Detection of SSVEP and Visual Response Mapping for Glaucoma

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Abstract— **Glaucoma is an eye condition that first manifests without any symptoms, and late identification leads to irreparable destruction of the retinal ganglion cells. The gold standard for diagnosing glaucoma is SAP , although this method is subjective and results might vary from test to test, making it difficult to interpret the results. By removing the cognitive component from the current visual field evaluation, we want to give glaucoma patients with quick point-of-care diagnosis. We used a multi-task learning architecture for visual response mapping to effectively record signals concurrently from the fovea and the neighbouring targets in the peripheral vision, creating a visual response map in contrast to previous approaches that primarily report the accuracy of the foveal target identification.**

Keywords—SAP, Visual Response Mapping.

I. Introduction

Glaucoma may impact 111.8 million people globally by 2040, making it the largest cause of permanent vision loss [1]. Due to the fact that glaucomatous vision field deficits develop without warning at first, this causes late diagnosis, at which point irreversible retinal ganglion cell degeneration has already taken place [2]. Up to 50% of glaucoma patients who were previously misdiagnosed had a severe visual field defect at the time of diagnosis, and many glaucoma suspects had silent peripheral vision loss [3].

Standard Automated Perimetry (SAP) is a diagnostic test used to evaluate the visual field of patients with Glaucoma. The test measures the sensitivity of a patient's vision in different regions of the visual field. SAP is the most widely used technique for the diagnosis and monitoring of Glaucoma.

The SAP test is performed using a machine that projects a series of small, dim lights of varying intensity onto a screen in front of the patient. The patient is asked to look at a central fixation target and press a button every time they see a light. The machine then records the patient's responses, which are used to create a map of the patient's visual field.

The SAP test consists of several steps, including:

1. Patient Preparation: Before the test begins, the patient is instructed to remove any eyeglasses or contact lenses. The patient's eyes are then dilated with eye drops to allow for a better view of the retina.

2. Calibration: The machine is calibrated to ensure that the stimuli are presented at the correct brightness and location on the screen.

3. Threshold Determination: The machine presents stimuli of varying intensity to different regions of the visual field. The patient is asked to respond when they see a stimulus. The machine then adjusts the intensity of the stimuli to determine the patient's threshold of vision in each location.

4. Analysis: The machine uses the patient's responses to create a map of the patient's visual field. The map shows areas of the visual field where the patient has reduced sensitivity or blind spots.

On the other hand, SSVEP has also been applied to the diagnosis and monitoring of Glaucoma. SSVEP stands for Steady-State Visually Evoked Potential, which is a type of EEG (Electroencephalogram) signal generated by the brain in response to visual stimuli that flicker or change in a repetitive, rhythmic manner at a fixed frequency. SSVEP signals are generated by the visual cortex in response to visual stimuli that flicker or change in a repetitive, rhythmic manner at a fixed frequency. The visual cortex is a region of the brain located at the back of the head, which processes visual information from the eyes.

In order to elicit SSVEP signals for the diagnosis and monitoring of ophthalmic disorders such as Glaucoma, flickering stimuli are presented to the patient's visual field. These stimuli can be presented in a variety of ways, including on a computer screen, LED lights, or a flashing pattern on a visual display unit.

The specific region of the eye that is accessed to take SSVEP data is the retina, which is a layer of tissue at the back of the eye that contains photoreceptor cells responsible for detecting light and transmitting visual information to the brain. When the flickering stimuli are presented to the retina, the photoreceptor cells generate electrical signals that are transmitted along the optic nerve to the visual cortex. The rhythmic nature of the stimuli results in the generation of SSVEP signals, which can be detected using electrodes placed on the scalp. Thus, SSVEP signals are elicited by flickering stimuli presented to the patient's visual field, and changes in the SSVEP signal amplitude and frequency can be used to detect early signs of visual field defects and monitor disease progression.

Traditional SSVEP detection methods involve the use of electroencephalogram (EEG) recordings and signal processing algorithms. However, recent advancements in machine learning techniques have led to the development of deep learning-based approaches, such as Convolutional Neural Networks (CNNs) and Multi-Task Learning (MTL), which have significantly improved the accuracy and efficiency of SSVEP detection and visual response mapping.

