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Research Article

EOG Region Detection using Fuzzy k-NN for Virtual Reality Applications

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ABSTRACT

Virtual Reality (VR) systems have become widespread for a decade with the mass production of VR headsets. Advancement in the VR industry benefits both biomedical and computer gaming fields to create better Human-Computer Interface (HCI) applications. In this study, Electrooculogram (EOG) signals are studied on a calibrated A4 paper to simulate reading and tracking eye movement in different regions for VR user interface applications. For that reason, eye activity features from EOG are used to identify relative 2D spatial coordinates and classified with the fuzzy k-Nearest Neighbor (fuzzy k-NN) method. Within the experimental setup, different behaviors such as blinking and depth focus change signals are recorded with constant depth regional borders are analyzed on an A4 paper with reading eye movement recordings. In experimental results, fuzzy k-NN classification results are obtained from observed regional eye movement. The study shows that the fuzzy k-NN method to detect regions at a reading distance is feasible for user interface applications in VR. So, by setting rendering focus at the detected regional area, eye strain can be reduced during prolonged VR sessions especially when reading and/or on user interfaces.

1. Introduction

With commercial expansion and improvements in Virtual Reality (VR) systems, a wide variety of sensors are used for tracking and navigating in VR headsets. Eye-tracking sensor usage is believed to be part of major VR devices in the near future [1]. Therefore, biomedical technologies and solutions will become useful for such devices. Using currently available VR headsets, controlling and navigating of virtual applications is possible by tracing eye movement. Electrooculogram (EOG) data allows the construction of a suitable non-invasive way to detect movement and behavior of user intention on applications.

Controlling interfaces and applications, and detecting regions of interest could give new opportunities in both healthcare and user-oriented daily life usage in VR systems. Reading a paper, following news, web surfing using eye movement navigation, and focusing to get related news could help new opportunities to emerge. Current VR headsets heavily rely on different types of controllers rather than EOG sensors for application control.

There are eye movement detection systems for foveated rendering such as Pico Neo brands and HTC Vive Pro Eye with Tobii. On HTC Vive eye tracking is detected by cameras while in the Pico Neo series eye tracking is done by sensors in front of the lens. As foveated rendering could reduce eye strain, EOG signals can also be used to track regional eye focus.

The need for health monitoring in VR devices also becomes apparent. Without EOG sensors eye strain and unhealthy light exposure on eyes are not directly monitored in the daily usage of such devices. So EOG sensors can be used to

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detect healthy conditions as well as increasing navigational ability with region of interest detection for applications.

Currently, many applications heavily rely on handheld controllers or keyboard/mouse for navigation in VR environments. Also, web surfing or reading activities only need simple actions without complicated input levels. Navigating between different sections in user interfaces or focusing at one point could be able to be recognized or user-defined actions could be carried with EOG sensors. Handheld devices come with hand gesture touch sensors or in personal computers mouse hardware comes with programmable buttons and predefined selective options for users to be able to control computers more easily. In that aspect, the same factors could be applied to VR headsets and systems to carry commands using EOG sensors so that basic navigation could be carried much more easily. In this study, for the same purpose navigational detection for real-life reading and VR counterpart is tested at a fixed distance so users can navigate more naturally and comfortably in VR applications.

In literature, many wearable devices and Human-Computer Interface (HCI) systems have been developed. For example, the brain-computer interface can be used to control the robotic arm using facial expressions [2]. With wearable Forehead EOG sensors, wheelchair control using a virtual keyboard is studied by Heo et.al. [3]. In their work, a user could drive a wheelchair through the 8-shaped course without collusion. Another application is mobile phone-based HCI usage for assistive healthcare where an Android app helps the users to emulate mouse behavior using eye or facial movements [4]. Sleep onset latency could be reduced using in VR environment with a sleep assistant when EOG sensors are combined with a VR headset [5]. With the use of EOG sensors, it is also possible to use eye movement detection and gaze estimation to control an asynchronous virtual keyboard with high accuracy [6]. Another application field for EOG usage as an input device is playing a game after taking sensor data using microprocessors [7]. EOG can also be used as an input device and controller for studies that have more advanced applications such as sculpting in virtual reality [8]. There is also a social aspect when using HCI systems and EOG sensors could be socially intrusive, based on a social point of view wireless EOG electrode usage is also studied [9].

