The Neural Mechanisms of Face Ensemble Processing: Decoding Facial Summary Statistics from ERP Signals

by

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Abstract

Previous behavioural work has demonstrated our ability to extract summary statistics from groups of faces such as identity. Because we know very little how the extraction of summary statistics for identity occurs in the cortex, I used electroencephalography (EEG) to explore the neural basis of identity summary statistics. I collected EEG data while participants viewed face ensembles or single faces presented one at a time. Different ensembles were designed so that they contained the same average face. Pattern analyses were then conducted across signals recorded from 12 occipitotemporal electrodes. The analyses revealed that ensembles with different averages could be decoded from one another suggesting that we possess a mechanism capable of summarizing identity well enough that the neural signal for one ensemble is decodable from that of an ensemble with a different average. This thesis investigation sheds new light on the neural basis of ensemble processing of identity.
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# Table of Contents

Acknowledgments .................................................................................................................................................. iii

Table of Contents ................................................................................................................................................ iv

List of Tables ........................................................................................................................................................ vi

List of Figures ...................................................................................................................................................... vii

Chapter 1 Introduction ...................................................................................................................................... 1

  1.1 Behavioural Research on Face Ensembles ................................................................................................. 1
      1.1.1 Emotional Summary Statistic Extraction .......................................................................................... 1
      1.1.2 Gender Summary Statistic Extraction ............................................................................................. 2
      1.1.3 Identity Summary Statistic Extraction ............................................................................................. 3

  1.2 Neural Research on Face Ensembles ........................................................................................................... 4
      1.2.1 Neural representations of gender as a summary statistic using FMRI ............................................. 4
      1.2.2 Electroencephalography and multiple face processing ..................................................................... 4

  1.3 Multivariate Pattern Analysis ..................................................................................................................... 6
      1.3.1 Background ...................................................................................................................................... 6
      1.3.2 Support vector machines ................................................................................................................. 7
      1.3.3 SVM and EEG ................................................................................................................................. 9

  1.4 Project Goals ............................................................................................................................................... 9
      1.4.1 Behavioural demonstration of summary statistic extractions ......................................................... 9
      1.4.2 Compare the neural signatures for individual faces and face ensembles ..................................... 10
      1.4.3 Confirm EEG is a viable data collection method for identity discrimination by MVPA ............ 10

Chapter 2 Methods and Analyses .................................................................................................................. 12

  2. Method .......................................................................................................................................................... 12
      2.1 Participant and Stimulus Selection ......................................................................................................... 12
          2.1.1 Participant selection ..................................................................................................................... 12
          2.1.2 Experimental stimuli selection .................................................................................................... 12
          2.1.3 Face ensemble design ................................................................................................................. 14

      2.2 Behavioural Pre-testing ........................................................................................................................ 16
          2.2.1 Procedure ..................................................................................................................................... 16
          2.2.2 One-back individual identity discrimination task ........................................................................ 19
2.2.3 One-back ensemble mean identity discrimination task............................... 21

2.3 EEG Experiment ................................................................................................. 23
  2.3.1 EEG individual face block design............................................................... 23
  2.3.2 EEG ensemble face block design................................................................. 26
  2.3.3 EEG data collection ....................................................................................... 26
  2.3.4 EEG data pre-processing .............................................................................. 27

2.4 Analyses ............................................................................................................. 31
  2.4.1 Behavioural pre-testing ............................................................................... 31
  2.4.2 Preparing EEG data for SVM ..................................................................... 31
  2.4.3 Preparing EEG data to compare different ensemble clusters ....................... 33

Chapter 3 Results, Discussion and Future Directions ............................................. 34

3 Results .................................................................................................................. 34
  3.1 Behavioural Pre-testing ................................................................................... 34
  3.2 ERP Comparisons ............................................................................................ 35
    3.2.1 Individual identity and face ensemble discrimination ............................... 35
  3.3 True Ensemble Cluster Discrimination ........................................................... 38
  3.4 Pair-Wise Individual Identity and Ensemble Discrimination ........................... 43
    3.4.1 Individual identity and face ensemble discrimination ............................... 43
  3.5 Discussion ......................................................................................................... 45
    3.5.1 Ensembles with different averages are processed differently .................. 45
    3.5.2 Summary statistic extraction may be automatic ....................................... 46
    3.5.3 Classification of individual identities and ensemble stimuli ..................... 47
  3.6 Future Directions ............................................................................................. 48
    3.6.1 Recruit more participants ......................................................................... 48
    3.6.2 Develop time courses of discrimination for face ensembles and individual identities .... 48
    3.6.3 Develop a regressive model of ensemble processing ............................... 49
  3.7 Conclusions ....................................................................................................... 50

References ............................................................................................................... 51

Copyright Acknowledgements ............................................................................... 53
List of Tables

Chapter 3

Table 3-1: Latency and amplitude comparisons of ERP signals ..........................37

Table 3-2: Averages of different training-testing conditions ............................42
List of Figures

Chapter 1

Figure 1-1: Visualization of SVM .................................................. 8

Chapter 2

Figure 2-1: Individual identity stimulus selection ................................ 13
Figure 2-2: Face ensemble stimuli design ........................................... 15
Figure 2-3: Sample behavioural trial in an individual face block ................. 17
Figure 2-4: Sample behavioural trial in a face ensemble block ................. 18
Figure 2-5: Participant arrangement for behavioural and EEG experiments ....... 20
Figure 2-6: Face ensemble stimulus size in visual space....................... 22
Figure 2-7: Sample EEG trial in an individual face block ......................... 24
Figure 2-8: Sample EEG trial in an individual face block ......................... 25
Figure 2-9: An example of eye-blink artifact removal ......................... 30
Figure 2-10: Electrode map with highlighted OT electrodes ................. 32

Chapter 3

Figure 3-1: Behavioural Pre-testing results .................................. 34
Figure 3-2: Averaged EEG waveforms with labelled ERP signals .......... 36
Figure 3-3: SVM classification accuracies of different ensemble subclusters .... 38
Figure 3-4: Confusability Matrix of Ensemble Subcluster Decoding .......... 40
Figure 3-5: Comparing Within Ensemble Cluster Decoding to Across Ensemble Cluster Decoding…………………………………………………………………………………………………40

Figure 3-6: Leave-one-block-out classification accuracies………………………………………………………44
Chapter 1
Introduction

1 Introduction

1.1 Behavioural Research on Face Ensembles

1.1.1 Emotional Summary Statistic Extraction

Human beings often encounter groups of faces in the natural world. Whether it be in an office, a classroom, or just walking down the street, humans are subjected to many faces in different situations. Despite the abundance of research conducted on how individual faces are represented using neuroimaging techniques, there exists a large gap in the literature on how groups of faces (i.e. face ensembles) are represented using neuroimaging techniques.

Behaviourally, face ensembles has been extensively researched. One of the first studies to investigate face ensembles examined our ability to extract summary statistics of face ensembles in terms of gender and emotion. Haberman and Whitney (2007) were able to demonstrate, in three separate behavioural experiments, that people are able to quickly identify the average emotion and gender of a face ensemble consisting of four faces. In one of the three experiments, participants were shown a set of four black and white faces for 2000 ms and were then shown a single face. The participants’ goal in this experiment was to identify if the individual face was happier or sadder than the overall emotion of the previously viewed ensemble of four faces. Participants succeeded at this task in that they were able to discern the ensemble’s average emotion. In a follow up study (Haberman & Whitney, 2009), a similar task was completed with two major modifications however. Compared to the previous study mentioned, the ensemble size now consisted of 16 faces and was only displayed for 500 ms compared to the ensemble of four faces displayed for 2000 ms. Despite the increased demand on participants, the study demonstrated that people are still able to extract the summary statistics in the form of an average emotionality of the face ensembles.
However, in these studies the ability of these participants to extract summary statistics did not help their ability to discern if an individual face may have been present in an ensemble. Using a two alternative forced choice (2afc) task, Haberman and Whitney (2007) flashed an ensemble of four faces to participants which was then followed by two individual faces with different identities. The experiment had participants guess as to which one of these faces were present in the ensemble they just viewed. Contrary to their results in which participants could estimate the “average” emotionality of a face ensemble, participants were unable to recognize if individual identities were part of an ensemble.