In CNN-based SSVEP detection and visual response mapping, raw EEG signals are transformed into spectrograms which are then used as input to a CNN model. The CNN model is trained to classify the SSVEP signals based on their frequency, allowing for accurate and efficient detection of ophthalmic disorders. CNN models have been shown to be highly effective at detecting SSVEP signals, with accuracies approaching 100% in some studies.

MTL is a powerful technique that allows the joint learning of multiple related tasks simultaneously. In the context of SSVEP detection and visual response mapping, MTL can be used to simultaneously predict the frequency of the SSVEP signals and map them to specific regions of the visual field. This joint learning approach has been shown to improve the accuracy and efficiency of both tasks, leading to more accurate and efficient diagnosis and monitoring of ophthalmic disorders.

The application of CNN and MTL in SSVEP detection and visual response mapping offers several advantages over traditional methods. Firstly, these techniques are highly accurate and can detect SSVEP signals with high sensitivity and specificity, allowing for early and accurate diagnosis of ophthalmic disorders. Secondly, CNN and MTL-based approaches are non-invasive and do not require the placement of electrodes on the scalp, making them more comfortable and less risky for patients. Additionally, these techniques are highly efficient, allowing for real-time detection and monitoring of SSVEP signals.

One of the main advantages of SSVEP detection over SAP is that it provides an objective and quantitative measure of visual function. SAP relies on subjective patient responses, which can be affected by factors such as fatigue, attention, and patient motivation. In contrast, SSVEP detection measures the brain's response to visual stimuli, which is an objective measure of visual function. This reduces the risk of false positives and provides more accurate and reliable measurements of visual field defects.

Another advantage of SSVEP detection is its ability to detect early visual field defects in Glaucoma patients. As mentioned earlier, SSVEP detection has been shown to be more sensitive than SAP in detecting early Glaucoma damage. This is important because early detection of Glaucoma is crucial for preventing further damage to the optic nerve and preserving visual function.

Furthermore, SSVEP detection is a faster and more efficient technique than SAP. SAP requires active participation and attention from the patient, which can lead to test-retest variability and long testing times. SSVEP detection, on the other hand, is a passive technique that does not require active participation from the patient, resulting in shorter testing times and increased patient comfort.

In summary, while SAP has been the gold standard for many years, SSVEP detection is emerging as a promising new tool that may offer several advantages over SAP. These advantages include more objective and quantitative measurements of the visual field, increased sensitivity for detecting early visual field defects, and faster and more efficient testing times

II. LITERATURE SURVEY

Glaucoma is a leading cause of blindness worldwide, with an estimated 80 million people affected by the condition. Early detection and treatment of glaucoma are essential to prevent vision loss. One promising approach to detect glaucoma early is through the use of steady-state visually evoked potentials (SSVEP) and visual response mapping techniques. These methods have shown promise in detecting glaucoma before vision loss occurs, but their accuracy is dependent on the skill and experience of the operator. To improve the accuracy and efficiency of SSVEP detection and visual response mapping, researchers have turned to machine learning and multi-task learning techniques. In recent years, several studies have explored the use of these techniques for the detection of glaucoma.

One such study by Zhang et al. (2019) used a multi-task learning approach to detect glaucoma using SSVEP and visual response mapping data. The researchers used a convolutional neural network (CNN) to extract features from the SSVEP and visual response mapping data, and then trained a multi-task learning model to predict the presence of glaucoma.

Another study by Wang et al. (2020) used a similar approach, but focused on the detection of early glaucoma. The researchers used a deep learning model to extract features from SSVEP and visual response mapping data, and then used a support vector machine (SVM) classifier to predict the presence of early glaucoma.

In addition to multi-task learning, other studies have explored the use of transfer learning and data augmentation techniques to improve the accuracy of SSVEP detection and visual response mapping for glaucoma. For example, a study by Xu et al. (2020) used transfer learning to adapt a pre-trained CNN to detect glaucoma using SSVEP and visual response mapping data.

Overall, these studies suggest that machine learning and multi-task learning techniques have the potential to improve the accuracy and efficiency of SSVEP detection and visual response mapping for glaucoma. Further research is needed to validate these findings and explore the potential of these techniques for other applications in ophthalmology

III. METHODOLOGY

A. SYSTEM ARCHITECTURE

Here, I used a model architecture provided by Hong Jing Khok, Victor Teck Chang Koh, Cuntai Guan ,DAMO Academy, Alibaba Group ,Department of Ophthalmology, National University Hospital, Singapore School of Computer Science and Engineering, Nanyang Technological University, Singapore.