Classifying and analyzing sensor data is a requirement to define the correct response for any application. For example, Dursun et al find EOG artifacts in sleep Electroencephalogram (EEG) signals and automatically eliminate them using regression methods so that their clinical utility increases [10]. Vidal et al studied EOG data to discriminate saccades, smooth pursuits, and vestibulo-ocular reflexive movements and identify them using EOG data from 19 different people [11]. EOG data classification is also tested using Dempster Shafer theory and k-Nearest Neighbor (k-NN) classifier with their accuracies in literature [12].

The k-NN algorithm is used in the biomedical field where sleep stages are distinguished with the usage of three different distance metrics [13]. Aside from k-NN, a Support Vector Machine (SVM) is also used to classify feature data [14]. As different types of signals have, noise and unwanted data are also present in data taken from EOG, so the removal of EOG and EMG data artifacts are studied to represent muscular signals better using the k-NN algorithm [15]. There are studies to improve signal analysis such as the usage of multi-resolution representation of EOG signals using wavelet decompositions [16]. In eye movement; blinking, saccades, and fixations are important behaviors where these actions are needed to be identified and should be processed according to the objective of the data process. So Toivanen et al studied this area and obtained high accuracy in detecting these behaviors by calculating temporal parameters and probabilistic method where uncertainty of detected events is considered [17].

In this paper, regional eye movement detection is studied with A4 paper reading at a 45cm distance in real life and its counterpart movement response in a computer. Distance of 45 cm from the observer's eye is used for many daily activities, such as reading or using a computer, making it a relevant distance for assessing visual abilities in daily life and sports [18]. 45cm distance has another importance which is recommended in Head Mounted Display (HMD) devices for the user against 40 cm due to the increased vergence-accommodation conflict [19]. In HCI devices, a 45 cm distance allows for controlled comparisons between different display types and provides insights into the impact of viewing distance on user experience and task performance [20].

Acquired data is classified using fuzzy k-NN to find which regions the user is focused on in the duration of experiments. So, with experiments calibrated real-life and computer counterpart signals are read and classified based on defined spatial regions.

In the study, a framework is constructed to be used in VR headsets in which EOG data responses could be used for computer interaction in both reading and web surfing with intended actions.

2. Materials and Methods

In this study, eye movement signals taken from Electrooculography are studied to identify A4 paper border regions in the real world to simulate paper reading in a computer interface to identify regional detection on a computer application. Instead of neural network-based approaches to define regions, fuzzy k-NN is used which is not based on learning and therefore easily modified and applied. The classic k-NN algorithm suffers from various limitations that lower classification success. The limitations that affect performance can be counted as being unbiased to all its classification-dependent neighbors, lack of distance calculation features between data points, and taking into account unnecessary dataset features [21].

For better classification fuzzy k-NN algorithm is selected which uses “membership” values for each class to define regions. For k-NN and variant algorithm performances, the study of Uddin S. et al. shows performance comparisons in disease prediction problems [22].

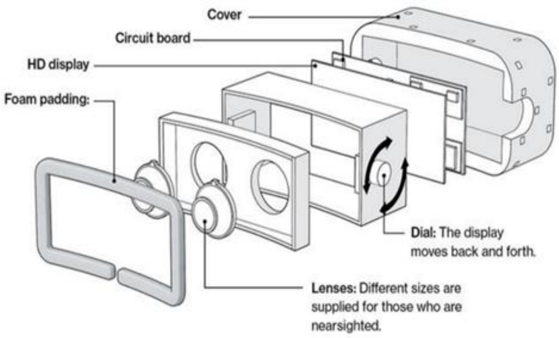


Figure 1. HMD device for virtual reality applications and its structure [23]

When reading a web page or a paper at a fixed distance, our eye movement captures and focuses on specific regions. So, to identify and detect reading in both virtual and real environments calibrated environment is created for testing purposes. A4 paper is used to create a 2D plane at a fixed depth in a 3D environment. So, the experiments measured regional eye movement at a reading distance. With these tests, real-life reading behavior can be measured with its application in a virtual environment. User interface navigation can be implemented with reading detection using EOG signals.