In addition to being able to extract the mean emotion of an ensemble, Sweeny, Grabowecky, Paller, and Suzuki (2009) demonstrated that we average the emotions of pairs of faces, not just large ensembles. Sweeny and colleagues presented two emotional faces (happy, surprised, or angry) for only 100 ms then instructed participants to rate one of the faces (cued with an arrow) on a scale ranging from 1 (most negative expression) to 4 (most positive expression). When opposing emotional faces were presented, participants rated happy faces as less positive than they were and conversely rated angry faces as less negative than they were. Two faces arguably fail to qualify as an ensemble however, the finding that we are able to average two emotions suggests that humans are able to quickly extract some sort of summary statistic between at least two faces (and more in the Haberman and Whitney studies).

1.1.2 Gender Summary Statistic Extraction

Emotions are not the only summary statistic that is able to be quickly extracted from a face ensemble. As mentioned previously, average gender is also able to be extracted from an ensemble of faces. Haberman and Whitney (2007) demonstrated that participants are able to discern if the average gender of an ensemble is either male or female. Even with the addition of a Gaussian noise mask, the average gender was still able to be estimated by participants. The addition of a noise mask is a simple, but key, manipulation to the experiment because it eliminates the possible argument that summary statistic extraction (from faces) may rely on low-level features such as contrast or brightness. The rapid extraction of a summary statistic counters a claim made my Fiser and Aslin (2001) which contended that summary statistic extraction required an extended period of time and is not possible with brief exposures to stimuli.
1.1.3 Identity Summary Statistic Extraction

In addition to gender and emotion, the extraction of mean identity has been the topic of research as it relates to face ensemble processing. To elucidate how identity is represented when face ensembles are processed would shed a great deal of light on how detailed summary statistics can be, specifically when processing multiple faces at the same time. de Fockert and Wolfenstein (2009) explored if identity could be quickly extracted as a summary statistic, in a way similar to that of gender or emotion discussed previously. To investigate this, participants were shown a set of four heterogenous faces for 2000 ms and then were asked to respond to a target face that fit in to one of four categories: 1) Matching face morph where this face could be a morph of all four faces presented; 2) Non-matching face morph where this face is a morph of a different set of four faces; 3) Matching member where this face is one of the four faces that was just presented; 4) Non-matching member where this face is neither a morph nor a member of the four faces presented. Unsurprisingly, participants were more likely to respond to a target as “present” if it was a matching target face from the ensemble they just viewed compared to if the face is a non-matching morph of a different group of faces. Interestingly however, participants were more likely to respond to a target face as being a member of the ensemble if the target face was a matching face morph of all four faces rather than a member of the ensemble they just viewed. These results suggest that participants were able to extract mean identity similarly to that of previous studies which investigated emotionality and gender. In addition, because

The studies discussed above are key studies in the face ensemble literature in that they were some of the first to demonstrate that face ensembles are processed differently than individual faces. Together, the studies have produced some theories as to what kinds of summary statistics people are able to extract from a group of faces in a relatively short amount of time (gender, emotionality, and identity) (de Fockert & Wolfenstein, 2009; Haberman & Whitney, 2007, 2009). These studies lay the behavioural and theoretical framework to further investigate how face ensembles are processed, but through a neural context, rather than a purely behavioural one.
1.2 Neural Research on Face Ensembles

1.2.1 Neural representations of gender as a summary statistic using fMRI

One of the first studies to investigate face ensembles in the context of a neural paradigm investigated the neural correlates of summary statistical processing of face ensembles and how, specifically, gender may be represented. Nagy and colleagues (2012) used a similar design to that of Haberman and Whitney (2007, 2009) in which participants were shown face ensembles (referred to as “multiple face stimuli”), then required them to indicate if the mean of the ensemble was male or female. The addition of functional magnetic resonance imaging (fMRI) to this experiment allowed for localization of any regions of interest (ROIs) for face ensemble processing. The ensembles, consisting of 8 concentrically arranged faces around fixation replicated previous findings in that participants were able to successfully determine if the average of an ensemble was male or female. Moreover, Nagy and colleagues were able to localize the right fusiform face area (rFFA) as a brain area heavily involved in processing face ensembles. Although this finding may be somewhat trivial as it is well established that the FFA is heavily involved in face processing (Kanwisher, McDermott, & Chun, 1997; Kanwisher & Yovel, 2006), the finding was one of the first to examine ensemble face processing from a neural perspective. Although not widely used at the time, robust modern techniques such as pattern analysis, may have been able to differentiate the signals from ensembles with varying ratios of male to female faces included in the stimuli.

1.2.2 Electroencephalography and multiple face processing

There still remains plenty to be investigated with respect to face ensembles however. Even with fMRI being used to investigate how groups of faces are represented neurally, electroencephalography (EEG) is severely underrepresented in face ensemble research. To date, there is a limited number of EEG studies investigating the neural representations of groups of faces and of these that exist, they fail to directly compare how the neural signal for individual faces compares to that of face ensembles.

One such study by Kaunitz and colleagues (2014) examines how, in a serial search task (similar to that of a “Where’s Waldo?” search task), the EEG signals are represented for a single face in
the context of a large group of faces. Specifically, they were interested in assessing what differences are represented in the EEG signal when people fixate on distractor stimuli compared to when people fixate on target stimuli. The study had participants search for target faces in pictures of crowds at various sports stadiums. Each target face was presented before each trial for 3 seconds then participant had to locate the target in a crowd containing between 23 and 25 distractor faces. Analyses of event-related potentials (ERPs) were only conducted when participants fixated on a face (aptly named fixation event-related potentials [fERPs]). In order to boost the signal-to-noise ratio (SNR), Kaunitz and colleagues conducted analyses solely on these fERPs. Although this study is admittedly more focused on developing a method of analysis that mitigates eye movement artifacts, it is not without its contributions to face ensemble processing, specifically in terms some general ERP differences between fixating on target stimuli versus distractors. Firstly, it was demonstrated that overall, the electrical activity was much more robust when fixating on targets compared to distractor stimuli. Secondly, this study is one of the first to demonstrate that a familiar face amongst a group of unfamiliar faces can result in a much stronger N170 ERP signal, which is reliably elicited around 170 ms after the presentation of a face (Bentin, Allison, Puce, Perez, & McGarthy, 1996). What this suggests is that the brain processes familiar faces differently than unfamiliar faces, even in the context of a crowd with many faces.

Although the previous study may appear to examine face ensemble processing, one could argue that the study is still one that emphasises individual face processing in the context of a group of faces rather than solely ensemble processing. Despite many faces being present at one time, participants were instructed to focus on one face at a time and therefore is not necessarily a face ensemble processing study. There is a striking lack of literature in this area and to date, there is only one study that directly compares the neural signature for face ensembles to that of individual faces, specifically comparing different ERPs.

In 2013, Puce and colleagues explored how changing the number of faces in an ensemble can affect different ERP signals. In a simple EEG experiment, participants viewed stimuli consisting of one, two, or three faces. Most major signals associated with face processing were modulated by the number of faces viewed. The P100, an ERP signal thought to be associated with the mental categorization of a viewed stimulus (Hermann, Ehlis, Ellgring, & Fallgatter, 2005), did not waiver much in amplitude nor in latency. However, Puce demonstrated that the N170 signal
appeared earlier and was stronger in amplitude compared to when only a single face was presented. Other ERP signals associated with face processing, the P250 and P400, signals associated with the transition in to semantic distinction of stimuli (Alison et al., 1994; Parker & Nelson 2005; Gandhi, Suresh, & Sinha, 2012), did not show any systematic modulation between the number of faces being viewed.