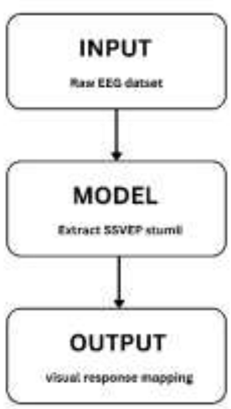


Figure 1.0 : System architecture

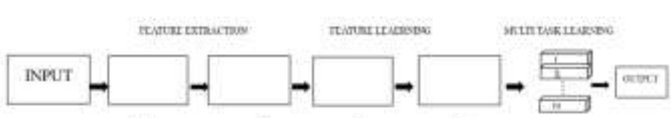


Figure 1.1 : Model Architecture

- Feature extraction layers function is to convert unprocessed EEG signals into features that our model can use as input. Each convolution block (Conv1 and Conv2) consists of an exponential linear unit, a batch normalisation, and a convolution layer.
- The two convolution blocks (C3 and C4) that form up feature learning are there to capture the temporal patterns across every extracted feature map.
- In the Multi task learning layer ,our model can be dynamically adjusted to scale to any number of tasks successfully, which makes it potentially applicable for additional multi-task learning applications. This enables us to train several tasks in parallel decisively on a single GPU. Each task in a multi-task learning architecture is broken down into task-specific layers, where every layer is in charge of learning how to recognise each task.

B. CLASSIFICATION OF STRONG AND WEAK SIGNALS

The visual response mapping is done using heatmap.Thus, In visual response mapping using heatmap, strong and weak signals can be identified based on the intensity of the colors in the heatmap. Heatmaps are graphical representations of data that use a color scale to represent different levels of intensity. In visual response mapping, the intensity of the colors in the heatmap represents the strength of the SSVEP signals generated by different regions of the visual field.

Strong signals are represented by intense colors in the heatmap, while weak signals are represented by less intense colors. For example, regions of the visual field that generate high-frequency SSVEP signals will be represented by intense colors such as red or orange in the heatmap, indicating a strong signal. In contrast, regions of the visual field that generate low-frequency SSVEP signals will be represented by less intense colors such as blue or green, indicating a weaker signal.

To identify strong and weak signals in visual response mapping using heatmap, it is important to have a clear understanding of the color scale used in the heatmap. The color scale should be chosen such that it accurately represents the range of signal strengths that are expected to be observed in the visual field. It is also important to consider the frequency range of the SSVEP signals being analyzed, as different frequency ranges may have different levels of signal strength.

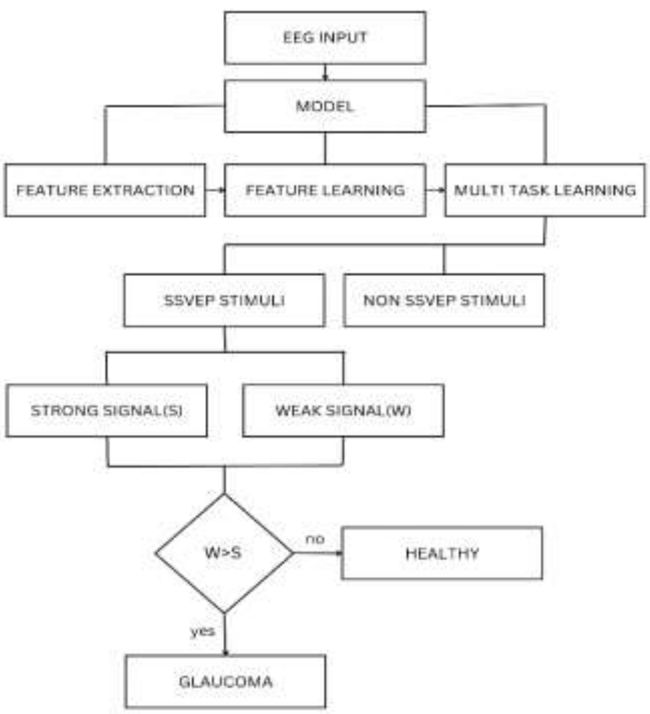
Once the heatmap has been generated, strong and weak signals can be identified by visually inspecting the intensity of the colors in the heatmap. Regions with intense colors indicate strong signals, while regions with less intense colors indicate weak signals. It is important to note that the identification of strong and weak signals in visual response mapping using heatmap is subjective and may vary between observers.

