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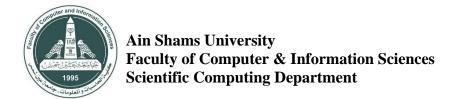
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# Development of Robust Electrooculography (EOG) Based Human Computer Interface

Thesis submitted as a partial fulfillment for the requirements for the degree of Master of Science in Computer and Information Sciences

By

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## Development of robust electrooculography (EOG) Based Human Machine Interface

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#### **Abstract**

Recently, the increase in the number of patients with motor disabilities has become a noticeable phenomenon all over the world. The reasons for this increase are due to the emergence of many diseases that cause motor nerves to atrophy and thus prevent the motor limbs from performing their vital role. This injury extends to all parts of the body and causes complete paralysis and only the neurons that control eye movement survive. Hence, patients do not have a way to communicate with their surrounding environment except through the movement of their eyes.

The human-computer interface (HCI) has emerged and become a new communication way and support tool for these patients. It allows a communication between the user and the computer that depends on the analysis of voluntary, controlled bio-signals to choose a specific action, execute, and display it on the computer screen. HCI systems are based on determining eye movement directions from Electrooculogram.

An electrooculogram (EOG) records eye movement as signals produced from variation in the polarity of the nerve of the eye. EOG recording is performed by a set of electrodes placed horizontally and vertically on the controlling muscles of the eye. The relationship between the electrooculography signals and eye movement is linear. The waveform of the electrooculography signal is completely in line with the eye movement, so it is easy to analyze and identify.

This thesis proposes a HCI writing system based on classifying EOG signals by a proposed deep learning model. This system helps all patients with diseases that cause severe motor disability and paralysis in all their limbs. In addition, it provides them with a new way of communicating with their external environment without always needing a companion. The proposed system detects six different directions of eye movement: up, down, right, left, center, and blinking, in addition, using them to select letters, write messages from a virtual keyboard, and vocalize them as well.

The vertical and horizontal EOG signals are filtered from noise using a second-order band-pass filter. Two different approaches have been considered to classify the signals. The first approach depends on extracting the statistical and morphological features from the filtered signals and concatenating them in a final feature vector that represents an entry for six machine learning classifiers. The six classifiers are Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), Multinomial Logistic Regression (MLR), K Nearest Neighbor (KNN), Decision Trees and Naïve Bayes (NB). The second approach relies on concatenating the horizontal and vertical filtered EOG signals into a vector as input to five deep learning models: Convolutional Neural Network (CNN), VGG Network, Inception Network, Residual Network, and ResNet-50 Network. Experiments have been conducted on two datasets: public small dataset and PSL-IEOG2 dataset

which is a large dataset collected by us using the PSL-IEOG2 device dedicated to measure eye signals.

The experimental results reveal that the inception deep learning model outperforms all the other considered models and traditional classifiers with an overall accuracy of 98.8%. The user interface has designed consisting of four forms: the first is the opening form and displays all the possibilities offered, the second is a virtual keyboard for writing messages, the third includes the daily activities which patients are accustomed to use, and the last one contains the trending news circulating on the most famous news sites. Finally, the processing time to complete a selection in any form is only one second.

#### **List of Publications**

- 1) Reda R, Tantawi M, Shedeed H, Tolba M F. Analyzing Electrooculography (EOG) for Eye Movement Detection. The International Conference on Advanced Machine Learning Technologies and Applications (AMLTA2019). Springer International Publishing, Cham. 2020;179-189.
- 2) Reda R, Tantawi M, Shedeed H, Tolba M F. Eye Movements Recognition Using Electrooculography Signals. Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2020). Springer International Publishing, Cham.2020;1153:490-500.
- 3) Reda R, Tantawi M, Shedeed H, Tolba M F. Development of Electrooculogram Based Human Computer Interface System Using deep learning. Bulletin of Electrical Engineering and Informatics, Indonesia.2021. (Q3, SJR 0.251)
- 4) Reda R, Tantawi M, Shedeed H, Tolba M F. Developing a Method for Classifying Electro-Oculography (EOG) Signals Using Deep Learning. The International Journal of Intelligent Computing and Information Sciences (IJICIS). Egypt.2021.

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#### List of Abbreviations

#### **Abbreviation Stands for**

ALS Amyotrophic Lateral Sclerosis
ADC Analog to Digital Converters

Ag/AgCl Argentum Chloride

ANN Artificial Neural Network

AR Auto-Regressive

CWT Continuous Wavelet Transform
CNN Convolutional Neural Network

DAQ Data AcQuisition
DC Direct Current

DWT Discrete Wavelet Transform

ECG ElectroCardioGram
EEG ElectroEncephaloGram

EMG ElectroMyoGram
EOG ElectroOculoGram
FN False Negative
FP False Positive

FFT Fast Fourier Transform

FFNN Feed Forward Neural Network

FT Fourier Transform

GBS Guillain-Barre Syndrome
HCI Human Computer Interface
HMI Human Machine Interface

ILSVRC ImageNet Large Scale Visual Recognition Challenge

IG Information Gain KNN K Nearest Neighbor

LDA Linear Discriminant Analysis
LSTM Long Short Term Memory

ML Machine Learning

MLR Multinomial Logistic Regression

NB Naïve Bayes

NN Nearest Neighbor

PAP Peak Amplitude Position
PAV Peak Amplitude Value
PC Personal Computer

PSL-DAQ PhySio Lab Data AcQuisition

PSL-IEOG2 PhySio Lab Industry ElectroOculoGram 2

PSD	Power Spectral Density
PDQ	Product Data Quality

RNN Recurrent Neural Network
STFT Short Term Fourier Transform

SVM Support Vector Machines
TDNN Time Delay Neural Network

TN True Negative TP True Positive

USB Universal Serial Bus

VAP Valley Amplitude Position
VAV Valley Amplitude Value
VGG Visual Geometry Group

WT Wavelet Transform