Although the study by Puce and colleagues is one of the first to compare ERPs when people view individual faces and face ensembles, there still remain many unaddressed concerns. Firstly, it may not be appropriate to classify a stimulus consisting of three faces could be hard to classify as an “ensemble”. Although there is no set definition of an “ensemble”, it could be argued that a stimulus consisting of three faces might be on the low end of that spectrum. Secondly, the study misses an opportunity to further explore how previously researched summary statistics (such as emotion, gender, or identity) may be represented within ensembles in terms of its neural signature using EEG. Using pattern analysis techniques, previous research has demonstrated that EEG contains enough information to not only discern which identity an individual is looking at, but also that the signal and method of analysis is robust enough to reconstruct individual faces from the EEG signal (Nemrodov, Niemeier, Ngo Yin Mok, & Nestor, 2016). In this thesis I use state-of-the-art techniques to explore the neural representation of face ensemble processing.

1.3 Multivariate Pattern Analysis

1.3.1 Background

Using pattern classification to discriminate facial identity is a novel method in the individual face processing literature however, its application to face ensemble research would shed a great deal of light on how people extract summary statistics from faces. If ensembles with a variety of different mean identities or emotions are uniquely represented, multivariate pattern analysis offers the opportunity to detect these variations in the neural signal that univariate analyses cannot detect. It would allow for the argument that, much like individual identity, each variation of a broader summary statistic may be represented differently at a neural level.

Previous work may have benefited from the utilization of multivariate analyses to further elucidate face processing in humans. The use of multivariate pattern analyses (MVPA) has
become more popular in recent neural studies and has offered great insights into how our brains process different kinds of information. First utilized in fMRI research, MVPA has provided considerable advancements in elucidating how humans process identity by classifying neural signals based on objective qualities of characteristics (i.e. the “uniqueness” of the neural signal for a certain stimulus compared to other; Haxby et al, 2001). Specifically, the use of support vector machines (SVM) has become a common tool for researchers in an attempt to differentiate between neural patterns not detectable by univariate analyses.

### 1.3.2 Support vector machines

SVM has become a common tool for multivariate analyses. Typically, there can be two kinds of SVM that can be used: 1) linearly separable; and 2) non-linearly separable (Bhuyaneswari & Kumar, 2013). For the purpose of this thesis, whenever SVM is discussed, I am talking about linear SVM unless otherwise explicitly stated. In machine learning, SVM is a supervised learning model which attempts to analyse data and recognize patterns within that data which is almost always divided into two categories. SVM training algorithms are used to familiarize the classifier with examples of each category and then attempts to assign novel examples of data into one of the two categories. To optimally categorize data, SVM uses a hyperplane with margins which, ideally, perfectly separates the data into two discrete categories with a maximal distance between the two margins in order to reduce misclassification errors (Lotte, Congedom Lécuyer, Lamarche, & Arnaldi, 2007, Fig. 1-1).
Figure 1-1. Visualization of SVM. Support vector machines (SVM) separate data into two distinct categories by maximizing the margin between an optimal hyperplane and instances of data from two groups (support vectors) (modified from Lotte, Congedom Lécuyer, Lamarche, & Arnaldi, 2007).
1.3.3 SVM and EEG

In the context of EEG, SVM offers a great opportunity for use as EEG data is typically represented in high dimensional features space and can be very difficult to interpret. Because EEG has high dimensionality, SVM is an ideal classifier for such data in an attempt to analyze the characteristics of brain patterns. For example, one use of pattern classification in EEG is with the attempt to classify the neural signal for different human emotions (Nie, Wang, Shi, & Lu, 2011). However, as it relates to face processing, recent research has demonstrated just how sensitive MVPA is to identity. In an EEG study using SVM at different time points, Nemrodov and colleagues (2016) investigated the time course of identity discrimination using EEG signals. SVM was applied to four electrodes thought to be the most involved in face processing (two electrodes on each side of the scalp), all of which are located occipitotemporally. Successful classification of identity was achieved at several ERP signals demonstrating the sensitivity of MVPA in the context of EEG, but also demonstrating that the N170 is not just a response to a face, but in fact holds information relating to identity. This was not exclusive to the N170 signal and was demonstrated at other signals such as the N250 and N400 and as early as 70 ms after stimulus presentation. This study demonstrated both the efficacy of pattern analyses in the context of EEG, but also the time course to aid in the elucidation of neural face recognition mechanisms.

1.4 Project Goals

The overarching goal of my thesis work is to investigate how face ensembles may be represented neurally compared to individual faces using EEG as the main tool of investigation. My thesis work investigated if summary statistics for mean identity can be represented neurally and that, by using MVPA, these different summary statistics are discernible from each other. In other words, are ensembles with different mean identities discriminable from each other using a combination of EEG and MVPA?

1.4.1 Behavioural demonstration of summary statistic extractions

The study at hand involves two different components. In the first portion, participants completed a 2afc behavioural task with two separate conditions. In one condition, participants were shown
two successive individual faces and were asked to indicate if the two faces were the same or different. In the second condition, participants were shown two successive face ensembles and were asked to indicate if the two face ensembles possessed the same or different average identity. This portion of the study has 3 major goals: 1) to familiarize the participants with the stimuli that will be used in the EEG part of the study; 2) to establish a participant’s eligibility for the EEG part of the study given their performance in this behavioural study; and 3) to replicate previous findings which suggest that people are able to extract summary statistics for face ensembles (de Fockert & Wolfenstein, 2009; Haberman & Whitney, 2007, 2009); and 4) to provide a behavioural correlate of EEG results.

1.4.2 Compare the neural signatures for individual faces and face ensembles

Previous research investigating the neural signatures of object and face processing demonstrate a clear distinction in the EEG signature. The N170 ERP signal is often elicited earlier and in much higher amplitude for multiple faces compared to individual faces (Puce et al., 2013). Comparing the neural signatures for face ensembles and individual faces will shed light on the topic of if we process face ensembles in a similar time course compared to that of an individual face.

1.4.3 Confirm EEG is a viable data collection method for identity discrimination by MVPA

Machine learning techniques have become a common tool in cognitive neuroscience studies especially with the increased focus on pattern classification. As discussed previously, one of the most popular pattern classifiers is SVM which attempts to classify novel data points in to one of two categories based on training. In the context of EEG, SVM has been successful in being able to classify the neural signals for discrete facial identities from each other (Nemrodov, Neimeier, Ngo Yin Mok & Nestor, 2016), and with this study, I will support and extend upon this previous research by demonstrating that SVM is a robust tool capable of not only discriminating
individual identities from each other using EEG data, but also of discriminating different mean identities from each other.

Previous studies have been successful in demonstrating that individual identities can be discriminated from each other using SVM (Nemrodov, Neimeier, Ngo Yin Mok & Nestor, 2016). However, face ensemble research has yet to explore how ensembles, with different mean identities, may be represented neutrally. In other words, is the neural signal for one ensemble cluster with one mean identity different than the neural signal for another ensemble cluster with a second mean identity and is this difference demonstrably different using pattern classification?

If mean identity is able to be extracted as is suggested in previous research, the corresponding neural signal for such summary statistics (or mean identities) should be related to the signal of the ensembles from which the summary statistic came from. To this end, if a pattern classifier is trained on the neural signals from two groups of ensembles, each of which with a distinct mean identity, can we successfully classify the signal for the mean identities in to their corresponding groups? In other words, can identity summary statics be represented such that they are discriminable from one another in the context of EEG?
2 Method

2.1 Participant and Stimulus Selection

2.1.1 Participant selection

Eleven healthy, right-handed participants were recruited to participate in this study (7 females, 4 males; age range: 20-26). However, 3 participants failed to qualify for the EEG portion of the study and were excluded for analyses purposed. Included for analyses were 8 participants which completed both the behavioural pre-testing and EEG portions of the experiment (5 females, 3 males; age range 20-25). Participants were recruited from a selection of research assistants and graduate students from various labs at the University of Toronto.

