Neural Correlates of Extended Dynamic Face Processing in Neurotypicals

by

Luke Urban

Submitted to the
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Abstract

This thesis explores the unique brain patterns resulting from prolonged dynamic face stimuli. The brain waves from neurotypical subjects were recorded using the electroencephalography (EEG) while viewing a series of 10 second long video clips. These clips were one of two categories: face or non-face. Modern signal processing and machine learning techniques were applied to the resulting waveforms to determine the underlying neurological signature for extended face viewings. The occipitotemporal (left hemisphere), occipitotemporal (right hemisphere), and occipital proved to have the largest change in activity. Across the 12 recorded subjects a consistent decrease in the 10 Hz power range and increase in the 20 Hz power range was found. This biomarker will serve later works in the study of autism.

Thesis Supervisor: Pawan Sinha
Title: Associate Professor
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Chapter 1

INTRODUCTION

Modern neuroscience to this day lacks a fundamental understanding of the neural activity of autistic individuals in comparison to neurotypicals. Despite the wealth of research there is no known unique brain signature found in ASD population. This is particularly surprising given the notable behavioral differences between these two groups. This experiment will lay the ground work towards finding just such a biomarker. Neurotypical patients will be studied using extend dynamic face stimuli with the hopes of finding a consistent underlying brain pattern. The discoveries made through this experiment will allow for future work on its presence in autism.

While there has been a great deal of work in the area of face processing, typical studies are only interested in breaking down when and where it begins. This is accomplished by evoking the brain’s transient response using very brief stimuli presentations (on the order of factions of a second). This approach provides great insight into when face/object discrimination occurs, but these experiments lose the temporal aspect of face processing. The dynamic nature of faces will be retained in this experiment by using stimuli which are much longer (on the order of 10 seconds).

It is the belief that this biomarker will serve well in the study of autism because it retains the temporal component of face processing. Autism’s main symptom is seen in abnormal social behaviors. Social activities unfold over time so by chopping face stimuli into 300 millisecond chunk, as modern studies do, a great deal of information is lost. The reason there is still no known underlying biomarker for autism could
be the result of modern approaches not evoking the aspect of face processing which is difficult for autistics. It is possible that face recognition functions perfectly but some problem in higher order integration exists. It is through this integration of faces through time that this experiment believes the neural correlates of extend dynamic face processing will serve as a valid biomarker in the study of autism.

In addition to autism research, another application of this knowledge is in the field of brain computer interfaces (BCI). This new area of research hopes to bridge the gap between man and machine by providing a channel of communication directly from the brain. Pieces of this technology are already knocking at our doors. In 2009, the toy company Uncle Milton introduced a Star Wars 'Force Trainer' containing a simplified EEG device which allows the user to control the position of a ball using only their brain waves. Researchers at the University of Wisconsin also recently designed an EEG system which allows the user to 'tweet' on the social networking site Twitter using only the EEG signal[16]. This technology is in its infancy, but as these devices become more commonplace a better understanding of the human brain will be needed to fully utilize them. Finding the neural correlates to extended and dynamic face viewings will provide a novel method of interacting with machines.
Chapter 2

BACKGROUND

2.1 Imaging Modality

There are two main noninvasive image recording devices used in neuroscience research; electroencephalography (EEG) and functional magnetic resonance imaging (fMRI). Each tool has a specific set of advantages and disadvantages. EEG measures the electrical activity of the scalp allowing for millisecond temporal resolution. This resolution comes at a price as electrical activity dissipates through the skull causing a lack in precise spatial resolution. FMRI detects blood flow and can be used to pinpoint exactly which sections of the brain are being activated, but because blood takes time to flow it fails to have the temporal resolution of EEG. In general, fMRI can only image the brain once every quarter second[14], much slower than EEG. For this experiment temporal resolution was weighed more important than spatial resolution, so EEG was the imaging modality of choice.

2.2 Event Related Potential (ERP)

One of the main techniques used in neuroscience is event related potentials (ERP). This process involves presenting a subject with a series of very brief stimuli (on the order of hundreds of milliseconds) and analyzing the brain’s transient response. Imaging tools like EEG are prone to noise, so a large number of trials are run and
the signals are averaged together. This averaging trick increases the signal-to-noise ratio because throughout the trials the brain pattern will remain constant while the random noise averages to zero. The rate at which the noise decays is related to the square root of the number of trials, so ERP studies can range anywhere from 50 to 500 repetitions for a given stimulus[24].

ERP studies are frequently used to study face processing. These experiments typically involve flashing a randomized series of face and non-face images to a subject.[12] Exactly what constitutes non-face image varies from experiment to experiment, but typical non-face images are: car, houses, and other everyday items[23][10]. The major discovery ERP studies have found in face processing is the N170 response.[23] It has been shown that at approximately 170 milliseconds after the initial presentation of face stimuli the occipital lobe makes a sharp negative spike as shown in Figure 2-2. This negative dip is unique to faces and is not evoked when viewing other objects, even human body parts like hands.[23] This result shows that within 170 milliseconds of the light entering the eye, the human brain can distinguish between face and non-faces.

