Estimating Romantic, Social, and Sexual Attraction by Quantifying Bodily Coordination using Wearable Sensors

Kapcak, Oyku; Vargas-Quiros, Jose; Hung, Hayley

DOI
10.1109/ACIIW.2019.8925137

Publication date
2019

Document Version
Final published version

Published in
2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos, ACIIW 2019

Citation (APA)
Kapcak, O., Vargas-Quiros, J., & Hung, H. (2019). Estimating Romantic, Social, and Sexual Attraction by Quantifying Bodily Coordination using Wearable Sensors. In *2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos, ACIIW 2019* (pp. 154-160). Article 8925137 (2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos, ACIIW 2019). IEEE. https://doi.org/10.1109/ACIIW.2019.8925137

Estimating Romantic, Social, and Sexual Attraction by Quantifying Bodily Coordination using Wearable Sensors

Öykü Kapcak
Delft University of Technology
Delft, Netherlands
Kapcak@tudelft.nl

Jose Vargas-Quiros
Delft University of Technology
Delft, Netherlands
J.D.VargasQuiros@tudelft.nl

Hayley Hung
Delft University of Technology
Delft, Netherlands
h.hung@tudelft.nl

***Abstract*—In this paper we introduce a novel method of estimating romantic, social and sexual attraction between two people by quantifying their bodily coordination using wearable sensors in a speed-date setting. We developed simple synchrony and convergence features, inspired from the literature and specifically adapted to be extracted from accelerometer data. To our knowledge, this is the first time that motion convergence is used for estimating attraction. Our features could predict one-way social attraction with a 73% Area under the ROC curve (AUC), out-performing previous work in a similar setting. We also showed that prediction performance increased when the male and female data are separated. We could also predict mutual romantic attraction with an AUC of 80%. Finally, we found that social attraction could be predicted better from movement correlation features whereas for romantic and sexual interest mimicry features were better indicators. Additionally, we found that "mimicking of female to male" and "convergence of female's movement to male's" were indicators of sexual and romantic mutual attraction in our data.**

***Index Terms*—Attraction, synchrony, convergence, wearable acceleration, dyadic interactions, speed-dates.**

I. Introduction

Gatica-Perez defines the term interest as "people's internal states related to the degree of engagement displayed, consciously or not, during social interaction" [1]. He also notes that this engagement arises because of different factors such as interest in the topic of a conversation, attraction to other person or social rapport. The goal of this study is to investigate the automatic detection of attraction in dyadic interactions using movement features that are automatically extracted from single body-worn accelerometers in an in-the-wild setting.

The advances in sensing technologies and the possibilities of sensing human behavior have brought interest in the automatic assessment of human behavior in several research communities. Assessing human behavior makes it possible to automatically analyze human-human interactions. This in turn makes it possible to build tools that improve the time and possibly quality of psychological and sociological research. Additionally, automatic assessment is of interest for the creation of more naturally behaving socially-aware computing systems. A further application is the creation of tools that can help people assess their own behavior in their relationships, enabling them to receive feedback about their behavior during social interactions which would increase the quality of their relationships with other people.

Recent promising advances in this field give insights into the relationship between little-understood phenomena like physical and emotional attraction and measurable human behavior. Attraction has been found to affect the way in which couples behave towards one another during interactions, affecting other known social phenomena like the level of synchrony in their movements [2], the degree to which they mimic one another [3]–[5] and the adaptation to one another's behavior [6]. Our work aims to investigate how we can automatically estimate interpersonal attraction by quantifying body coordination using wearable sensors. Concretely, the contributions of this study are three-fold. First, we proposed novel behavioral coordination features that can be extracted from a single body-worn accelerometer. We show that behavioral features such as synchrony and convergence can be extracted from motion and used to predict attraction between two people. Second, we used these features to model interpersonal attraction and tested them in a real life in-the-wild setting with a less intrusive approach. Finally, we obtained experimental evidence that supports the existing theories from psychological literature about behavioral differences between men and women in a courtship setting.

II. Related Work

Interpersonal interest and its associated non-verbal behavior have been studied by psychology researchers. The automatic quantification of this behavior has also been of interest to computer scientists. Therefore, studies from both fields are reviewed here. First, related work about romantic interest is discussed. Research on other forms of interest is mentioned briefly. Finally measures of coordination that are used in the literature are summarized.