2.1.2 Experimental stimuli selection

A total of 26 images of individual faces were used to design the experimental stimuli (26 images of individual faces, four unique 6-face face ensembles). Faces to be used in the ensembles were selected from a set of 60 neutral expression, Caucasian, male faces that have been used in previous research (Nestor, Plaut, & Behrmann, 2016). These 60 faces were projected into a face space using a multidimensional scaling algorithm which compared pixel-wise values of faces. The goal from this pixel-wise comparison was to identify two distinct groups of faces that are maximally distant from each other in face space which indicates that these two groups are maximally different. These two large clusters of faces (consisting of 12 faces each; 24 faces total) were selected such that they could have a maximally different average identity from each other (Group 1 and Group 2; Fig. 2-1). The remaining two individual faces were designed by averaging the pixel-wise values of the two clusters of faces. Importantly, these averaged identities retained 2 important qualities about them after processing: 1) the two averaged identities remained relatively normal in terms of face structure; and 2) the two averaged identities were obviously different from each other.
Figure 2-1. **Individual identity stimulus selection.** Two clusters of 12 individual identities were selected using pixel-wise comparisons such that each group was maximally different from the other. Each cluster (Cluster 1 and Cluster 2) were further separated into two subclusters each (Cluster 1A/1B and Cluster 2A/2B) to select the stimuli that will be used in the face ensemble stimuli. The averaged face identities are the result of a pixel-wise averaging and are not just objectively different using pixel-wise comparisons, but are also subjectively different simply by viewing them.
2.1.3 Face ensemble design

After clusters of individual identities were isolated, the 12 faces in each group were adjusted such that each face in the cluster was equally distant from the mean face in the face space. Despite the manipulation of the face images, the images still maintained a natural appearance ensuring ecological validity and, more importantly, distinctly identifiable stimuli from each other. (Fig. 2-1). These two clusters of adjusted face images were then further divided in to two subclusters of 6 faces (Subcluster 1A and 1B, Subcluster 2A and 2B) each of which made up the 4 original face ensembles that are used in the experiment Fig. 2-1). Importantly, the purpose of this manipulation of the individual identities is to ensure that each of the two subclusters have the same mean. It is important to note that each of the four ensembles have 6 different variations. Each variation of an ensemble consisted of a “rotation” of the ensemble in that from one variation to the next, the faces shifted clockwise one position in the ensemble (Fig. 2-2). This manipulation of the face ensembles was done to make it more difficult for participants to focus on one position of an ensemble to determine if the ensemble belongs to one group or another.
Each of the original 4 ensembles underwent 5 “rotations” to create the remaining face ensemble stimuli used in the study, for a total of 24 face ensemble stimuli.
2.2 Behavioural Pre-testing

2.2.1 Procedure

Prior to the EEG portion of the study, participants completed a behavioural pre-testing experiment to familiarize themselves with the stimuli that would be seen in the EEG portion as well as a screening tool to ensure that only participants who could successfully complete the behavioural portion of the experiment could participate in the EEG experiment. It also served to reduce any training effect during the EEG portion of the experiment which may reduce the signal to noise ratio. This session was done either the day before the EEG portion or immediately prior to the EEG portion depending on participant availability. In this behavioural session, participants completed seven blocks (50 trials in the first block, 75 trials in the remaining 6 blocks) of a one-back identity discrimination task. In the first three blocks participants were shown an individual face followed by a second individual face and then responded using the keyboard to indicate if the two faces they saw were the same or different (Fig. 2-3). For the remaining four blocks, participants were shown one ensemble of 6 male faces, followed by a second ensemble of 6 male faces. The participants were then required to indicate if the two ensembles they just viewed had the same or different mean identity, similar to that of Haberman and Whitney (2007) (Fig 2-4).
Figure 2-3. Sample behavioural trial in an individual face block. This sample trial of the behavioural pre-test in which participants had to discern two individual identities. Face 2 was an individual that shared the same identity in 50% of trials and in the remaining trials face 2 was a different identity.
Figure 2-4. Sample behavioural trial in a face ensemble block. Sample trial of the behavioural pre-test in which participants had to discern if two ensembles possessed the same average identity. Ensemble 2 was an ensemble that shared the same average identity in 50% of trials and in the remaining trials ensemble 2 was one that had a different averaged identity. Ensemble 2 was always an ensemble from a different subcluster see Fig. 2-1) even if the trial was designated as a “same average” trial.
2.2.2 One-back individual identity discrimination task

As mentioned above, the first three blocks of the behavioural component of my study consisted of a one-back individual identity discrimination task lasting approximately 5 minutes per block with self-paced breaks between blocks. The first block consisted of 50 trials in which trials began with an initial fixation cross for 400 ms followed by the presentation of an individual face for 1000 ms then an interstimulus interval (ISI) of 600 ms which was followed by a second individual face for 1000 ms then a fixation cross until the participant responded (Fig. 2-3). For the remaining 2 blocks, there were 75 trials in which the faces appeared on screen for only 300 ms with the ISI remaining the same (600 ms). The first block has extended stimulus presentation to ensure that participants were well versed in the task for the remaining 6 blocks of the behavioural session. After the second face had disappeared, participants were instructed to respond on a keyboard, using the “A” key to indicate they were different and “L” key to indicate they were the same, if the two identities that were presented were the same or different. The order of the faces was pseudorandomized such that that the participants saw the same identity in 50% of the trials. The face images, which measure 175 pixels tall (or 3 degrees of the visual field by 115 pixels wide (or 1.97 degrees of the visual field), were displayed in the center on a black 1920x1080 pixel screen in a dimly lit room to participants who sat approximately 80 cm away. Feedback on performance was provided on screen after each trial with either a green “V” for correctly indicating the identities were the same or different or a red “X” if they did not. (Fig 2-5). In addition, after each block, participants were given a percent correct for the block they just completed.
Figure 2-5. Participant arrangement for behavioural and EEG experiments. This was the arrangement for participants in both the behavioural and EEG portions of the study. Participants sat 80 cm away from a screen with a resolution of 1920x1080 pixels.
2.2.3 One-back ensemble mean identity discrimination task

The last four blocks of the behavioural pre-testing consisted of a one-back ensemble averaged identity discrimination task and consisted of 75 trials per block lasting approximately 5 minutes per block with self-paced breaks between blocks. Within a single trial, one face ensemble appeared on screen for 300 ms, followed by an ISI of 300 ms, then a second face ensemble appeared on screen for 300 ms. After the second face ensemble had disappeared, participants were instructed to respond on a keyboard if the two ensembles that were presented had the same or different averaged identity (Fig. 2-4). The face ensemble images were designed such that the faces occupied the parafoveal field of view while participants maintain central fixation. At a distance of 80 cm away from the screen, the face ensemble images occupied 9º of visual space vertically and approximately 7º horizontally (Fig. 2-6). Feedback on performance was provided after every trial as well as after every block. This portion of the behavioural pre-testing is not only designed to reduce any training effect during the EEG portion of the study, but it will also support previous research that demonstrated people are able to extract summary identity statistics from a group of faces (Haberman & Whitney, 2007, 2009).
The stimulus design for ensembles ensured that ensembles would be presented parafoveally (between 7° and 10° from fixation). Vertically, ensembles occupied 9° of visual space and 7° horizontally. Each face in the ensemble was presented 1.5° away from central fixation. The faces were the same size in both the ensembles and individual face trials. Face occupied 3° of visual space vertically and 1.97° of visual space horizontally.
2.3 EEG Experiment

2.3.1 EEG individual face block design

There were two types of blocks that participants completed throughout the EEG experiment. In one type, referred to as “individual face blocks”, participants viewed individual faces for 300 ms with a variable ISI of 600-700 ms in a go-no go paradigm. In an individual face block, each of the 26 individual identities were presented 8 times each, for a total of 208 experimental trials. The order of the stimulus presentation was pseudorandomized such that they did not see the same identity two times in a row. In these trials, participants were not required to make any keyboard response (i.e. “no go trials”).

