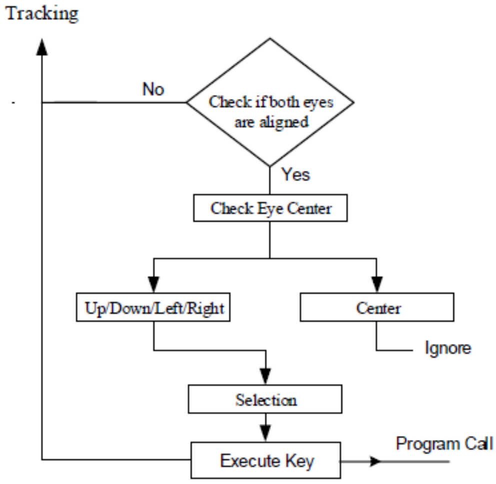

Figure 6: Flow chart of the classification phase

5. TESTING RESULTS

The main purpose of the testing was to check the system that initially trains SVMs for face detection and to observe performance after training. As discussed in Section 4, for facial features detection, the steps included processing images until a confidence level is reached. This measure determines how much an SVM weight matrix resembles an image. If this calculated measure exceeds a threshold set at 0.5 (as discussed in section 4.2), the detection is considered a success. During calibration and face detection, this confidence level was found to be 0.7388 and then compared to a threshold of 0.5 set based on trial and error method.

Table 1: Testing results of the tracking algorithm

Test	Gender	Environment	Tracking Results
1	Female (age 30)	2 fluorescent bulbs and afternoon sunlight	Both eyeballs tracked

2	Female (age 25)	2 fluorescent bulbs, afternoon sunlight, black and white patterned scarf	successfully in all cases, with a runtime of 0.15 seconds
3	Male (Child) (age 12)	Only evening sunlight	
4	Female (age 22)	2 fluorescent bulbs	
5	Female (age 39)	2 fluorescent bulbs and evening sunlight	
6	Male (age 45)	2 fluorescent bulbs, sunlight and black scarf	
7	Female (Child) (age 15)	Only afternoon sunlight	
8	Female (age 48)	2 fluorescent bulbs	
9	Male (age 28)	2 fluorescent bulbs, afternoon sunlight, colorful floral scarf	
10	Female (age 20)	Only evening sunlight	
11	Male (age 50)	Only afternoon sunlight	
12	Female (age 52)	Only evening sunlight	
13	Male (Child) (age 11)	2 fluorescent bulbs	
14	Female (Child) (age 13)	2 fluorescent bulbs	
15	Male (age 25)	2 fluorescent bulbs and evening sunlight	

People of different ages and gender in an indoor environment with incandescent bulbs and different periods of sunlight provided the data. Different lighting conditions helped test accuracy using an i7 dual-core processor with built-in webcam and Matlab10. The run time calculated for eye tracking came out to be 0.15 seconds (Table 1). The sample results are in Figure 7.

Figure 7: (Left: Eyes detected; Right: Tracked eye centers)

The SVM-based approach outperformed [41], which uses the morphology to detect eyes. The morphology approach failed due to low-resolution webcam under incandescent lamps in our environment setting. The keyboard, eye-blink, and eyeball tracking were integrated, and the system was tested indoors with incandescent bulbs and under periods of sunlight (Table 2). The success rate is computed as:

$$\frac{Number\ of\ correct\ display}{Total\ number\ of\ trials} = \frac{23}{25} \times 100\% = 92\% \qquad (8)$$

The authors in [33] used 1944×1296 sample resolution with an efficiency of 94%, with single eye detection, and 50% both eye detection, whereas the authors [35] applied to skin color segmentation, and circular Hough transform with performance efficiency of 77.78% for single eye detection, and 66.67% both eye detection. Similarly, [22] detected face and later iris detection with best results amounting to 80% and 70% on left and right click respectively as a cursor click on the computer screen, whereas authors in [34] use trials to estimate fatigue detection based on eye-state, with performance accuracy of an average of 85% on the left and closed eyes (refer to Table 3).

6. DISCUSSION

The keyboard can be customized and persons with physical challenges to speak through eyes during rehabilitation can easily use it. However, more activities or functionalities can be added. For example, commonly used symbols, native words or the ones adopted in Augmented and Alternative Communication (AAC) can be used.

There are many approaches to building an eye tracking solution, as discussed earlier. Here, in this work, a low-cost (involving only the webcam) software solution was proposed with comparatively best-tracking results. For calibration, the SVM approach was presented as it provided 100% results.