In VR applications, devices that help to create human-machine interfaces are widely used as in Figure 1. Currently, many HMD devices use controllers or standard keyboard and mouse devices to control web surfing or user interface navigation. Keyboard and mouse usage limits the user to a fixed position and viewing angle, whereas controller usage to navigate through the content takes more time as the cursor needs to have motion if the navigation sections are not bound to the buttons.

So, without any hand motion requirement, reading and navigation using EOG signals in VR applications helps to navigate more naturally and also creates a possibility to use more inputs when controlling the device. Therefore, in this paper, gazing at different sections and reading is measured when looking at A4 paper and its machine counterpart VR application within Unity 3D is studied.

2.1. Experimental setup

In the experimental setup, to acquire eye movement EOG signal data BIOPAC Systems

MP36 device from Sakarya University Electrical-Electronics Engineering Department Lab is used as can be seen in Figure 2, and two-channel input is calibrated through the computer.

Hardware supports up to 4-channel inputs for EOG data. Also, electrode placement is done before the calibration session which can be seen in Figure 2(c). A vertical channel is placed around the right eye and a horizontal channel encompasses both eyes. Ground electrodes were placed on the forehead near the vertical electrode 'Vin+' side.

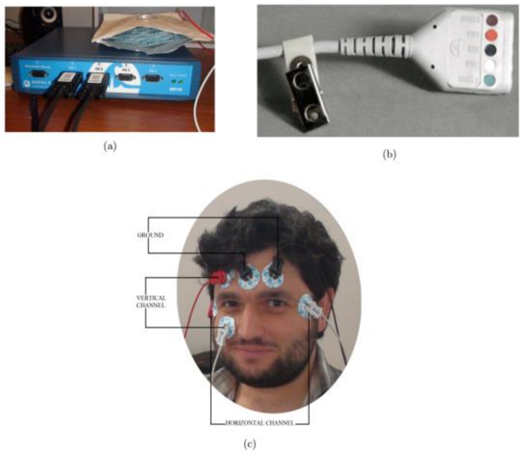


Figure 1. (a) BIOPAC Systems MP36 device for getting signals, (b) Shielded electrode adapter and color definitions [24], (c) Electrode placement for EOG data acquisition

As can be seen in Figure 2(b), in Figure 2(c) red-colored electrode represents the 'Vin+' electrode, white-colored electrodes represent the 'Vin-', whereas black-colored electrodes are ground for vertical and horizontal channels each.

Reading A4 paper is measured at a 45cm distance with a 2.1 cm horizontal length for both virtual and physical interface. Calibrated A4 paper can be seen in Figure 3.

In the study, two calibration steps were required to record the signals on the computer. In the first phase, MP36 device software is used to calibrate both vertical and horizontal signal accuracy. The second calibration phase is conducted for both resolution and eye movement change at 45 cm depth.

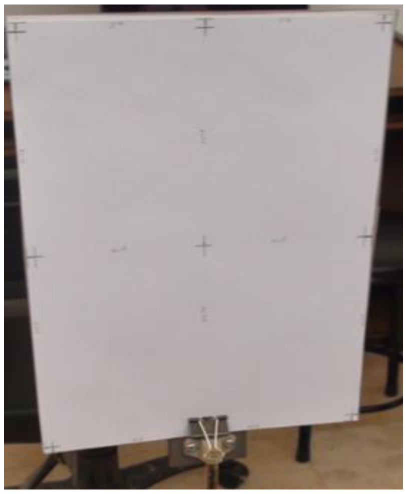


Figure 3. Reference A4 paper at 45cm to define regions and test eye movement differences

As higher depth means more content at a given window of view, accuracy reduces as the measured distance increases. So same eye movement means different amounts of content reading (or view) at different depths. In the virtual environment, different Z-axis positions mean different objects or content focus. Therefore, second calibration measurements are carried out to identify virtual and physical world differences in captured data.