Studies on the differences between the N170 response in neurotypicals and people with autism has been relatively inconclusive. One noted difference is a decreased
ampitude[1][15] and delayed latency[13] of the N170 response in subjects with ASD. This difference should be regarded cautiously, as other factors besides neurological underpinnings can be the cause. Anatomical properties of subject, such as the thickness of the skull[19], can effect electrical conductivity resulting in such distortion of the underlying signal. In general, comparison of ERP data between subjects needs to be done carefully as differences in waveform peaks do not inherently correspond to differences in the underlying brain activity.[24]

Another noted difference between neurotypicals and the ASD population is an atypical spatial distribution of face processing. A lack of right hemisphere lateralization has been found[9], implying no cortical specialization. This finding has been question by MEG studies showing right hemisphere preference of faces when compared against other objects[1]. In total results in this area are at odds and can not be used to make any strong case either way.

The literature on ERP studies involving ASD populations is relatively sparse and inconclusive[4]. As it stands there exists no concrete biomarker which separates subjects with ASD and neurotypicals. As postulated in the introduction, this may be the result of the ERP framework. Since autism's most striking symptoms come from atypical social behavior, the brief nature of stimuli presentation may not test the appropriate aspect of ASD neurological function. This could be the reason neuroscience has yet to find a firm biomarker.
2.3 Brain Computer Interface (BCI)

The field of Brain Computer Interface (BCI) attempts to connect man and machine through the analysis of brain waves. This technology has a three fold mission:

1. Provide a means of communication for people with severe muscular paralysis.

2. Help neuroscience researcher better understand the brain.

3. Create a novel means of interaction between man and machine.

This new research area takes advantage of the progress in neuroscience and signal processing to provide a real time communication pathway between the brain and a computer. It draws on findings from all field of neuroscience to make such things a reality.

An example of how ERP studies have developed into BCI methods is the P300 response. This spike is elicited in response to an oddball paradigm[21]. In this setting two possible stimuli are presented, one being much rarer than the other. When the unlikely stimulus is presented, a sharp positive swing is found at approximately 300 milliseconds later.

This paradigm is used to communicate using a P300 matrix[2]. This matrix is a 6x6 grid containing both letters and numbers. The subject is asked to fixate on a character while the rows and columns are flashed randomly. Most of the time the character remains in its unflashed state, but every so often its column or row will blink. This flashing serves as the oddball stimulus and results in the P300 response. By combining which row and column evoke the response, a computer is able to determine which character the subject is attending to. It is through this method that paralyzed patients are able to spell words[25][6] and do things like 'twitter'[16] using their brain.

In addition of analyzing ERP style experiments, brain computer interface devices are also used to monitor more continuous brain activity such as alertness. Numbers of EEG experiments on short term memory tasks have found neurophysiological effects of mental workload. Real-time BCI system have been built to monitor subjects in tasks like alertness behind the wheel[11]. To quantify alertness, these systems use the
power spectral density in specific frequency bands as features for linear discriminate analysis. This classifier is then used to assign a high or low mental workload rating. Techniques used in BCI devices are directly applicable to the type of analysis needed for this experiment on extended dynamic face viewings.
Chapter 3

EXPERIMENTAL SETUP

3.1 Stimuli

The stimuli set for this experiment contains 30 face videos and 30 non-face videos. Face videos are defined as containing a single person speaking in the direction of the camera. It was not required that the speakers face directly towards, as many faces are slightly angled away from the camera. Non-face videos are defined as any video which did not contain a human face. These non-face videos are allowed to contain human hands, which have been shown not to evoke face specific responses like the N170. [23]

Non-face stimuli are as follows:

- Moth getting caught in Venus fly trap
- Airplane taking off
- Arthur Ganson’s kinetic sculpture of wishbone walking
- Arthur Ganson’s kinetic sculpture of chair exploding
- Arthur Ganson’s kinetic sculpture device with swinging head
- Bridge wobbling
- Windmill exploding
Figure 3-1: Example images of the videos used in the experiment. The top two are face videos. The bottom two are non-face videos.

- Ferrofluids
- Sidewinder snake moving over desert
- Firework
- Time-lapse Popsicle melting
- Whale breaching
- Helicopter taking off
- Tornado
- Big Dog walking through woods
- Lego toy robot
- Industrial robotic arm constructing car
- Folding a paper airplane
• Slow motion water droplet

• Slow motion water droplet hitting another droplet

• Flower blooming

• Wrecking ball crushing building

• Backhoe digging dirt

• Waves crashing over deck

• Car swerving on the highway

• Tactile electronic sensor

• A swarm of birds

• Domino Ouroboros

• Glass Blowing

• Magnetic Pendulum

### 3.2 Stimuli Collection

Source videos were downloaded from YouTube using the free software 'YouTubeDownloader.' The majority of the face videos were downloaded from personal YouTube blogs as well as various clips of celebrities. There was an attempt to balance race, gender, age, and notoriety. No video contained computer generated graphics.