Most of the existing work that studied romantic interest conducted experiments in speed-date scenarios. The reason for using these events in attraction studies is that the responses to the questionnaires that are filled after the dates can be used as ground truth for the prediction tasks. Madan et al.

978-1-7281-3891-6/19/$31.00 ©2019 IEEE

investigated romantic, friendly and business interest between people by extracting four types of social signal measures from audio: activity, engagement, emphasis and mirroring and successfully predicted each type of interest using these features [7]. Michalsky et al. investigated pitch convergence and found that speech of interactants became more similar over the course of conversation when perceived attractiveness and likability is higher [6]. Ranganath et al. used prosodic, dialogue, and lexical features extracted from audio recordings to investigate the participant's flirtation behavior and could predict both flirtation intention and flirtation perception [8].

Veenstra et al. found that positional features extracted from video such as position, distance, movement and synchrony are indicators of attraction. Their results also indicated that addressing male and female behavior as two different tasks for prediction increased the task performances [2]. With the aim to recreate similar results, Cabrera-Quiros et al. attempted to classify attraction levels between participants using motion features extracted from accelerometer data [9]. Even though they only used the mean and variance of the magnitude of acceleration as features, they obtained good classification results. An interesting finding of their study is that separating male and female data did not improve their prediction performance unlike [2].

Research has been done in psychology about attraction focusing on the mimicry behavior [3]–[5]. Instead of doing an automatic feature extraction, they manually annotated non-verbal mimicry events of the interacting partners by watching the recordings of the interactions. They found that mimicry was positively correlated with romantic interest. Research from psychology also showed that people use different mechanisms and strategies when it comes to searching for short-term and long-term partners [10]. Moreover, these strategies are different for men and women. It is indicated also in other research that men and women show differences in mate selection [11] and courtship behavior [12] such as women flipping their hair and moving their shoulders and men uncrossing their legs often. These research suggest that men and women should be treated separately in attraction prediction tasks.

In research about other types of inter-personal interest, researchers studied head motion synchrony of spouses during interactions [13], [14], estimated team cohesion in meeting settings using audio-visual cues and mimicry features [15], [16] and used behavioral synchrony and correlation features to predict interaction quality and outcome [17], [18].

In conclusion, previous literature shows that features that capture behavioral coordination and similarity between people's behavior are indicators of affect between people and used for modeling interest by extracting them from different modalities and settings. These features can be grouped into two categories as *synchrony* and *convergence*. In this study we also used these types of features for modeling attraction.

III. Data

We used *MatchNMingle*, a multimodal and multisensor dataset recorded with the aim to be used in research about automatic analysis of social signals and interactions for both social and data sciences [9]. It was collected in an indoor in-the-wild setting instead of a lab setting. Therefore the social interactions between participants were as natural as possible.

A. Experiment context

The whole dataset was recorded during a set of activities taking place over 3 days in total in a local bar. Each day the event started with a speed dating round where participants of opposite sex had a 3 minute date with each other, followed by a mingle party. In this research, only the data from the first part of the event is used. Participants were recruited from a university and expected to fit the criteria of being single, heterosexual and between the ages of 18 and 30. In total of 92 participants attended the event, with equal number of men and women and most of them did not know each other. During the event, participants were asked to wear devices around their necks, which record tri-axial acceleration and proximity. After removing malfunctioning devices, in total 72 participants had sufficient data recorded by wearable devices.

B. Data collection

Acceleration data was collected using tri-axial accelerometers at a frequency of 20 Hz. After each 3-minute date with the participant of opposite sex, participants were given 1 minute to fill a booklet with a questionnaire about their date partner indicating their interest in each other. Responses for these questionnaires constitute the ground truth for the tasks in this study. After removing the dates which at least one of the participants have a malfunctioning device and unreadable booklet responses, a total number of 398 date interactions were left. Since each participant had their own label for each date, male and female participants of one date interaction were treated as separate samples, resulting in total of 796 samples.

C. Defining the ground truth

The questionnaire that participants filled after their dates consisted of following questions with responses on a 7-point Likert scale (low = 1, high = 7):

- How much would you like to see this person again?
- How would you rate this person as a potential friend?
- How would you rate this person as a a short term sexual partner?
- How would you rate this person as a long term romantic partner?

