CAMERA BASED DETECTION OF THE ONSET OF COGNITIVE FATIGUE

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ABSTRACT OF THE THESIS

Camera based Detection of the Onset of Cognitive Fatigue

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The onset of cognitive fatigue is associated with a period of transient, subconscious decrease in maximal cognitive ability, typically influencing decision making. The ability to visually detect this early stage of fatigue can help prevent numerous workplace hazards where top cognitive performance is of utmost importance. In this work, we developed a camera-based system that utilizes visual symptoms of fatigue to estimate its early stage.

For the first part of the work, in collaboration with the Magnetoencephalography Lab at MIT, we conducted a 3-hour long, fatigue inducing experiment on 13 test subjects and collected synchronous camera (visual) and Magnetoencephalography MEG (brain) data. We extracted 8 eyelids and 6 head-movement related features to train binary classifiers like Support Vector Machine, k-Nearest Neighbor, Random Forest and Artificial Neural Network to distinguish between Non-Fatigue (early stage) and Fatigue (late stage), achieving test accuracy of 89%, 90%, 95% and 98% respectively. We propose a temporal sliding window technique of using these binary classifiers for detecting a gradual change in the level of fatigue. We observed a progressive increment in detection of Fatigue class inside this window as it moves towards the later stages of the experiment time-line. For validation, we compared our models results with fatigue-induced brain signals from the MEG data, namely the alpha band (8-12 Hz) power.

Regressing alpha power on camera-based features yielded an average r-squared value of 0.6.

For the second part of the work, we conducted a similar experiment at the Laboratory for Computational Brain at Rutgers. We recorded synchronous camera and Electroencephalography (EEG) data for a 90-minute long experiment conducted on 4 test subjects. For this experiment, the fatigue-inducing task involved was made adaptive to the cognitive abilities of the test subject, aiming to make the subject tired in a shorter amount of time. We repeat our analysis for the camera based and the brain data based fatigue detection models. We obtained similar progressive increment in the "Fatigue" class for all subjects. By regressing the alpha power from EEG data on the visual features, we obtained average r-squared up to 0.8 for fatigue-induced brain regions. We validate our camera model based on the EEG indicator of fatigue.

Our results demonstrate promise in terms of using a vision-guided fatigue estimation model for designing a real-time fatigue detection system.

Acknowledgements

I would like to sincerely thank my advisor, Dr. Konstantinos Michmizos for continued guidance and support during this research.

This research has been performed as joint work with Neelesh Kumar, whom I would like to thank for his assistance, ideas and sharing his knowledge throughout this journey.

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A special mention to Dr. Dimitrios Pantazis and Yalda Mohsenzadeh at MIT for collaborating and sharing the data from their experiment. Moreover, I would also like to thank Dr. Lloyd and Mark from Cortech Solutions who trained and assisted us in using the EEG system at Rutgers.

Next, I would like to thank Sepehr and all the test subjects who helped us out in conducting the experiments successfully. Many Thanks!

Lastly, I would like to thank my family and friends who have always been supportive of me and have enabled me to be involved in this research.

Thanks for all your encouragement!

Dedication

This thesis is dedicated to my parents.

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Chapter 1

Introduction

1.1 Cognitive Fatigue

Cognitive fatigue involves the progressive decrease in one's cognitive performance due to mental tiredness. This affects the decision making, task productivity and physical awareness of the person experiencing mental tiredness. Its early manifestation can be characterized by experiencing sleepiness and facing difficulty in concentrating on simple problem solving tasks. This type of fatigue usually lasts for a short time, until the brain receives adequate rest in the form of sleep or simply by decreasing the difficulty of the task being performed. It is known as circadian fatigue, which means it roughly follows a twenty-four hour biological cycle.

Certain tasks in health, military and transportation fields require humans to perform at their top cognitive condition. Even a slight drop in attention levels can affect the decision making, resulting in unwanted disastrous situations. Air Traffic Controller staff, medical surgeons, pilots are some of the jobs that require absolute highest level of alertness. Any slack in these workplaces can lead to potential loss of many lives. Thus, it becomes vital to identify early onset of fatigue if we want to prevent occurrence of disasters stemming from tiredness of the workers involved.

1.2 Cognitive Fatigue: Neuroscience Perspective

We saw some of the physical symptoms that manifest from mental fatigue. However, from the neuroscience perspective, we try to understand the neurobiological changes occurring in the brain due to mental tiredness.

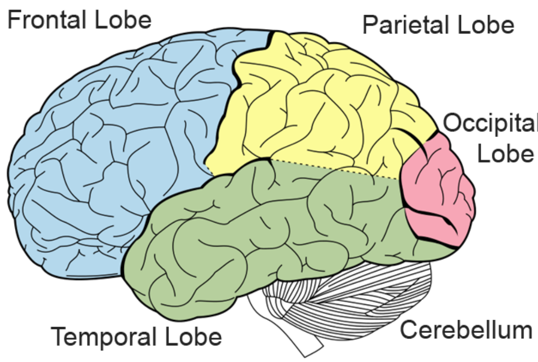


Figure 1.1: Brain Regions monitored for Neural Activity

The neural activity in our brain gives us good indication of its cognitive state. Functional MRI, EEG and MEG recordings are commonly used techniques for detecting the level of activity going on in different regions of the brain, accurate up to pinpointing an ensemble of around 50,000 neurons. Zhang et al. [1] show significant activity in the frontal lobe, parietal lobe, occipital lobe, cingulate gyrus, thalamus and cerebellum regions of the brain while performing cognitive tasks of simple mathematical calculations. Changes in the activity of neurons belonging to these regions, shown in 1.1, have been shown to be a good indicator of mental fatigue.

1.3 Literature Review

Sigari et al. [2] review the different driver-fatigue detection systems using visual indicators of fatigue and list the features most indicative of mental fatigue arising during driving.

Li and Duc [3] conduct a study using Functional MRI of brain for 10 subjects while performing a 25 hour sleepless experiment. It shows that the neurobiological effects of fatigue are characterized by the decrease in neural activity in certain regions of the brain. The study found direct correlation between the reported fatigue level and the neural activity of regions including right superior temporal gyrus, left thalamus, right inferior frontal and middle frontal parietal cortex.

Trejo et al. [4] show the relation of mental fatigue with increasing alpha power in frontal theta and parietal alpha EEG rhythms. It shows how EEG can be used to track the state of mental fatigue levels with high accuracy.

1.4 Thesis Statement

In this study, we take a look at the relation between the visual physical symptoms and the neurobiological symptoms of mental fatigue. Using various tools and techniques from the field of Machine Learning, we extract various features based upon these symptoms and model these against the level of mental fatigue.

1. First, we present various classifiers like Random Forest, K-Nearest Neighbor and Neural Networks on these features. We show two approaches to detect early stages of fatigue using these classifiers.

2. Next, we present a Regression Model that correlates these visual symptoms with the neural activity recorded by Magnetoencephalography (MEG), specifically the alpha band power of this MEG recording.

3. Last, we conduct the experiment with our own Electroencephalography (EEG) machine and re-run the above analysis. We present the results from this experiment and compare them to the analysis from MEG experiment.

Chapter 2

Data

2.1 Data

2.1.1 Data Procurement

The data used in our research has originally been acquired for an experiment at McGovern Institute for Brain Research, Massachusetts Institute of Technology. The recordings from the camera and MEG from this experiment have been sent over to Rutgers University for the purpose of this research work.

2.1.2 Experiment Details

15 test subjects were asked to perform the task of playing a game of tracking dots on a computer screen. The experiment was conducted for a duration of about 3 hours for every subject.

The game is called Multiple Object Tracking (MOT) and involves four tasks of increasing difficulty. Each task involves tracking of 2, 3, 4 or 5 dots on screen, as shown in a demo of game in [Figure 2.1]. For the task of tracking 2 dots, there are 2 dots of one color and 2 dots of another color moving randomly on the screen. After a few seconds of all these dots moving in a random fashion on the screen, the dots would pause their movement and all 4 dots would be turned to the same color, except one dot that would be highlighted. The test subject has to identify which color group did this highlighted dot belong to before the movement stopped. Naturally, keeping track of more dots meant the game became harder due to increased requirement of attention and memory.

For a duration of 30 minutes, the subject performs all four tasks in a random order.

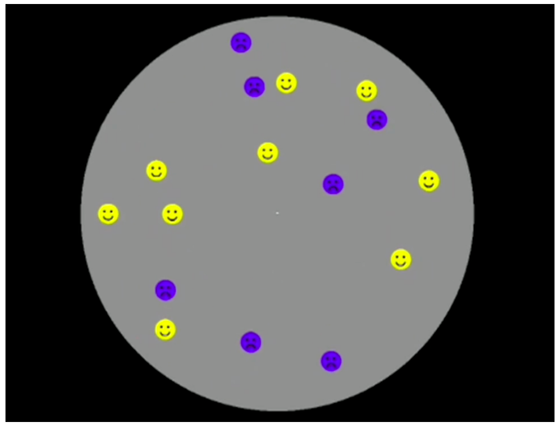


Figure 2.1: Demo MOT game. Source: Google, not the actual game.

After this, the subject is given a break of one minute before resuming another round of 30 minutes of playing this game. This entire cycle is repeated 6 times, for a duration of 3 hours.

The game has been designed to test the subject with tasks of varying cognitive performance requirement. This way, the subject's mental fatigue state can be observed relative to both time as well as the task difficulty. Simultaneously during the game, the subject's face was recorded using a camera and the brain activity was monitored using MEG recording.

2.1.3 MEG Recording

The subjects were asked to perform this experiment while in the Magnetoencephalography (MEG) machine.

The activity of brain waves [Figure 2.2] were recorded for the following 6 regions of the brain from the Parietal and Occipital regions:-

1. Inferior Parietal Left
2. Lateral Occipital Right
3. Inferior Parietal Right
4. Superior Parietal Left
5. Lateral Occipital Left
6. Superior Parietal Right

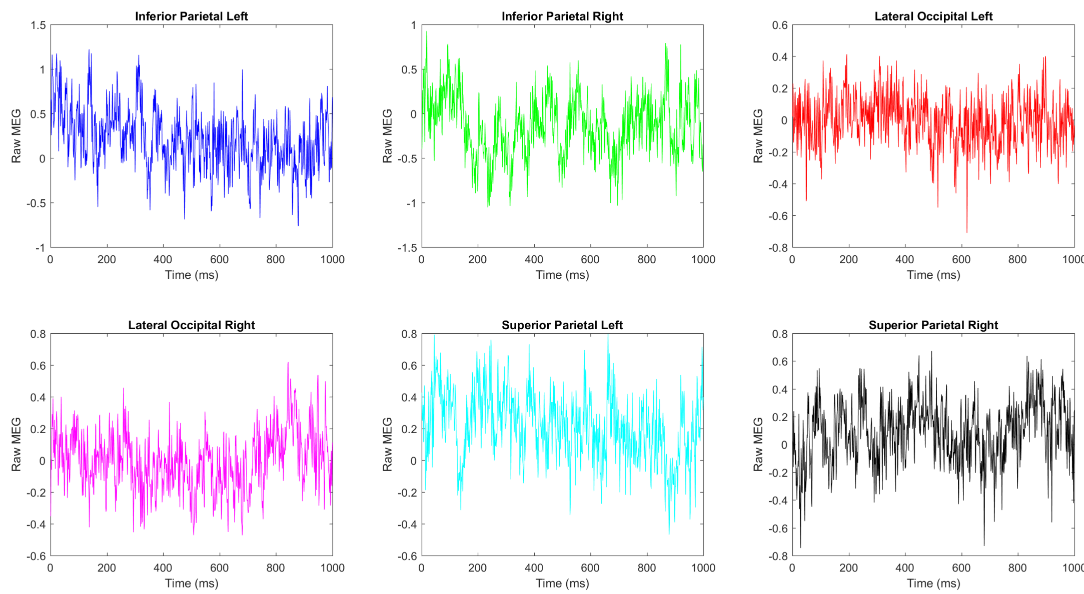


Figure 2.2: Sample recording of 1 second long raw MEG signal for 6 brain regions.

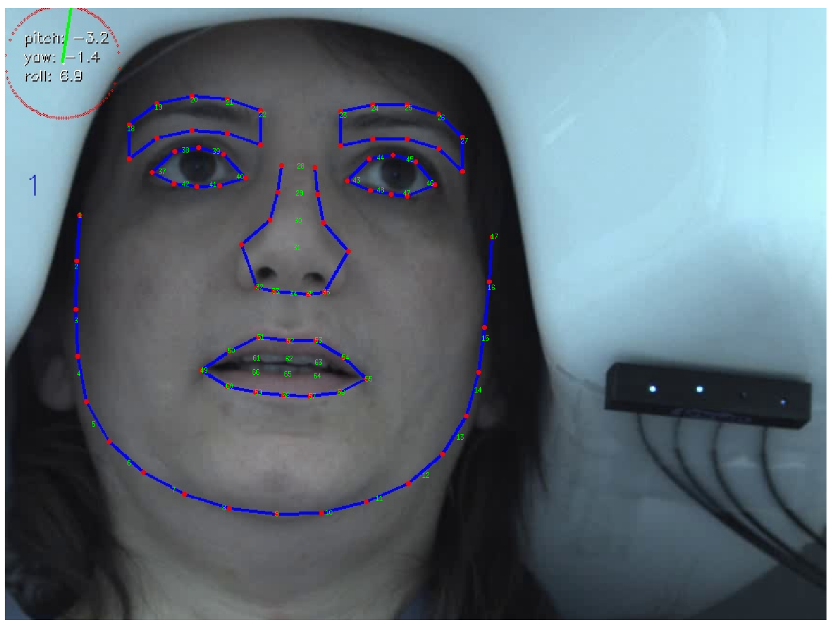
2.1.4 Camera Recording and Face Tracking

The recording of the faces of these subjects during the experiment was done with a high speed camera, with video recordings of different subjects ranging from 60 frames per second to 90 frames per second. Video resolution is constant for all subjects, with frame width being 864 and frame height being 648 pixels.