C. DETECTION OF GLAUCOMA

In the case of glaucoma, the spread of the disease affects the optic nerve, leading to weak signals in the visual response mapping. Low-intensity colors represent weak signals, and the spread of glaucoma can be identified by the amount of low-intensity color value in the heatmap.

The identification of low-intensity color in the heatmap can be achieved by thresholding. Thresholding is a method in which a threshold value is set to separate high and low-intensity values in the heatmap. The threshold value can be set based on the mean or median value of the intensity in the heatmap.

Once the low-intensity colors in the heatmap are identified, further analysis can be performed to determine the spread of glaucoma. The amount of low-intensity color value can be quantified and compared with a healthy control group to determine the severity of glaucoma. Machine learning algorithms can also be trained on the low-intensity color values to develop a predictive model for the progression of glaucoma



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IV. EXPERIMENTAL RESULT

Figure 1.2 : Raw EEG data

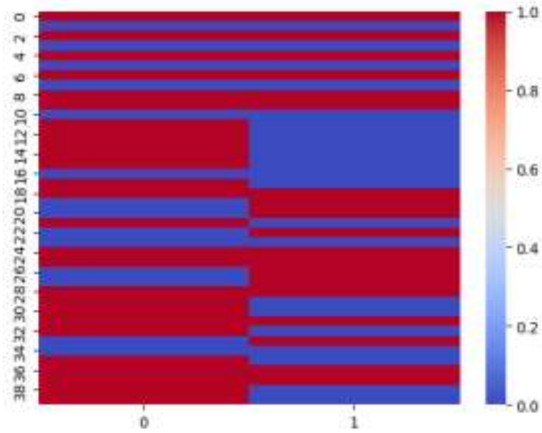

Figure 1.3 : SSVEP with strong and weak signals

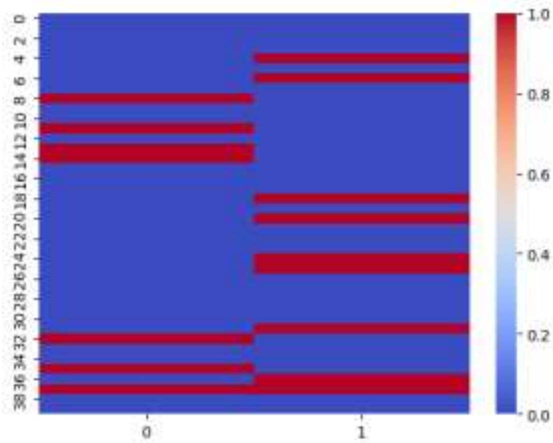

Figure 1.4 : High-intensity colors (Strong signals)

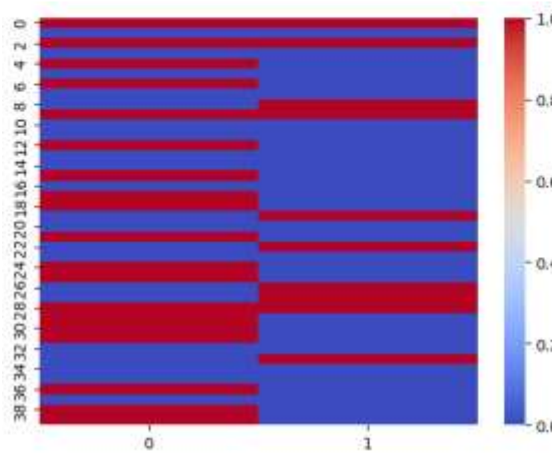

Figure 1.5 : Low-intensity colors (Weak signals)

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Patient is affected by Glaucoma
0.7120322101496717
0.29593060499020873
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Figure 1.6 : Result

V. CONCLUSION

Studies on steady-state visual-evoked potential (SSVEP) have traditionally concentrated on finding the target stimulation frequency in the fovea while classifying the other flickering stimuli as interference. In order to identify the answers from the peripheral vision, our work offered an end-to-end multi-task learning strategy. Our research demonstrate that MTL model can successfully classify a single target SSVEP, which suggests that it may be applicable to additional SSVEP research and applications. A map of the patient's visible field of vision was produced as a result to our observation that the MTL technique can learn each target frequency individually.

.By simultaneously detecting several SSVEP targets and producing a visual response map, assessment time might be reduced. This technique could be appropriate for giving glaucoma patients quick point-of-care tests.

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