Each of these questions was used to define different tasks for the interest prediction problem as respectively *See Again*, *Friendly*, *Sexual* or *Romantic*. The problem was treated as a binary classification problem, meaning each date of a participant would have binary labels for each one of these tasks. For clarification, a *date* refers to the information from a single person during a speed date, whereas a *date interaction* refers to the interaction between two participants during a speed date. These two concepts are used in two challenges of this study. The first one is to predict if one participant is *attracted* or *not attracted* to his/her date partner. This would require labeling a person's *date* thus for each speed date interaction male and female participant have their own labels. The second challenge is to predict if a *date interaction* ends with a *match* or *no match*. To obtain labels for these situations, first the responses on Likert scale need to be binarized. Initially, each person's scores for all of his/her dates are normalized with z-score normalization. Following this, *dates* that have positive score are labeled as *attracted* and negative score as *not attracted*. Following this, *date interactions* are labeled and a *match* label is given to a *date interaction* if both participants have *attracted* labels for their date and for all other cases a *no match* label is assigned.

D. Data Analysis

Distribution of labels over each class showed that *SeeAgain* and *Friendly* tasks have a balanced class distribution with 49% positive labels. On the other hand, *Romantic* and *Sexual* tasks have a bias on *not attracted* class with 40% and 42% positive labels respectively. With the match labels, it is observed that for all tasks the datasets are highly biased towards *no match* class with 30% positive labels for *SeeAgain* and *Friendly*, 13% for *Romantic* and 19% for *Sexual* task. Additionally, the class distribution difference between genders is also analyzed and observed that *Friendly* and *Romantic* tasks have similar number of positive labels in female group and male group (f:52% m:48% for Friendly, f:38% m:42% for Romantic) whereas *SeeAgain* task has significantly more positive labels in female group and *Romantic* task has significantly more positive labels in male group (f:52% m:45% for SeeAgain, f:36% m:48% for Sexual). From these we can claim that female and male participants did not differ in their inclinations toward friendship and long term romantic relationship but male participants had a higher tendency towards a short term sexual relationship.

IV. Features

Our method aims to model the coordination of behavior between two people having a date, using nonverbal behavioral features extracted from accelerometer readings.We describe the feature extraction process in more detail below.

A. Preprocessing

The accelerometer data consists of 3-dimensional readings with the X axis capturing the left-right movements; the Y axis up-down movements and Z axis forward-backward movements. Initially each axis of each person's recordings is normalized by computing the z-score within itself to remove interpersonal differences in movement intensity. Then, these normalized raw recordings are treated in multiple ways: raw values of each axis, absolute values of each axis and the magnitude of the acceleration which is computed as $\sqrt{(x^2 + y^2 + z^2)}$. Each of these 7 signals is divided into *n*-second windows using a sliding-window approach, with *n/2* second shifts between each window. Since the optimal window size that captures necessary information is not known, the possible values of *n* are chosen as 1, 3, 5 and 10 seconds.

Similar to [19], statistical (mean, variance) and spectral (power spectral density) features are extracted from each window. Power spectral density (PSD) per window is computed using 6 logarithmically spaced bins between 0-10 Hz, to increase the resolution at low frequencies. Each bin gives information about the characteristic of behavior of the person at that time window, therefore each bin is treated as a single feature. Combining these features results in 8 feature dimensions per window.

Computing these 8 features for each 7 types of signal mentioned earlier and for 4 different window-sizes results in 224 low-level features that will further be used to extract behavioral coordination features that are explained in the following subsection. An illustration of the pre-processing steps is shown in Figure 1.

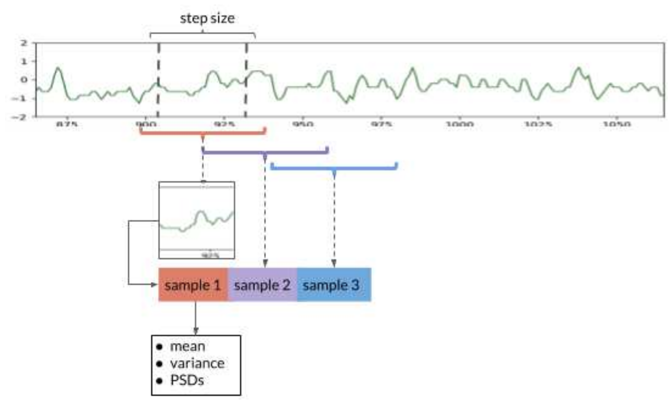

Fig. 1. Pre-processing step: Using a sliding window approach, the signal is divided into samples from which the statistical and spectral features are extracted.