Face Landmark Points Tracking

In order to extract visual features from the camera recordings, we tack 66 face landmark points for all test subjects using a tracking algorithm developed by Yu et al. [5]. These landmark points include all major face points [Figure 2.3] required to construct a human face with its major facial features. The face tracking algorithm worked perfectly for 13 out of 15 test subjects. We discard data from the 2 subjects and perform our analysis on the remaining 13 subjects.

(a) Data: Video Frame



(b) 66 Face Landmarks Tracking Points

Figure 2.3: Camera Recording for one test subject

Chapter 3

Features

3.1 Extraction of Visual Features

Once we have the face landmark points, we are interested in extracting meaningful features from them that are related to the eyes and blinking of the eyelids as they are the visual symptoms of mental fatigue.

3.1.1 Extraction Technique

To extract temporal features from the video frames, we utilize the sliding window technique over the time line of the 3 hour long videos. We take a fixed length window of 60 seconds to extract certain features for that time period. These features extracted from this window represent one data point in d dimensions for a total of d features. Then, we move the start of this window over to the end of first window and so on, in a sliding fashion.

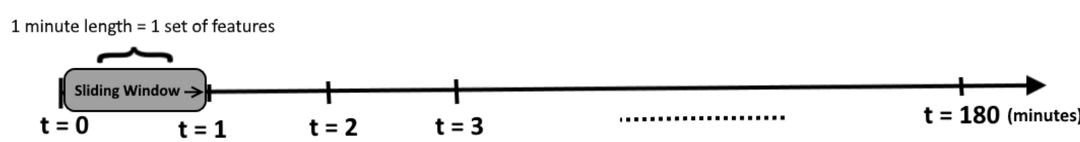


Figure 3.1: Sliding Window Technique for Feature Extraction from a 3 hour video.

Here, as shown in [Figure 3.1], the overlap created between consecutive windows is kept zero. Thus, for a 3 hour video, we get 180 data points for the feature set. The parameters of window size and overlap have been set after experimentation with features so that it represents meaningful visual information regarding the test subjects.

3.2 Eye Related Features

For the purpose of our research, we specifically take a look at eye related visual features that are good indicators of mental fatigue. A total of 8 features were extracted for the 3 hour period, giving an 8 dimensional data point. Face tracking points 37 through 48 from [Figure 2.3] have been used for extracting the various eye related features stated below.

1. Average Eyelid Distance
2. Eye Closure Time
3. Eye Blink Rate
4. Surface Area of Eye
5. Circularity of Eye
6. Distance of Eye Corners from Fixed Point
7. Eye Opening Velocity
8. Eye Closing Velocity

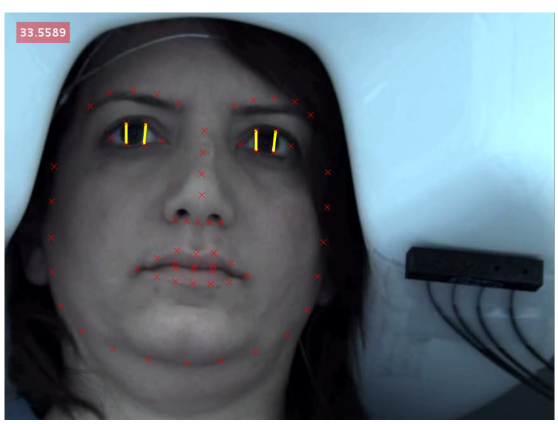


Figure 3.2: Eyelid Points used to calculate the feature *Eyelid Distance.*

[Figure 3.2] highlights the eyelid points used to calculate these features, described next.

3.2.1 Average Eyelid Distance

The Euclidean distance between the upper eyelid and the lower eyelid, averaged over both eyes. It is measured in number of pixels.

3.2.2 Eye Closure Time

This measures the number of frames upon the total frames in a window where the eyes of the subject were below a particular threshold level.

This threshold is selected to be different for every subject manually since everyone has a different size of their eye and different level at which they keep their eyes open.

3.2.3 Eye Blink Rate

The blink rate measures how many times the subject blinked for the duration of one window.

3.2.4 Surface Area of Eye

This measures the area covered by the polygon formed by connecting all the 6 eyelid points per eye. So, we have two polygons formed by the two eyes, and the surface area is calculated as the average of the two areas.

3.2.5 Circularity of Eye

Similar to the surface area, we take the circularity of the polygons and average over both eyes.

$$Circularity = \frac{4\pi \times Area}{Perimeter^2} \tag{3.1}$$

3.2.6 Distance of Eye Corners from Fixed Point

This feature measures the average distance of the eye corners from the nose tip.

3.2.7 Eye Opening Velocity

The number of frames required to take the eye from closing position to above threshold position, divided by the total number of times eye opening action occurs in the window.

3.2.8 Eye Closing Velocity

The number of frames required to take the eye from open position to below threshold position, divided by the total number of times eye closing action occurs in the window.

3.3 Data Cleaning

We extract 180 instances or values of a particular feature from a 3 hour video. These raw values are quite noisy with abrupt changes in values. Moreover, face tracking is lost when the subjects occlude their faces with hands or simply look away from the camera momentarily or for a few seconds during the break. These reasons give rise to missing values of features extracted for certain windows over the three hour time period. We can consider an array of these features ordered by time as a signal. We proceed to solve the aforementioned issues by using various signal processing techniques for pre-processing.

3.3.1 Noise Reduction with Median Filtering

First, we perform noise reduction for every feature by performing a one dimensional low pass median filter over every feature. This smoothens out the signal as shown in [Figure 3.3]. We slide a window of size 10 over the one dimensional feature array and replace the center value of a window with the median value of that window.

3.3.2 Data Normalization: Z-Score

Different subjects foster values of the same feature in different ranges. In order to bring them to the same scale for making comparisons across different subjects, we normalize

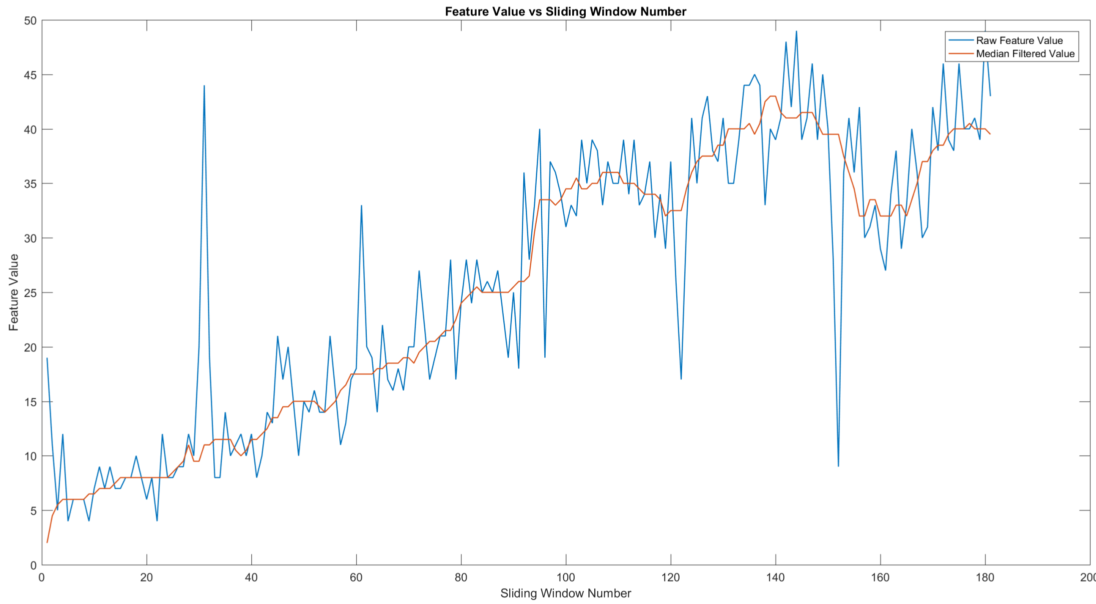


Figure 3.3: Median Filtering for a noisy signal.

the feature values subject-wise. We use Z-Score Normalization for this.

$$f_i = \frac{x_i - \mu_i}{\sigma_i} \tag{3.2}$$

3.3.3 Trend Analysis with Polynomial Curve Fitting

After Median Filtering, we fit an order 3 polynomial to each feature. By the method of least squares best-fit, the order 3 polynomial curve describes the increasing or decreasing trend for our feature.

$$p(x) = p_1x^3 + p_2x^2 + p_3x + p_4 \tag{3.3}$$

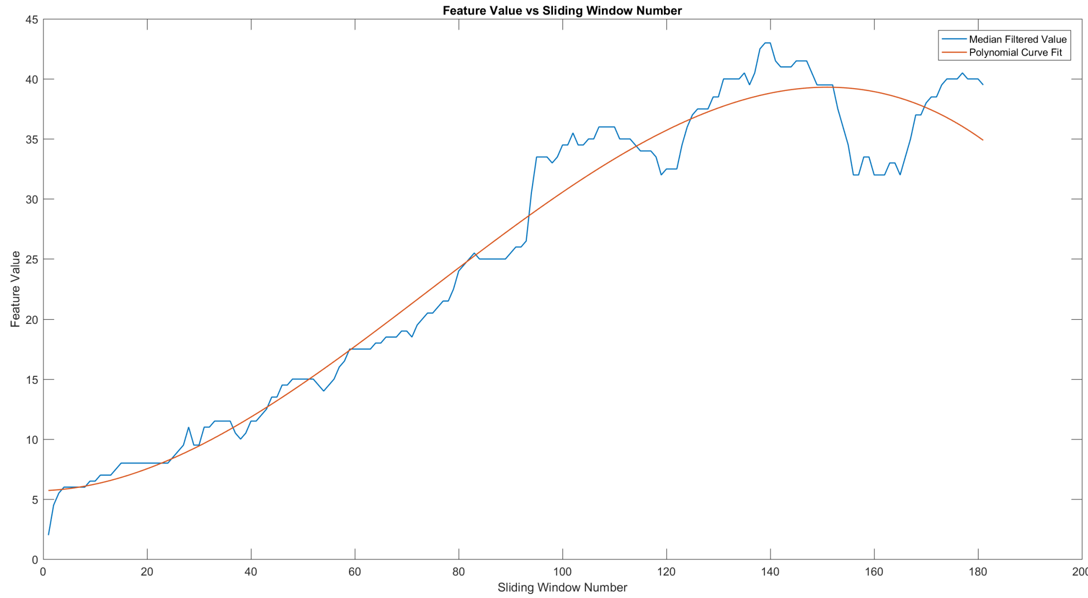


Figure 3.4: Polynomial Curve fit for Median Filtered Feature Value.

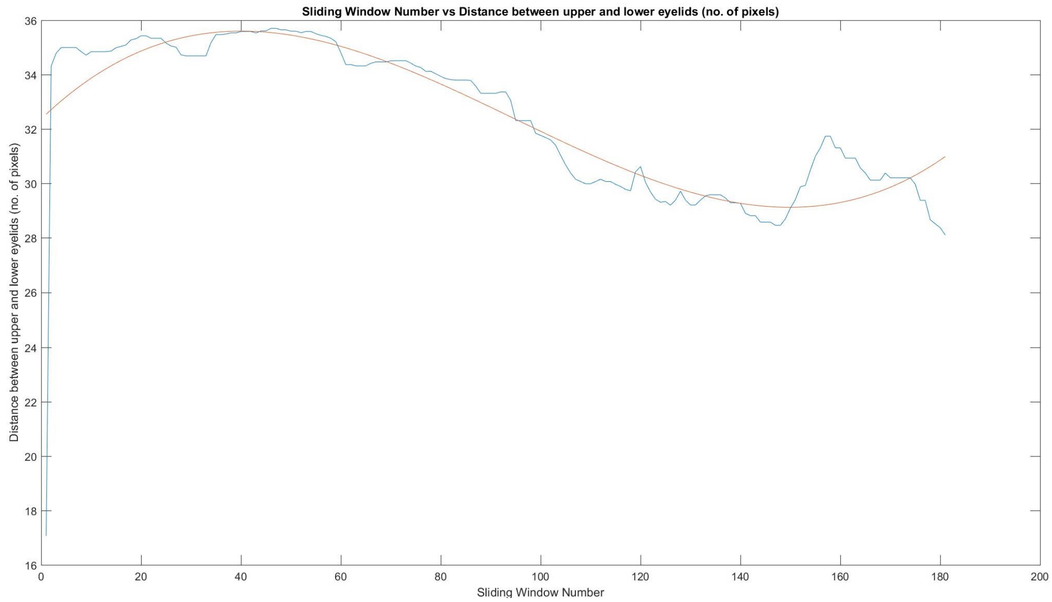
3.4 Feature Trends

By applying these techniques to the data collected from the 13 test subjects, we obtain the following trends [Table 4.1] in feature values for the duration of three hours.