In the experiments, signals are recorded with 100 MHz frequency. After initial setup, experiments reached 115 different observations where focus and different depth gazing were included. For VR applications focus change and blinking are recorded for analysis.

2.2. Methodology

Several steps are needed to be taken into account to represent a methodology that turns signal data into recognition of user action. First, signals are sampled and related features with statistical properties are analyzed. Signal sampling can be seen in Figure 4 where outliers are also taken into account in the sampling procedure. Also, Figure 4 shows full A4 paper content reading line by line under page-in boundaries.

In experiments, when gazing from the page center to different regions muscular activity is observed to last around 1-2 seconds from starting until it comes to the resting condition.

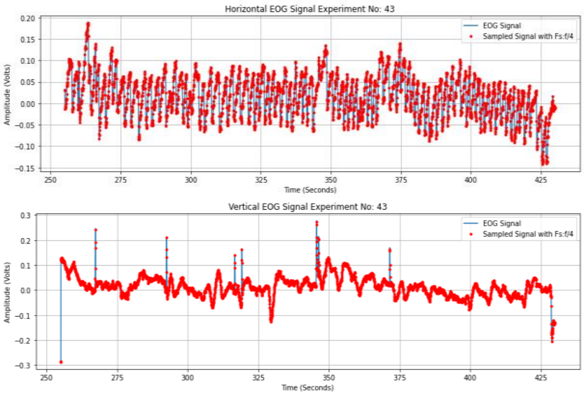


Figure 4. EOG signal with sampling results (red overlay) from horizontal (up) and vertical (below) channels

As for blinking and depth changes, these activities are transferred as more rapid responses in signal data. To measure eye movement changes correctly, overlapping tests are conducted starting from the page center to different directions. Horizontal eye movement data can be seen in Figure 5(a) with muscular activity falling after the target point is reached. The resting phase and eye movement sections give necessary cues to construct depth-eye activity resolution information with the help of calibrated A4 measurement.

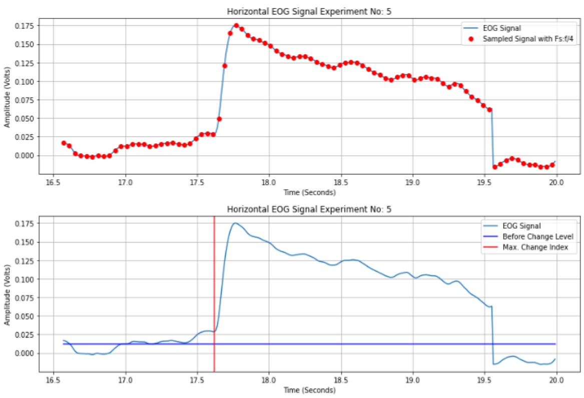


Figure 5. Sampled signal with original data (up), horizontal eye movement base within a frame according to maximum change (below)

According to the recorded data, the MP36 device stores 100 samples for every second. Re-sampling which is represented by red points in Figure 5(up) has a sampling frequency lowered by 4 times. According to the tests, to measure eye movement changes at 45cm depth, down-sampling by 4 retains the necessary information to analyze eye movement. In methodology, both original input signal and re-sampled data are used in conjunction for blinking, focus change, and eye movement analysis. On the other hand, if focused depth increases, the sampling frequency and accuracy of sensors need to be more sensitive to the changes because, between two points, the eye needs less movement. So, the amplitude of the signal will be lower than the values seen in Figure 5(up). Therefore at higher depths, system detection of movement becomes more susceptible to the noise.

To detect relative changes, windows in one-second intervals are analyzed using a given signal. When the eye moves from the center of the paper to the off-page region, after the initial amplitude jump, amplitude values have a more gradual change. This event spread over a longer time frame until rest condition was achieved which is different from rapid blinking and focus changes. As eye movement gives different responses in signal, the maximum changes in each second interval are detected for the categorization of an event in EOG.