B. Feature Extraction

The aforementioned low-level features are used to extract more complex behavioral coordination features that are grouped into two categories.

1) Synchrony: To measure the synchrony of behavior of two interacting people, two different measures are used.

a) Correlation: Correlation has been used in the literature as a measure of similarity of overall body motion and also motion of specific body parts such as the hands or head of two people [17], [18], [20]–[22]. Here, as in the previous studies, we used Pearson correlation:

$$\rho_{xy} = \frac{\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y)}{\sigma(X)\sigma(Y)} \tag{1}$$

In our context, it captures the liner correlation between two person's signals and it is expected to give a score closer to 1 when two people have positive feelings towards each other.

b) (Normalized) Mutual Information: This measure has also been used in the literature to capture the dependence between two people's behavior [19], [23]. In our case it captures the dependence of two people's behavior on each other. It is calculated as follows:

$$I(X;Y) = H(X) + H(Y) - H(X,Y) \tag{2}$$

where H(X) and H(Y) represents the entropy of random variables X and Y and H(X,Y) represents the joint entropy of X and Y.

Additionally, normalized mutual information is computed by dividing by $\sqrt{H(X)H(Y)}$ to obtain a score between 0 and 1. A higher score is expected when two people have an influence on each other's behavior.

c) Mimicry: This mimicry measure is inspired by the work of Nanninga et al. [16]. The goal is to capture when one person imitates their partner's behavior. Figure 2 illustrates how this feature is computed. Each sample window of Person A's signal is compared with the consecutive window of Person B's signal. To compare these windows, the distance between low-level features of these windows are computed, resulting in distance scores $D = [d_0, d_1, ...d_n]$ for the entire interaction. From these distance scores, minimum ($min(D)$), maximum ($max(D)$), mean ($mean(D)$) and variance ($var(D)$) are computed and used as features. Since this feature only captures the mimicry of Person B to Person A, the reverse is also computed.

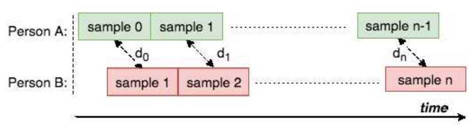

Fig. 2. Mimicry feature. Each time sample is compared with the other person's preceding time sample.

d) Time-lagged correlation: Correlation with a time lag has also been used to measure the linear relation of a follower's movement with the interlocutor's movement [20], [21]. The following formula computes the correlation between X and Y signals at a positive lag of τ samples, following formula is used:

$$\rho_{xy} = \frac{\sum_{i=1}^{N-\tau}(x_i - \mu_x)(y_{i+\tau} - \mu_y)}{\sigma(X)\sigma(Y)} \tag{3}$$

This metric can indicate the leader-follower relationship of two people in a conversation by showing who is driving the interaction. In an example case of measuring the correlation between person A and person B's movement, if a higher score is obtained when person B's signal is positively lagged, this indicates that person B is leading the interaction. Following the literature, we use +/- 1 time step lags.

2) Convergence/Divergence: To measure convergence, three different metrics are developed that, inspired in various literature. These features aim to measure if two people's behavior style is diverging or converging through their interaction. The idea is that people's feelings for each other would be more positive if they show a more converging behavior.

a) Symmetric convergence: This feature is inspired by the works of [6], [16]. It compares two people's behavior at each time step and aims to capture if the difference between their behavior decreases over time. In order to compute it, corresponding windows of two participants' signals are compared with each other. To measure the similarity at each time step, the distance between these corresponding samples' low-level features are computed as illustrated in Figure 3, resulting in distance scores $D = [d_1, d_2, ..., d_n]$, for each sample. After that, the correlation of these scores with time is computed to understand if they increase or decrease using Pearson correlation formula (eq. 3) and a correlation coefficient is obtained. Since the goal is to capture convergence, a decreasing distance indicates converging behavior. Therefore, the correlation coefficient is expected to be more negative for converging interactions where participants show similar behavior over the interaction.