In addition to the experimental trials, 26 catch (or “go”) trials were randomly interspersed in to a block. These catch trials were implemented to ensure a participant’s attention was directed at the screen. The catch trials consisted of a simple gender discrimination task in that whenever a female face appeared on screen, participants were to respond by pressing the space-bar on the keyboard (Fig. 2-7). Despite the catch trials being a gender discrimination catch trial, in the instructions for the experiment, participants were explicitly told to pay attention to the identity of the faces, not the gender.
**Figure 2-7. Sample EEG trial in an individual face block.** A typical trial design for individual face blocks in the EEG experiment. Jitter is important in the ISI fixation crosses as it reduces the likelihood of any adaptation artifacts in the neural data.
Figure 2-8. Sample EEG trial in a face ensemble block. A typical trial design for ensemble face blocks in the EEG experiment. Jitter is important in the ISI fixation crosses as it reduces the likelihood of any adaptation artifacts in the neural data.
2.3.2 EEG ensemble face block design

As mentioned previously, the EEG portion consisted of two types of experimental blocks. In one type, participants viewed individual faces with catch trials being a simple gender discrimination task. The other type of experimental block, referred to as “face ensemble blocks”, consisted of participants viewing face ensembles for 300 ms with a variable ISI of 600 – 700 ms. In a face ensemble block, each variation of the 4 ensembles (6 variations of 4 ensembles; Twenty-four total ensemble stimuli) was presented 8 times each, for a total of 192 experimental trials. The order of the ensemble stimuli was pseudorandomized such that each successive ensemble stimulus did not share the same average identity as the ensemble in the previous trial. For example, if in one trial a participant was presented with a face ensemble from Group 1, the following stimulus could not be from Cluster 1, but had to be from Cluster 2 and vice versa. In these trials, participants were not required to make any keyboard response (i.e. “no go trials”).

Much like the individual face blocks, the face ensemble blocks contained catch-trials (again referred to as “go” trials) to ensure that the participants were paying full attention to the screen. 24 catch trials were interspersed through each block to make the total number of trials in a block 216 trials. Catch trial stimuli consisted of 6 variations of a face ensemble that was composed of entirely female faces and when participants saw one of these ensembles of all female faces, they were to the press space-bar on the keyboard (Fig. 2-7, Fig. 2-8). Participants were explicitly instructed to avoid directing their gaze to single faces of the ensembles and to instead maintain fixation on the centrally located fixation cross, even during catch trials.

2.3.3 EEG data collection

Participants sat in a dimly lit room approximately 80 cm away from a computer monitor that measured 55 cm diagonally and had a resolution of 1920x1080 pixels. The size of both types of stimuli (individual faces and face ensembles) remained identical to the behavioural session of the experiment.
Participants completed 32 experimental blocks, with self-paced breaks between blocks, over 2 sessions held no more than 3 days apart. Each session began with two blocks of training (one individual face block and one face ensemble block) to familiarize participants with the task prior to completing the 16 experimental blocks. The training blocks also allowed for the opportunity to correct any noise or artifacts in the EEG recording such as, for example, an electrode no being properly connected to the scalp because of a lack of gel, thus creating a noisy signal that is not representative of an accurate neural signal. After the training blocks, the block type alternated every four blocks, always beginning with individual face blocks. This alternation of blocks was implemented in order to avoid any stimulus adaptation which can be common in long-session studies such as this, resulting in a less informative signal.

2.3.4 EEG data pre-processing

EEG data was collected with a high density 64 channel system using BioSemi (BioSemi, Amsterdam, Netherlands) from gelled electrodes mounted on an elastic cap using the International 10-5 electrode system (Waveguard, ANT, and ElectrodeArrays). Electrodes CMS and DRL operated as the online reference electrodes while AFz operated as the ground. The reference was computed offline based on the average of all electrodes. The EEG signal was amplified (STATS) at a sampling rate of 512 Hz.

In order to make the EEG data suitable for proper analyses, pre-processing steps were implemented offline separately for each participant using Letswave 6 (http://www.nocions.org/letswave/). Firstly, all trials which contained false alarm responses, hits and misses were removed from the data. Next, electrodes were analyzed for bridging. If electrodes are bridged, it can often occur because too much electrode gel was injected in to one or more electrode wells. This results in two electrodes sharing a signal, but luckily can be rectified using bridging corrections. The next step in pre-processing was to perform a Butterworth filter to remove frequency based noise from the EEG data. Data was Butterworth filtered between 0.01 and 40 Hz based on previous research (Nemrodov, Neimeier, Ngo Yin Mok & Nestor, 2016). This step of pre-processing removes high frequency noise that may result from an EEG machine being sensitive to any surrounding sources of electricity. After the frequency filtering, the EEG data files were segmented in to individual files per block. At this
point in pre-processing, there are still only 2 files (one per session) and the segmentation of the files in to blocks breaks the two files in to 32 files (one per block) where each underwent direct current (DC) removal. This step is necessary as it removes electrical noise that is given off from the EEG amplifier involved in data collection.

Once the DC is removed, extremely noisy electrodes were interpolated to their closest three electrodes. This was only conducted on electrodes that were not one of the key electrodes thought to be involved in face processing (Nemrodov, Neimeier, Ngo Yin Mok & Nestor, 2016). Avoiding the interpolation of these electrodes is key to preserving the validity of the EEG data, but by itself, interpolation is a key step in pre-processing in that when independent component analysis is conducted (to be discussed later), it will make eye-blink artifacts more detectable to remove from the signal. The most common type of electrode that was interpolated typically was located in the frontal areas. After interpolation is completed, noisy trials are removed. Ideally, a noisy trial will affect multiple electrodes to fully justify removal, but rarely a single electrode will only be afflicted with a noisy trial. In these rare instances, a noisy trial which exceeded +/- 1000 µV was removed from the data (normal trials are typically no more than +/- 400 µV).

Importantly, it should be noted that no more than two repetitions of one stimulus per block were removed in order to preserve as much data for the SVM algorithms to train on as possible to help boost classification accuracies.

After artefactual trials were removed, the next step was to merge all the blocks together by condition then by block. What this means is that all the pre-processed individual face blocks of one session were merged in to one data file and all the face ensemble blocks of one session were merged in to one data file, creating four data sets. Each of the four data sets underwent independent component analysis (ICA) which is commonly used in EEG studies to detect the presence of eye-blink and eye movement artifacts. ICA for EEG pre-processing is based on two reasonable foundations: 1) EEG data recorded is composed of linear sums of temporally independent components arising from unique or overlapping brain networks which are spatially fixed; and 2) the spatial spread of an electric signal from cortical sources does not have significant time delay (Jung, Makeig, Westerfield, Townsend, Courchesne, & Sejnowski, 2000).
After the ICA was ran on the four merged data sets, the computed ICA matrix was assigned back to their respective blocks based on condition (individual face or face ensemble) and session (1 or 2) then eye-blinks were removed (Fig. 2-9).

Following eye-blink artifact removal, the data at all electrodes was re-referenced prior to any kind of baseline correction. The electrode DRL served as ground electrodes and the CMS acted as the active reference electrode. Re-referencing is computed by averaging the signals from all channels. Following re-referencing, baseline corrections were made such that the data for each trial ranging from 100 ms prior to stimulus onset was centered around 0. This step in pre-processing helps visualize ERPs in to their classic shape.
Figure 2-9. An example of eye-blink artifact removal. In the top frame, we can see an example of a distinct spike in the EEG data on a single trial indicative of an eye-blink. The red line indicates what the neural signal will look like after the IC is removed. In the bottom frame, we can see an example of a trial without an eye-blink. It should be noted that if the same IC is removed from such a trial, the neural signal does not change as much as if an eye-blink was present.
2.4 Analyses

2.4.1 Behavioural pre-testing

For each participant, accuracies were averaged within condition and compared to chance level performance (50%) using a one-sample t-test. Reaction times were recorded but were not utilized in any further analyses since the behavioural portion of the study was more focused on accuracy of performance and not currently interested in correlating reaction time to any other index of performance.

2.4.2 Preparing EEG data for SVM

As mentioned previously, SVM is a robust tool for pattern classification in EEG, especially in the context of being able to discriminate the neural signals for individual identities (Nemrodov, Niemeier, Ngo Yin Mok, & Nestor, 2016). However, the data must undergo several steps of preparation in order to be usable for pattern classification. For the purpose of this thesis, I followed a similar pipeline of analysis to that of Nemrodov and colleagues (2016). All pattern classifications were conducted in MATLAB using the LIBSVM package (Chang and Lin, 2011).