As can be seen in Figure 5(below), maximum change is related to eye movement direction. So, to detect the vector of eye movement relatively, the maximum change in a second time frame is calculated. After that eye resting condition level before the event is approximated to find the movement vector. Using the maximum change index, 'before change level' determined by average prior values in the frame if there is no other event is present. After the event, the area above the resting condition is measured. This area represents a positive relative change in right-side eye movement.

After signals are processed according to movement changes, change vectors are determined. According to the relative movement in time, change vectors are mapped in 2D coordinates. In the study, eye movements within page or off-page regions are taken and classified for region detection application. In classification tests, eye movements starting from the page center were used to measure the difference in real life and the corresponding action on the 2D map in the virtual environment.

$$u_i(x) = \frac{\sum_{j=1}^{K} u_{ij}(1/|x-z_j|^{2/(m-1)})}{\sum_{j=1}^{K}(1/|x-z_j|^{2/(m-1)})}) \tag{1}$$

To classify eye movements, a well-known fuzzy k-NN algorithm is adopted and used as shown in Equation 1 above [25]. In the equation, $u_i(x)$ means fuzzy membership of sample x in class i. Also, u_{ij} represents the membership of the j sample in class i. So the closest K-nearest neighbor defines fuzzy membership of the sample x. The parameter m is called the fuzzifier, which is given a value of 2, where membership values are proportional to the inverse of the square. The distance of x to each class sample is calculated using $|x-z_j|$.

Parameter-independent algorithms for fuzzy k-NN can also be used which would eliminate the need for a neighbor count parameter. So, the Parameter Independent Fuzzy class-specific Feature Weighted k-Nearest Neighbor (PIFW k-NN) classifier become another alternative for more adaptable solutions [26].

3. Virtual Reality Projection Results

In the experimental phase of the study, a total of 155 different eye movements were carried out. Within the data, the first 42 signal records consist of eye movement at 45cm depth where their starting point is on the center of A4 paper. In experiment data 43, eye actions when reading A4 paper content are recorded. So, eyes always were in the boundary of A4 paper for this data. Also in experiments 44-115, signals have eye focus shift. In these recordings, random focus locations are examined in experiment 68-77 data. All recorded signals contain vertical and horizontal eye movements separately. Furthermore, experimental data in this study is available online at GitHub [27].

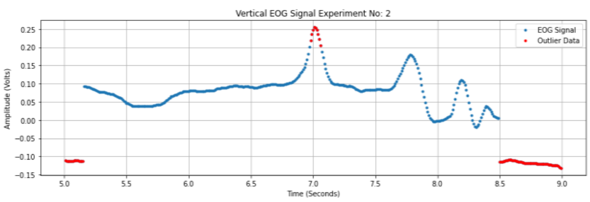


Figure 6. Original EOG signal with IQR Outliers (red samples)

2D tests where A4 paper is present were conducted mainly for algorithm implementation on the detection of regional movements. So, when eye movement is out of the A4 paper boundary, an action can be bound to the application to perform certain tasks according to the regional section.

To observe statistical changes in signal sampling, the Inter Quartile Range (IQR) Outlier is calculated. Blinking and other spikes can be caught by an outlier filter. Both IQR outlier and sampling effects can be seen in Figure 6. For uncategorized EOG signals, Symlet wavelet becomes useful for blinking event elimination on signals [28]. There is a neural correlation of eye blinking as the medial frontal gyrus is responsible for spontaneous eye blinking [29]. So aside from signal processing, detection of specific brain regions can also be used for accurate blinking removal.

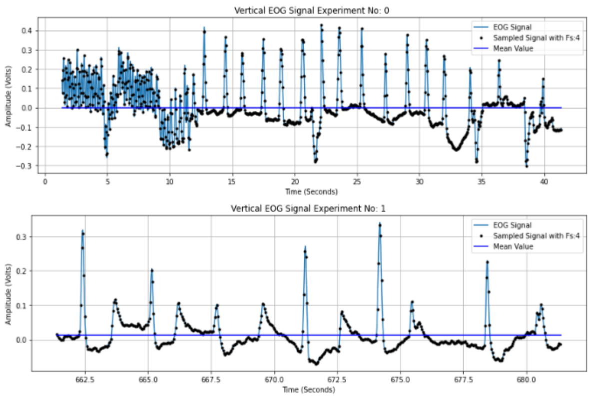


Figure 7. Fast (0-12 sec.) and normal repeated blinking (12-40 sec.) times (Up), eye focus change over 10 cm to 3 meters (Bottom)

