Decoding spatiotemporal features of emotional body language in social interactions

Johannes Keck^{1,2}, Adam Zabicki¹, Julia Bachmann¹, Jörn Munzert^{1,2}, Britta Krüger¹

- 1 NeuroMotor Behavior Lab, Department of Psychology and Sport Science, Justus-Liebig-University, Giessen, Germany
- 2 Center for Mind, Brain and Behavior-CMBB, Universities Marburg and Giessen, Marburg, Germany

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Author Note

Johannes Keck	https://orcid.org/0000-0002-8035-0953
Adam Zabicki	https://orcid.org/0000-0002-0527-2705
Julia Bachmann	https://orcid.org/0000-0001-9001-6505

Kugelberg 62

35394 Giessen

Germany

Telephone: +49 (0) 641 / 99-25251

Fax: +49 (0) 641 / 99-25209

Corresponding author: johannes.keck@sport.uni-giessen.de

Abstract

How are emotions perceived through body language in human interactions? Although emotion perception is a complex phenomenon integrating various features, humans are highly adept at recognizing and expressing emotions through body movements within social interactions. This study used point-light displays of social interactions portraying emotional scenes to address two issues. First, we examined quantitative intrapersonal kinematic and postural body configurations. Second, we calculated interaction-specific parameters and analysed how far both contribute to emotion and valence perception. By using ANOVA and classification trees we investigated emotion-specific differences in the calculated parameters. Further, we applied representational similarity analyses to determine how perceptual ratings relate to intra- and interpersonal features. Results showed that within an interaction, intrapersonal kinematic cues corresponded to emotional ratings, whereas postural cues reflected valence ratings. Furthermore, perception of emotional content was driven by interpersonal orientation, proxemics, the time spent in the personal space of the counterpart, and the balance in motion energy between interacting people. Both the latter and balance in orientation related to valence ratings. Hence, intrapersonal and interpersonal features of emotional body language relate to not only the emotional content in human interactions but also their perception.

Introduction

In everyday life, the expression of emotions is an essential part of human social interaction (Atkinson et al., 2004; Michalak et al., 2009; Roether et al., 2009). It is linked inseparably to the ability to observe, recognize, and evaluate the emotions of our conspecifics (Bänzinger et al., 2009; Derntl and Habel, 2011; Frith and Frith, 2012; Lorey et al., 2012; Kaletsch et al., 2014).

Affect expression occurs through combinations of verbal and nonverbal communication channels (Kleinsmith and Bianchi-Berthouze, 2013). To judge other people's emotional states reliably, information can be decoded through nonverbal communication channels such as facial expressions or body movements and posture (Clarke et al., 2005; de Gelder, 2006; Atkinson et al., 2007; de Gelder, 2009; Aviezer et al., 2012; Goldberg et al., 2015; Bachmann et al., 2018; Bachmann et al., 2020). Up to the present, most research in this field has focused on facial expressions. It has shown not only that people can express at least six different emotional states through their faces—anger, happiness, sadness, fear, surprise, and disgust—but also do this with a high level of intercultural stability (Ekman & Friesen, 1971).

In recent decades, the focus has shifted from faces towards bodies. It has been suggested that recognition performance for bodily expressions is very similar to that for faces, and evidence has been provided that movements of the body or its segments also contain significant aspects of nonverbal communication (Atkinson et al., 2004; de Gelder, 2006; de Gelder, 2009; Barliya et al., 2012; Halovic and Kroos, 2017). For example, postural and kinematic features vary depending on the emotional state and influence the perception of emotion categories (Wallbott, 1998; Paterson et al., 2001; Pollick et al., 2001; Michalak et al., 2009; Roether et al., 2009; Glowinski et al., 2011; Kleinsmith and Bianchi-Berthouze, 2013; Poyo Solanas et al., 2020). These features can be summarized under the heading emotional body language (EBL). EBL is described as behaviour used to express emotions via the whole body coordinated in its movements across multiple joints and often accompanied by a meaningful action (de Gelder, 2006; Gross et al., 2012). This indicates that the use of space or the arrangement of body posture, gestures, trunk, and arm movements are tools through which the body can express an emotion (Paterson et al., 2001; Pollick et al., 2001; Michalak et al., 2009; Kleinsmith and Bianchi-Berthouze, 2013; Poyo Solanas et al., 2020; Bachmann et al., 2020). In contrast to facial expressions, EBL is often more reliable, accessible, and action-oriented; and it can be identified even when the face is not clearly visible (Van den Stock et

al., 2007; Goldberg et al., 2015; Bachmann et al., 2018). It further enables the observer to recognize a situation and simultaneously acknowledge the action undertaken by an individual (de Gelder, 2006; Van den Stock et al., 2007).

Consequently, EBL carries important information about not only the emotional state but also interindividual signalling (Bachmann et al., 2018; Goldberg et al., 2015). Therefore, emotions can preferably be described as a dynamic relational process occurring between the individual and the environment (Clarke et al., 2005). In this vein, it has been demonstrated that contextual social information provided by interacting persons enhances the recognition of the emotional content of a scene and increases the observer's confidence in their perceptual judgement (Clarke et al., 2005; Lorey et al., 2012). Important contextual cues in social interactions might be embodied synchronization or proxemic measures such as distance and orientation (Moreau et al., 2016, Yokozuka et al., 2018, Lahnakoski et al., 2020). Taken together, we suggest that interaction-specific parameters also contribute, in an emotion-specific manner, to the perception and identification of emotions. However, up to now, which features drive emotion perception in social interactions on the intra- and interpersonal level remains largely unknown.

The aim of the present study was to determine a quantitative representation on two different levels of bodily affect expression and perception. First, we investigated intrapersonal EBL by computing several kinematic and postural features and relating them to emotion perception. Second, we focused on interaction-specific characteristics that contribute to emotion perception. Specifically, we used 48 point-light displays (PLDs) of human interactions portraying four emotions (happiness, affection, sadness, and anger). Participants observed these stimuli and were asked to categorize both the depicted emotional content and the valence of the perceived stimulus. We quantified different intra- as well as interpersonal movement features and analysed differences between emotional categories. To evaluate the relative importance of each calculated feature in the classification of emotional content, we trained different decision tree classifiers. Finally, we explored the correspondence of both the perceived emotional content and the perceived valence of a scene to the computational features on intra- and interpersonal levels via representational similarity analysis (RSA).