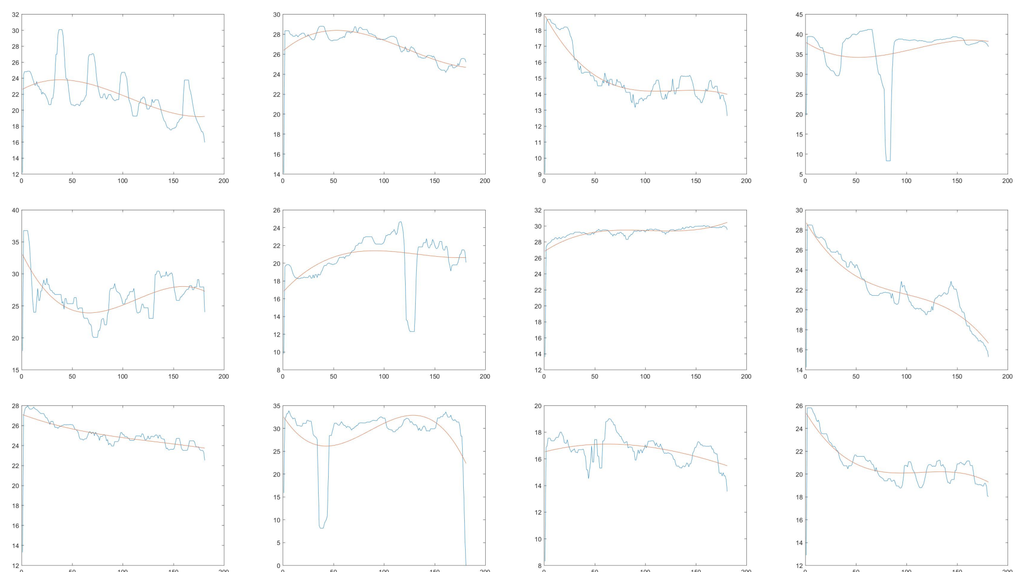
Table 3.1: 3 hour trend for all features

FEATURE	EXPECTED TREND	OBSERVED TREND
Average Eyelid Distance	$\downarrow$	$\downarrow$
Eye Closure Time	$\uparrow$	$\uparrow$
Eye Blink Rate	$\uparrow$	$\uparrow$
Surface Area of Eye	$\downarrow$	$\downarrow$
Circularity of Eye	$\downarrow$	$\uparrow$
Distance of Eye Corners from Fixed Point	-	none
Eye Opening Velocity	-	$\uparrow$
Eye Closing Velocity	-	$\uparrow$

1. **Average Eyelid Distance Trend [Figure 3.5]**



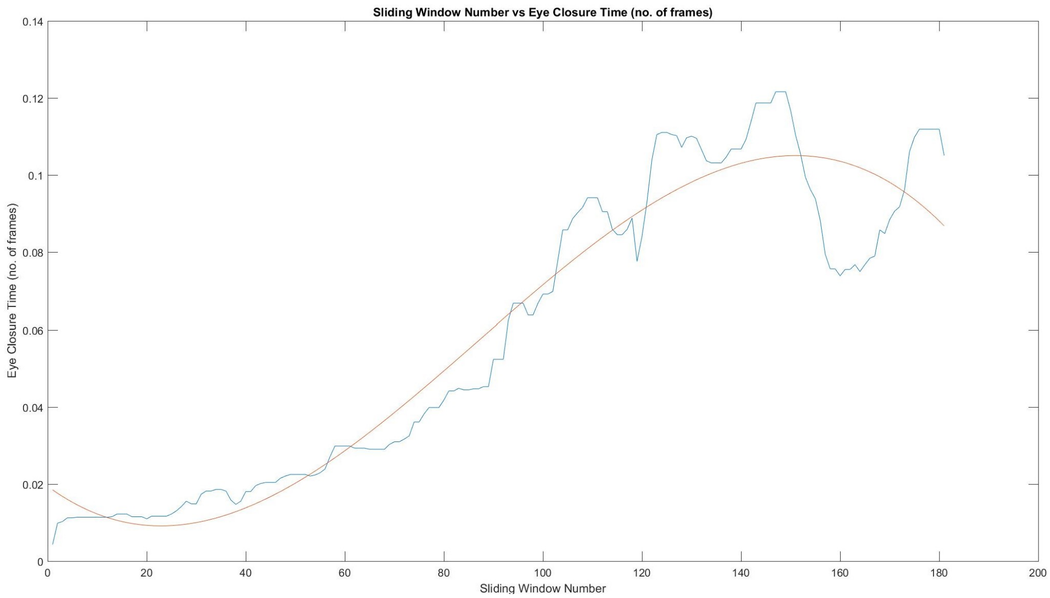
(a) Trend for one subject (camera 13)



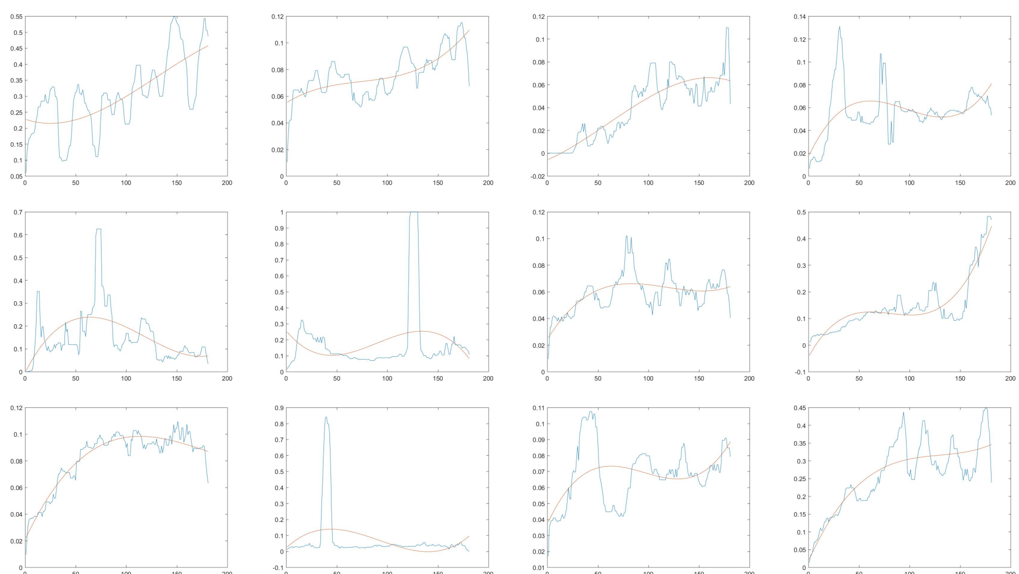
(b) Trend for other 12 subjects

Figure 3.5: 8 out of 13 subjects showing downward trend

2. Eye Closure Time Trend [Figure 3.6]



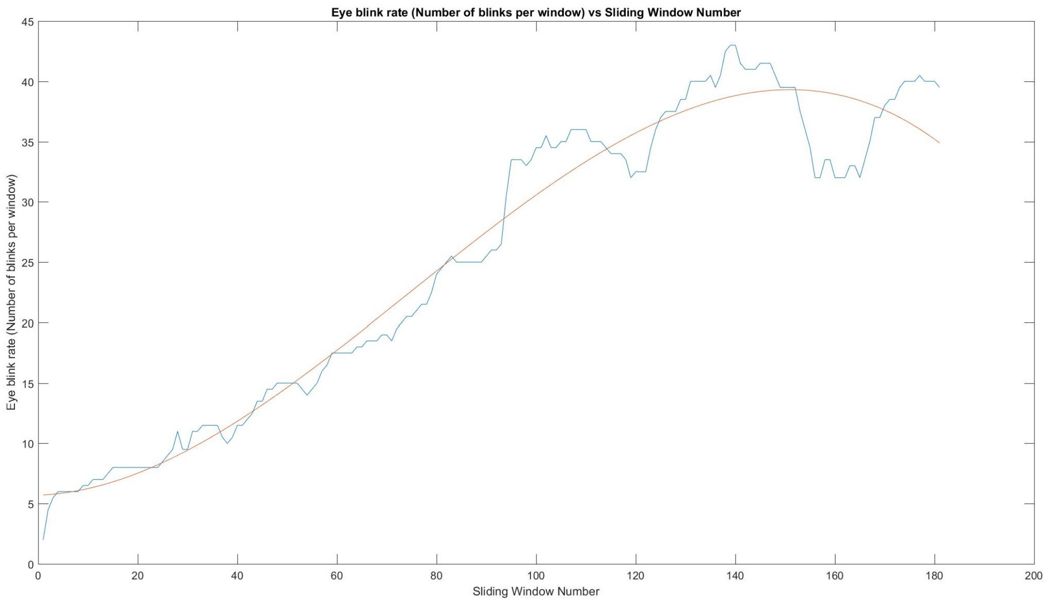
(a) Trend for one subject (camera 13)



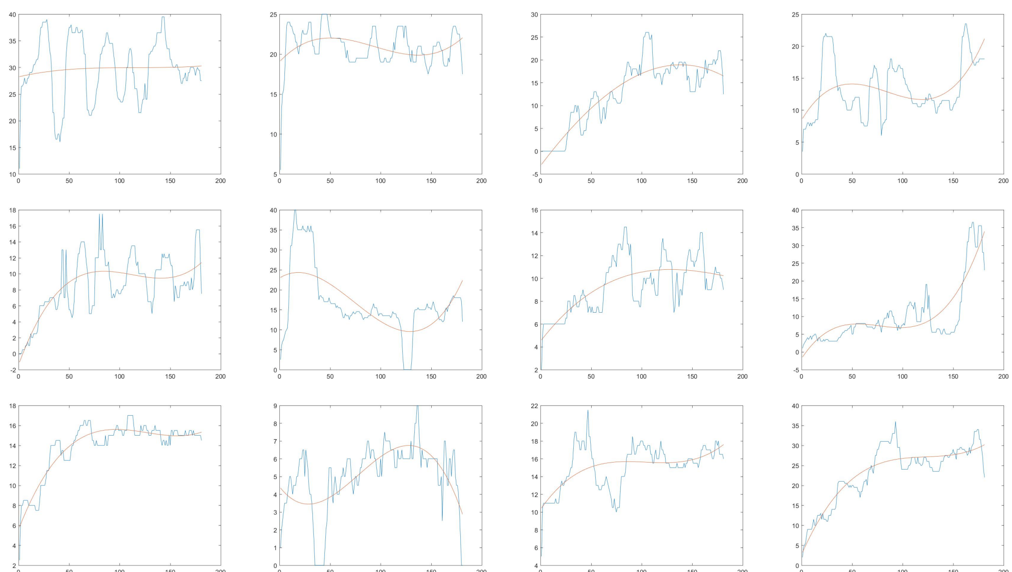
(b) Trend for other 12 subjects

Figure 3.6: 10 out of 13 subjects showing upward trend

3. Eye Blink Rate Trend [Figure 3.7]



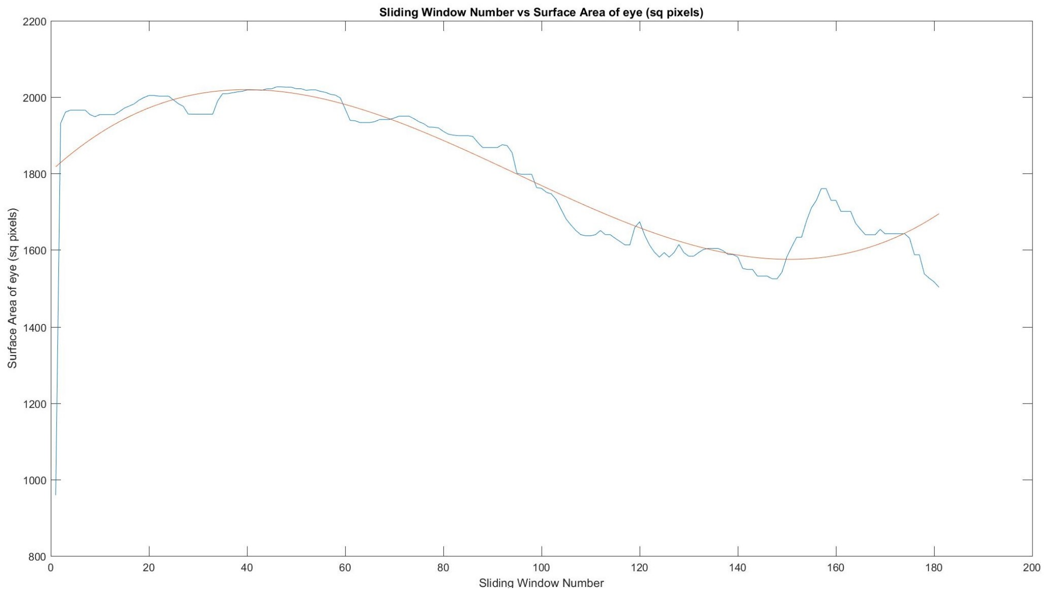
(a) Trend for one subject (camera 13)