In experimental data, it is observed that frequency responses for blinking and eye depth change create similar structures where low-pass filtering eliminates both information. The similarity of blinking and focus change on vertical EOG signal can be seen in Figure 7. Non-sequential blinking and focus change therefore are fairly similar. That means the elimination of blinking also removes focus change information, especially on vertical channels. On the other hand, focus change can have differences in amplitude based on depth information. Two-dimensional gazing at a certain depth changes the recorded amplitude differences where far-away locations need minimal effort. So, depth also affects the vertical and horizontal reading resolution of a signal.

As for eye movement either in content reading or regional movement starting from page-center is converted to two-dimensional position values by detecting amplitude changes of the signal in both horizontal and vertical readings. After positional changes are calculated, samples are processed using the fuzzy k-NN classification. As relative positioning is important, from page center to region eye movements are taken as class samples in conducted tests for the virtual environment. In Figure 8(a), positive ‘+’ labeled fields show the A4 paper field where reading content resides. Text reading data was acquired to represent content-based eye movement. Regions outside of the border of the A4 paper are divided into 4 regions. Based on the regional classification, action could be changed according to the defined application purpose.

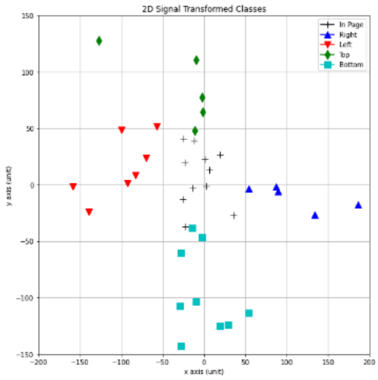
In conversion from signals to 2D positions, signals are processed according to time and amplitude changes. The input signal at a time t is defined as a $s(t)$. Every action starting from the page center (origin) represents an eye movement vector. These vectors are defined as $\vec{A}$ vectors according to the equation below. Vector magnitude is calculated by taking an integral of eye movement action from the start of movement until the rest condition is achieved.

$$\vec{A} = [(d_x.a_x)(d_y.a_y)]^T \qquad (2)$$

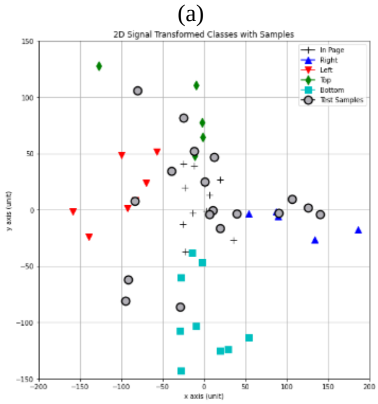
$$a_{x,y} = \left|\int_{t=t_{start}}^{t_{rest}} s(t)dt\right| \qquad (3)$$

In vector $\vec{A}$, the length of vertical and horizontal vector components are calculated by finding an area of action and multiplied by the direction (d_x and d_y) of the signal so four quadrants can be mapped in the Cartesian coordinate system. 2D representation of class and test signals are mapped in Figure 8 where each point represents movement with respect to origin using vector $\vec{A}_i$ where i is an action (experiment number) recorded in EOG data.

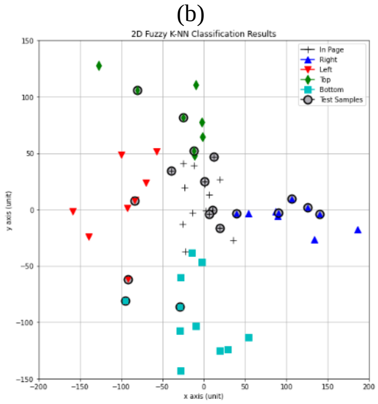
Pre-defined samples at defined regions in Figure 8(a) are taken from experiment measurements in real life and their corresponding values are entered in the Unity 3D application. Within defined regions, EOG recordings for testing are added as shown in Figure 8(b) using a filled circle. As experimental EOG observation data are not focused on equally distributed spatial experiments, pre-defined samples, and test samples are given to test the performance of the fuzzy k-NN algorithm. So, classification is tested on different density regions in terms of samples.