Materials and methods

Participants

A total of 21 participants, 16 women and 5 men (mean age 23.2 ± 3.02 years), participated in the experiment. Due to a lack of ratings caused by the forced-choice paradigm, we included the data of only 19 participants. None of the participants reported any history of psychiatric or neurological disorders and they had no history or current use of psychoactive medication. All procedures were approved by the local ethics committee of the Department of Psychology and Sports Science of the Justus Liebig University Gießen and adhered to the declaration of Helsinki. All participants provided written informed consent prior to participating.

Stimuli

Stimuli were selected from a larger motion-capture data set created by Bachmann et al. (2020). Eight pairs of non-professional actors were instructed to perform an interaction portraying one out of four emotional scenes: happiness, affection, sadness, or anger. To ensure a congruent behavioural pattern, actors were given a script of emotional situations and directed specifically to perform the same emotion. They were instructed to express their emotions intuitively within the context of the given situation, thereby allowing freedom and enhancing the variability of expression (Bachmann et al., 2020). Interactions were recorded with an optical motion capture system (Vicon Motion Systems, Oxford, England) operating at 100 Hz. MATLAB software (Mathworks, Natick, MA) was used to create video files of 4-s sequences from the original coordinate 3D (C3D). In each video, 15 markers per person were plotted as white spheres on a black background to present a standard PLD model (Troje et al., 2005).

The final stimulus selection was based on prior validation of emotion and valence categories from 24 participants who did not take part in the present experiment. Valence was judged on an 11-point scale ranging from -5 (*extremely negative*) to +5 (*extremely positive*). Validation criteria were: first, at least 50% of the participants had to recognize the displayed emotion (e.g. anger). The second criterion ensured that the second highest emotion rating did not exceed 25%. This allowed us to identify and exclude ambiguous scenes in which a specific emotion could not be recognized reliably. After validation, 12 stimuli that met both criteria were selected randomly for each emotion category. This resulted in a set of 48 (4

emotions x 12 scenes) stimuli. For more information on stimulus creation and validation, see supplementary materials and Bachmann et al. (2020).

Experimental procedure

Prior to the present experiment, participants were instructed and acquainted with the task. They subsequently performed a test run containing 12 trials that were not included in the main experiment.

In the experiment, each sequence was presented once, resulting in a series of 48 sequences. Sequences were displayed in a pseudo-randomized order on a 12-inch screen. The distance between each test person's eyes and the screen was approximately 40 cm. Each trial started with a fixation phase (1 s) followed by a stimulus sequence (4 s) and two behavioural ratings. After observing this sequence, participants were asked to assess the emotional valence of the videos on the same scale that had been used for stimulus validation (7 s). The second step was to sort emotions into one of the following categories: happiness, affection, sadness, and anger (4 s) (Fig. 1A).

Feature definition

To investigate EBL characteristics that drive the perceptual judgement on an intra- and interpersonal level, we calculated several features using MATLAB software. From the 15 markers displayed, we calculated 13 anatomical points that presented anatomical landmarks on the upper body (including shoulders, elbows, wrists, and head) and the lower body (including hips, knees, and ankles). Features were calculated from the x, y, and z coordinates.

On an intrapersonal level, the eight kinematic features (calculated for each anatomical point) addressed *velocity*, *acceleration*, and *vertical movement*. We implemented *symmetry*, *limb angles* (shoulder, elbows, hips, knees), *limb contraction* (distance from head to wrist and ankles), *volume*, as well as *its standard deviation (volume STD)* as postural features. Each feature was calculated within each of the 400 frames and averaged across time and actors.

In a next step, we computed 12 interpersonal parameters. Proximity measures included *interpersonal distance (IPD)* and its variance over time (*IPD STD*), the percentage of time spent in the personal space of the other agent (*personal space*), as well as *interpersonal orientation (IPO)* and the ratio of orientation from one person to another to detect imbalances (*IPO balance*) in which the persons are turned towards each other (Kleinsmith and Bianchi-Berthouze, 2013; Overhill, 2014; Sorokowska et al., 2017; Lahankoski et al., 2020). To investigate how the spatial distance between two people affects velocity, acceleration, limb

angles, and limb contraction (with included time information), we correlated these measures with the distance profile (*distance correlations*). We examined the synchronization of the velocity and acceleration profiles (*synchronisation velocity & acceleration*) (Thepsoonthorn et al., 2016; Yokozuka et al., 2018). Finally, we calculated the proportion of the displayed motion energy (*motion–energy balance*) of each person (Wallbott, 1998; Kleinsmith and Bianchi-Berthouze, 2013; Thurman & Lu, 2014). For more detailed information on feature definition and calculation, see supplementary materials.

Data analysis and statistics

As a first step, we calculated the recognition rates (accuracy) of stimuli for each emotional category by comparing the target emotion with the behavioural response. To ensure a sufficient degree of stimuli recognizability, we tested each emotional category against chance (25%) using Bonferroni-corrected one-sample t tests.

Influence of emotional categories

We tested for the emotion specificity of EBL features with a one-way ANOVA. The intrapersonal and interaction-specific features calculated from each stimulus were averaged across anatomical points and used as input. The ANOVA contained a four-level factor emotion (happiness, affection, sadness, anger). Alpha was set at .05 for all statistical tests and post hoc pairwise comparisons were Bonferroni-corrected. Due to violations of the normal distribution in the values of interaction-specific features (*distance correlation*, *synchronization*), we normalized our data with a Fisher z transformation (Silver and Dunlap, 1987; Berry and Mielke, 2000).

Emotion classification with decision trees

To evaluate the relative importance of each calculated feature in the classification of emotional interactions, decision tree classifiers were trained using Matlab Statistics and Machine Learning Toolbox (Version 11.6). Classification of stimuli was based on the weighted majority of multiple decision trees (bootstrap-aggregating approach) to avoid overfitting and enhance generalization (Opitz & Maclin, 1999; Loh, 2002; Poyo Solanas et al., 2020).

Three different classifiers were trained for classification of emotions using averaged time-information and averaged anatomical landmarks with different predictors: (1) M1 = intrapersonal features, (2) M2 = interpersonal features, and (3) M3 = combination of the two feature sets (M1+M2).

To minimize the influence of the random subdivision of the displayed 48 stimuli into the training and the validation dataset, we repeated this process and validated accuracy using different proportions between training and validation data. In the following, we report averaged results for 10,000 different validation samples and a proportion of 80% training data. For more information, see supplementary materials.

Representational similarity analysis

We used representational similarity analysis (RSA) (Kriegeskorte et al., 2008; Nili et al., 2014) to characterize the relationship between the perceptual ratings and computed EBL feature sets for each of the 48 stimuli. By relating the stimuli to each other and arranging the values horizontally and vertically in the same order, we created a symmetrical representational dissimilarity matrix (RDM) (48 x 48). Each entry describes the relation between two stimuli. In the main diagonal, the stimuli values are compared with themselves, resulting in a diagonal defined as zeros.