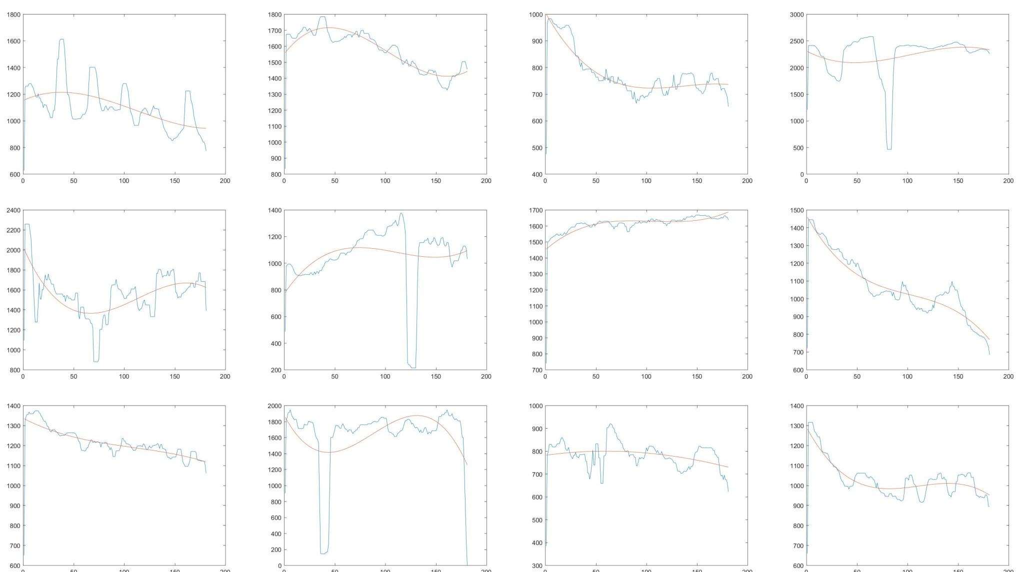
(b) Trend for other 12 subjects

Figure 3.7: 10 out of 13 subjects showing upward trend

4. Surface Area of Eye Trend [Figure 3.8]



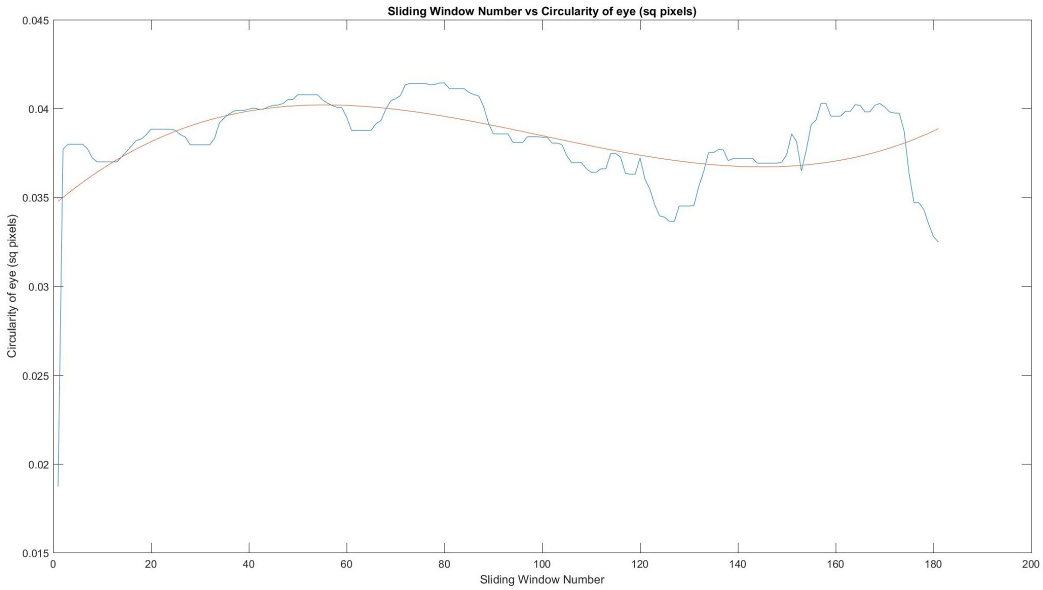
(a) Trend for one subject (camera 13)



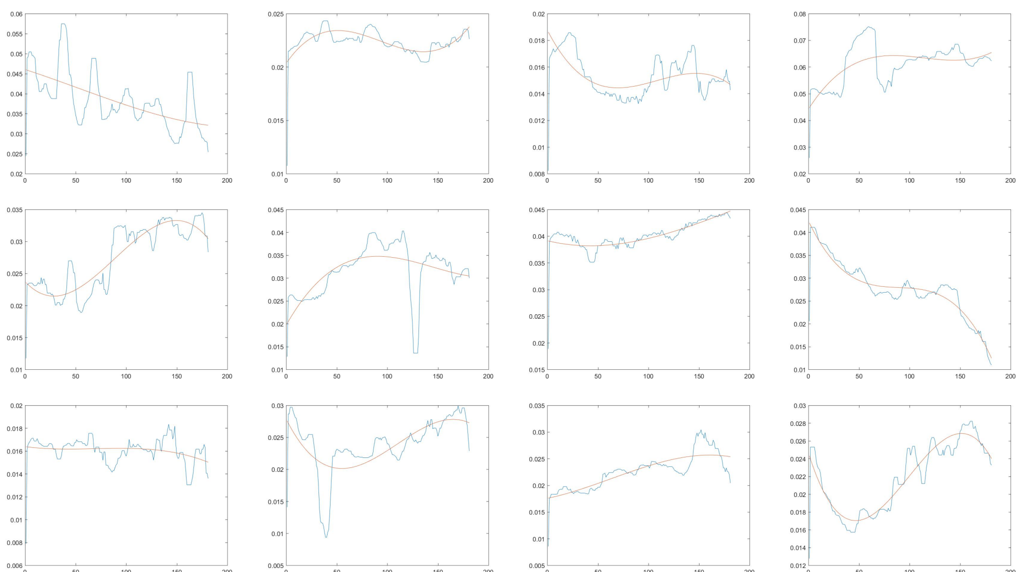
(b) Trend for other 12 subjects

Figure 3.8: 9 out of 13 subjects showing downward trend

5. Circularity of Eye Trend [Figure 3.9]



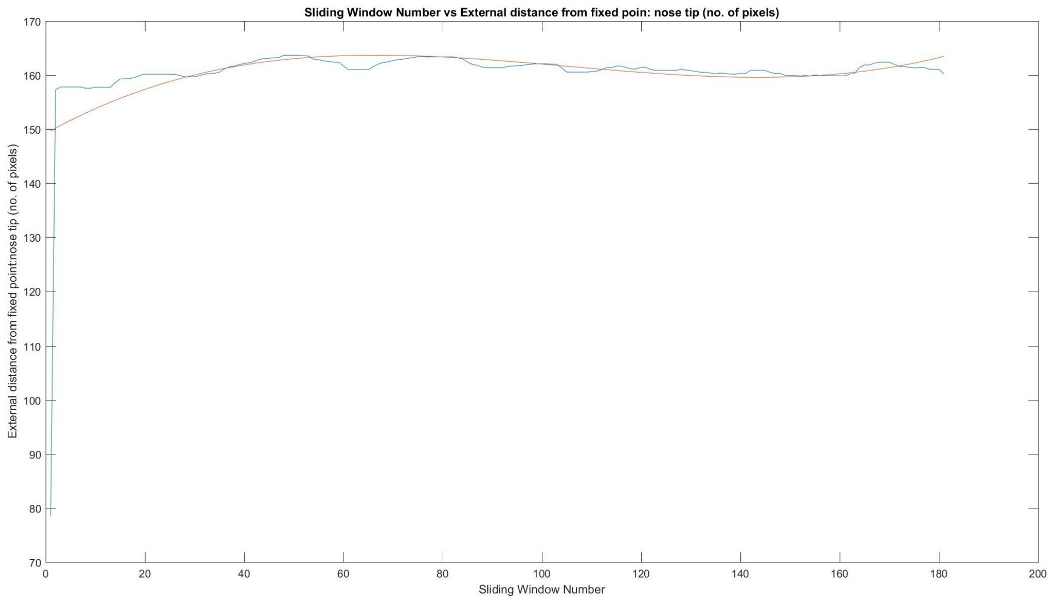
(a) Trend for one subject (camera 13)



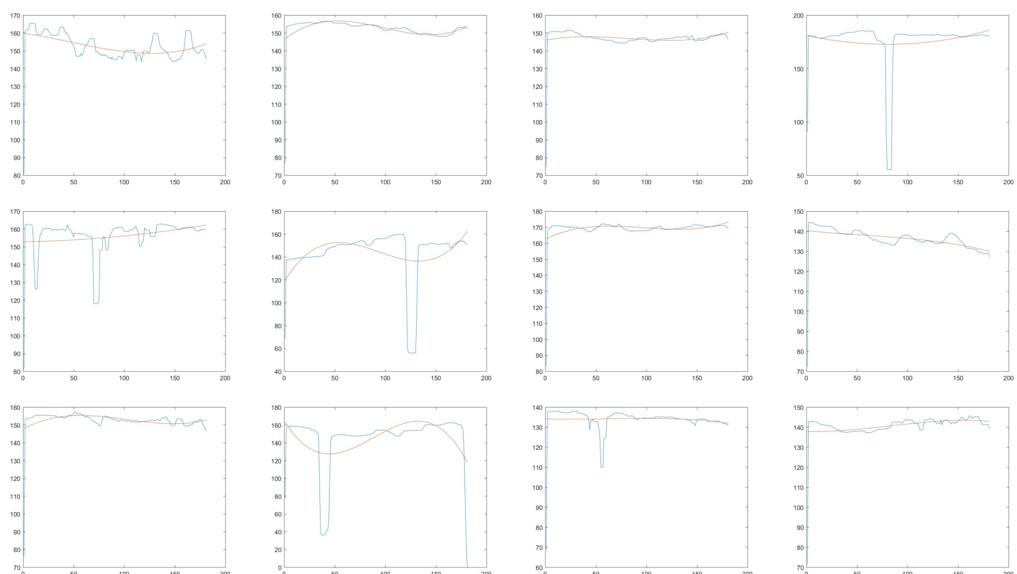
(b) Trend for other 12 subjects

Figure 3.9: 9 out of 13 subjects showing upward trend

6. Distance of Eye Corners from Fixed Point Trend [Figure 3.10]



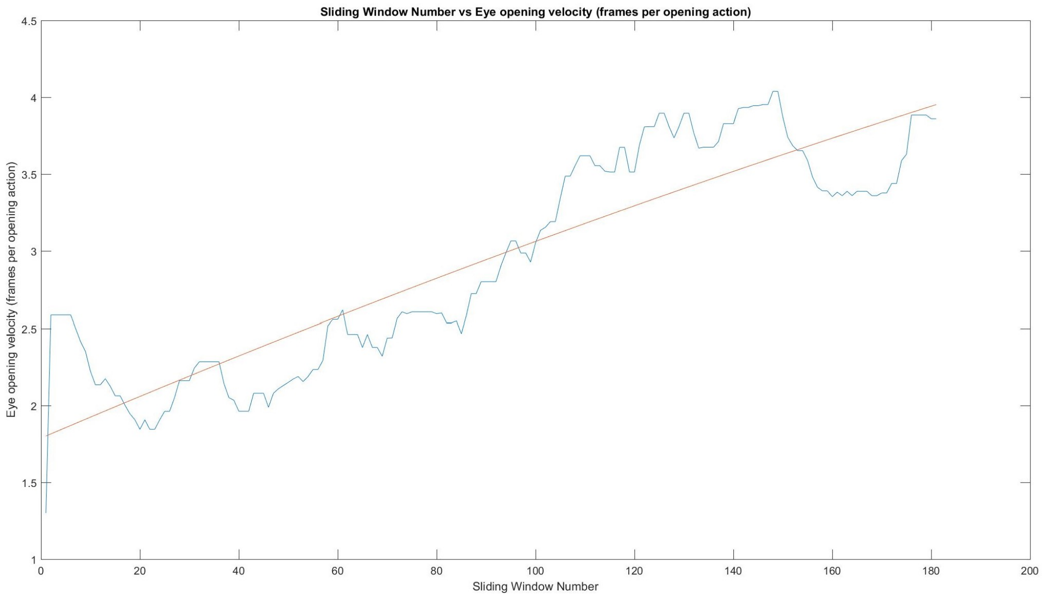
(a) Trend for one subject (camera 13)



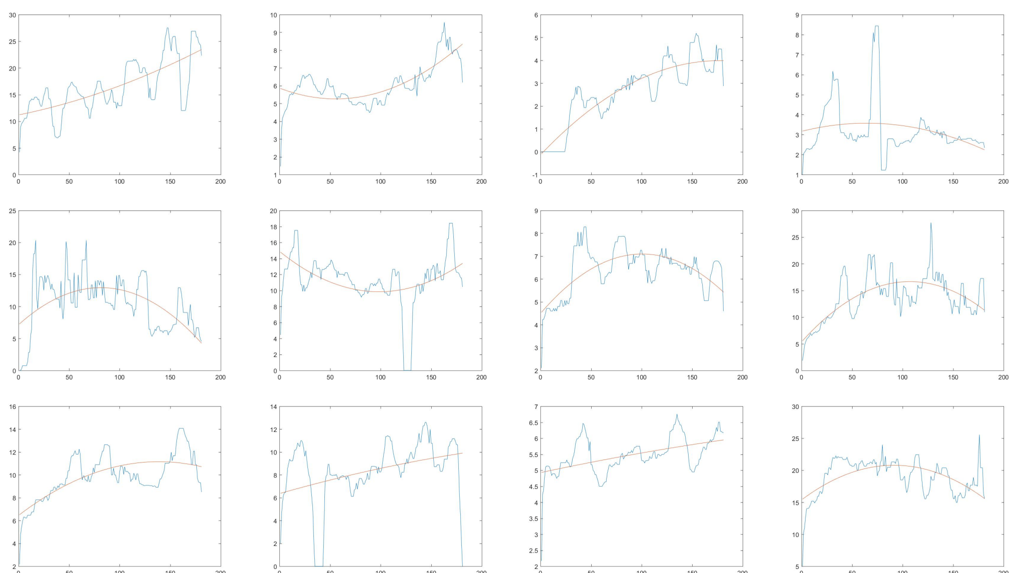
(b) Trend for other 12 subjects

Figure 3.10: No noticeable trend observed over all 13 subjects.

