The association of Facial Mimicry and Personal Social Traits

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Abstract

Facial mimicry (FM) is a fundamental aspect of human social interactions, influencing our empathic capabilities and responses to others. Recent research was able to show in some extent the effects that facial expressions has in social interactions, as well as their ability to predict behavior. This research seminar delves into the electromyographic (EMG) signals of dyads engaged in various social activities to explore the synchronization of facial expressions and its potential correlation with personality traits. EMG data from 30 dyads of healthy, right-handed, Hebrew-speaking women were analyzed using cross-correlation sliding window methods in order to extract a numeric expression of FM. Those values were then compared to personal traits, measured through psychometric scales, which included concern for appropriateness, empathy, interpersonal reactivity, and trust. Surprisingly, statistical analyses revealed no significant correlations between participants' FM values and the assessed personal traits. Several factors may contribute to this lack of correlation, including the complexity of facial expressions, individual differences in expressivity and responsiveness, and potential limitations in the chosen variables. This study provides valuable insights into the intricacies of FM analysis during social interactions and suggests avenues for future research, emphasizing the need for refined methodologies and a more comprehensive consideration of intrapersonal factors to unravel the complex dynamics of facial mimicry in social psychology.

Introduction

Mimicry is an essential part of social interactions in humans, as we begin to mimic in an early stage of our development (Charman et al., 1997; Meltzoff, 2002). In adults, mimicry can be expressed in a form of following gestures, body posture and hand movement, or by imitating facial expressions of other people with whom we interact (Dimberg, 1982). The manifestation of the latter is also referred to as Facial Mimicry (FM). This phenomenon is considered to be an unaware and involuntary action, such that it is very hard to avoid doing even if concsiously trying to (Dimberg et al.,2002), and it could be affected by one's attention, mood and social motives (Seibt et.al,2015).

FM, and mostly spontaneous FM, is an important component of our empathic capabilities (Hermans et al., 2006), and our ability to understand and respond to social interactions. Some conditions like Autism Spectrum Disorder (ASD) or Parkinson's disease (PD) are associated with FM impairment, which, among other factors, may result in diminished social abilities (Cattaneo et al.,2007, Argaud et al.,2016).

Facial expressions and mimicry are also able to predict preference and behavior. For example, using participants facial responses (e.g., smile and disgust) to adverts, researchers could predict ad liking and purchase intent (McDuff et al., 2015). In another research, facial expression (and smiling in particular) were shown to be related with rapport and cooperation in a simulated prisoners dillema (Hoegen, R. et al., 2018). Nonetheless, relying exclusively on facial expressions alone, and mostly in virtual environments, for predicting decisions proves inadequate. A study examining the prediction of bargaining behavior emphasized the essential need to incorporate nuances of social interaction to achieve a higher degree of precision in behavioral estimations (Mussel et al., 2014).

In the physical world, FM is expressed in the overlapping movement of a person's face muscles in direct response to a certain emotional facial expression of another person, which forms his or her own unique facial expression. For instance, when the *Zygomaticus Major*, a facial muscle located in the cheek, contracts, it lifts the tips of the mouth upwards, creating a smile. The movement of the Orbicularis Oculi, located in the eybrows area, pushes the medial part of the forehead downwards and towards the midline, resulting with a frown (Fridlund & Cacioppo, 1986). There are over 40 functionally inidependent facial muscles (Matsumoto, D., & Ekman, P. , 2018) so that different combinations of activation of these muscles define various, distinct facial expressions, as well as imperial biological functions such as chewing and breathing (Dimberg et al. 2002). Hence, FM is also derived from the movement combinations of these defined muscles. In order to accurately measure and compare FM, it is customary to represent facial muscle activity in mathematic terms. To accomplish this, several methods have been developed, including Facial Action Coding System (FACS) (Gat et al. 2022). In the past few decades, one of the most frequently used methods to measure this kind of data is Electromyography(EMG) (Sato, W. et al., 2008, Sims et al. 2012, Riehle et al. 2017, Cerone et al 2019), due to its ability to accurately detect muscle movement across the face and convey it to an electric signal.