In a first step, we created two different model RDMs by assuming a categorical distinction between the emotion and the valence category of the stimuli. Therefore, the dissimilarities between identical categories were 0 and those between different categories were 1 (Fig. 1B).

Second, we calculated 19 individual single-subject RDMs for emotion categorization, also by using binary variables (0 if identical emotional rating, 1 otherwise). Furthermore, we used individual valence ratings to create RDMs in which each cell corresponded to the pairwise absolute difference. Here and in the following step, we used the Euclidean distance measure (Fig. 1B) (Nili et al., 2014; Poyo Solanas et al., 2020).

To test which of the features related to the geometry of the model RDMs and the behavioural rating RDMs, we built feature RDMs representing the intrapersonal and interpersonal level (Fig. 1B). This step resulted in eight intrapersonal RDMs and 12 interpersonal RDMs.

To describe and test the relationship between all RDMs, we calculated a matrix of pairwise correlations (Kendall's τ_A) between model and feature RDMs separately on the intrapersonal and interpersonal level. To account for multiple testing, we applied Bonferroni corrections based on the number of features in each set. We used multidimensional scaling (MDS) to gain a graphical impression of representational distances (computed as 1- Kendall's τ_A).

Furthermore, each feature RDM was tested against the behavioural RDMs using Kendall's τ_A for emotion categorization and Pearson correlation coefficients for valence ratings. Multiple testing was corrected using Holm–Bonferroni and the false-discovery rate was set at .05. The variance within the emotions and valence ratings across participants was represented by the noise ceiling and determined the amount of variance a model could explain.

In the last step, we aimed to explore perceptual judgements by merging the intra- and interpersonal level, analogous to M3. Therefore, we focused on the feature that best explained the behavioural rating on both levels and additionally outperformed the remaining features in pairwise comparisons. We normalized the representational geometry and created a common feature space by averaging the corresponding RDMs. Next, we investigated the relationship between the produced feature combination RDM and single-participant behavioural RDMs and tested the resulting model against all other feature RDMs in the same manner as described above.

To calculate features and perform data analysis we used SAMI toolbox, which is available on Github and archived in Zenodo (Zabicki & Keck, 2021).

Fig 1. Experimental timeline and RDM creation. (A) Temporal structure of one trial. (B) Three different RDM types are created. First, model RDMs are created assuming categorical differences between emotions and valences by using binary variables (0 if identical, 1 otherwise). Second, feature RDMs were created representing each parameter on intra- and interpersonal level, using Euclidean distance as similarity measure. Behavioural RDMs were created using binary variables for emotion (1 if correct, 0 otherwise) and Euclidean distance for valence ratings.

Results

Emotion recognition of full body stimuli interactions

The present data revealed that overall emotion recognition was high. Anger sequences were categorized with the highest accuracy ($M = 90.8\%$, $SEM = 2.62$), followed by happiness ($M = 89.91\%$, $SEM = 2.1$), sadness ($M = 88.6\%$, $SEM = 1.93$), and affection ($M = 76.75\%$, $SEM = 3.8$). All four emotions were classified above chance level (happiness: $t(18) = 31.32$, $p < .001$; affection: $t(18) = 13.62$, $p < .001$; sadness: $t(18) = 32.90$, $p < .001$; anger: $t(18) = 25.12$, $p < .001$). For more information, see supplementary results.

Feature-based discrimination between emotion categories

We examined whether the calculated features represent a specific emotional category by conducting, one-way repeated-measure ANOVAs for each intrapersonal and interpersonal feature.

On the intrapersonal level, the kinematic feature *velocity* ($F(3, 44) = 10.87$, $p < .001$, $\eta^2 = 0.43$) revealed a significant main effect of emotion category. Bonferroni-corrected post hoc pairwise comparisons showed significantly faster movements for happiness ($M = 374$ mm/s, $SEM = 41.30$ mm/s) compared to affection ($M = 204.71$ mm/s, $SEM = 31.16$ mm/s) and sadness ($M = 124.14$ mm/s, $SEM = 14.80$), as well as for anger ($M = 335.24$ mm/s, $SEM = 45.05$ mm/s) compared to sadness. *Vertical movement* also presented a significant main effect of emotion category ($F(3, 44) = 21.69$, $p < .001$, $\eta^2 = 0.6$): happiness ($M = 748.63$ mm, $SEM = 88.53$ mm) was associated with more vertical displacement than anger ($M = 497.18$ mm, $SEM = 47.63$ mm), affection ($M = 248.46$ mm, $SEM = 31.44$ mm), and sadness ($M = 188.81$ mm, $SEM = 31.72$ mm). *Volume average* ($F(3, 44) = 5.66$, $p < .01$, $\eta^2 = 0.3$) was significantly higher for happiness ($M = 0.38$ m³, $SEM = 0.05$ m³) and anger ($M = 0.38$ m³, $SEM = 0.02$ m³) than for sadness ($M = 0.22$ m³, $SEM = 0.02$ m³). The same was found for *volume STD* ($F(3, 44) = 5.58$, $p < .01$, $\eta^2 = 0.3$), in which happiness ($M = 0.1$ m³, $SEM = 0.02$ m³) and anger ($M = 0.11$ m³, $SEM = 0.01$ m³) interactions were depicted through higher variance in volume than sadness ($M = 0.04$ m³, $SEM = 0.01$ m³).

For the interpersonal features, we found a significant main effect for *IPD* ($F(3, 44) = 8.47$, $p < .001$, $\eta^2 = 0.4$) showing that the distance between two people was smaller when affection was expressed ($M = 622$ mm, $SEM = 38.14$ mm) compared to happiness ($M = 1023$ mm, $SEM = 89.65$ mm) and anger ($M = 1191$ mm, $SEM = 97.89$ mm). Likewise, *IPD STD* ($F(3, 44) = 3.02$, $p < .05$, $\eta^2 = 0.2$) revealed smaller variability while expressing sadness

($M = 45.90$ mm, $SEM = 9.58$ mm) compared to affection ($M = 122.34$ mm, $SEM = 23.33$ mm).

Examining the relation between IPD and intrapersonal features (distance correlations) revealed that *IPD* was associated more strongly with *limb contraction* ($F(3, 44) = 4.18$, $p < .05$, $\eta^2 = 0.22$) when expressing affection ($M = 0.55$ Pearson's r , $SEM = 0.05$ Pearson's r) compared to anger ($M = 0.39$ Pearson's r , $SEM = 0.03$ Pearson's r). The distance between interacting people affected *volume* ($F(3, 44) = 3.49$, $p < .05$, $\eta^2 = 0.19$) to a higher degree when showing affection ($M = 0.49$ Pearson's r , $SEM = 0.06$ Pearson's r) compared to anger ($M = 0.28$ Pearson's r , $SEM = 0.04$ Pearson's r).