7. Eye Opening Velocity Trend [Figure 3.11]



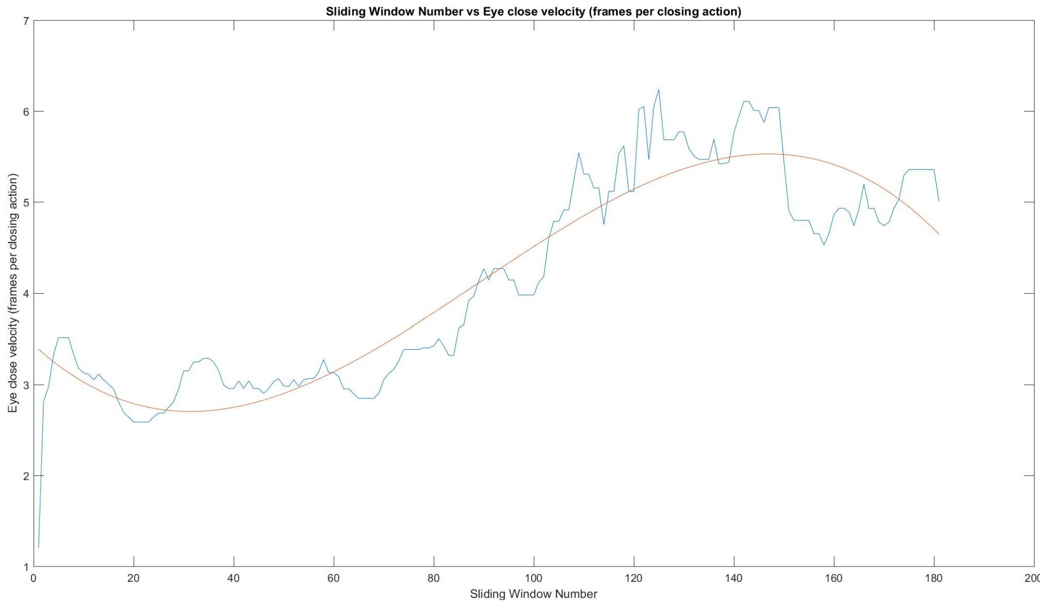
(a) Trend for one subject (camera 13)



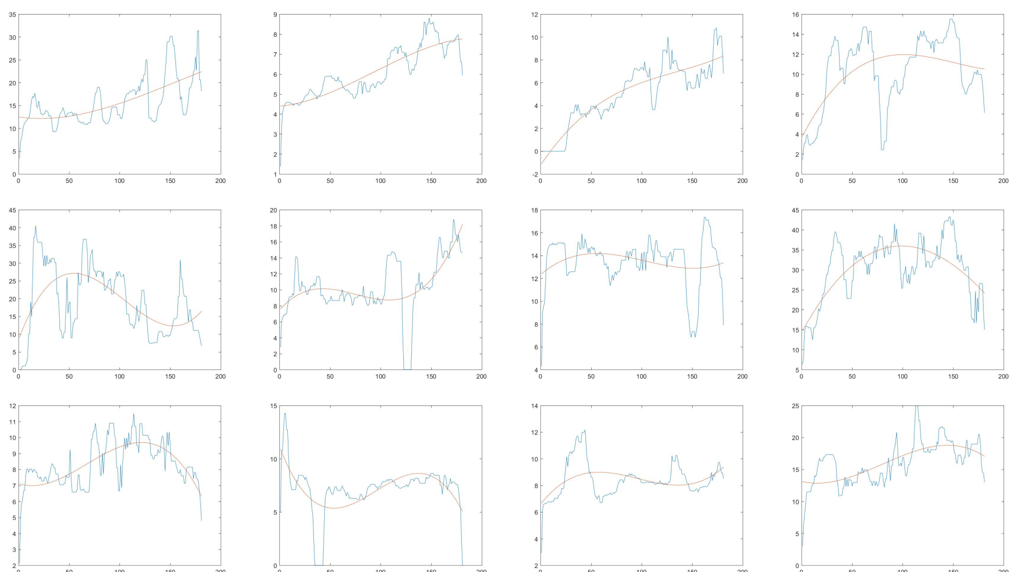
(b) Trend for other 12 subjects

Figure 3.11: 8 out of 13 subjects showing upward trend

8. Eye Closing Velocity Trend [Figure 3.12]



(a) Trend for one subject (camera 13)



(b) Trend for other 12 subjects

Figure 3.12: 9 out of 13 subjects showing upward trend

Chapter 4

Classifier

4.1 Establishing Ground Truth

After extracting the features, we establish the ground-truth by assigning a class label corresponding to these feature values. We are interested in determining fatigue levels during the duration of 3 hours of the experiment. All subjects are assumed to be non fatigued at the beginning of the experiment and fatigued towards the end of the experiment.

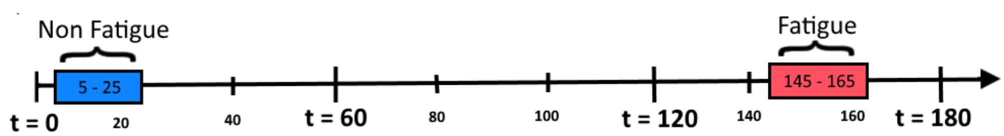


Figure 4.1: Determining Fatigue and Non - Fatigue periods over 3 hours.

[Figure 4.1] shows the time periods for which we consider these two classes. All sliding windows lying in the window from 5 minutes to 25 minutes are under Non-Fatigue class. Features extracted from these windows are assigned the label of "Non-Fatigue". Similarly, sliding windows in the 145 to 165 minute time range are under the class Fatigue and the corresponding features are labeled as "Fatigue".

4.2 Data Visualization

Once we have the labels assigned for our two classes Fatigue and Non-Fatigue, we try visualizing how different the feature sets are for the two classes in the ambient 8 dimensional space.

[Figure 4.2] shows the histogram of number of points. Here, we select at random and fix a data point from the feature set comprising of features of all 13 subjects. We measure the Euclidean distance of every other data point in the feature set from this fixed data point. A histogram of these distances is plotted, with each bin colored according to the percentage of points belonging to both classes. More the red color indicates more points belonging to the Fatigued class while blue color indicates more points belonging to the Non-Fatigue class. Thus, a purple colored bin indicates almost equal points in both classes.

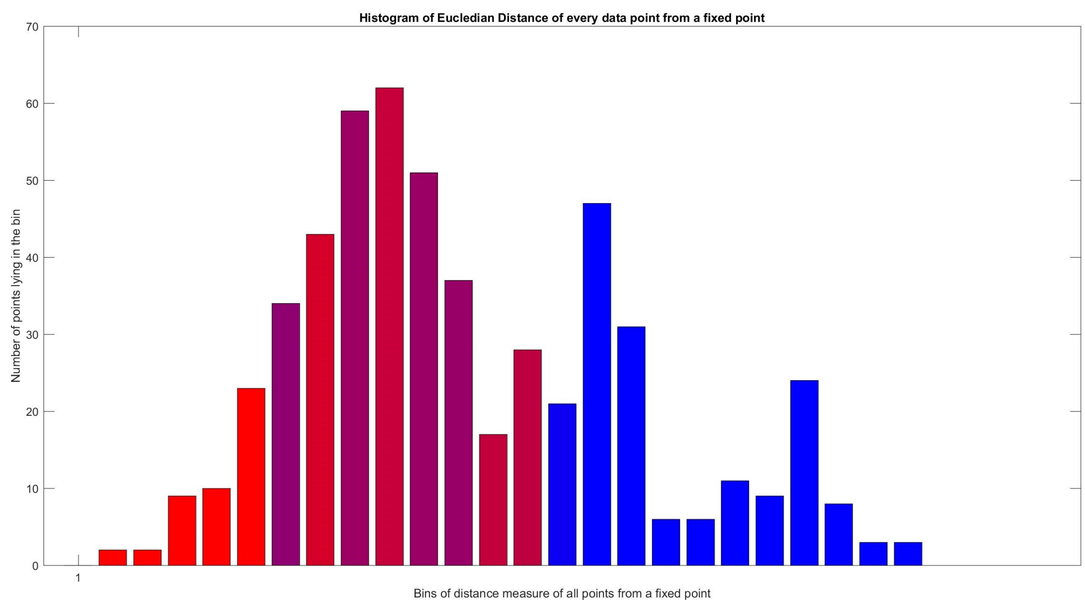


Figure 4.2: Histogram of Euclidean Distances of all data points from a fixed data point.

This plot indicates that the data from two different classes has some amount of linear separability in the 8 dimensional Euclidean space. Since most points from fatigue class are nearer to the fixed data point and the rest from non fatigue class are at a greater distance from that point, we could build a linear classifier that learns a hyperplane to separate the points from two classes.

4.3 Classifier Training

To train our classifier, we partition the data set in training and testing sets. We have data from 13 subjects combined as one feature matrix X. We split it into random 70% as training set and the rest 30% as testing. The labels of fatigue and non fatigue have been assigned to these data points as described in 4.1.

We use multiple classifiers for learning the classifier function. We train the following classifiers:-

- **Support Vector Machine (SVM)**
- **Random Forest (RF)**
  $number\ of\ decision\ trees = 50$
- **k-Nearest Neighbor (kNN)**
  $k = 3$
- **Artificial Neural Network (ANN)**
  $one\ hidden\ layer\ of\ 15\ neurons$

4.4 Classifier Results

Table 4.1: Classifier Training and Testing Accuracy

Classifier	Training Accuracy	Testing Accuracy
SVM	92%	89%
RF	98%	95%
kNN	97%	90%
ANN	98%	98%

We have classifiers that are able to separate the data points with fairly high accuracy. For further analysis, we use the SVM classifier as it consistently gives high accuracy with different subjects.

Chapter 5

Detecting Early Onset of Fatigue

5.1 Early Stage of Fatigue

We showed that our classifier identifies non fatigue and extreme fatigue stages reasonably well. Now, we want to find an early indication of increase in the fatigue state. This stage can be characterized by slight changes in the visual symptoms from our feature set. In order to detect this early stage using our classifier, we apply a couple of techniques for detecting onset of cognitive fatigue.

5.2 Detection Techniques

5.2.1 Technique 1: Sliding Middle Window Technique

First, we try to check what the classifier thinks about the time period in between the stages that we categorized as fatigue and non fatigue and trained the classifier on such class labels. The time period to be examined by the classifier ranges from the beginning of the non fatigue class to the end of the fatigue class. A sliding window of the same length as the training classes, i.e., 20 minutes is selected for testing. This technique is shown in [Figure 5.1].

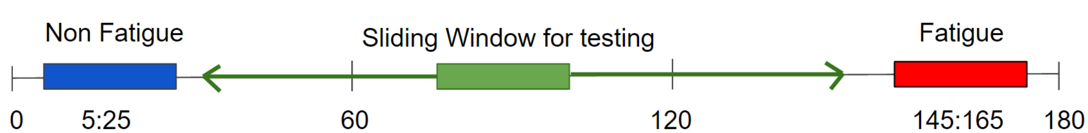


Figure 5.1: Non Fatigue and Fatigue Classes used for training the classifier and the sliding window in between used for testing.

Here, for each sliding window of length 20 minutes, we use the same technique for feature extraction that we used previously for acquiring training data [3.1.1]. We obtain 20 features for these 20 minutes in one window and we see how many data points were classified in each class. The expectation is that during the starting of the time line, majority of the points should be classified as non fatigue and towards the end, majority should be fatigue.

Technique 1 Results: Averaged over all 13 subjects

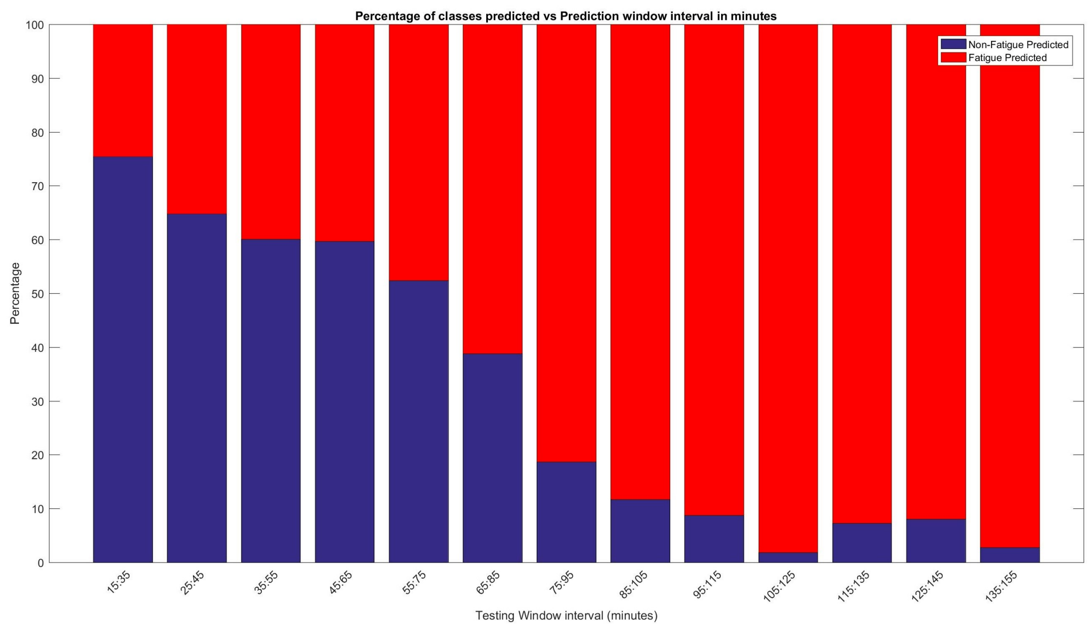
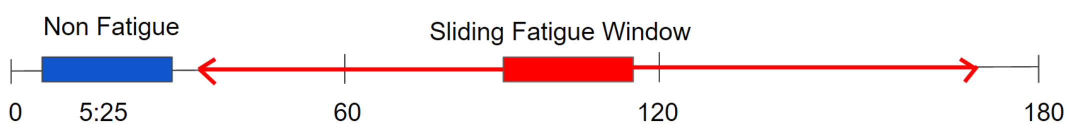


Figure 5.2: Percentage of points classified as Non-Fatigue decreases and Fatigue increases as we move towards end.