(a)



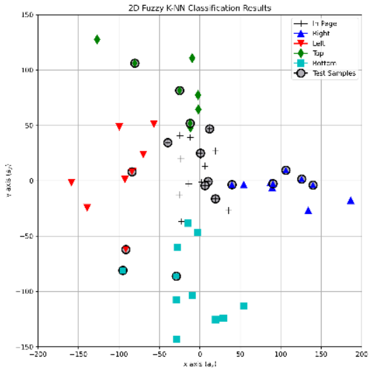
(b)



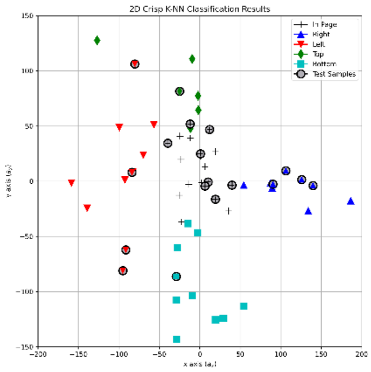
(c)

Figure 8. Region classes with pre-defined samples (a) and test samples with filled circles (b), classification test results with overlay shape on test samples (c)

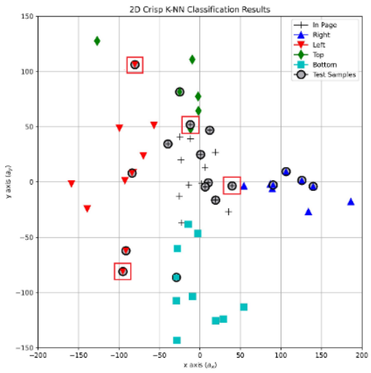
Experimental test sample prediction starts from page content region with experiment numbers 68, 69, 70, 99, 100, 101, and 102, the right side starts with 78, 79, also the left region is represented by 81, and the bottom 83. Unknown locations in the experiment numbered 103, 104, 105, 106, 108, 109, 110. So, in Figure 8(c), 7 known test samples are classified for verification along 11 uncategorized regions.



(a)



(b)



(c)

Figure 9. Fuzzy k-NN (a), crisp k-NN (b), crisp k-NN differences (red rectangles) with respect to fuzzy k-NN (c)

In Figure 8 (c), classification results on given test samples can be seen with overlay class shapes. As fuzziness is introduced in the classification method, it helps to eliminate errors as the number of class samples increases in the processed neighbors shown in Figure 9.

Differences caused by crisp k-NN are seen in Figure 9(c). The differences between fuzzy k-NN and crisp k-NN are observed mostly in boundary lines. In fuzzy k-NN, since the distances affect the weights, the points in the regions where the sample classes are dense belong to that class, whereas in crisp k-NN, after taking *k* number of samples according to the distance, there is no distinction and difference between the samples. For this reason, in crisp k-NN, even if the class samples are far apart, as long as the majority belong to the distant region, the test sample will be identified as that distant class.

In Unity 3D environment EOG results are created in real-time with basic 2D shapes using vertices at the start of the scene to show the results of classification. A4 paper is defined according to the real-world size of 210mm x 297mm in Unity 3D. However, it should be noted that perspective and orthographic projection will give different results if sample geometry objects are not drawn at the correct depth. So, camera properties and depth information of objects need to be taken into account in real-life to virtual environment conversion. You can see the results in a stereo-view (side-by-side) 3D environment in Figure 10.