A further main effect of emotion category was revealed for *personal space* ($F(3, 44) = 7.49$, $p < .001$, $\eta^2 = 0.34$). *Personal space* differed significantly between affection ($M = 88.91\%$, $SEM = 6.92$) and happiness ($M = 33.71\%$, $SEM = 11.96\%$) and between sadness ($M = 46.86\%$, $SEM = 13.50\%$) and anger ($M = 24.25\%$, $SEM = 7.85\%$), showing that interacting people spent significantly more time in the *personal space* of their counterpart while expressing affection. Additionally, *IPO* ($F(3, 44) = 9.01$, $p < .001$, $\eta^2 = 0.4$) revealed a significant main effect of emotion category showing that actors turned more towards each other while expressing affection ($M = 79.63\%$, $SEM = 8.56\%$) compared to happiness ($M = 40\%$, $SEM = 9.52\%$), sadness ($M = 32.21\%$, $SEM = 7.96\%$), and anger ($M = 25.15\%$, $SEM = 5.91\%$). Regarding *motion–energy balance*, we found a significant main effect of emotion ($F(3, 44) = 6.83$, $p < .001$, $\eta^2 = 0.32$) revealing lower motion energy balance for sadness ($M = 0.78$ AU, $SEM = 0.05$ AU) and anger ($M = 0.76$ AU, $SEM = 0.04$ AU) compared to happiness ($M = 0.93$ AU, $SEM = 0.01$ AU) and affection ($M = 0.90$ AU, $SEM = 0.02$ AU). Finally, balance in the time facing face each other showed a main effect of emotion category ($F(3, 44) = 8.42$, $p < .001$, $\eta^2 = 0.36$) revealing the highest *IPO balance* for interacting agents portraying affection ($M = 0.85$ AU, $SEM = 0.08$ AU) compared to sadness ($M = 0.17$, $SEM = 0.1$ AU) and anger ($M = 0.31$, $SEM = 0.11$ AU). For more information, see supplementary results.

Feature importance for emotion classification

To examine the relative importance of specific features for emotion classification, we trained and tested three decision tree classifiers. The models differed in terms of the features used as predictors. Model M1 (intrapersonal features) provided an overall classification accuracy of $M = 56.75\%$ (happiness: $M = 54.48\%$, affection: $M = 40.46\%$; sadness: $M = 67.14\%$; anger: $M = 64.91\%$) compared to $M = 59.41\%$ for Model M2 (interpersonal features;

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happiness: $M = 45.01\%$, affection: $M = 73.65\%$; sadness: $M = 50.07\%$; anger: $M = 68.90\%$).

Highest overall classification accuracy was provided by the combined Model M3 with an overall classification accuracy of $M = 69.54\%$ (happiness: $M = 64.18\%$, affection: $M = 71.07\%$; sadness: $M = 74.44\%$; anger: $M = 68.50\%$). M1 revealed the highest predictor importance for *vertical movement* and *limb angles* on an intrapersonal level (Fig. 2A). M2 showed that *IPD* and *motion–energy balance* were the most relevant features for classification on an interpersonal level (Fig. 2B). The combination model (M3) revealed the highest importance of *vertical movement*, *velocity*, *IPD*, and *motion–energy balance* (Fig. 2C).

Fig 2. Estimated feature importance for emotion classification. A) model M1 = intrapersonal features as predictors (overall classification accuracy 56.75%). B) model M2 = interpersonal features as predictors (overall classification accuracy = 59.41%). C) model M3 = M1+M2 combination model (overall classification accuracy of 69.54%). Bars and errorbars showing mean and standard deviation of predictor importance for different validation samples. Chance level of emotion classification at 25%. LA = Limb Angles; LC = Limb Contraction; SM = Symmetry; VEL = Velocity; ACC = Acceleration; VM = Vertical Movement; VOL = Volume; VOL STD = Volume Standard deviation; DC VEL = Distance Correlation Velocity; DC ACC = Distance Correlation Acceleration; DC LC = Distance Correlation Limb Contraction; DC VOL = Distance Correlation Volume; IPD = Interpersonal Distance; IPD STD = Interpersonal Distance Standard Deviation; IPO = Interpersonal Orientation; IPO BAL = Interpersonal

Orientation Balance; ME BAL = Motion Energy Balance; PS = Personal Space; SYNC VEL = Synchronization Velocity; SYNC ACC = Synchronization Acceleration

Representational similarity analysis: relatedness of perceived emotions and EBL features

To determine the relationship between perceptual impression and EBL features, we carried out an RSA. In a first step, we compared model RDMs (Fig. 3A) and feature RDMs on the intrapersonal and interpersonal levels (Fig. 3C & D). Representational distances (computed as “1 – Kendall's τ_A correlation”) of the categorical and feature RDMs are depicted via MDS plots. Visual inspection of the intrapersonal MDS plot (Fig. 4A) showed a clear separation between kinematic and postural features. Within the interpersonal RDMs (Fig. 4B) *motion–energy balance* was located closest to emotion and valence category RDMs.

Feature RDMs of *vertical movement*, *velocity*, *limb angles*, *limb contraction*, and *volume & volume STD* correlated positively with the emotional model RDM. *Limb angles* and *limb contraction* also correlated positively with the valence model RDM. Regarding interpersonal features, we found weak positive correlations between *IPO balance*, *IPD*, *personal space*, *IPO*, and *motion–energy balance* and the emotion model RDM; as well as between *IPO Balance*, *motion–energy balance*, and *IPD* and the valence model RDM (Fig. 4A & B).