Once the source videos were downloaded, all clips were processed using Final Cut Pro. Video segments were cut down to approximately 10 seconds and saved in a 240x320 M-PEG format, maintaining aspect ratio. Each clip contains one continuous sequence video; no cuts were allowed. The shortest of all the videos was 7 seconds.
3.3 Lab Setup

The Sinha laboratory is set up with the following equipment:

- NetStation EGI EEG Amplifier
- 4 Electrode caps
- Windows PC
- Mac Laptop
- Subject Monitor
- Video Splitter

EEG experiments are designed on the Windows PC using E-Prime psychology software. This computer is connected to the Mac laptop via an Ethernet cable, allowing programs running on both machines to communicate. The Mac laptop contains NetStation software and handles data acquisition from the EEG amplifier. The amplifier is connected through a USB port on the laptop. The electrode cap worn by the subject is connected to the amplifier and allows the laptop to record brain activity. The subject is placed in front of a monitor which is connected to a video splitter. This splitter allows the experimenter to display either the laptop or PC screen. The Mac laptop screen is displayed to help measure impedances of electrodes and to show subjects their brain activity. The PC screen is used to display the experiment. Each time a stimulus is presented on the subjects monitor, the PC notifies the Mac laptop which in turns marks the EEG signal for later segmentation.

3.4 Subject Collection

Subjects were drawn from the MIT Brain and Cognitive Science subject mailing list (bcs-subjects@mit.edu). This list is available to the public and contains a collection of people in the Boston area who are interested in participating in non-invasive brain experiments. The make up of this list tends to be college students, MIT faculty, and
surrounding residents. A short email was sent to the list asking for volunteers for an EEG experiment lasting approximately 1 hour. It can be found in APPENDIX D. The pay was $10. 12 people responded and were individually scheduled for time slots.

3.5 Capping Subject

When the subject entered the lab they were given a consent form. This waiver explained the EEG set up and that no physical or mental harm would come to them. While this waiver was not specifically geared toward this experiment, it provides a blanket approval for EEG experiments in the Sinha laboratory. This waiver explicitly states they could leave at any time, should they want to. After they signed and dated the waiver, the size of the subject’s head was measured to fit an electrode cap. The end of a measuring tape was placed at the top of the bridge of the nose and wrapped horizontally around the head. From this measurement the correct electrode cap was selected.
The electrode cap was then placed in a saline solution of Potassium Chloride and shampoo and allowed to soak for 5 minutes. In the mean time, the experiment was explained to the subject and the center of their skull was measured to help correctly place the cap. This was accomplished by measuring distance across the top of the skull from ear to ear and from the bridge of the nose to the ridge in the back of the head. The intersection of these two lines was defined as the center of the skull and was marked with an 'X' using a red grease pencil.

Once the cap finished soaking, the subject was instructed to close their eyes and the cap was placed over their head. The reference electrode (electrode 129) was positioned such that it rested over the 'X'. A series of straps beneath the subjects chin help tighten the electrode cap such that all electrodes made contact with the scalp and were correctly positioned.

3.6 Connecting Subject to Amplifier

After the electrode cap was fitted, the subject was positioned in front of a computer screen. The connector at the end of the electrode cap was connected to the NetStation amplifier and a new recording session was created in the Netstation software on the Macintosh laptop. After the gains were measured, the impedance display screen was loaded. This screen displayed a 2-D map of the electrodes. Electrodes with an impedance higher than an acceptable threshold were displayed as red, and electrodes with an impedance below the acceptable threshold were displayed in green. This screen was placed on the subject's monitor for ease of the experimenter and every red electrode was adjusted until they turned green. These electrodes were repositioned to insure a good connection to the scalp and pipetted with the saline solution. Once each electrode displayed as green on the impedance screen, the measurements were saved and the window was closed. Next, the dense waveform display was opened and the subject was allowed to look at their own brain activity. The subject was asked to blink and take note of the corresponding wave pattern. It was explained that the process of blinking involves large electrical activity in the brain which overwhelms
the small signals being tested. The subject was told that the experiment involved watching a series of 10 second long videos clips and that there would be a 10 second gap between each video. It was asked that the subjects try their best to hold off blinking until the gaps, but that occasional blinking during a video presentation was fine.

3.7 Running Experiment

The subject’s screen was switched to the PC and E-Prime was loaded. The Extend Face Viewing experiment was opened and executed. The door to the EEG room was closed and the lights were shut off to block out any distraction. An information screen explaining the experiment was shown to the subject and once they felt ready they began. The experiment was initiated by the researcher hitting 'Space Bar’ on the PC, the subject had no control. The researcher sat behind the subject and monitored the EEG waveforms to ensure no complications through out the experiment.
Figure 3-4: Experimental Process. Video was displayed for ten seconds, then a grey screen. Process was repeated for all 60 videos.