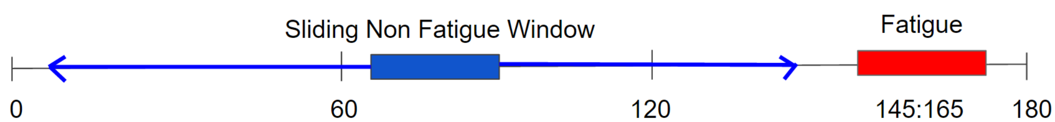
[Figure 5.2] shows the trend of the progressive decrement in number of points that the classifier thinks is non fatigue, and a subsequent increment in the other class fatigue. Here, if we consider the crossing mark of 50% of points classified as non fatigue to be an indication of early fatigue, then the classifier shows that at an hour mark, fatigue starts to kick in on an average over multiple subjects. This is interesting because one would have expected this point to have arrived at half mark, i.e., after 1 hour 30 minutes simply based on what the classifier has been trained on. This suggests keeping concentration levels up might be difficult after one hour of cognitive intensive task. To verify this, we try out another technique, described next.

5.2.2 Technique 2: Sliding Training Class Window Technique

For this technique, instead of pre-training the classifier on fixed classes and testing on unseen middle time period, we take a different approach. We fix one class and slide the other class for training the classifier and then proceed to check how easily the classifier is able to differentiate the two classes through out the 3 hour time period. This technique is illustrated in [Figure 5.3] with both possible cases.



(a) Keeping Non Fatigue class fixed and sliding Fatigue class.

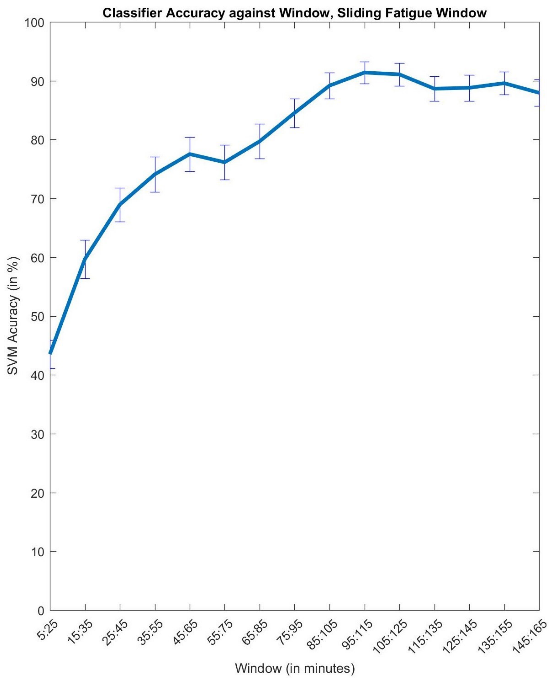


(b) Keeping Fatigue class fixed and sliding Non Fatigue class.

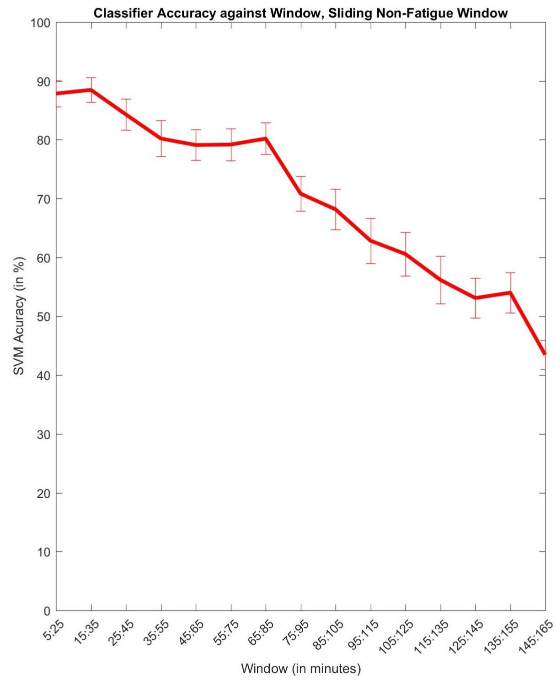
Figure 5.3: Technique observing difficulty for the classifier in differentiating non fatigue and fatigue classes.

In this technique, when both classes are kept at the same time period, the classification accuracy of the classifier trained based on these class labels should be around 50% mark. This is because the classifier is trying to differentiate essentially the same data points into two separate classes, hence half the accuracy. As we slide the other class, it is expected that the classifier should be achieving higher accuracy with greater separation between the two classes. We repeat this for two cases, once keeping non fatigue class fixed and once with the fatigue class fixed.

Technique 2 Results: Averaged over all 13 subjects



(a) Keeping Non Fatigue class fixed and sliding Fatigue class.



(b) Keeping Fatigue class fixed and sliding Non Fatigue class.

Figure 5.4: Results for the Technique observing difficulty for the classifier in differentiating non fatigue and fatigue classes.

[Figure 5.4] shows the increasing and decreasing trend of classifier accuracy with sliding window for fatigue and non fatigue classes respectively. Considering the half way mark again, 75% for this technique, to consider the onset of cognitive fatigue, we again see the trend crossing the 75% mark at around one hour. As seen in the first technique, averaging over all subjects indicates the concentration level of subjects starts decreasing one hour into the task.

Chapter 6

Correlation with Brain Waves

6.1 Magnetoencephalography (MEG)

The neural activity in the brain comprises of many electrical impulses. These impulses being short lived currents, create a constantly varying magnetic field around the brain. A magnetometer can be used to capture these variations in the magnetic field. A Magnetoencephalography machine does exactly that, being able to capture the changing magnetic field with an array of magnetometers called SQUIDs (Superconducting Quantum Interference Devices). It is good at avoiding distortions coming from the electrical currents stemming from the skull and the scalp. It can record neural activity with accurately being able to narrow down to a group of 50000 neurons, giving a good spatial resolution of the brain activity.

6.2 Creating Response Variable from MEG recording

To quantify the brain activity, we create a response variable from this MEG recording. The MEG records the changing magnetic fields from the cortical region of the brain, i.e., the outer layer of the brain near to the scalp. This recording comprises of the superimposed signals consisting of multiple signals of different frequencies. These bands and their frequencies are as follows:-

1. Delta (less than 4 Hz)
2. Theta (4 to 8 Hz)
3. Alpha (8 to 12 Hz)
4. Beta (above 14 Hz)

Trejo et al. [4] have shown the effects of mental fatigue on the alpha band signals. For our response variable, we will extract the oscillations corresponding to this alpha band for further analysis.

6.3 Band Pass Filtering

To extract the alpha channel lying in the 8 to 12 Hz frequency band, we apply a 3^{rd} order bandpass butter filter to the raw recording. This filter allows frequencies in the band range of 8 to 12 Hz to pass and rejects the rest. [Figure 6.1] shows the alpha oscillations in red for the raw MEG signal shown in blue.

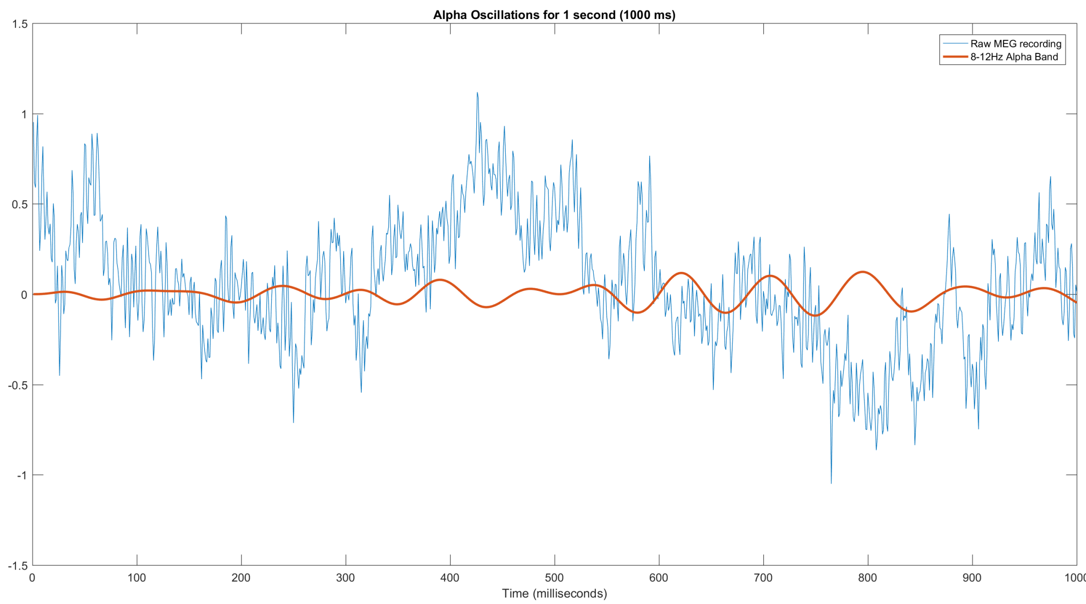


Figure 6.1: 8 to 12 Hz Alpha Band for one second long recording

6.4 Alpha Band Power

The power of a signal signifies the amplitude of the signal. As mental fatigue creeps in, this amplitude of the alpha wave is expected to go up. Hence, the power of the alpha band towards the end of the experiment is expected to progressively increase as well.

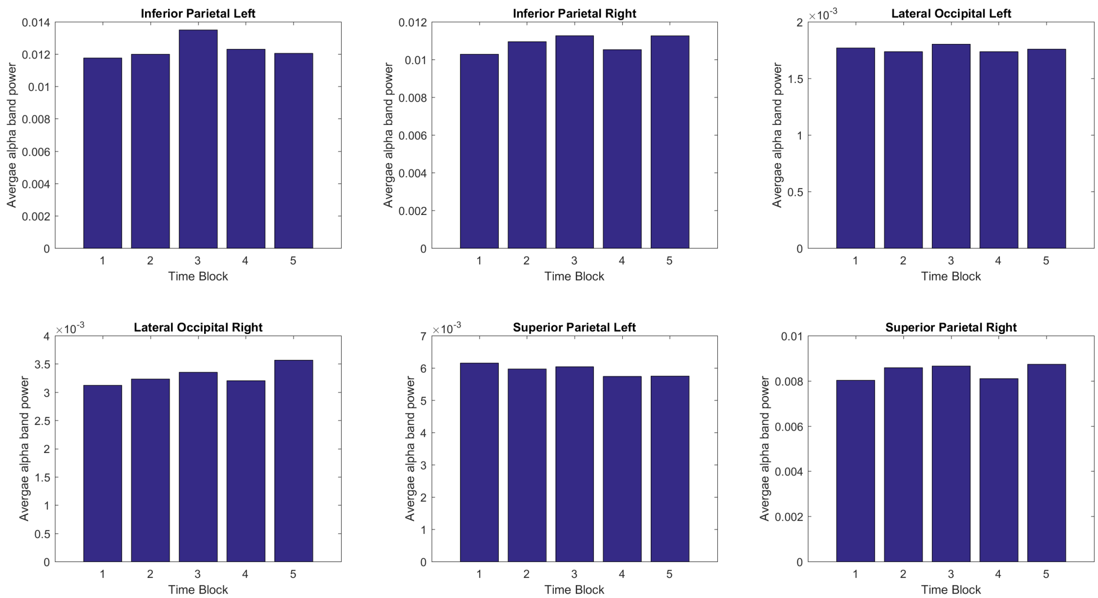


Figure 6.2: Alpha Band Power over 3 hours, divided in time blocks of 30 minutes.

[Figure 6.2] shows the alpha power for 3 hours, segmented into 30 minute time blocks, averaged over all 13 subjects. Regions Inferior Parietal Right, Lateral Occipital Right and Superior Parietal Right seem to show a slight increasing trend.

6.5 Regression Model

Here, the alpha power is not very representative of fatigue induced brain signals. The average correlation obtained by regressing alpha power on 14 visual features is 0.6. We leave out in depth analysis of this Regression Model as it is not indicative of the progressive increment in alpha band power that was expected. We explain this model in detail for the EEG experiment, in the following chapters.

Chapter 7

EEG Experiment

7.1 Experiment

We conducted an experiment to obtain synchronous camera and brain data of test subjects when they were involved in a cognitively taxing task. The experiment was performed for 90 minutes duration on 4 test subjects [Figure 7.1] at the Laboratory of Computational Brain, Rutgers University. The camera data was acquired using a 720p HD camera and the brain data was acquired using a 128-channel Electroencephalography System.

7.2 Electroencephalography (EEG)

The voltage fluctuations arising due to the electrical activity of the cortical regions of the brain can be recorded from the scalp. An Electroencephalography (EEG) system [Figure 7.2] utilizes electrodes placed on the scalp to record this activity. An electrolyte gel applied to the scalp helps conduct the electrical impulses to the electrodes placed on the head using an EEG cap. The brain waves from this setup are recorded at 1024 Hz in a computer connected via a fiber-optic cable.