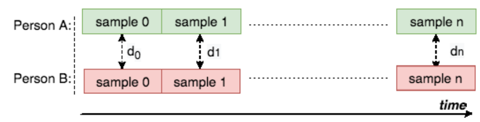

Fig. 3. Symmetric convergence feature. Each time sample is compared with the other person's corresponding time sample.

b) Asymmetric convergence: This feature has also been inspired by [16]. The first two minutes of the date interaction are taken as the learning period in which the behavior of one participant is modeled and the last one minute of the interaction is compared to this learned model. To understand if the second person's behavior converges to the first person's behavior, the low-level features of the samples from the last one minute are compared to the learning part's low-level features. To measure the similarity, distances between these features are computed as illustrated in Figure 4, resulting in distance scores $D = [d_1, d_2, ..., d_n]$, for each sample in the last one minute of interaction. Then, the correlation of these scores with time is computed using Pearson correlation. A smaller and negative correlation coefficient indicates high convergence and more positive affect between two people. Since this feature only captures the convergence of Person B's behavior to Person A, it is also computed by changing the order of people.

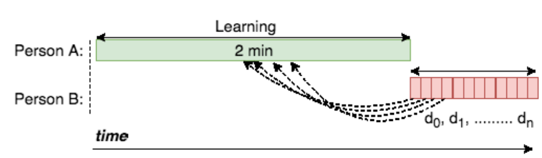

Fig. 4. Asymmetric convergence feature. Each time sample in the last 1 minute period is compared with the other person's first 2 minutes by computing a distance score between sample features.

c) Global convergence: This feature has been inspired by the work of [6]. The idea is to measure the similarity of two people's behavior in the beginning and at the end of their date interaction and compare these similarities. It is expected that the behavior will be more similar at the end of the interaction due to convergence. To capture this, the first and second half of the signals are taken as illustrated in figure 5. The similarity d_0 between the first half's features of the two

TABLE I
FEATURE VECTOR

Feature type	Feature	ID
Synchrony	Correlation	0-223
	Mutual Information	224-559
	Mimicry	560-2351
	Time-lagged correlation	2352-2799
Convergence	Symmetric convergence	2800-3135
	Asymmetric convergence	3136-3583
	Global convergence	3584-3807

persons is computed. An equivalent similarity d_0 is computed for the second half. The difference between these similarities is computed by subtraction as: $c = d_1 - d_0$. This difference is expected to be negative when convergence occurs.

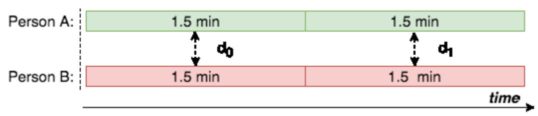

Fig. 5. Global convergence feature. The difference between both persons' features is computed for each half of the interaction.

Table I summarizes all the features that are used in our experiments with the corresponding IDs. Additionally, symmetric features are colored with red and asymmetric features are colored with blue.

C. Feature pre-processing

After extracting the features, they were pre-processed with the objective of reducing the dimensionality of the feature space. The features were first normalized to zero mean and unit standard deviation. Second, we selected a set of representative features by computing the ANOVA F-value between each feature and target labels and taking the features with significantly high F-value ($p < 0.05$). Finally, we applied principal component analysis (PCA) and the top principal components preserving 95% of the variance were kept.

V. RESULTS

A logistic regressor was chosen as classifier for the task of predicting interest, as in [24]. To evaluate the predictive performance of classifiers for each task, a nested 10-fold cross-validation was applied. To obtain a measure that is unaffected by the class imbalance, the Area under the Receiver Operator Characteristic (AUC) was used to determine performance.

The first problem investigated in this study was that of predicting if a person is attracted to his or her date partner. Performances for different attraction type predictions are compared to the random baseline classifier which assigned every data point to the most frequent class. Obtained mean AUC scores are shown in the first column of Table II. For all tasks our features performed significantly better than the random baseline of 50% AUC.

We also compared the performance of our features with the features from [9], the closest to our setting in terms of approach and modality. The examined features were: mean of the magnitude of acceleration, variance of the magnitude of acceleration, mean of the variance of acceleration over 1 second windows, variance of the variance of acceleration over 1 second windows. Obtained mean AUC scores using these features are shown in the second column of Table II. As is seen they are out-performed by our features for all tasks. Even though the same dataset is used in [9], since to compute our features it is required to have valid data from both of the participants in a date, we had to discard a larger amount of dates. Moreover, we used a different method for obtaining the ground truth from the questionnaires, resulting in a dataset with different statistics.