In this research seminar, I will look into the EMG signal of dyads of female subjects as they sit across from each other while participating in various reading and listening assignments. This is a part of a multi-level experiment testing whether it is possible to predict decision making based on facial expression synchronization during social interactions. My goal will be to extract various representations for FM between the dyads by looking at their signal synchronization, while also comparing it to personality traits, as measured in several well-known scales that were also in use in this experiment.

Methods

EMG data of smiling activity from 30 dyads of healthy, right-handed, Hebrew speaking women who participated in a multi-level experiment was examined. Each participant's EMG signal was preprocessed to remove 50 Hz DC noise, and was applied a bandwidth filter with a range of 20Hz to 400Hz. I compared between each pair of signals by calculating the cross-correlation(CC) and the lag between them, focusing on the listening part of the paradigm so that both participants EMG is only affected by genuine facial expressions and not by lip movement while reading. Each session is called a 'trial', in which both participants were listening to the same story together, facing each other.

Preparing the data

First, each participant's signal was z-scored in order to standartize the data and avoid variability due to scale differences between subjects, as EMG signals often differ depending on skin conductivity, electrode placement, and muscle mass. By using z-scores we can focus on the relative intensity rather than the absolute one (De Luca, C. J. ,1997, Halaki, M., & Gi, K. ,2012). Then, each signal was downsampled calculating the mean value of subsequent samples (original sampling rate was 4000) in order to reduce the computation time without losing accuracy . I chose to downsample the signal to 400 pixels (samples) per second, according to earlier EMG research which showed that leg muscle recordings begin to lose accuracy when sampled below 400 Hz (Li, G. Et al., 2011).

Cosine Similarity

Cosine similarity is a method to measure the similarity between two vectors by computing the cosine of the angle between them. It is often used to compare the orientation of vectors rather than their magnitude. The cosine similarity $\cos(\theta)$ between vectors A and B is calculated by dividing the dot product $A \cdot B$ by the dot product of their Euclidean norms (the square root of the sum of squares of a vecor) $||A|| \cdot ||B||$;

$$\mathrm{Cos}(\theta) = \frac{A \cdot B}{||A|| \cdot ||B||} = \frac{\sum_{i=1}^{n} Ai \cdot Bi}{\sqrt{\sum_{i=1}^{n} Ai^2} \cdot \sqrt{\sum_{i=1}^{n} Bi^2}}$$

Cross-Correlation

I calculated cross-correlation between each dyad signals by operating a moving window on both signals and computing the cosine similarty between the windows. First, a one second window (400 pixels) from the reference signal (A) is assigned, then it is compared to similar-sized, moving windows from the second signal (B), as the cosine similarity is computed for each window as a measure of correlation. The moving window of signal B starts with a lag of one second behind and jumps two pixels (5 miliseconds) at a time until one second after the reference window. The lag that produced the highest correlation value is then marked. In the proccess, correlation values that are below a threshold of 0.05 were diminished. This threshold value was estimated to be the best fit after performing permutation test for correlation significance (DiCiccio, C. J., & Romano, J. P., 2017). Correlation values from 3 dyad's smiles were each used as baseline signal to generate 1000 permutations of a random signal. Then, cosine similarity between them and each of the permutations was calculated, resulting in a mean correlation value threshold of 0.05, meaning that by average, only 5 percent of correlation values exceeded this threshold. This process is repeated for the next one-second window from reference signal A, as lag markers are accumulated.

Leader Score and Cross-Correlation Intensity score

After the best-correlated lag marker is computed for each window of signal A, it is assigned to the Leader Score(LS) of either participant A or B. Before the assortment, another condition was applied to remove matching signals that correlated earlier than the assumed time-to-mimic-smiles (Korb, S., Grandjean, D., & Scherer, K. R., 2010). This research found that when people mimic smiles of virtual people on a computer screen, their EMG signal begins to change 125 milliseconds after stimulation onset. Therefore, I added the response time condition. If the best-correlated lag marker is **greater than the response time** (meaning that the best correlation was calculated when the moving window of signal B was at least 125 milliseconds *later* than the current window in A), the LS of participant A increases by one. Accordingly, the LS of participant B increases for every best-correlated lag marker that is **smaller than minus the response time**. Hence, the LS of each participant is a relative measure for the amount of times in which they smiled just before the other, possibly leading the other to mimic their smile. In addition, the computed CC values of best-correlated lag markers are added to that participant's Cross-Correlation intensity (CCI) score, expressing the correlation-intensity to which it's LS is calculated. This is a way to measure the credibility of each participant's LS. Both variables are divided by the number of window correlation comparisons made in each trial, in order to normalize the scores (see Fig. 1)