For each participant, all the signals for each individual identity and face ensemble stimulus were loaded into a 26x16 and 24x16 cell matrix respectively. For individual faces, each row represented a unique identity and each column represented a block. Within each cell of the matrix, the neural data for each stimulus was contained within a 3-dimensional matrix with the three dimensions being [stimulus repetitions x electrodes x time-points]. After pre-processing, the number of repetitions that remained for all stimuli (26 individual identities and 24 face ensemble stimuli) ranged from 5 to 8. Next, the EEG data was normalized across all stimuli and by z-scoring data at each time point and outliers deviant by more than ±3 z-scores were thresholded and replaced with corresponding values equal to ±3 z-scores. Then EEG signals corresponding to each stimulus was averaged within blocks and only 12 bilateral (6 left and 6 right) occipitotemporal (OT) of the 64 total electrodes were involved in SVM analysis (Fig. 2-10). The 12 OT electrodes were utilized in analyses as they have been shown to be involved in identity processing based on a similar EEG-SVM paradigm (Nemrodov, Niemeier, Patel, & Nestor, under review).
SVM classification was then carried out on normalized signals across the 12 selected electrodes (penalty parameter $c = 1$) using a one-against-one pattern classification by use of a leave-one-block-out cross-validation paradigm. It is important to remember that the experimented consisted of 32 total blocks, but only 16 of these blocks consisted of individual identities and the other 16 consisted of face ensembles. Thus, in this classification paradigm, all 26 signals corresponding to individual identities and 24 signals corresponding to face ensemble stimuli in 15 of their 16 respective blocks were used to train the pattern classifier. The remaining block was used as a testing set of data to determine the effectiveness of the pattern classifier. This procedure is done by systematically leaving out any one block and is not the result of testing the pattern classifier on only the last block for instance. Pattern classification was deemed successful if it was significantly above chance (50%).

Figure 2.10. Electrode map with highlighted OT electrodes. The 64-channel electrode cap used in the EEG data collection. Analyses utilized the signals from 12 OT electrodes indicated by the red circles, 6 on each side of the cap (modified from BioSemi, 2006).
2.4.3 Preparing EEG data to compare different ensemble clusters

As mentioned previously, EEG data corresponding to face ensembles for each participant is processed into a 24x16 cell matrix where each row is a different face ensemble stimulus and each column is a block. Each cell is composed of a 3-dimensional array composed of [stimulus repetitions x electrodes x time points]. It should be noted here as a reminder that there are 2 distinct groups of ensembles with discrete mean identities. The first 12 rows in the 24x16 cell matrix compose the first face ensemble cluster and the last 12 rows correspond to the second ensemble cluster, and each group contains two sub-groups x 6 rotations totaling 24 different face ensemble stimuli (See Fig. 2-2). Contrary to the previous SVM paradigm, to be able to discern different ensemble clusters from one another, a different signal averaging procedure was implemented. Each ensemble sub-group (ensemble subcluster 1A, 1B, 2A, and 2B) were pooled together and averaged by sub-group. Much like the previous SVM paradigm, I am only interested in using the 12 OT electrodes as it has shown to boost identity classification using SVM (Nemrodov, Niemeier, Patel, & Nestor, under review).

However, unlike the previous SVM paradigm which utilized a leave-one-block-out cross-validation schema, this SVM analysis will simply train itself on defined data sets and then novel data sets will be introduced to the SVM to determine how discriminable different data sets are from each other. For instance, if we tell the classifier to train on ensemble cluster 1A and 2A, can it correctly classify the signals from ensemble subclusters 1B and 2B in to the appropriate categories? In addition, if the pattern classifier is trained on ensemble cluster 1 and 2, can it correctly classify the signal for the mean identities of ensemble cluster 1 and 2 in to their appropriate categories?
Chapter 3 Results, Discussion and Future Directions

3 Results

3.1 Behavioural Pre-testing

For the behavioural pretesting, a participant’s accuracy and response time were recorded, however for the purpose of analyses, reaction time was not utilized. Using a one-sample t-test, all participants performed above chance and reached near ceiling levels of performance in the individual identity one-back discrimination task. (mean accuracy = 96.67%, sd = 2.17%, p < 0.01; Fig. 3-1). In the one-back ensemble average identity discrimination task, participants performed significantly above chance (mean accuracy = 62.58%, sd = 3.47%, p < 0.01; Fig. 3-1).

Figure 3-1. Behavioural pre-testing results. Mean performances for a one-back individual identity discrimination task and a one-back ensemble average identity discrimination task for 8 participants. The error bars represent ±1 standard error.
3.2 ERP Comparisons

3.2.1 Individual identity and face ensemble discrimination

For the purpose of my thesis, I have decided to compare two early ERP signals from those stemming in response to viewing individual faces and face ensembles, namely, the P100 and the N170 ERP signals. These two signals will be compared using the same 12 OT electrodes utilized in the SVM portion of analyses. Overall, I will compare the ERP signals in terms of latency and amplitude in each condition, but I will be using these statistical comparisons on only the right and left electrodes separately to investigate any possible lateralized effects in processing individual faces and face ensembles.

Firstly, the P100 ERP signal in participants did not exhibit any significant differences in latency for ensembles compared to that of individual faces in the left electrode subset (p = 0.24), right electrode subset (p = 0.185), or in all 12 OT electrode (p = 0.229) using a two-tailed one-sample t-test (Fig. 3-2 a-c; Table 3-1a). Despite the lack of significant difference in latency of the P100 between individual face and face ensembles, it should be considered that these statistical analyses are utilized in only eight participants and with the recruitment of more participants would allow for a more thorough exploration of these effects or lack thereof.

With respect to the amplitude of the P100 signal, participants did not show a significant difference in left OT electrodes (p = 0.449), right OT electrodes (p = 0.665), or in the 12 OT electrodes (p = 0.516) using a two-tailed one-sample t-test (Fig. 3-2 a-c; Table 3-1a).

Secondly, the N170 signal did not exhibit any significant differences in the latency for face ensembles compared to that of individual faces in the left electrode subset (p = 0.351), right electrode subset (p = 0.306), or in the 12 OT electrodes (p = 0.104. The N170 signal occurs earlier when people view ensembles of faces compared to when we view an individual face, however these findings are not significant and more participants are required to explore these findings (Table 3-1).

In terms of amplitude comparison, the N170 signal did not significantly differ when viewing a face ensemble or an individual face in three subsets of analyses: left electrode subset (p = 0.882); right electrode subset (p = 0.844); or in 12 OT electrodes (p = 0.958).
Figure 3-2. Averaged EEG waveforms with labelled ERP signals. ERP signals of averaged EEG signals (n = 8) are labelled. P100, is thought to peak between 100 and 150 ms and is clearly visible. In addition, N170, a common ERP signal associated with face processing elicited approximately 170 ms after stimulus viewing is clearly visible as well. Overall, latencies and amplitudes of these two ERP signals were not significantly different when comparing the ERP signals between face ensembles and individual faces in a) 6 left OT electrodes; b) right OT electrodes; and c) 12 OT electrodes (p > 0.1).
Table 3-1. Latency and amplitude comparisons of ERP signals. As reported above, significant differences in (a) latency and (b) amplitude were not found in the analysis of eight participants. This table depicts the mean numbers used in the analysis to investigate the differences in: a) latencies; and b) amplitudes of the ERP signals.
3.3 True Ensemble Cluster Discrimination

SVM classification was utilized to determine if different ensemble clusters can be correctly classified based on their EEG signal. In all combinations of training and testing, the classifier achieved above chance level performance. When the classifier was trained on ensemble subclusters 1A and 2A, the classifier successfully sorted the neural data for ensemble subclusters 1B and 2B in to the correct categories well above chance ($\mu = 82.81\%$, $sd = 8.01\%$, $p < 0.01$; Fig. 3-3; Table 3-2). When the classifier was trained on ensemble subclusters 1B and 2A, the classifier successfully sorted the neural data for ensemble subclusters 1A and 2B well above chance as well ($\mu = 85.16\%$, $sd = 8.96\%$, $p < 0.01$; Fig. 3-2; Table 3-1). Likewise for the remaining two ensemble combinations of training-testing, above chance classification was achieved for training-testing conditions 1A/2B-1B/2A and 1B/2B-1A/2A ($\mu = 83.20\%$ and 82.42\% respectively; Fig. 3-3; Table 3-2).