Fig 3. Representational Dissimilarity Matrices. (A) Theoretical model RDMs that assume different similarities based on emotion and valence categories (0 if identical, 1 otherwise). (B) Behavioral, over participants averaged emotion (1 if correct, 0 otherwise) and valence rating RDMs (Euclidean distance as similarity measure). RDMs for (C) intrapersonal features, (D) interpersonal features & (E) combination features using Euclidean distance as similarity

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measure. LA = Limb Angles; LC = Limb Contraction; SM = Symmetry; VEL = Velocity; ACC = Acceleration; VM = Vertical Movement; VOL = Volume; VOL STD = Volume Standard deviation; DC VEL = Distance Correlation Velocity; DC ACC = Distance Correlation Acceleration; DC LC = Distance Correlation Limb Contraction; DC VOL = Distance Correlation Volume; IPD = Interpersonal Distance; IPD STD = Interpersonal Distance Standard Deviation; IPO = Interpersonal Orientation; IPO BAL = Interpersonal Orientation Balance; ME BAL = Motion Energy Balance; PS = Personal Space; SYNC VEL = Synchronornization Velocity; SYNC ACC = Synchronization Acceleration

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Fig 4. Relationship between model RDMs and feature RDMs for (A) intrapersonal features, (B) interpersonal features, as indicated by Kendall's τ_A correlation. Significant correlations

shown by asterisks (ns = not significant; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$). MDS plots approximate Kendall's τ_A correlation distance (1-Kendall's τ_A) among RDMs. The closer the points to each other the more similar their corresponding RDMs.

Second, we determined the relatedness between EBL features and perceptual impressions of interactions between emotion- and valence-rating RDMs as well as intra- and interpersonal model RDMs. Regarding the relationship between perceived emotion and intrapersonal features, we found significant correlations for all kinematic and postural parameters except *acceleration* (Fig. 5A). The highest correlations were for *vertical movement* ($r = 0.1$) and *velocity* ($r = 0.08$). It has to be mentioned that all correlations were rather low ranging from 0.01 to 0.1. Nevertheless, it is worth mentioning that *vertical movement* performed better than the remaining features revealed by pairwise comparisons between the feature RDMs (Fig. 5A). None of the feature RDMs came close to the noise ceiling (0.29 to 0.31).

When comparing intrapersonal features with valence ratings, we identified significant correlations for each kinematic and postural feature ranging from 0.03 to 0.14. Data revealed that postural parameters performed better than kinematic parameters. As revealed by pairwise comparisons, limb *angles* correlated most strongly ($r = 0.14$) with valence ratings and performed significantly better than all other models (Fig. 5D). The second strongest correlation ($r = 0.09$) was found for *limb contraction*, which additionally outperformed all kinematic features except for *acceleration*. Thus, kinematic intrapersonal EBL features related more strongly to the perceived emotion category and postural intrapersonal EBL features related more strongly to perceived valence.

The comparison between interpersonal feature RDMs and emotion category rating RDMs (Fig. 5B) revealed the highest correlation for *IPO balance* ($r = 0.07$). Furthermore, *personal space* ($r = 0.06$) and *motion–energy balance* ($r = 0.06$), as well as *IPO* ($r = 0.06$) and *IPD* ($r = 0.06$) performed significantly better than the remaining models ($p < .001$).

Regarding the comparison between interpersonal features and valence ratings (Fig. 5E), the highest explanatory value was provided by *motion–energy balance* ($r = 0.20$). This also outperformed all other models ($p < .001$) with the exception of *IPO balance* ($r = 0.19$). Except for the four *distance correlations* RDMs, all interpersonal features attained weak significant correlations with valence ratings. Thus, the emotion and valence perception of interacting people seems to depend on the displayed balance in motion energy and orientation as well as on proxemic measures (*IPD*, *IPO*, *personal space*).

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Furthermore, we conducted an explorative analysis of feature combinations (Fig. 5C & F). Regarding emotion perception, we averaged vertical movement with each of the five highest performing interpersonal features (*IPO balance*, *personal space*, *motion–energy balance*, *IPO*, *IPD*). Only feature combinations between *vertical movement* and *IPO* ($r = 0.11$), as well as *vertical movement* and *motion–energy balance* ($r = 0.11$) performed significantly better than the remaining combination models and all intra- and interpersonal models ($p < .001$). This indicates that emotion perception of EBL was best predicted not by a single feature in isolation, but by a combination of several features.

Regarding valence perception, averaging *limb angles* and *IPO balance* ($r = 0.22$), as well as *limb angles* and *motion–energy balance* ($r = 0.21$) revealed higher correlations. However, pairwise comparisons revealed no significant difference between combination RDMs and feature RDMs on both levels. For more information, see supplementary results.

Fig 5. Relationship between behavioural RDMs and feature RDMs. (A & D) Intrapersonal Features; (B & E) Interpersonal Features; (C & F) Combination Features. Kendall's τ_A correlation between emotion rating RDMs and Pearson correlation between valence rating RDMs. Significant correlations shown by asterisks (ns = not significant; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$, controlling FDR at 0.05). Lower and upper bounds of the noise ceiling are depicted by gray bar. Pairwise comparisons indicate which feature RDMs perform significantly

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different. Colour corresponds to significance level (black: n.s; orange: $p < 0.05$; red: $p < 0.01$; calculated via two-sided signed-rank test across subjects, controlling FDR at 0.05). LA = Limb Angles; LC = Limb Contraction; SM = Symmetry; VEL = Velocity; ACC = Acceleration; VM = Vertical Movement; VOL = Volume; VOL STD = Volume Standard deviation; DC VEL = Distance Correlation Velocity; DC ACC = Distance Correlation Acceleration; DC LC = Distance Correlation Limb Contraction; DC VOL = Distance Correlation Volume; IPD = Interpersonal Distance; IPD STD = Interpersonal Distance Standard Deviation; IPO = Interpersonal Orientation; IPO BAL = Interpersonal Orientation Balance; ME BAL = Motion Energy Balance; PS = Personal Space; SYNC VEL = Synchronization Velocity; SYNC ACC = Synchronization Acceleration

Discussion

Our data provide a detailed description of the movement features in the emotional interactions that determine emotion perception. The systematic quantitative decomposition of an interaction into an intrapersonal and interpersonal level reveals that both levels relate substantially to the emotional content of the scene as well as to its perception. We show that the emotional content of social interactions has a specific kinematic and postural fingerprint and can be described via quantitative intra- and interpersonal parameters. Both levels are linked to each other inseparably as reflected by M3 having the highest predictive accuracy and by the explorative analysis of feature combinations. We further show a strong correspondence between features that characterize the emotional content and features that are critical for perception (Roether et al., 2009). Representational similarity analysis reveals that especially kinematic parameters contribute to the perception of emotional content on an intrapersonal level, whereas on an interpersonal level, balance and proxemics parameters are important cues for the observer. It also becomes apparent that observers use mainly interaction-specific information to decode relational emotions such as affection. Regarding valence perception, we found that intrapersonal postural parameters such as *limb angles* and interpersonal balance parameters such as *motion–energy balance* and *IPO balance* relate specifically to the valence percept.