Table 2: Testing results of the integrated system

Test	Activity Selection Result	Details on eye detection
1	No	correct as ‘center’
2	Yes	correct as ‘left’
3	Yes	correct as ‘down’
4	No	wrong as ‘up’
5	No	correct as ‘center’
6	No	correct as ‘center’
7	Yes	correct as ‘right’
8	No	correct as ‘center’
9	Yes	correct as ‘right’
10	Yes	wrong as ‘right’
11	No	correct as ‘center’

12	No	correct as 'center'
13	Yes	correct as 'down'
14	No	correct as 'center'
15	Yes	correct as 'down'
16	No	correct as 'center'
17	No	correct as 'center'
18	No	correct as 'center'
19	Yes	correct as 'left'
20	Yes	correct as 'center'
21	Yes	correct as 'up'
22	Yes	correct as 'down'
23	Yes	correct as 'up'
24	Yes	correct as 'left'
25	Yes	correct as 'down'

Table 3: Comparative results

	Research Work	Accuracy	No. of samples
1	[33]	94%, with single eye detection, and 50% both eye detection	50 samples
2	[35]	77.78% single eye detection, and 66.67% both eye detection	9 samples
3	[22]	80% and 70% on left and right click	3 samples
4	[34]	85% on the left and closed eyes	Not mentioned
5	Proposed Approach	92% on both eyes detection	25 samples

For prototyping purposes, a single-board computer was used that connects to the keyboard and other peripherals to develop a solution. This platform is easy to program and debug the functions written for selected activities on the keyboard, though other platforms can also be used for IoT prototyping hardware.

To implement the proposed tracking system, some points should be noted: (1) any object whose color is similar to skin in the surroundings degrades the performance of the system, (2) the performance is affected if the person's face is not aligned

horizontally or the person is not looking straight into the webcam, and (3) the system allows only a distance from 60 cm to 180 cm away from the camera.
The proposed method uses an ordinary webcam available in laptops for 30 frames per second at 640×480 resolution. The algorithm captures one frame only for processing. The solution can be transported easily to other hardware platforms such as smartphones with a keyboard and eye tracking implemented in software.

7. Limitations

Persons who are "only" paralyzed are often the minority in real-life clinical settings. From a clinical point of view, there exist many other patients, who suffer from different kinds of plegias, motor disabilities etc., which have many-fold additional clinically relevant affections and not only pure paralyzes. The proposed approach in this work may help with the assumption that the brain of the paralyzed person is amenable for brain exercise. As said earlier, people with hemiplegia, e.g., may have a heminaopsia. These people suffer from less vision existing in half of the visual field. Some people might even be suffering less vision on the same side of both eyes. Likewise, a neurological condition may cause a deficit to awareness of half of visual field. Obviously, these classes of patients may not be trained for exercise of nerves. On the other side, many patients are suffering from comorbidities and multi-morbidity. Therefore, special training methods might be necessary if at all possible.
Therefore, the approach and tools developed in this work are applicable for a class of people only and can be considered an important first visionary step to tackle out or evaluate at a later stage application for real-life patients, respecting the context in which paralyzes occurred. For blind people or those with very low vision, there are no solutions as well as for very young children, it is assumed. There is still a long way for further investigations to follow.

8. CONCLUSIONS

A customized real-time solution to enhance assisted living of paralyzed persons was developed and tested indoors under varied lighting conditions for male and female aged 11 to 52. The solution integrated software keyboard, eye blink, eyeball tracking and classification using an SVM classifier. The testing results showed a performance efficiency of 92% with a run time of 0.15 seconds. The performance efficiency can be improved by involving dual camera or availability of depth sensor camera, and a faster processor or multicore environment, for any future enhancements, can further reduce run time. The solution can be used for wheelchair users, on-bed patients, for instance. The solution can be transported to different platforms including smartphones. For future work, various improvements can be explored, for example: (1) SVM performance during classification can be enhanced using more training samples with additional head orientations; (2) hardware solution is likely to generate a real-time solution; (3) stand-alone chips might provide add-on features to the product; and (4) more variation can be allowed in environmental lighting conditions.

Face recognition can help to guarantee legitimate blinking. Given that the system needs at least 2 secs to process one command, the system does not have to work in real time. Since face recognition often requires one dimensionality reduction (in the feature extraction phase), motion estimation can help to study the face as an expanded ROI [42-46].

9. Conflict of interest statement

We certify that there is no conflict of interest with any financial organization in the subject matter or materials discussed in this manuscript.

10. Authors' biography

Qurban A Memon has contributed at levels of teaching, research, and community service in the area of electrical and computer engineering. He graduated from University of Central Florida, Orlando, US with PhD degree in 1996. Currently, he is working as Associate Professor at UAE University, College of Engineering, United Arab Emirates. He has authored/co-authored over ninety publications in his academic career. He has executed research grants and development projects in the area of intelligent based systems, security and networks. He has served as a reviewer of many international journals and conferences; as well as session chair at various conferences.

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