TABLE II
MEAN AUC SCORES OBTAINED IN ONE-WAY INTEREST PREDICTION TASKS

	Our features	SOA features	Only female	Only male
SeeAgain	0.67($\pm$0.06)	0.53($\pm$0.05)	0.77($\pm$0.06)	0.76($\pm$0.07)
Friendly	0.73($\pm$0.05)	0.50($\pm$0.06)	0.75($\pm$0.08)	0.76($\pm$0.07)
Romantic	0.68($\pm$0.04)	0.57($\pm$0.08)	0.80($\pm$0.06)	0.79($\pm$0.04)
Sexual	0.69($\pm$0.07)	0.50($\pm$0.08)	0.75($\pm$0.10)	0.80($\pm$0.07)

TABLE III
MEAN AUC SCORES OBTAINED IN MUTUAL INTEREST PREDICTION TASKS

	Our features
SeeAgain	0.82($\pm$0.09)
Friendly	0.79($\pm$0.06)
Romantic	0.80($\pm$0.11)
Sexual	0.78($\pm$0.09)

The second problem investigated in this study was predicting if both people who had an interaction are attracted to each other or not (ie. if they are a match). Obtained mean AUC scores are shown in Table III. We observe that the mutual attraction prediction tasks have shown better performance than one-way attraction prediction tasks. We could not compare our results with the state-of-the-art features' performance because they did not use their features for predicting mutual attraction.

As in previous literature [2], [9], we also experimented separating and combining male and female data. The third and fourth columns of Table II shows the scores obtained by using male and female data separately. The results showed that separation increased the prediction performance for all tasks compared to the combined dataset's performance. The least amount of improvement is seen in the *Friendly* tasks indicating that men and women show similar behavior when they have a friendly attraction towards each other. On the other hand for *Romantic* and *Sexual* tasks we have a larger increase, in line with the literature, suggesting that men and women show different behavioral characteristics when experiencing romantic or sexual attraction.

VI. DISCUSSION

A. Correlation analysis

In this analysis, features are correlated with the label of each task, in order to have a deeper understanding of the contribution of each one. The features with the highest correlation coefficients were found to vary with different tasks. This indicates that each type of attraction manifests in different behavioral characteristics. One interesting finding of this analysis is that *Correlation* features that are computed over the Z-axis are negatively correlated with *Friendly* attraction as opposed to the expectation of positive correlation as explained before. Z-axis captures the forward-backward acceleration of the body. Therefore, negative correlation could be because of one person's backward and other person's forward movement occurring simultaneously. Considering the fact that during the interactions people were sitting opposite to each other, this might be due to people's simultaneous movement occurring along the same axis but in different directions. On the other hand, most of the *Correlation* features that are extracted using PSD bins indicating correlation in the movement frequencies of couples showed positive correlation with the *Friendly* and *Sexual* attraction. It shows that the correlation of movement did not occur necessarily in the direction of movement but also the frequency of movement of two people were similar.

It is also seen that *Mutual Information* features had high positive correlation with only the *SeeAgain* and *Friendly* tasks whereas the *Mimicry* features had high positive correlation with only the *Romantic* and *Sexual* tasks. From that, we hypothesize that people enjoying a friendly conversation show more synchronic behavior. On the other hand, in a flirtatious interaction mimicking behavior becomes more prominent.

Convergence features were expected to have negative correlation with the labels, because more negative convergence values indicate a higher convergence, which we hypothesize to be an indicator of positive attraction. This is obtained in *SeeAgain* and *Romantic* tasks but the opposite is observed in most features of *Friendly* task. We can conclude that actually the divergence in behavioral characteristics might be an indicator of friendly attraction to the other person.

Another observation is that there are not many features with high correlation for the *SeeAgain* task. This can be because the labels for this task are obtained by the answers to "wanting to see the person again" question and this is a vague description for any attraction. Therefore the ground truth might not be a very clear indicator of any attraction.