3.8 Experiment

E-Prime was used to create the experiment for this EEG study. At the start a description of the experiment was presented to the subject. Once the subject was prepared to begin, pressing any key on the keyboard initiated the videos. Once the experiment began, a gray screen with a set of cross hairs was presented. This screen lasted for approximately 10 seconds and the cross hairs provided a fixation point for the subject. After the 10 seconds were up, a video was presented. These videos were presented in a random fashion with each subject’s run being unique. After the video ended, the gray screen and cross hairs were presented again and the cycle repeated. This continued until all 60 videos had been displayed. Audio was not cut out from the videos, so the speakers were manually turned off.
Chapter 4

PREPROCESSING

4.1 Segmentation

The EEG system records one long continuous signal from the start of the experiment to the end. As stimuli are present the system tags their location in the stream. The first preprocessing step was to segment out only the regions of interest from the EEG signal. This was accomplished by breaking the EEG trace into 60 clips starting at the moment of presentation for each stimulus. Each clip was cut to 7 seconds, the length of the shortest video. This guaranteed each clip will contain the brain signal of the subject while exposed to a stimulus.

4.2 Filter Design

By default the EEG amplifier samples at 1 kHz. The choice of sampling rate defines what types of signals can be recorded. Based on Nyquist’s criterion a signal can faithfully be represented by a discrete set of sample points as long as the sampling rate is more than twice its highest frequency. In the case of the EEG amplifier, sampling at 1 kHz allows for frequencies up to 500 Hz.

This range of signals is much wider than needed for EEG data analysis. Having such a large spectrum can cause a problem by allowing noise to creep in. One such source of noise come from the fact that the United State the power lines operate at 60
Hz. Since the EEG amplifier is powered by the grid, it is common for the alternating current in the power lines to cause 60 Hz artifacts in the signals. Typical ways to cope with this and other sources of noise is to use a filter.

There are four main types of filters: low-pass, high-pass, band-pass, and notch filters. A low-pass filter cancels out all frequencies above a certain cutoff point. A high-pass filter does the opposite by canceling out all frequencies below a certain cutoff. The band-pass is a combination of the two. It allows only a specific band (a pass band) of frequencies to pass through, while canceling out all the rest. A notch-filter only cancels a specific portion of the frequency content and can be thought of as the inverse of the band-pass. Notch-filters typically can be used to cancel out the 60 Hz power line noise as it is a known and specific problem.

It is typical for EEG experiments to low-pass filter EEG data after acquisition. A common cutoff frequency is 50 Hz[7]. It is also common to high-pass filter since EEG sensors tend to drift over time it. High-pass filtering serves to baseline by removing any DC (0 Hz) component of the signal. This method of low-pass and high-pass
filtering is identical to running the signal through a single band-pass filter. For this experiment a band-pass filter with a pass band starting at .1 Hz (to baseline) and ending at 50 Hz (to low-pass filter) was used.

Since the EEG signal is saved as a discrete set of sample point, the signal is defined in the discrete time domain. In this domain filters come one of two types: infinite impulse response (IIR) or finite impulse response (FIR). This labeling corresponds to how the filter responds to a given input. In the case of the IIR filter, each input has an effect on every other input before and after it for infinity. Since this filtering needs to happen on a computer in finite time, IIR filters are not possible. This leave the subset of FIR filters.

The ideal filter has a pass band of magnitude exactly one and a stop band of exactly zero. Having such a magnitude profile serves to cancel out all unwanted frequencies without distorting the others. In the real world ideal filters fall under the IIR domain. Since computers need to run in finite time approximations to the ideal filter are made. Four common filters are used as approximations: Butterworth, Chebyshev I, Chebyshev II, and Elliptic. All four of these filters work well and are often used in neuroscience signal processing [20]

Unfortunately these filters are IIR, so for each approximation there is an additional FIR approximation. In this experiment a Chebyshev II filter was used. This filter has a monotonic pass band and equiripple in the stop band. This type of filter typically has a sharper transition band than the others which make it ideal for band-pass filtering. The FIR approximation of a Chebyshev II filter is implemented using the Parks-McClellan algorithm[27]. For this experiment the pass-band defined above (pass-band starting at 0.1 Hz and ending at 50 Hz) was used with an acceptable transition band of .1 Hz. To cancel out any phase distortion the filter is run twice over the signal, once forward and once backwards.
Figure 4-2: Magnitude plot of filter designed through the Parks-McClellan algorithm.

### 4.3 Down Sampling

After the filtering stage the EEG trace contains a 50 Hz signal sampled at 1 kHz. The Nyquist criterion states that a 50 Hz signal only needs to be sampled at 100 Hz for faithful reproduction. This means the EEG signal is oversampled by a factor of ten. To help reduce the size of data the EEG signal is decimated by saving only every tenth point. This cuts every EEG trial to one tenth of the size of the original recording without losing any information.