Interestingly however, when the classifier was trained on only one of the two ensemble clusters, the pattern classifier was successful at correctly sort the mean individual identities of each ensemble cluster in to their appropriate category ($\mu = 56.25$, $sd = 6.68\%$, $p = 0.0331$; Fig. 3-3; Table 3-2). For example, if I trained the pattern classifier on all the data from ensemble clusters 1 and 2 (each of which with their own distinct mean identity), then tested the classifier with data corresponding to the mean identity of cluster 1, it was successful in sorting in to the correct category at levels above chance. This suggests that, at least in a modest sample size such as this, the statistically averaged individual identity is closer in terms of neural signal to that of the ensemble cluster it was formed from.

In addition to true SVM ensemble cluster classification, a leave-one-block-out schema was used to determine to if ensemble subclusters can be decoded from each other. In other words, this analysis examined how confusable the neural signals are for ensemble sub-clusters that have the same or different mean identity. This analysis demonstrated that the neural signals corresponding to ensembles with the same mean identity were highly confusable with each other. The two ensemble subclusters in cluster 1 and 2 were only decoded at mean scores of 48\% and 51\% respectively, which are not significantly variant from chance levels ($p = 0.719$ and 0.826 respectively; Fig. 3-4). However, when subclusters of different mean identities were decoded from each other, all combinations were decoded at levels significantly above chance ($p < 0.01$;
Fig. 3-4). Alternatively, this finding can be reduced to a within cluster-across cluster comparison of decoding accuracy and ultimately, across cluster decoding yielded much more successful decoding suggesting that the neural signals for ensembles with the same mean identity, despite being composed of entirely different individual identities, are more similarly represented in terms of neural signal when compared to the neural signal for a face ensemble with a different mean identity (p < 0.001; Fig 3-5).

**Figure 3-3. SVM classification accuracies of different ensemble subclusters.** Mean classification accuracies using SVM using a variety of combinations from the different subclusters of ensembles. Each bar is the accuracy of a training-testing condition using true SVM in that it is training itself on two groups of signals then it is being tested using novel data and in all four conditions of ensemble subgroup classification it was well above chance (p < 0.01). Even when the classifier was trained only on two ensemble clusters, the classifier was able to successfully discriminate the individual mean identities in to their appropriate categories (p < 0.0331). Error bars represent ±1 standard error.
Figure 3-4. Confusability Matrix of Ensemble Subcluster Decoding. Using a leave-one-block-out schema, decoding accuracies were obtained using different training and testing combinations. Presented in the matrix are mean decoding accuracies from 8 participants. The neural signals from ensembles that share the same mean identity were highly confusable with each other, seen in the green squares. Neural signals from ensembles that did not share the same mean identity were much more successful in being decoded from each other, seen in the yellow squares. (* indicate significantly above chance levels of decoding at p < 0.01)
Figure 3-5. Comparing Within Ensemble Cluster Decoding to Across Ensemble Cluster Decoding. Here the mean scores of decoding for within ensemble cluster decoding and across ensemble cluster decoding for 8 participants are depicted. Decoding ensembles with different mean identities was found to be much more successful to that of within cluster decoding (p < 0.01). Error bars represent ±1 standard error. * indicate significant difference at p < 0.01.
<table>
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<th>Participant</th>
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<th>1B/2A-1A/2B (2)</th>
<th>1A/2B-1B/2A (3)</th>
<th>1B/2B-1A2A (4)</th>
<th>EC 1 and 2 – Mean Identities of EC 1 and 2 (5)</th>
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<td><strong>83%</strong></td>
<td><strong>82%</strong></td>
<td><strong>56%</strong></td>
</tr>
</tbody>
</table>

**Table 3-2. Averages of different training-testing conditions.** Averages of each SVM training-testing condition (in blue) for each of the 8 participants. Ensemble Clusters (EC). There were four SVM training-testing condition of ensemble classification to investigate if ensembles with different averages can be correctly sorted using SVM. From left to right:

1) Training on ensemble subclusters 1A and 2A; testing on ensemble subclusters 1B and 2B;
2) Training on ensemble subclusters 1B and 2A; testing on ensemble subclusters 1A and 2B;
3) Training on ensemble subclusters 1A and 2B; testing on ensemble subclusters 1B and 2A;
4) Training on ensemble subclusters 1B and 2B; testing on ensemble subclusters 1A and 2A.

In addition (5), the pattern classifier was trained on the data from all the data from ensemble cluster (EC) 1 and 2 and then tested on the data for the individual mean identity of each ensemble cluster.
3.4 Pair-Wise Individual Identity and Ensemble Discrimination

3.4.1 Individual identity and face ensemble discrimination

Using a leave-one-block-out cross-validation schema, individual identity classification was successful in all participants in that classification was significantly above chance level (µ = 64.44%, sd = 4.74%, p < 0.01; Fig. 363). When examining the correlation between an individual’s performance on the one-back individual identity discrimination task and their respective individual classification accuracy, it was found that there is a significant negatively correlation (Pearson correlation, r = -0.612) However, this may be driven by the small sample size (n = 8) and garners further evaluation once a sample size is appropriately large enough.

In addition, all face ensemble stimuli (24 total) underwent the same schema of classification as individual identities. The pattern classifier was trained on all the data from the 24 ensemble stimuli from 15 of the 16 blocks. Then the classifier was tested using the remaining block containing data for each of the 24 ensemble stimuli. Despite having a lower classification accuracy than individual faces, ensemble stimuli still scored significantly above chance in terms of classification (µ = 57.20%, sd = 1.67%, p < 0.01; Fig. 3-6). Much like the individual identities, the correlation between a participant’s score on the behavioural pre-testing involving face ensembles was negatively correlated to the face ensemble classification accuracy (Pearson correlation, r = -0.524) but once again, more participants will be required before any conclusions can be drawn from this correlation finding.
Figure 3-6. Leave-one-block-out classification accuracies. The classification results for the leave-one-block-out cross-validation schema. Identity and ensemble discrimination was significantly above chance in all participants (p < 0.01). The error bars represent ±1 standard error.
3.5 Discussion

The overall goal of this thesis project was to investigate the neural differences in how we perceive and process individual faces and face ensembles. This project included a behavioural component which investigate the ability of people to discern individual identities from each other, but, more notably, ensembles with different average identities from each other. Unsurprisingly, in a 2-afc task, participants were successful in deciding if two faces they saw in succession were the same or different identity. With respect to face ensembles, in a 2-afc task similar to that of Haberman and Whitney (2007), participants were successful in being able to determine if two face ensembles possessed the same or different averages., despite being composed of different individual identities. Although not a novel finding, the method of assessing behavioural measures of ensemble processing was unique to this thesis in that when participants compared mean identity of face ensembles, the ensembles participants were comparing, regardless if they had the same mean identity or not, were composed of different individual identities. In addition, this study was the first of its kind to truly investigate face ensemble processing using EEG.

Using a combination of machine learning and EEG, this study also aimed to determine if ensembles with different averaged identities can be discriminated from each other and if the neural signals corresponding to the mean identities of ensemble clusters could be correctly classified in to their appropriate categories using SVM.

This study confirmed the findings of previous research which claims that people are able to extract some sort of summary statistic in a short amount of time (Haberman & Whitney, 2007, 2009; Sweeny et al., 2009). With ensembles being presented for only 300 ms each, this portion of the study demonstrated just how quick we are able to extract identity as a summary statistic, which is arguably harder than discerning emotions from each other. These results also counter some who suggest that rapid summary statistical extraction is not possible (Fiser & Aslin, 2001).

3.5.1 Ensembles with different averages are processed differently

This study was interested in replicating previous research which suggests that identities are represented uniquely in the cortex and is able to be captured using a combination of EEG and
machine learning techniques (such as SVM in this case) (Nemrodov et al., 2016; Nemrodov et al., under review). Using a leave-one-block-out SVM schema, I was able to successfully demonstrate that EEG is a viable technique in terms of collecting data that is sensitive enough to perform multivariate analyses in that individual identities can possess discriminable neural signatures.