When analyzing the high correlated features with *Match* tasks, we could also pay attention to the direction of asymmetric features that will give us information about the leader-follower behavior of each gender. In *SeeAgain* and *Friendly* tasks, *male convergence to female* features have a positive correlation with matches. This is the opposite of what is expected because a positive convergence score shows a non-converging behavior and it was not expected to be correlated with attraction. On the other hand, in the *Sexual* task *female convergence to male* feature shows a negative correlation with attraction, indicating that when there is a mutual sexual attraction during an interaction it is revealed by female's behavior converging to the male's. Additionally, *female mimicking male*-mimicry features show the highest positive correlation with mutual *Romantic* and *Sexual* attraction. Interestingly even though both are synchrony features, *Correlation* shows higher correlation with *Romantic* matches whereas the *Mutual Information* shows higher correlation with *Sexual* matches.

In summary, we see that different types of attraction are indicated with different behavioral features. Therefore, depending on the task, a subset of features can be selected for better prediction performance. Even though we can not be certain that our features are capable of modelling exactly the behavior that we aim to model since we do not have ground truth about the synchrony and convergence, they are shown to be good at predicting the goal outcome which is to predict interpersonal attraction. In addition, synchrony and convergence terms are not very well defined and there is no consensus over them in the literature which makes it even more difficult to generalize our findings.

B. Comparison symmetric and asymmetric features

As is known attraction is an asymmetric property, meaning that it might not be reciprocal. Therefore, it is important to consider that symmetric and asymmetric features may have different meanings. Symmetric features are the same for both participants of the date. On the other hand, asymmetric features can capture the direction of mimicry or convergence and thus have a different meaning for each participant in a date. For example, if the male participant is mimicking the female, this can be interpreted differently for each side.

We ran classification tasks using symmetric and asymmetric features. AUC scores of one-way attraction prediction tasks using only symmetric features are 0.59($\pm$0.05) for SeeAgain, 0.65($\pm$0.03) for Friendly, 0.61($\pm$0.05) for Romantic, 0.58($\pm$0.06) for Sexual tasks and using only asymmetric features 0.64($\pm$0.05) for SeeAgain, 0.67($\pm$0.05) for Friendly, 0.68($\pm$0.05) for Romantic and 0.65($\pm$0.06) for Sexual. In mutual-attraction prediction tasks both feature groups showed similar performance. Therefore we did not add their results here. Our results show that asymmetric features outperformed the symmetric features in all tasks for predicting one-way attraction. Considering the fact that attraction is an asymmetric property, these results align with our expectations.

VII. Conclusion

In this study, we have presented a method for automatically predicting attraction between people using behavioral coordination features extracted from data recorded by a single body-worn accelerometer. We used synchrony and convergence features and our proposed approach out-performed the state-of-the art [9] which was the most similar setting to our case. To our knowledge, this is the first time that motion convergence is used for estimating interpersonal attraction. Our results also showed that prediction performance increases when male and female data is separated, indicating that men and women have different behavioral characteristics when showing attraction.

Acknowledgment

This research was partially funded by the Netherlands Organization for Scientific Research (NWO) under project number 639.022.606.

REFERENCES

[1] D. Gatica-Perez, "Modelling interest in face-to-face conversations from multimodal nonverbal behaviour," *Multimodal Signal Processing*, 03 2012.

[2] A. Veenstra and H. Hung, "Do they like me? using video cues to predict desires during speed-dates," in *2011 IEEE International Conference on Computer Vision Workshops (ICCV Workshops)*, Nov 2011, pp. 838–845.

[3] N. Guguen, "Mimicry and seduction: An evaluation in a courtship context," *Social Influence*, vol. 4, pp. 249–255, 10 2009.

[4] J. C. Karremans and T. Verwijmeren, "Mimicking attractive opposite-sex others: The role of romantic relationship status," *Personality and Social Psychology Bulletin*, 2008.

[5] S. D. Farley, "Nonverbal Reactions to an Attractive Stranger: The Role of Mimicry in Communicating Preferred Social Distance," *Journal of Nonverbal Behavior*, vol. 38, no. 2, pp. 195–208, 2014.

[6] J. Michalsky and H. Schoormann, "Pitch convergence as an effect of perceived attractiveness and likability," in *INTERSPEECH*, 2017.

[7] A. Madan, R. Caneel, and A. Pentland, "Voices of attraction," 2004.

[8] R. Ranganath, D. Jurafsky, and D. McFarland, "It's not you, it's me: Detecting flirting and its misperception in speed-dates," in *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Volume 1*, ser. EMNLP '09. Stroudsburg, PA, USA: Association for Computational Linguistics, 2009, pp. 334–342.