Emotions are characterized via movement features

The present data show that the emotional content of a scene is systematically referenced to intra- and interpersonal movement features such as *velocity* or *motion–energy balance*. For example, happy interactions are characterized by higher *velocity* profiles than affection and sadness but not higher than anger. These findings are broadly consistent with those reported in the existing literature (Pollick et al., 2001; Michalak et al., 2009; Roether et al., 2009; Barliya et al., 2012; Halovic and Kroos, 2017). Affectional and sad interactions show a high degree of similarity regarding their intrapersonal kinematic and postural parameters. These emotions, however, reveal characteristic differences on the interpersonal level (e.g., *IPO*, *IPO Balance*, *IPD STD*, *personal space*).

In contrast to some research reports (Aronoff et al., 1992; Dittrich et al., 1996; Atkinson et al., 2007; Poyo Solanas et al., 2020), we are unable to distinguish emotional categories via postural features such as *limb angles* and *limb contraction*. Here, it has to be taken into account that most former studies used stimuli depicting a single person mainly in a

frontal view and not social interactions observed from a third-person perspective as in the present study.

Emotion perception as a function of inherent kinematics and displayed balance

The qualia of emotion perception are associated with characteristic bodily expressions on both the intra- and the interpersonal level. Representational similarity analysis reveals that *vertical movement*, *IPO (average & orientation)*, and *motion–energy balance* emerge as the best features for explaining the emotion percept.

The present data show that participants confused happiness with anger, although only to a small extent. Conversely, anger trials were more often confused with sadness than with happiness. Most often, affection stimuli were confused with happiness. A study investigating emotions in gait (Roether et al., 2009) has demonstrated that confusions occur preferentially between emotions that share a similar level of movement activation: angry gaits tended to be confused with happy gaits, and sad gaits with fearful ones. However, these authors concluded that *velocity* is particularly important for the perception and expression of emotions (Wallbott, 1998; Pollick et al., 2001; Roether et al., 2009). We suggest that the velocity of movements is necessary to identify but not sufficient to distinguish emotions such as anger and happiness (Roether et al., 2009; Halovic and Kroos, 2017). Interpersonal cues such as *motion–energy balance* between two agents allows a perceptual distinction between happiness and anger. Balance explains (1) the high degree of confusion between happiness and affection and (2) the low degree of confusion between anger and happiness when social information is available. Balance within interactions, therefore, seems to be an important property for the observer to generate an emotional percept. Hence, social context information is particularly important for recognizing emotional content, especially when the depicted emotions depend more on reciprocal interactions (e.g., affection; see Clarke et al., 2005; Kret and de Gelder, 2010). The present results provide a computational framework for this observation. For example, affection differs from other emotions only regarding its interpersonal movement characteristics. This is underpinned by emotion-specific performance of the prediction models: the intrapersonal model is less accurate than the interpersonal model, underlining that emotions such as affection have a strong interpersonal character, and that the spatiotemporal coupling of two moving agents seems to be of great significance for perceiving strong socially expressible emotions (Clarke et al., 2005; Bachmann et al., 2020).

Valence perception is predicted by posture and interpersonal balance

Besides emotion recognition, we were interested in the perceived emotional valence—a dimension that reflects the subjective perception of an observed situation. Our data reveal that on the intrapersonal level, postural features such as limb angles best explain the participants' valence perception.

Regarding interpersonal features, balance in motion energy and orientation between interacting people are the best predictors of perceived valence. Thereby, *motion–energy balance* correlates most strongly with valence ratings. Finally, we observed a noteworthy, albeit not significant, trend towards a synchronization of *velocity* profiles, indicating that higher synchronization between people is associated with a positive impression of the perceived interaction. A study investigating interpersonal behaviour in a social task showed that patterns of proxemic behaviours and interpersonal distance predicted the subjective quality of interactions (Lahnakoski et al. 2020). Thus, balance and spatiotemporal harmony are predictors for both the experienced and the observed quality of an interaction.

Altogether, we found a set of EBL features that characterizes emotional content and predicts perceptual qualities of human interactions. These features are defined on an intra- and interpersonal level and include kinematic, postural, as well as proximity, balance, and synchronization characteristics. We conclude that the perception of human emotional interactions is a function of not only inherent kinematics of the agent but also interpersonal balance and proximity between agents.

Limitations and Future Implications

Naturally, the present and comparable studies differ with respect to the stimulus material used, stimulus length, emotional content, contextual information, and feature calculation (Bachmann et al., 2020; Poyo Solanas et al., 2020). These differences explain the partly heterogeneous results on emotion perception. Despite this heterogeneity, perception and recognition of emotional content are robust regardless of the stimulus material used. Thus, humans seem to weigh the relative importance of different movement features flexibly depending on the specific stimulus properties presented to them.

We have to acknowledge that neither an intrapersonal nor an interpersonal feature correlates with the perceptual performance on the noise ceiling level, and that we found only weak positive correlations in the present study (cf. Poyo Solanas et al., 2020). One possible explanation for this lies in the difference between emotion categories combined with the simultaneous similarity of individual parameters. Hence, it would seem appropriate to develop

models that integrate multiple dimensions of the observed scene. First solutions are offered by the present attempt to use a combination of features to classify the emotional content as well as to predict the emotional percept. Future studies, however, might apply more ecologically valid stimuli and combine different features in a multidimensional space in order to phenotype emotion specific properties of EBL in social interactions.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

Conceived and designed the experiments: JK, AZ, JB, JM, BK. Performed the experiments and analysed the data: JK, AZ. Discussed the results and wrote the paper: JK, AZ, JB, JM, BK.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author JK upon reasonable request. The source code is available at <https://zenodo.org/record/4764552#.YKXvC-23mE> (MATLAB).