### 4.4 Artifacts

The EEG signal can often be plagued by biological artifacts. The muscular activity of blinking is strong enough to register as a significant spike in the EEG trace. The spike caused by a blink is comprised of a number of frequencies, many of which blend into the underlying signal, making it hard to filter out.

Typical ERP studies deal with artifacts by removing any trials containing blinks. Because ERP studies record a large number of trials, losing a few will not greatly effect the overall result. In the case of this experiment, removing tainted trails can not be afforded. With each trial lasting approximately 10 seconds the likelihood of some
trials containing blinks is high. This, coupled with the small numbers of stimulus presentations, means eye blinks in the signal are inevitable and something which will have to be compensated for in the processing stage.
Chapter 5

ANALYSIS

5.1 Amplitude Time Analysis

Typical analysis in ERP experiments involve studying signals in the amplitude-time domain. In the case of EEG experiments, this means looking at brain signals as a function of electrical activity over time. As ERP studies have shown, this approach can have rewarding results. Response like the N170, P100, and P300 all are derived by analyzing signals in this manner.

As in all methods of analysis, studying signals in the amplitude-time domain involves defining features of interest. Usually, these features are peaks and valleys. These are called extrema and can be defined mathematically as points in the signal where the slope is zero. Computationally, these extrema can be found using the first derivative[8]. Since the first derivative is the instantaneous rate of change of a signal over time, the extrema of a signal will be the points where the first derivative is equal to zero. To determine whether a extrema is a peak or valley, the second derivative can be computed[8]. If the value of the second derivative at the point of the extrema is positive then the signal has positive curvature, meaning the extrema is a minimum. If the second derivative is negative, then the extrema is a maximum. The value of these extrema and their location in the signal can be used to compare the effect of different stimuli on neural activity.

This style of analysis lends itself well to the ERP framework. Since ERP studies
only look a few hundred milliseconds after the presentation of a stimulus there are relatively few peaks and valleys. Also, since the time line is so short the likelihood of the signal accumulating large amounts of phase lag is low. Therefore comparing peaks from two different stimuli conditions is a viable option, even possible by hand. Unfortunately the time course is much longer for extended dynamic faces. Since signals for this experiment are on the order of seconds, the ability to make one-to-one comparisons between extrema across multiple trials is low. As a result, analyzing the brain functions in the time domain is not the ideal method for this experiment.

5.2 Frequency Analysis

All is not lost. Another approach to signal analysis is to look at the frequency domain. Fourier showed that any arbitrary function can be represented as an infinite series of sines and cosines. From this rule the Fourier transform is defined. In the case of
the EEG signals, the Fourier transform converts a signal from a function of electrical activity over time to a function of electrical activity over frequency. Mathematically this transform is defined as:

$$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-i\omega t} dt$$

This transformation holds over all frequencies, but because of the filtering stage described in the preprocessing section the transform of the signals used in this experiment will is zero above 50 Hz. Brain imagine studies often use the Fourier transform in their analysis. These studies involve more long term signals designated by mental states like sleep, stress, and awareness [5][22][18]. The approach Fourier analysis takes in these experiments involve computing the power spectral density in specific frequency regions. Mathematically the power spectral density is defined as:

$$\phi(\omega) = \frac{F(\omega)F^*(\omega)}{2\pi}$$

This equation computes how much activity there is in specific frequency of a signal.
Table 5.1: Traditional Frequency Bands

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta</td>
<td>1-4 Hz</td>
</tr>
<tr>
<td>Theta</td>
<td>4-8 Hz</td>
</tr>
<tr>
<td>Alpha</td>
<td>8-13 Hz</td>
</tr>
<tr>
<td>Beta</td>
<td>13-40 Hz</td>
</tr>
<tr>
<td>Gamma</td>
<td>40+ Hz</td>
</tr>
</tbody>
</table>

This is a continuous function, so to make analysis easier the power spectral density is integrated into a series of bins. Neuroscientists historically divide the frequency space of brain waves into the 5 categories: delta, theta beta alpha and gamma. These are purely traditional frequency groupings and are not used in this experiment.

This approach is a step in the right direction, but it is missing one critical fact about EEG signals. Brain patterns tend to be very transient spikes. The signals of interest do not typically oscillate at a constant frequency, they change and decay over time. These brief spikes can cause noise in the Fourier transform as they contain a large amount of high frequency data. Distinct spikes will also have similar frequency content, leading to an overlap in the Fourier domain. This overlap can make it difficult to piece out which aspects to the signal are of interest. In general the Fourier transform loses all time information, making it difficult to determine where activity takes place. As a result it is a poor tool for studying EEG signals.