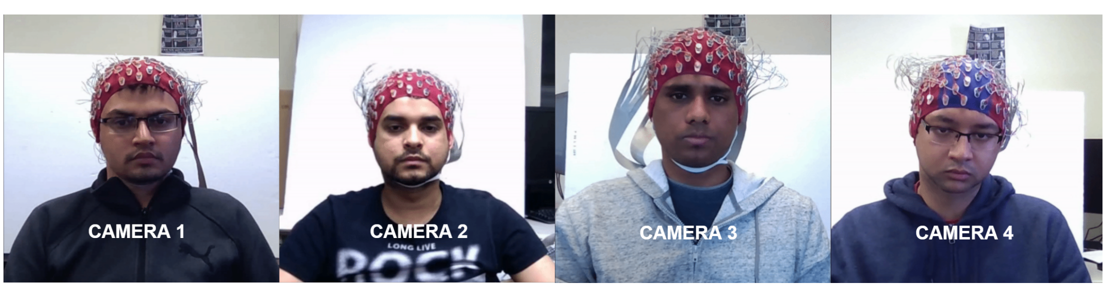
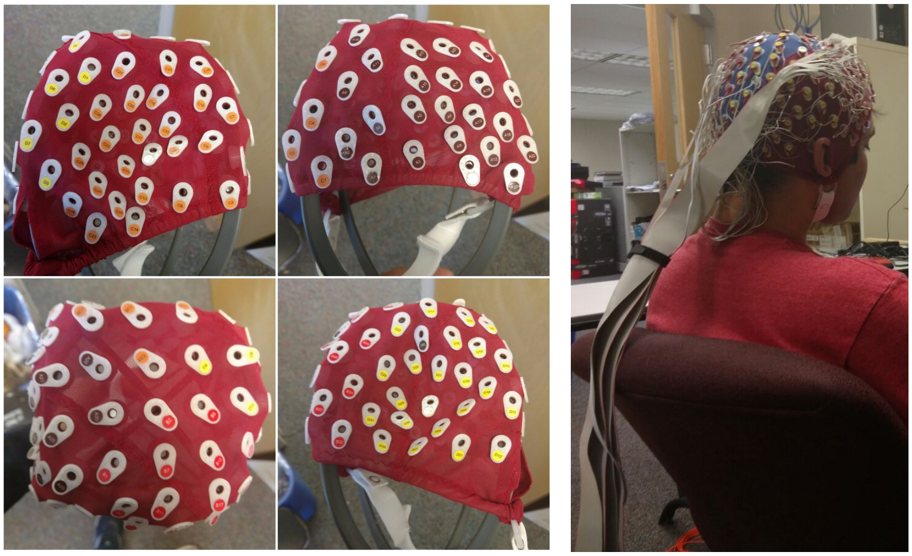


Figure 7.1: Camera recording of 4 test subjects during the EEG experiment



(a) EEG cap with 128 electrodes (b) EEG System setup

Figure 7.2: Electroencephalography System at Rutgers

7.3 Game

The participants were asked to stay fresh and not be tired at the start of the experiment. Then, for the duration of 90 minutes, the subjects were made to play a cognitively exhausting object tracking game [Figure 7.3]. The game was developed by Konstantinos Nikolakakis at Rutgers University.

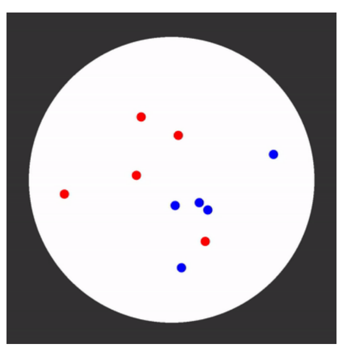


Figure 7.3: Adaptive object-tracking Game

It involves tracking a set of blue and red dots that move with certain velocity in random directions. The task is to keep track of every dot until the movement stops and one of the dots disappear at random. The subject is then asked to press ’r’ or ’b’ based on which dot has disappeared. If the subject focuses on this task for the entire duration, the setup is designed to make the subject tired. The game is made adaptive by adjusting the speed of the moving dots according to the correctness of the answer entered by the subject playing the game. Thus, the aim of this adaptive game is to adjust its difficulty to the subject’s abilities in order keep him engaged and make him tired when played for a long time.

7.4 Visual Indicator of Fatigue

Based on the sliding window technique described earlier for detecting early stages of fatigue, we obtain the similar plots for each of the test subject involved in the experiment.

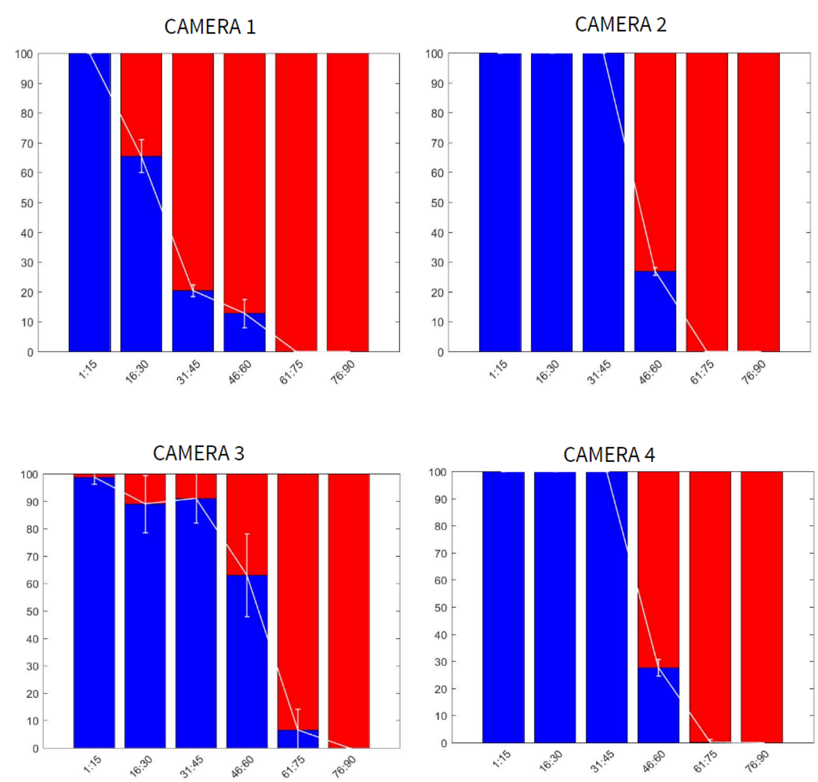


Figure 7.4: Visual indicator of early stages of fatigue for all 4 subjects

[Figure 7.4] shows the early stages of fatigue for all subjects, indicating a progressive increment in the fatigue level. However, the training of the classifier includes data points from all test subjects due to the limited availability of subjects in this experiment. The results show that there is a sharp decline decline in fatigue level for subjects 2 and 4 but a more gradual decrement for subjects 1 and 3. On average, for all subjects, the early stages of fatigue arise just before the one hour mark in the 46 to 60 minute time window.

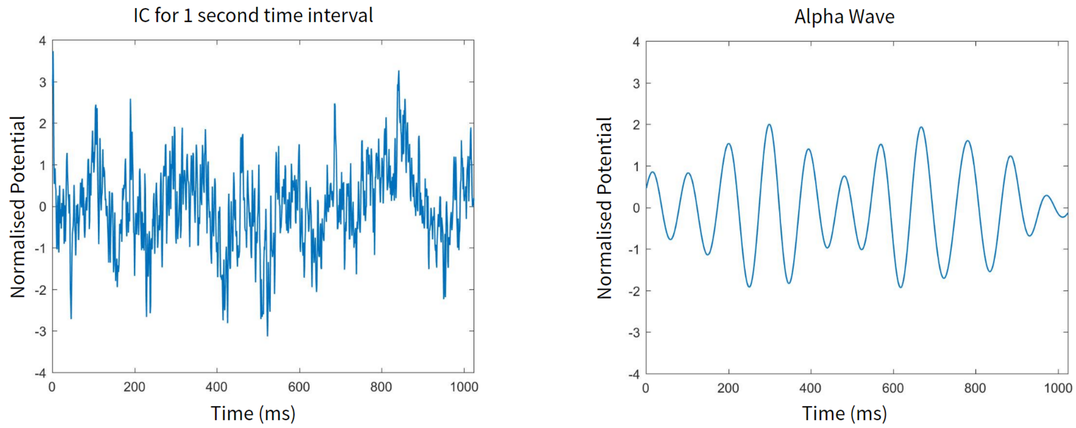
7.5 EEG based Indication of Fatigue

Now that we have the visual indicator of fatigue level derived from the camera data, we want to ascertain the correctness of our assumption that the subject is tired for the last 15 minutes of the experiment. For this, we utilize the EEG brain data recorded along with the camera data. Similar to MEG data analysis, we singled out the alpha frequency band and used the alpha power as the neural indicator of fatigue.

7.5.1 EEG Artifacts Removal

Before we get the alpha oscillations, we need to clean the data of any contamination. The raw data obtained form the EEG system is contaminated with artifacts arising due to eye and muscle movements. These show up as unusual peaks in amplitude of the oscillations of the potential value measured at every electrode. Moreover, contamination arises from the fact that electrode recordings tend to be a linear combination of signals of the neighboring electrodes due to their closeness and the conductivity of the gel applied on the scalp.

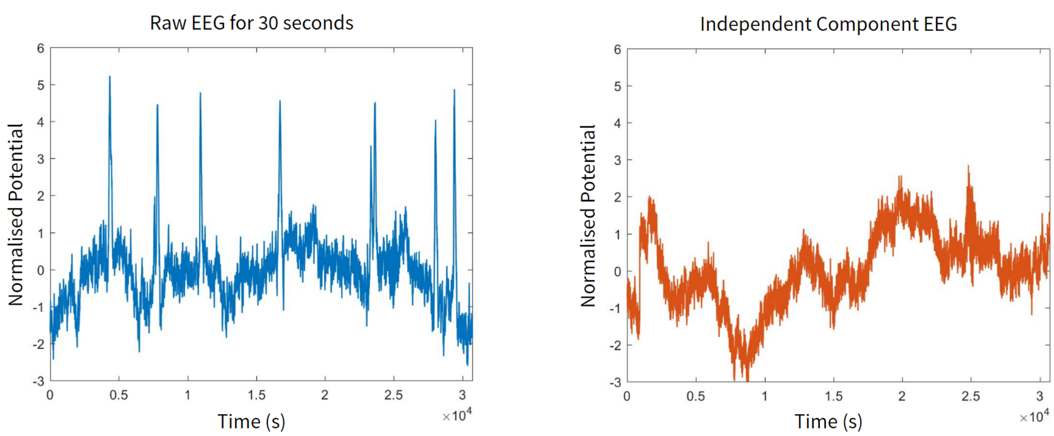
Jung et al. [6] suggest using an Independent Component Analysis (ICA) based Blind Source Separation technique for cleaning out ocular and other artifacts that show up in the raw brain data. In order to obtain 128 independent signals from each of the electrode, ICA requires at least 128 sources to separate out correlated components from each source. Using all 128 electrode recordings, we are thus able to decompose them into independent signals that are intended to be recorded at every electrode source. [Figure 7.5] shows the removal of ocular artifacts from raw data and also the reconstructed independent source free of any such contamination.



(a) EEG independent component for an electrode

(b) Corresponding Alpha Wave

Figure 7.6: Extracting Alpha Band from EEG.



(a) EEG contamination due to Ocular Artifacts (Blinks) signified by the sudden peaks in the data

(b) Corresponding Independent component recovered by ICA, removing blinks

Figure 7.5: Before and After ICA EEG recordings for one electrode.

7.5.2 Band Pass Filtering

Once we have reconstructed the independent components for all electrodes, we extracted the alpha channel in the 8 to 12 Hz frequency band by applying a 3^{rd} order bandpass butter filter. [Figure 7.6 (b)] shows the alpha waves extracted with the butter filter from the recovered independent component [Figure 7.6 (a)] for one second time duration.

7.5.3 Alpha Band Power

For the EEG based estimation of fatigue, we have used the alpha power as a marker for fatigue level. [Figure 7.7] shows the EEG indicator of fatigue level based on the power (Root Mean Square) of the alpha signal we extracted.

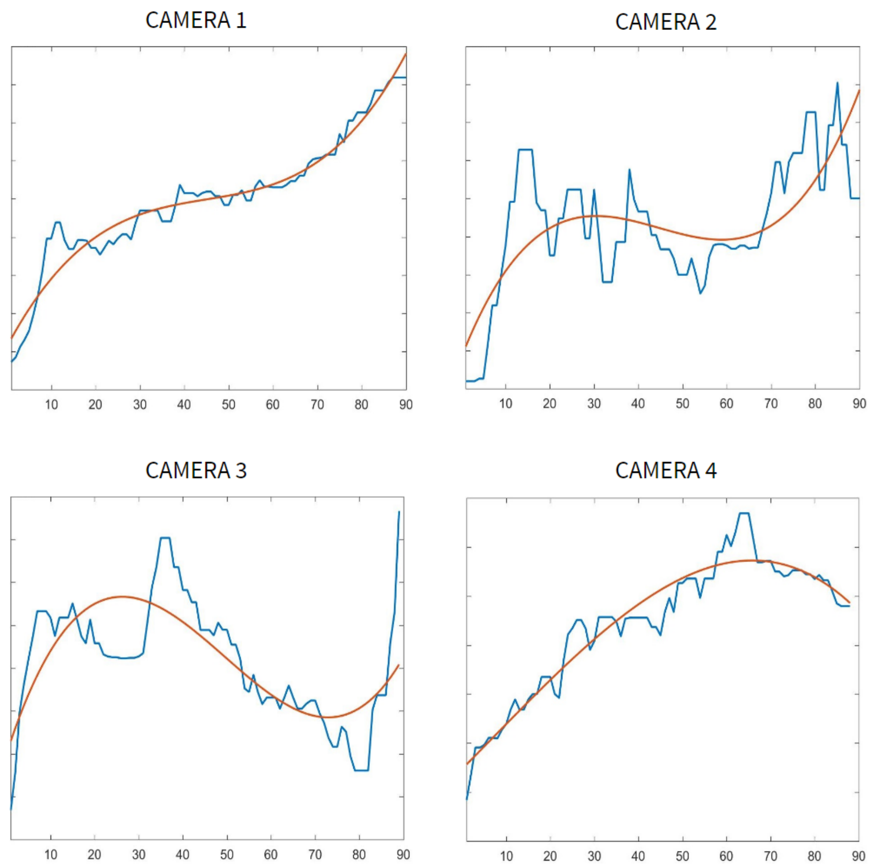


Figure 7.7: Alpha Band Power over 90 minutes for all 4 subjects.