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References

- Aronoff, J., Woike & B.A., Hyman L.M. (1992) Which Are the Stimuli in Facial Displays of Anger and Happiness? Configurational Bases of Emotion Recognition. *Journal of Personality and Social Psychology*, 62(6), 1050–1066 doi: 10.1037/0022-3514.62.6.1050
- Atkinson, A.P., Dittrich, W.H., Gemmell, A.J., & Young, A.W. (2004) Emotion Perception from Dynamic and Static Body Expressions in Point-Light and Full-Light Displays. *Perception*. 2004;33(6):717-746. doi:[10.1068/p5096](https://doi.org/10.1068/p5096)
- Atkinson, A.P., Tunstall, M.L., & Dittrich, W.H. (2007) Evidence for distinct contributions of form and motion information to the recognition of emotions from body gestures. *Cognition*. 104(1):59-72. doi:[10.1016/j.cognition.2006.05.005](https://doi.org/10.1016/j.cognition.2006.05.005)
- Aviezer, H., Trope, Y., & Todorov, A. (2012) Body Cues, Not Facial Expressions, Discriminate Between Intense Positive and Negative Emotions. *Science* ;338(6111):1225-1229. doi:[10.1126/science.1224313](https://doi.org/10.1126/science.1224313)
- Bachmann, J., Munzert, J., & Krüger, B. (2018) Neural Underpinnings of the Perception of Emotional States Derived From Biological Human Motion: A Review of Neuroimaging Research. *Front Psychol.* ;9:1763. doi:[10.3389/fpsyg.2018.01763](https://doi.org/10.3389/fpsyg.2018.01763)
- Bachmann, J., Zabicki, A., Munzert, J., & Krüger B. (2020) Emotional expressivity of the observer mediates recognition of affective states from human body movements. *Cognition and Emotion*;34(7):1370-1381. doi:[10.1080/02699931.2020.1747990](https://doi.org/10.1080/02699931.2020.1747990)
- Bänziger, T., Grandjean, D., & Scherer, K.R. (2009) Emotion recognition from expressions in face, voice, and body: The Multimodal Emotion Recognition Test (MERT). *Emotion* ;9(5):691-704. doi:[10.1037/a0017088](https://doi.org/10.1037/a0017088)
- Barliya, A., Omlor, L., Giese, M.A., Berthoz A., & Flash, T. (2012) Expression of emotion in the kinematics of locomotion. *Exp Brain Res.*;225(2):159-176. doi:[10.1007/s00221-012-3357-4](https://doi.org/10.1007/s00221-012-3357-4)
- Berry, K.J., & Mielke, P.W. (2000) A Monte Carlo Investigation of the Fisher Z Transformation for Normal and Nonnormal Distributions. *Psychological Reports*, 87, 1101-1114. doi:[10.2466/pr0.2000.87.3f.1101](https://doi.org/10.2466/pr0.2000.87.3f.1101)

- Clarke, T.J., Bradshaw, M.F., Field, D.T., Hampson, S.E., & Rose, D. (2005) The Perception of Emotion from Body Movement in Point-Light Displays of Interpersonal Dialogue. *Perception* ;34(10):1171-1180. doi:[10.1068/p5203](https://doi.org/10.1068/p5203)
- de Gelder, B. (2006) Towards the neurobiology of emotional body language. *Nat Rev Neurosci.* 2006;7(3):242-249. doi:[10.1038/nrn1872](https://doi.org/10.1038/nrn1872)
- de Gelder, B. (2009) Why bodies? Twelve reasons for including bodily expressions in affective neuroscience. *Phil Trans R Soc B.* 2009;364(1535):3475-3484. doi:[10.1098/rstb.2009.0190](https://doi.org/10.1098/rstb.2009.0190)
- de Gelder, B., Terburg, D., Morgan, B., Hortensius, R., Stein, D.J., & van Honk, J. (2014) The role of human basolateral amygdala in ambiguous social threat perception. *Cortex*; 52:28-34. doi:[10.1016/j.cortex.2013.12.010](https://doi.org/10.1016/j.cortex.2013.12.010)
- Derntl, B., & Habel, U. (2011) Deficits in social cognition: a marker for psychiatric disorders? *Eur Arch Psychiatry Clin Neurosci.* ;261(S2):145-149. doi:[10.1007/s00406-011-0244-0](https://doi.org/10.1007/s00406-011-0244-0)
- Dittrich, W.H., Troscianko, T., Lea, S.E.G., & Morgan, D. (1996) Perception of Emotion from Dynamic Point-Light Displays Represented in Dance. *Perception* ;25(6):727-738. doi:[10.1068/p250727](https://doi.org/10.1068/p250727)
- Ekman P, & Friesen W.V. Constants across cultures in the face and emotion. *Journal of Personality and Social Psychology.* 1971;17(2):124-129. doi:[10.1037/h0030377](https://doi.org/10.1037/h0030377)
- Frith, C.D., & Frith, U. (2012) Mechanisms of Social Cognition. *Annu Rev Psychol.* ;63(1):287-313. doi:[10.1146/annurev-psych-120710-100449](https://doi.org/10.1146/annurev-psych-120710-100449)
- Glowinski, D., Dael, N., Camurri, A., Volpe, G., Mortillaro, M., & Scherer, K. (2011) Toward a Minimal Representation of Affective Gestures. *IEEE Trans Affective Comput.*;2(2):106-118. doi:[10.1109/T-AFFC.2011.7](https://doi.org/10.1109/T-AFFC.2011.7)
- Goldberg, H., Christensen, A., Flash, T., Giese, M.A., & Malach, R. (2015) Brain activity correlates with emotional perception induced by dynamic avatars. *NeuroImage.* ;122:306-317. doi:[10.1016/j.neuroimage.2015.07.056](https://doi.org/10.1016/j.neuroimage.2015.07.056)
- Gross, M.M., Crane, E.A., & Fredrickson, B.L. (2012) Effort-Shape and kinematic assessment of bodily expression of emotion during gait. *Human Movement Science* ;31(1):202-221. doi:[10.1016/j.humov.2011.05.001](https://doi.org/10.1016/j.humov.2011.05.001)