5.3 Short-Time Frequency Analysis

There exists a solution which straddles both the temporal and frequency worlds. A short-time Fourier transform computes the frequency content of windowed portions of the signal. Mathematically, this is defined as:

\[
F(\omega) = \int_{-\infty}^{\infty} w(t)f(t)e^{-i\omega t} dt
\]

Where \( w(t) \) is some windowing function. There is no one window inherent to the short-time Fourier transform, but a typical function is the Hann window. This windowing
function takes the form:

\[ w(t) = \frac{1}{2} \left[ 1 - \cos \left( \frac{2\pi t}{N-1} \right) \right] \]

Where the width of the window is defined by the value \( N \). The Hamming window is well suited for the short-time Fourier transform because it has low aliasing. This means its Fourier transform has lower frequency content then most other windowing functions allowing for better temporal resolution. All studies which use Fourier analysis have some form of windowing function. The first step of any EEG study involves cutting out a region of interest in the original signal, which can be thought of as using a simple rectangular window. Beyond that, most studies break the signal into a series of epochs and compute the Fourier transform individually.\(^5\)\(^2\)\(^2\)\(^2\)\(^1\)\(^8\) This helps compensate for the transient nature of the brain activity. In this experiment it will be additionally helpful in dealing with blinking artifacts. Since blinks happen for very brief periods of time, most windowed portions of the signal will section out blinks. This means individual eye blinks will not destroy entire trials.

Sliding the windowing function down the signal allows frequency content to be defined at discrete time points in the signal. This is how the short-time Fourier transform preserves both temporal and frequency information. Unfortunately there is a trade off between resolution in the time domain and resolution in the frequency domain. Setting a wide windowing function allows for accurate frequency analysis, but knowing exactly when those frequencies occur suffers. Vise versa, narrowing the
windowing function increases the understanding of when things occur, but because the small window function only allows a small chunk of signal to pass through the frequency information suffers. Typically a balance is made between frequency and temporal resolution, as done by this experiment.

This type of analysis is ideal for this experiment. It is not known where or when specific neural activities occur which are unique to extended face viewings. Keeping both frequency and temporal data will provide a better understanding of the underlying signal. As stated above, a Hamming window function was used with a width of .64 seconds and a 93.75% overlap between each epoch. Computing the short-time Fourier transform turns a signal into a 2D signal called a spectrogram. In a spectrogram frequency is on one axis and time is on the other. To define a set of features from the spectrogram, blocks 1 hertz tall and .5 second wide were integrated, resulting in 700 individual blocks for each EEG trace. Example spectrograms for each subject are listed in Appendix A.
Figure 5-5: Spectrogram gridded into 1 Hz by .5 second blocks. The different size is a result of rounding.
Chapter 6

CLASSIFICATION

6.1 Machine Learning

Breaking the spectrogram into 1 Hz and 0.5 second blocks results in 50 blocks for every 14 half second epoch, resulting in 700 total features per trial. More than that, each trial is recorded over 128 sensors, making it 700 features for each 128 sensors. Attempting to piece out which of the 89,600 total features are correlated to face processing using only 60 examples is a Herculean task to do by hand. Thankfully the field of machine learning provides a tractable solution. Algorithms from this field are used to automatically learn the difference between two different classes of stimuli (for this experiment face and non-face). By running these algorithms on subsets of features, the important aspects of the EEG signal can be teased out.

Machine learning algorithms learn by training off a subset of data. They assume patterns in the overall data set are represented in this smaller collection, so any difference found in a training set will generalize to the overarching data. The boundary found by these algorithm normally is tested on the remaining set of data to determine it how well it classifies the two types of data. Typical approaches involve breaking the entire data set into a series of groups and training multiple algorithms. Each group serves as the test set for one algorithm, and from the average classification rate the separability of the data can be judged. In this experiment the classification rate will be used to determine the information content of features. If a feature has a high
classification rate then it is assumed that it is helpful in determining face processing. If classification is near chance then it is assumed it is playing no role.

In machine learning there are three general types of algorithms: supervised, semi-supervised, and unsupervised. In the case of the supervised learning algorithm, the entire training set is labeled. This tells the algorithm which data points are in the positive class (face) and which are in the negative class (non-face). In semi-supervised learning only a portion of the training set is labeled and in unsupervised learning none are labeled. Each type of algorithm has different applications, but for this experiment a supervised learning algorithm is ideal. Every trace from the EEG data is automatically labeled as a face or non-face data point. Not including this information will only hinder the algorithm’s performance. Semi-supervised and unsupervised learning algorithm are reserved when there are a large number of data points and acquiring labels is too expensive.

6.2 Support Vector Machine (SVM)

One of the biggest revolutions in the field of machine learning has been the support vector machine (SVM). This algorithm maps input vectors onto a high-dimensional space where it computes the hyperplane which optimally separates the data into two classes. Optimality for the SVM is the hyperplane which maximizes the margin between the two classes. The margin is defined as the shortest line perpendicular from the hyperplane to any data point. This type of learning algorithm is called a support vector machine because this hyperplane is only constrained by the select few training points (support vectors) which lie on the margin. Adding additional points outside of the margin has no effect on overall the classification boundary. In cases where no linear hyper-plane can divide the training set, slack variables can be introduced to allow data points to lie within the margin.