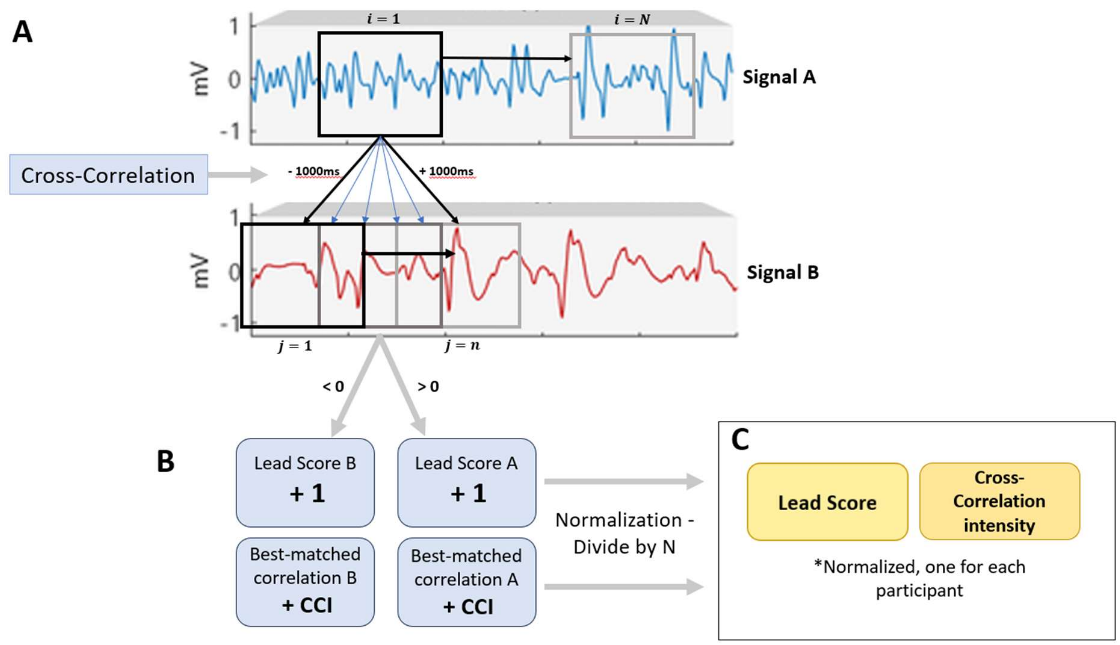

Figure 1: A diagram of the data analysis pathway: ***A*** *Moving window cross-correlation between signals A and B is calculated by computing the cosine similarity between sliding windows* (i, j) *from each signal, at different time lags.* ***B*** *The best-matched (highest cosine similarity value) time lag is then marked and added to either A or B depending on it's sign (positive/negative) as well as the cross-correlation intensity value (CCI).* ***C*** *After all sliding windows between each dyad are compared, the accumulated values are normalized to the total amount of comparisons made.*

<u>Questionnaires</u>

Concern for appropriateness scale (CFA)

Self-monitoring and self-presentation are conceptual frameworks that pertain to individuals' deliberate efforts to shape and manage the impressions they convey to others, thereby exercising control over how they are perceived. The Concern for Appropriateness Scale is a psychometric tool used to assess an individual's proclivity for employing a protective self-presentation strategy and self-monitoring behavior with the primary goal of seeking social acceptance and approval. (Lennox & Wolfe, 1984). Self-monitoring occurs even without awareness and individuals rated as high self-monitors are more likely to mimic others (Cheng & Chartrand, 2003)

Interpersonal reactivity index (IRI)

The Interpersonal Reactivity Index is a psychometric questionnaire designed to evaluate empathy from a multi-dimensional perspective (Davis, 1983). The IRI serves as a robust and validated tool to comprehensively measure the various components of empathy, providing valuable insights into both affective and cognitive aspects of empathic responses.