[9] L. Cabrera-Quiros, A. Demetriou, E. Gedik, L. van der Meij, and H. Hung, "The matchnmingle dataset: a novel multi-sensor resource for the analysis of social interactions and group dynamics in-the-wild during free-standing conversations and speed dates," *IEEE Transactions on Affective Computing*, 2018.

[10] D. Buss and D. Schmitt, "Sexual strategies theory: An evolutionary perspective on human mating," *Psychological review*, vol. 100, pp. 204–32, 05 1993.

[11] R. Fisman, S. Iyengar, E. Kamenica, and I. Simonson, "Gender differences in mate selection: Evidence from a speed dating experiment," *The Quarterly Journal of Economics*, vol. 121, pp. 673–697, 02 2006.

[12] K. Grammer, M. Honda, A. Juette, and A. Schmitt, "Fuzziness of nonverbal courtship communication: Unblurred by motion energy detection," *Journal of personality and social psychology*, vol. 77, pp. 487–508, 10 1999.

[13] B. Xiao, P. G. Georgiou, C.-C. Lee, B. Baucom, and S. S. Narayanan, "Head motion synchrony and its correlation to affectivity in dyadic interactions," in *Multimedia and Expo (ICME), 2013 IEEE International Conference on*. IEEE, 2013, pp. 1–6.

[14] B. Xiao, P. Georgiou, B. Baucom, and S. S. Narayanan, "Head motion modeling for human behavior analysis in dyadic interaction," *IEEE Transactions on Multimedia*, 2015.

[15] H. Hung and D. Gatica-Perez, "Estimating Cohesion in Small Groups Using," *IEEE Transactions on Multimedia*, vol. 12, no. 6, pp. 563–575, 2010.

[16] M. C. Nanninga, Y. Zhang, N. Lehmann-Willenbrock, Z. Szlávik, and H. Hung, "Estimating verbal expressions of task and social cohesion in meetings by quantifying paralinguistic mimicry," *Proceedings of the 19th ACM International Conference on Multimodal Interaction - ICMI 2017*, pp. 206–215, 2017.

[17] F. Ramseyer and W. Tschacher, "Nonverbal synchrony in psychotherapy: coordinated body movement reflects relationship quality and outcome," *Journal of consulting and clinical psychology*, vol. 79, no. 3, p. 284, 2011.

[18] W. Tschacher, G. M. Rees, and F. Ramseyer, "Nonverbal synchrony and affect in dyadic interactions," in *Front. Psychol.*, 2014.

[19] E. Gedik and H. Hung, "Detecting conversing groups using social dynamics from wearable acceleration: Group size awareness," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 2, no. 4, pp. 163:1–163:24, Dec. 2018.

[20] Y. Hart, E. Czerniak, O. Karnieli-Miller, A. E. Mayo, A. Ziv, A. Biegon, A. Citron, and U. Alon, "Automated video analysis of non-verbal communication in a medical setting," *Frontiers in Psychology*, vol. 7, no. AUG, pp. 1–8, 2016.

[21] A. S. Won, J. N. Bailenson, and J. H. Janssen, "Automatic detection of nonverbal behavior predicts learning in dyadic interactions," *IEEE Transactions on Affective Computing*, vol. 5, no. 2, pp. 112–125, 2014.

[22] A. S. Won, J. N. Bailenson, S. C. Stathatos, and W. Dai, "Automatically detected nonverbal behavior predicts creativity in collaborating dyads," *Journal of Nonverbal Behavior*, vol. 38, no. 3, pp. 389–408, Sep 2014.

[23] C. Martella, E. Gedik, L. Cabrera-Quiros, G. Englebienne, and H. Hung, "How was it?: Exploiting smartphone sensing to measure implicit audience responses to live performances," in *Proceedings of the 23rd ACM International Conference on Multimedia*, ser. MM '15. New York, NY, USA: ACM, 2015, pp. 201–210.

[24] L. Cabrera-Quiros, E. Gedik, and H. Hung, "Estimating self-assessed personality from body movements and proximity in crowded mingling scenarios," in *Proceedings of the 18th ACM International Conference on Multimodal Interaction*, ser. ICMI '16. New York, NY, USA: ACM, 2016, pp. 238–242.