By default the SVM looks for a linear hyperplane, but by using the 'kernel trick' it can be extended to nonlinear classification. Conceptually this can be thought of as manipulating the mapping of the input vectors on to a nonlinear dimension
space. Solving for the ideal hyperplane in this new mapping results in a nonlinear classification boundary in the original space. This 'trick' allows more complicated data sets to be correctly classified.

Data with complex but known relationships lend themselves to nonlinear classification, but the data in this experiment is new. Using such a classifier is unjustified and could result in an overly constrained classification boundary. In cases where the underlying relationship is unknown, linear classifiers are typically used. For this reason linear SVM were chosen for this experiment. To estimate the performance of the SVM a five fold cross-validation set up was used,[17] The 60 trials were be broken up into 5 groups of 12. The SVM was trained on four of the groups and tested on the remaining one. This process was be repeated such that every group served as the test set once. Cross validation insured the classification performance was not a fluke of the data and was the result of more generalized underlying pattern.

6.3 Feature Selection

To find which aspects of the EEG signal contain important face processing data, the features created from the spectrogram were broken into subsets. As stated above, there were 700 features for each of the 128 sensors. For this experiment each sensor was treated independently and acted as its own classifier. To find an underlying
Figure 6-2: Example of frequency feature used to create frequency histogram

biomarker three different types of information where looked for: spatial, frequency, and temporal.

To determine spatial information, the entire set of 700 features was given to the SVM. This defines an overall classification rate for a particular sensor. By looking at where these sensors lie on the skull and how they compare to their neighbors spatial information about face processing can be determined.

Frequency information can be determined by submitting individual frequency bands. Looking at the spectrogram, this can be thought of as only using one row at a time. This frequency vector will contain the power content of a specific frequency over the time course. Analysis in this manner will show the role of specific bands throughout extended face processing.

Finally, basic temporal information will be computed by splitting the spectrogram in two. The exact same frequency analysis described above will be run, except instead of providing the SVM with the entire time course only have will be given. This process will be run once on the first 3.5 seconds and again on the last 3.5 seconds. Splitting
the spectrogram up in this manner provides basic information about when specific frequencies play a role.

Looking at particular sensors individually can be misleading. Sensor values are unlikely to match across subjects because of variations in skull size and how the EEG sensor cap was positioned. Luckily regions of the brain tend to act together, so looking at group statistics will provide a more reliable insight into how the brain is functioning. For this experiment there are 9 brain regions used to group sensors:

- Frontal
- Parietal
- Temporal-parietal (LH)
- Temporal-parietal (RH)
- Temporal (LH)
- Temporal (RH)
- Occipitotemporal (LH)
- Occipitotemporal (RH)
- Occipital

The classification results from each sensor will be aggregated into these groups and statistical tests of significance will be run. Each brain region will contain a list of results for all of the feature sets. A Student’s t-test will be used to compute how likely these results were drawn from a random classification. A t-test computes the probability that a given set of observations were drawn from a distribution centered around some specific mean. For the purposes of this experiment, the list of classification rates (the set of observations) will be compared against a 50% mean. That is to say, the t-test will determine how likely the results for a given feature came from classifiers that perform at chance. Likelihoods below 5% will be considered statistically significant.
Chapter 7

RESULTS

7.1 Spatial

After processing each sensor was grouped into its respective brain region. A list was compiled of the classification rates for each sensor when the entire spectrogram was given to the SVM. The mean classification rate was computed and the whole process was repeated for each of the 12 subjects. At the end there were 12 observations for the classification rates of each of the 9 brain region. The average classification rate across subjects for each brain region was above chance and after running a t-test to see if the 12 observations could have resulted from chance each brain region proved to be statistically significant. The average classification results across all subjects are plotted in Figure 7-1 and the probabilities they resulted from chance are shown in Table 7.1. The classification rates for the Occipitotemporal (Left Hemisphere), Occipitotemporal (Right Hemisphere), and Occipital regions performed significantly higher than the other 6 regions and were selected for for further analysis.

7.2 Frequency

The average frequency histogram (classification rates as function of frequency) for each of the three brain regions was computed and plotted. A t-test was run for each frequency band across all sensors each brain region to determine if the frequency
Figure 7-1: Average classification rate of the 9 brain regions across all subjects

Table 7.1: Probability brain region classifications resulted from chance

<table>
<thead>
<tr>
<th>Brain Region</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frontal</td>
<td>0.29%</td>
</tr>
<tr>
<td>Parietal</td>
<td>0.35%</td>
</tr>
<tr>
<td>Temporal-parietal (LH)</td>
<td>1.26%</td>
</tr>
<tr>
<td>Temporal-parietal (RH)</td>
<td>1.52%</td>
</tr>
<tr>
<td>Temporal (LH)</td>
<td>2.32%</td>
</tr>
<tr>
<td>Temporal (RH)</td>
<td>2.92%</td>
</tr>
<tr>
<td>Occipitotemporal (LH)</td>
<td>0.04%</td>
</tr>
<tr>
<td>Occipitotemporal (RH)</td>
<td>0.12%</td>
</tr>
<tr>
<td>Occipital</td>
<td>0.04%</td>
</tr>
</tbody>
</table>
band was statistically significant. If the frequency band performed above chance and passed the t-test then it was displayed as blue, if it failed either test it was displayed as red. Visual inspection showed a consistent spike around the 10 Hz and the 20 Hz frequency range across the subjects. Figure 7-2 and Figure 7-3 show example frequency histograms displaying the noted frequency spikes. The plots of every subject can be found in Appendix B.