- Halovic, S., & Kroos, C. (2017) Not all is noticed: Kinematic cues of emotion-specific gait. *Human Movement Science* ;57:478-488. doi:[10.1016/j.humov.2017.11.008](https://doi.org/10.1016/j.humov.2017.11.008)
- Kaletsch, M., Pilgramm, S., Bischoff, M., Kindermann, S., Sauerbier, I., Stark, R., Lis, S., Gallhofer, B., Sammer, G., Zentgraf, K., Munzert, J., & Lorey, B (2014) Major Depressive Disorder Alters Perception of Emotional Body Movements. *Front Psychiatry*. 2014;5. doi:[10.3389/fpsyt.2014.00004](https://doi.org/10.3389/fpsyt.2014.00004)
- Kleinsmith, A., & Bianchi-Berthouze, N. (2013) Affective Body Expression Perception and Recognition: A Survey. *IEEE Trans Affective Comput.* ;4(1):15-33. doi:[10.1109/T-AFFC.2012.16](https://doi.org/10.1109/T-AFFC.2012.16)
- Kret, M.E., & de Gelder, B. (2010) Social context influences recognition of bodily expressions. *Exp Brain Res.* ;203(1):169-180. doi:[10.1007/s00221-010-2220-8](https://doi.org/10.1007/s00221-010-2220-8)
- Kriegeskorte, N., Mur, M., Ruff, D.A., Kiani, R., Bodurka, J., Esteky, H., Tanaka, K., & Badetini, P.A. (2008) Matching Categorical Object Representations in Inferior Temporal Cortex of Man and Monkey. *Neuron* ;60(6):1126-1141. doi:[10.1016/j.neuron.2008.10.043](https://doi.org/10.1016/j.neuron.2008.10.043)
- Lahnakoski, J.M., Forbes, P.A.G., McCall, C., & Schilbach, L. (2020) Unobtrusive tracking of interpersonal orienting and distance predicts the subjective quality of social interactions. *R Soc open sci.* 2020;7(8):191815. doi:[10.1098/rsos.191815](https://doi.org/10.1098/rsos.191815)
- Loh, W.-Y (2002) Regression tress with unbiased variable selection and interaction detection. *Stat.Sin.* 361-386
- Lorey B., Kaletsch, M., Pilgramm, S., Bischoff, M., Kindermann, S., Sauerbier, I., Stark, R., Zentgraf, K., & Munzert, J. (2012) Confidence in Emotion Perception in Point-Light Displays Varies with the Ability to Perceive Own Emotions. Wenderoth N, ed. *PLoS ONE* ;7(8):e42169. doi:[10.1371/journal.pone.0042169](https://doi.org/10.1371/journal.pone.0042169)
- Michalak, J., Troje, N.F., Fischer, J., Vollmar, P., Heidenreich, T., & Schulte, D. (2009) Embodiment of Sadness and Depression—Gait Patterns Associated With Dysphoric Mood: *Psychosomatic Medicine* ;71(5):580-587. doi:[10.1097/PSY.0b013e3181a2515c](https://doi.org/10.1097/PSY.0b013e3181a2515c)
- Moreau, Q., Galvan, L., Nazir, T.A., & Paulignan, Y. (2016) Dynamics of Social Interaction: Kinematic Analysis of a Joint Action. *Front Psychol.* ;7. doi:[10.3389/fpsyg.2016.02016](https://doi.org/10.3389/fpsyg.2016.02016)

- Nili, H., Wingfield, C., Walther, A., Su, L., Marslen-Wilson, W., & Kriegeskorte, N. (2014) A Toolbox for Representational Similarity Analysis. Prlic A, ed. *PLoS Comput Biol.* ;10(4):e1003553. doi:[10.1371/journal.pcbi.1003553](https://doi.org/10.1371/journal.pcbi.1003553)
- Opitz, D., & Maclin, R. (1999) Popular ensemble methods: An empirical study. *Journal of artificial intelligence research*, 11, 169-198. doi: [10.1613/jair.614](https://doi.org/10.1613/jair.614)
- Overhill, H. (2014) Apple Pie Proxemics: Edward T. Hall in the Kitchen Work Triangle. *Design Issues* ;30(2):67-82. doi:[10.1162/DESI_a_00263](https://doi.org/10.1162/DESI_a_00263)
- Paterson, H.M., Pollick, F.E., & Sanford, A.J. (2001) The Role of Velocity in Affect Discrimination. :6.
- Pollick, F.E., Paterson, H.M., Bruderlin, A., & Sanford, A.J. (2001) Perceiving affect from arm movement. *Cognition* ;82(2):B51-B61. doi:[10.1016/S0010-0277\(01\)00147-0](https://doi.org/10.1016/S0010-0277(01)00147-0)
- Poyo Solanas, M., Vaessen, M.J., & de Gelder, B. (2020) The role of computational and subjective features in emotional body expressions. *Sci Rep.* ;10(1):6202. doi:[10.1038/s41598-020-63125-1](https://doi.org/10.1038/s41598-020-63125-1)
- Roether, C.L., Omlor, L., Christensen, A., & Giese, M.A. (2009) Critical features for the perception of emotion from gait. *Journal of Vision* ;9(6):15-15. doi:[10.1167/9.6.15](https://doi.org/10.1167/9.6.15)
- Silver, N.C., & Dunlap, W.P. (1987) Averaging Correlation Coefficients: Should Fisher's z Transformation Be Used? *Journal of Applied Psychology*, 72 (1), 146-148, doi:[10.1037/0021-9010.72.1.146](https://doi.org/10.1037/0021-9010.72.1.146)
- Sorokowska, A., Sorokowski, P., & Hilpert, P. (2017) Preferred Interpersonal Distances: A Global Comparison. *Journal of Cross-Cultural Psychology* ;48(4):577-592. doi:[10.1177/0022022117698039](https://doi.org/10.1177/0022022117698039)
- Thepsoonthorn, C., Yokozuka, T., Miura, S., Ogawa, K., & Miyake, Y. (2016) Prior Knowledge Facilitates Mutual Gaze Convergence and Head Nodding Synchrony in Face-to-face Communication. *Sci Rep* ; 6 (1):38261. doi:[10.1038/srep38261](https://doi.org/10.1038/srep38261)
- Thurman, S., & Lu, H. (2014) Perception of Social Interactions for Spatially Scrambled Biological Motion. Reid VM, ed. *PLoS ONE*; 9 (11):e112539. doi:[10.1371/journal.pone.0112539](https://doi.org/10.1371/journal.pone.0112539)

- Troje, N.F., Westhoff, C., & Lavrov, M. (2005) Person identification from biological motion: Effects of structural and kinematic cues. *Perception & Psychophysics*; 67 (4):667-675. doi:[10.3758/BF03193523](https://doi.org/10.3758/BF03193523)
- Van den Stock, J., Righart, R., & de Gelder, B. (2007) Body expressions influence recognition of emotions in the face and voice. *Emotion* ;7(3):487-494. doi:[10.1037/1528-3542.7.3.487](https://doi.org/10.1037/1528-3542.7.3.487)
- Wallbott, H.G. (1998) Bodily expression of emotion. *Eur J Soc Psychol.*; 28 (6), 879-896. doi: [https://doi.org/10.1002/\(SICI\)1099-0992\(1998110\)28:6<879::AID-EJSP901>3.0.CO;2-W](https://doi.org/10.1002/(SICI)1099-0992(1998110)28:6<879::AID-EJSP901>3.0.CO;2-W)
- Yokozuka, T., Ono, E., Inoue, Y., Ogawa, K.-I., & Miyake, Y. (2018) The Relationship Between Head Motion Synchronization and Empathy in Unidirectional Face-to-Face Communication. *Front Psychol.* 2018;9:1622. doi:[10.3389/fpsyg.2018.01622](https://doi.org/10.3389/fpsyg.2018.01622)
- Zabicki, A. & Keck, J. (2021) SAMI: Similarity Analysis of Human Movements and Interactions (Version v0.1.0). Zenodo [http://doi.org/10.5281/zenodo.4764552](https://doi.org/10.5281/zenodo.4764552)