As it relates to ensemble processing, I was able to demonstrate that the neural signature for ensembles with different averages are detectable using pattern analyses. When the pattern classifier was trained on data from one subgroup from each ensemble cluster, then tested on the other subclusters, the pattern classifier correctly sorted the testing data sets into their appropriate categories. For example, if the pattern classifier was trained on subclusters 1A and 2A (one subcluster each from ensemble cluster 1 and 2 respectively) and then the classifier was tested on subclusters 1B and 2B, the classifier was able to determine that the neural signal corresponding to subcluster 1B was similar to that of 1A and the neural signal for 2B was more similar to that of 2A (see Table 3-1 for a complete list of training-testing conditions). In addition, when the classifier was trained on the data from each ensemble cluster and tested on the data corresponding to each of the mean identities of ensemble cluster 1 and 2, the pattern classifier was successful at correctly sorting the neural signal into its appropriate categories. In other words, the signal for the mean identity of ensemble cluster 1 more closely resembles that of all the signals from ensemble cluster 1 and likewise for the mean identity of ensemble cluster 2. This may suggest that we possess a neural mechanism that is able to extract some sort of summary statistic from faces, in this case identity, and that this mechanism is sensitive to different variations of the same summary statistic.

3.5.2 Summary statistic extraction may be automatic

These results are the first of their kind to demonstrate that face ensembles with different average identities are represented differently in terms of the neural signature. In addition, these results also demonstrate that despite being composed of entirely different faces, ensembles with the same average identities are processed more similarly compared to that of an ensemble with a different average identity. What this suggests is that there exists some neural mechanism capable of quickly extracting summary statistics, at least with respect to identity, and it is able to perform
such a task when a stimulus is present for only 300 ms. Evolutionarily, the development of this sort of mechanism makes sense. In any sort of social setting, the ability to quickly extract a summary statistic may be beneficial to quickly get a general feeling of a crowd. Although my study focused on identity, it would be just as important to be able to quickly gauge the general attitude of a crowd. For example, if you got caught in the middle of an angry group of people, the neural mechanism that extracts summary statistics would be able to quickly inform you that this might not be a pleasant situation to be in.

It has been suggested that because of how rapid this extraction happens, extracting mean identity may be the result of a default mode by the face processing system (de Fockert & Wolfenstein, 2009). This hypothesis is corroborated by the fact that participants were not given any instructions or tips on how compare the ensembles in the behavioural pre-testing. In addition, when asked to consciously perform this task, participants are only able to average ensembles in a 2-afc at levels just significantly above chance. However, when we examine the neural signals from the same ensembles and attempt to decode them from each other, we see much high discrimination accuracies when we compare the neural signals for ensembles with different mean identities. This may speak to the hypothesis that our brains are able to perform this averaging of ensembles (i.e. extraction of summary statistics) automatically. Admittedly, I achieved higher decoding accuracies for ensemble sub-clusters than I did for individual identities. Although one may suggest that our brains are better at processing face ensembles than individual faces, I would attribute this finding to large difference in the number of repetitions of stimuli. In the individual faces, participants saw individual faces only eight times per block where as participants saw an ensemble with the same mean identity 48 times per block, thus creating a much higher signal to noise ratio than in individual face blocks. In addition, during the EEG experiment, participants were completing a task that is orthogonal to extracting mean identity. Participants were told to respond whenever they saw an ensemble of female faces. This further speaks to the idea that extracting average identity may be an automatic process.

### 3.5.3 Classification of individual identities and ensemble stimuli

Using a leave-one-block-out SVM schema, I was able to demonstrate that individual identities possess a unique neural signal that is detectable using pattern analysis techniques. This part of
the study is merely a replication of previous work that demonstrated similar findings, but using a larger set of identities (Nemrodov et al., 2016; Nemrodov et al., under review). Interestingly however, the same multivariate technique applied to different face ensemble stimuli also yielded successful discrimination (see Fig. 2-2 for all face ensemble stimuli). What this means is that face ensembles are discriminable from each other, even when they are made up of the same faces, just in different positions. This is the first finding to combine multivariate analyses with ensemble decoding to investigate if ensembles are processed similar to individual identities. Do unique face ensemble stimuli also possess unique neural signatures? The answer appears to be yes, albeit to a lesser degree than individual face (Fig. 3-3). Perhaps face ensemble processing rely on a different neural mechanism of represent them that is not ideally detectable by the 12 OT electrodes used in this study. Moving forward, it would be interesting to investigate if there is an ideal combination of electrodes that is able to better capture ensemble discrimination. Nonetheless, in the current study, I was able to demonstrate that different face ensemble stimuli exhibit a unique neural signal that is able to be discerned using multivariate analyses.

3.6 Future Directions

3.6.1 Recruit more participants

Firstly, although some aspects of my thesis project yielded significant results, the small sample size of 8 limits how conclusive these effects and findings may be. That being said, there are several effects which are trending towards significance with respect to ERP latency and amplitude differences between face ensembles and individual faces. With the inclusion of more participants, these effects may indeed become significant and allow for more conclusive arguments. The ideal number of participants would be 14.

3.6.2 Develop time courses of discrimination for face ensembles and individual identities

Secondly, time courses of discrimination need to be investigated. One benefit EEG offers over fMRI is that EEG allows one to establish temporal profiles of processing. That said, I would like to determine how the accuracies of ensemble discrimination fluctuate over the time, much akin
to that of Nemrodov and colleagues (2016) which demonstrated that individual identity discrimination occurred well outside of the range of classic face processing ERPs such as N170. This would help establish a temporal generalizability of an ensemble in that when we view a face ensemble, how is the information represented over time? Does the information for that face ensemble move back and forth within a face processing network resulting in varying degrees of identity classification over time? Or is it confined to a certain time window and does not generalize over time as is suggested in the literature (Cichy, Pantazis, & Oliva, 2014). It would be interesting to compare the time courses of discrimination between individual faces and face ensembles. If the time courses mirror each other, it may suggest a common mechanism of identity extraction in both summary statistics and individual statistics. Arguably they may rely on the same mechanism but may take longer to compute based on the size of the face group involved. For example, the summary statistic of one face is the face itself and therefore the summary statistic is derived almost immediately. However, with six faces for example, the neuro-computational power required may be much higher for the same mechanism to complete and is therefore a longer computation to complete. In the future, it may be of interest to see if summary statistic extraction time (reaction time in a 2-afc discrimination task, for example) is positively correlated with the size of the ensemble.

3.6.3 Develop a regressive model of ensemble processing

In statistics, regressive models help estimate relationships between different data sets or variables (Neter, Kutner, Nachtsheim, & Wasserman 1996). In this context, it would be interesting to investigate if a regressive model could be established between face ensembles and the individual identities used in this study. In other words, can a face help predict the neural signal of the ensemble it is a part of? This regressive model of face processing would help further elucidate how relatable the neural signals are between ensembles and the parts that make up the ensembles. If the signal from an individual face is able to be a predictive variable for the neural signal of an ensemble, this would suggest further evidence for a common mechanism of ensemble processing. Alternatively, rather than one face being a predictor of the neural response to a face ensemble, can a specific location within in an ensemble be weighted more in terms of being a stronger predictor of an ensemble. It would be intriguing to determine which may carry more weight in ensemble processing, specific individual identities, or certain positions of faces, regardless of the identity that is contained within that location.
3.7 Conclusions

The work highlighted here in my thesis is one of the first attempts to look at face ensemble processing through a behavioural and neural lens since previous work has only implemented behavioural paradigms. Behaviourally, I demonstrated that people are able to extract identity summary statistics from ensembles well enough that they can discriminate ensemble pairs as having a different and same average. Although I was unable to demonstrate significant differences in ERP signals between individual faces and face ensembles, I was able to demonstrate that ensembles with different average identities are processed differently and the signals corresponding to ensembles with different average identities are discriminable through the use of multivariate analyses. In addition, using multivariate analyses demonstrated that ensemble stimuli exhibit unique neural signatures such that we are able to classify them above chance levels. These results are the first step towards elucidating how people process face ensemble and how this process compares to how individual faces are processed.
References


Copyright Acknowledgements

Figure 1-1 Adopted from Lotte, Congedom Lécuyer, Lamarche, & Arnaldi, 2007.

Figure 2-11 Adopted from BioSemi, 2006.