7.3 Temporal

There appeared to be little difference between the frequency histogram for the first half of the stimuli presentation against the second half. This seems to show that the resulting 10 Hz and 20 Hz information spikes are not the result of transient signals evoked by the onset of the stimuli. Figure 7-4 and Figure 7-5 show examples of the
Figure 7-3: Example of frequency histogram from subject 10
Figure 7-4: Effect of temporal information from subject 7

relatively consistent frequency histograms for the first and second half of the time
course. The same color scheme described in the Frequency section was used. The
plots for every subject can be found in Appendix C.

7.4 Energy Content

To determine the unique brain signature for extended face viewings, the power content
of these two frequency bands was computed. The average power across the 10 Hz
band (averaged from 8 Hz to 12 Hz) and the 20 Hz band (averaged from 18 Hz to 22
Hz) for the entire time course was computed during face and non-face viewings. A
two Hz margin was used to account for subject variability. Comparing the two values
for each band showed that the power density decreases in the 10 Hz range during and
extended face viewing and increases in the 20 Hz range. Figure 7-6 and Figure 7-7
show the comparison between the face and non-face power conditions.
Figure 7-5: Effect of temporal information from subject 1
Figure 7-6: Log power content in the 10 Hz frequency band.
Figure 7-7: Log power content in the 20 Hz frequency band
Chapter 8

CONTRIBUTIONS

This thesis discovered a distinct brain signature for extended dynamic face processing in neurotypical subjects. With this biomarker future work can begin on its presence in autism. This brain pattern is defined by the following three findings:

1. The Occipitotemporal (Left Hemisphere), Occipitotemporal (Right Hemisphere), and Occipital regions contain the most information during extended face processing.

2. In those brain regions the 10 Hz and 20 Hz frequency bands play a consistent and statistical significant role.

3. Activity in the 10 Hz range decreases and activity in the 20 Hz range increases.
Appendix A

Spectrograms
Figure A-1: Spectrogram for Subject 1
Figure A-2: Spectrogram for Subject 2
Figure A-3: Spectrogram for Subject 3
Figure A-4: Spectrogram for Subject 4
Figure A-5: Spectrogram for Subject 5
Figure A-6: Spectrogram for Subject 6
Figure A-7: Spectrogram for Subject 7
Figure A-8: Spectrogram for Subject 8
Figure A-9: Spectrogram for Subject 9
Figure A-10: Spectrogram for Subject 10
Figure A-11: Spectrogram for Subject 11
Figure A-12: Spectrogram for Subject 12
Appendix B

Frequency Plots
Figure B-1: Frequency Information for Subject 1
Figure B-2: Frequency Information for Subject 2
Figure B-3: Frequency Information for Subject 3
Figure B-4: Frequency Information for Subject 4
Figure B-5: Frequency Information for Subject 5
Figure B-6: Frequency Information for Subject 6
Figure B-7: Frequency Information for Subject 7
Figure B-8: Frequency Information for Subject 8
Figure B-9: Frequency Information for Subject 9
Figure B-10: Frequency Information for Subject 10
Figure B-11: Frequency Information for Subject 11
Figure B-12: Frequency Information for Subject 12
Appendix C

Temporal Plots
Figure C-1: Temporal Information for Subject 1
Figure C-2: Temporal Information for Subject 2
Figure C-3: Temporal Information for Subject 3
Figure C-4: Temporal Information for Subject 4
Figure C-5: Temporal Information for Subject 5
Figure C-6: Temporal Information for Subject 6
Figure C-7: Temporal Information for Subject 7
Figure C-8: Temporal Information for Subject 8
Figure C-9: Temporal Information for Subject 9
Figure C-10: Temporal Information for Subject 10
Figure C-11: Temporal Information for Subject 11
Figure C-12: Temporal Information for Subject 12
Appendix D

BCS-Subjects Email
Hi,

The Sinha Lab is looking for volunteers for an EEG experiment this week and next. Sessions will last roughly 1 hour, and you'll be paid $10 for participating.

Our only requirements are that you have normal or corrected to normal vision and normal hearing.

Be prepared to have your hair get a little damp, since we have to keep an electrolyte solution on the EEG net at all times in order for a recording to be transferred from your head to the net.

If you are interested in volunteering, please reply to lsurban@mit.edu.

The lab is in 46-4089. If you need directions, they can be provided when your appointment is confirmed.

Thanks,
Luke Urban
Sinha Lab
Bibliography