These plots suggest that all but camera 3 are showing signs of increase in tiredness. This indicates that the assumption made for the camera based model where we say that the subject is taken to be tired at the end of the experiment does not hold true for camera 3. We can use this information from EEG for validating the camera based model by removing the subjects from training of classifiers so as to only use features of those subjects that demonstrate the symptoms of fatigue.

7.6 Regression Model

We now have a camera based estimation and an EEG based estimation of the fatigue level. We proceed to correlate the two models by regressing the alpha power on the camera based features. Consider the alpha power to be Y and the visual features $x_1, x_2, ...x_8$. We fit the following regression model with necessary transformations to correct linearity

$$\frac{-1}{\sqrt{Y}} = \beta_0+\beta_1 x_1+\beta_2 log(x_2)+\beta_3 log(x_3)+\beta_4 \frac{1}{x_4}+\beta_5 \frac{1}{x_5}+\beta_6 x_6+\beta_7 log(x_7)+\beta_8 x_8+\epsilon \quad (7.1)$$

where

$\beta_0 ... \beta_8$ are the regression coefficients,

ϵ is the error,

x_1 = Average Eyelid Distance,

x_2 = Eye Closure Time,

x_3 = Eye Blink Rate,

x_4 = Surface Area of Eye,

x_5 = Circularity of Eye,

x_6 = Distance of Eye Corners from Fixed Point,

x_7 = Eye Opening Velocity and

x_8 = Eye Closing Velocity.

7.6.1 Visualizing Regression Plane with 2 Features

We then tried to visualize the regression model in order to decide whether assuming a linear model is a fair assumption or not. Since we cannot visualize more than 3 dimensions intuitively, we used the two most indicative features of camera based model, namely the Eye Blink Rate and the Eye Closure Time in order to visualize the linear regression plane alpha power regressing on these two features. [Figure 7.8] shows this visualization for all four cameras.

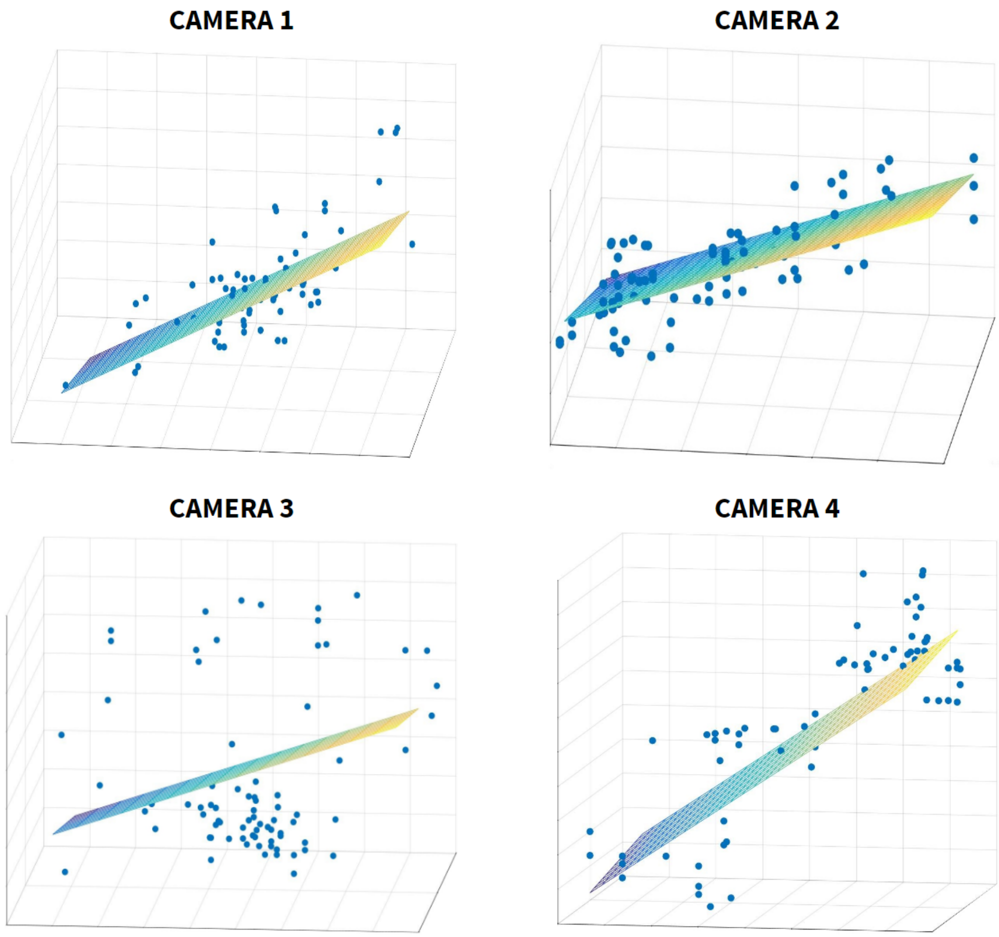


Figure 7.8: All 4 subjects, Linear Regression Plane with X axis = Closure Time, Y axis = Blink Rate and Z axis = Alpha Power.

As evident from the figure, camera 3 again shows no noticeable trend in terms of correlating the two indicators of fatigue, leading us to believe that the subject is indeed not getting tired. Hence, we choose to drop this test subject out during training our camera based model.

7.6.2 Regression for all 128 electrodes

We fit this regression model for the alpha power for every electrode on the EEG cap. We then studied the correlation values of all these regression models and plotted a histogram of correlations (ρ^2) and observed an average correlation of 0.55 while certain electrodes achieved a correlation of 0.8 indicating that they are the regions o scalp that are the most indicative of fatigue level. [Figure 7.9] shows the histogram of correlations for all 4 subjects.

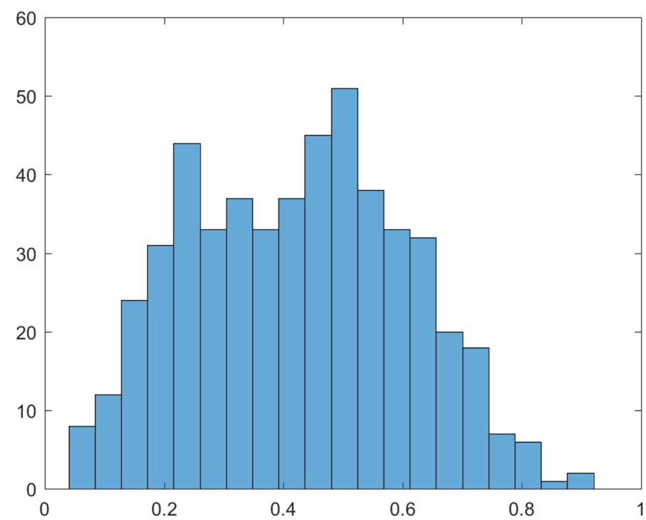


Figure 7.9: Histogram of correlations of Regression Models for all 128 electrodes. This histogram includes all 4 test subjects.

7.7 Comparison with the MEG model

Here, the EEG experiment was conducted with all parameters controlled by us while conducting the experiment. By designing an adaptive game, this experiment gives a clearer indicator of the fatigue levels of the test subjects involved compared to the MEG experiment. We achieve higher correlation values for validating our classifier and are able to verify our assumption that the subject is tired towards the end of the experiment. Based on this information, we say that our EEG-validated camera model provides a better indication of fatigue levels compared to the MEG model.

Chapter 8

Conclusion

We showed a novel sliding window technique to estimate an early stage of fatigue purely based on visual symptoms using a camera model. We validated this model by showing correlation with the fatigue induced brain waves and decide what subjects to include in the development of the camera based model. These results show promise in terms of designing a reliable model using just the visual symptoms of fatigue.

8.1 Future Work

Based on this work, we outline the possible directions where this research could head towards next.

8.1.1 Conduct experiment on more subjects

The natural extension of this work includes demonstrating the same results for many more test subjects. Based on EEG validation, we could train a single classifier while eliminating those subjects that do not get tired during the experiment.

8.1.2 Neuroscience: Fatigue-Source Localization

Based on the correlation values of the regression model, obtained for every electrode, we could try to isolate the parts of brain that are the most indicative of fatigue. Essentially, we can try to find if there are any specific locations that are highly indicative of fatigue across many subjects. [Figure 8.1] shows the source localization for the 128 electrodes of the experiment. Further studies are required to isolate common positions or electrodes across many subjects that consistently indicate signs of fatigue.

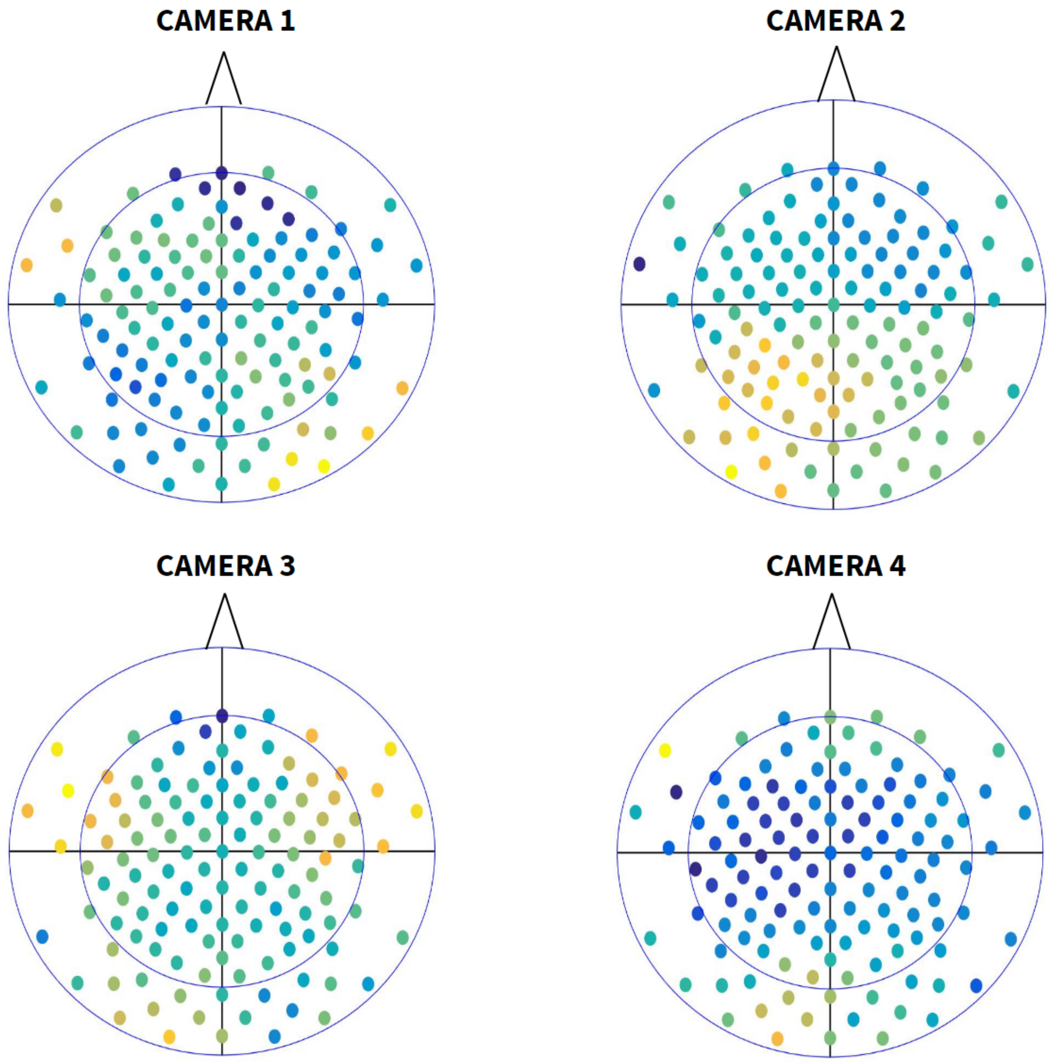


Figure 8.1: Top View of head with 128 electrodes. Color-Map: Yellow indicates high correlation, blue indicates low correlation.

8.1.3 Real Time Fatigue Detection

In our work, we compute the features for our models by looking at the entire duration of the video and brain recordings. The challenge lies in designing a real time system that has no access to the final fatigue stage but still can estimate early stages. Moreover, when the system runs on a new test subject, it is unaware of the operative range of feature values for that person, hence it requires some training before estimating the fatigue level of that subject. Here in lies the opportunity to design a real time robust system that adapts well to different unseen individuals. Such a system will also potentially have good commercial application and value.

8.1.4 Automatic Feature Learning and Extraction

In our study, we have used a feature set for the camera model comprising of well known visual symptoms of fatigue. An alternate study could include exploring the different undiscovered visual symptoms. Automatic Feature Extraction from videos could enable achieve this by learning features based on labeled data. Convolution and Recurrent Neural Networks have the ability to learn features from spatial and temporal data respectively based on supervised learning methods. These could be used to design the camera based model and also discover interesting information about these symptoms.

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