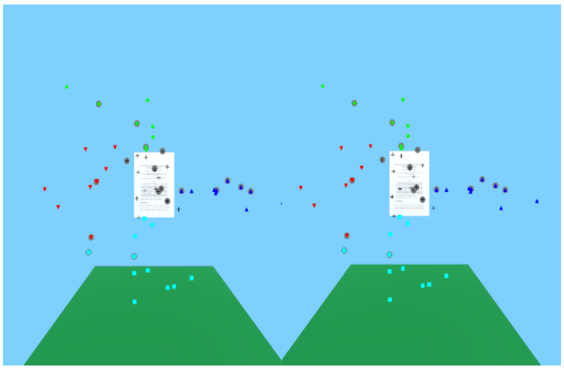


Figure 10. Stereoscopic (side-by-side) view of classification test results on Unity 3D application

The transformation from the 2D mapping of a signal to a VR environment is done by using the linear transformation matrix defined in the equation4. In transformation for a VR environment at a 45 cm depth, coefficients c_x and c_y give the best results when set at 0.036 units. Paper and the origin point of vectors defined as 1.84 units in height with other axes are zero. In Unity 3D version 2019.3.0f1, to be able to get a 2D view of all samples in Figure 10 side-by-side, the camera is located 8 units before the origin in the Z-axis.

$$\vec{V_i} = \begin{bmatrix} c_x & 0 \\ 0 & c_y \end{bmatrix} . [\vec{A_i}] \qquad (4)$$

Stereo separation is defined as 0.064 units as human interpupillary distance changes from person to person [30]. Normally eye automatically converges according to when the object is focused. As the stereographic camera has a fixed convergence it is set to 10 units in the system.

Aside from signal-related errors, errors can be caused by the user view (camera in VR) vector which is assumed to be aligned in the z-axis. However, in real life head orientation and view vector changes frequently. Results may be affected by the view vector changes because there was no user head orientation movement sensing hardware at the time of experiments. Another point to be considered is that when the depth value increases eye travels less and the related vector $\vec{A}$ changes by it. So, either the transformation matrix needs to be changed based on depth information or depth information should be approximated by the change of voltage when the focus change section is detected.

There are also shortcomings in the fuzzy k-NN method, it is important to have more samples near boundary sections to get better estimations as distances become important. For low sample count cases, users can give inputs in the calibration phase for VR applications. So necessary sample input can be fed into the system. Also defining a buffer zone for each region can prevent changing regions quickly without any action because of noise and other errors.

4. Conclusion

HCI systems make life easier especially in the field of biomedical engineering. With the development of technology, HCI systems have become affordable for daily life use, thanks to higher quality and lower pricing. In the market where VR-based applications are increasing, it is possible to create more interactive systems with the use of EOG sensors. Users can navigate in VR applications using natural eye gestures if EOG is implemented in headsets. For these applications, defining regions and gestures becomes an important part of the multi-motion input systems. Multi-motion input systems can help convert human behavior into an application input. So, the usage of EOG signals can be a section for the multi-motion input systems.

In the study, the regional data was measured in a real environment using calibrated A4 paper processed with the help of EOG signals and classified with the fuzzy k-NN algorithm in virtual reality. As the nature of user interfaces in VR applications, content reading should start at a certain depth. With the usage of EOG sensor reading, controlling applications can become much more natural and easier. Application results show that the fuzzy k-NN method to detect regions at a reading distance is feasible for user interface applications in VR. Also, experiments show that focus depth and user view vector are important parameters that affect the definition of eye behavior in virtual reality applications. Another important factor is a virtual camera implementation which can limit natural eye movement feeling. So, aside from supported stereographic methods, virtual multi-camera implementations are advised to be able to set more specific camera properties.

In the tests and implementation, only distinct actions are selected and analyzed. However, live data processing has more importance in terms of applicability. So, for the next step, it is planned to acquire a live data stream from an embedded system to be able to view directly from a mobile VR application using the experimental and constructed basis discussed in this paper. The next step after that may also have an Augmented Reality (AR) side so that VR differences can be compared with real-world segments and boundaries.

Article Information Form

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Authors' Contribution
E.G: Conception, design, data collection, data analysis, interpretation, technical support, material support, literature review, and writing.

S.S: Technical support, material support, literature review, and writing.

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No conflict of interest or common interest has been declared by the authors.

The Declaration of Ethics Committee Approval

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