Inclusion of self in other scale (IOS)

Through the utilization of two movable circles on the x-axis, participants are enabled to determine their desired placement, yielding a floating-point output that corresponds to the spatial separation between these circles. A result of 0 signifies perfect overlap of the circles, while a value of 1 indicates complete non-intersection. This variant of the scale constitutes a Visual Analog Scale (VAS) rendition derived from the original Item Overlap Scale (IOS). (Aron et al., 1992). Inter-brain synchrony is connected to social closeness as measured with IOS and the personal distress subscale of the IRI (Dikker et al., 2017, 2021).

Trust Question

Participants were asked how much they trust the other person before and after the experiment, in a scale of one to nine (one marking the least trust and nine marking the most trust).

Results

In this research I tested the correlation between facial mimicry and personal traits. Facial mimicry of each participant in a dyad was measured by her lead score (LS) (the tendency to smile just before the other participant, suggesting that they led the activity) and cross-correlation intensity (CCI), while listening to similar stories. Personal traits were measured in four different scales (CFA, IRI, IOS and trust). Statistical analysis showed no significant correlation between participant's LS and CCI to any of the personal traits.

Further analysis tested whether the follow score, rather than the lead score, of each participant is correlated with the same personal traits. To do this, I simply replaced the LS between participants A and B of each dyad. These tests also showed no significant connection between the follow score and personal traits.

Discussion

The present study aimed to investigate the relationship between facial mimicry (FM) during social interactions and various personal traits, including concern for appropriateness, empathy, interpersonal reactivity, and trust. Our analysis focused on the normalized lead score (LS) and normalized cross-correlation intensity (CCI) as measures of FM, while personal traits were assessed using well-established psychometric scales. Contrary to our initial hypotheses, the results did not reveal significant correlations between participants' LS or CCI and the measured personal traits. The absence of such associations may be attributed to several factors.

Complexity of Facial Mimicry:

As mentioned earlier, facial expressions are a complex phenomenon influenced by a range of factors, including attention, mood, and social motives (Seibt et al., 2015). The intricacies of these variables may contribute to the lack of a straightforward relationship between FM and specific personal traits. For example physical attraction or charisma are traits that could easily affect FM one way or the other. Perhaps those and other personal attributes needs to be measured and monitored when analyzing the results.

Individual Differences:

Individual variability in facial expressivity and responsiveness may have played a significant role in the observed results. Traits such as response time and smile intensity may differ between subjects. Each individual's response time to another's facial expression, as well as the time it takes them to initiate an expression of their own, could be a parameter that needs to be considered when calculating the lags between correlating signals. Smile intensity is expressed as the amplitude of the signal, and can vary between individuals according to their personality traits and behavioral tendencies. On one hand, although I tried to limit the effect that these variability factors impose, it might not have been the adequate treatment of the data, and further analysis needs to be done. But on the other hand, it might just be that these very differences in amplitude and response time are the parameters that have an effect on mimicry, and by normalizing the data to diminish their impact we actually lose information. In any case, it is crucial to take these parameters into account in future research.

Validation of the variables:

The reliance on the lead score and correlation intensity as the sole indicators of FM raises questions about its adequacy in capturing the richness of facial mimicry dynamics. This numeric variable includes several complex calculations such as standardization, cross-correlation and normalization of that data. As these steps encapsule several sensitive parameters such as sampling frequency, correlation window size, and response time, further adjustments and validation of this scale needs to be done.

In conclusion, while our study did not reveal significant correlations between facial mimicry and assessed personal traits, it provides valuable insights into the methods of data analysis used in the field of FM during social interactions. Future research should consider refining methodologies, expanding the consideration of intrapersonal factors, and exploring additional contextual paradigms to enhance our understanding of the complex dynamics of facial mimicry in the realm of social psychology.

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