Mutual Behaviors during Dyadic Negotiation: Automatic Prediction of Respondent Reactions

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***Abstract*—In this paper, we analyze face-to-face negotiation interactions with the goal of predicting the respondent's immediate reaction (i.e., accept or reject) to a negotiation offer. Supported by the theory of social rapport, we focus on mutual behaviors which are defined as nonverbal characteristics that occur due to interactional influence. These patterns include behavioral symmetry (e.g., synchronized smiles) as well as asymmetry (e.g., opposite postures) between the two negotiators. In addition, we put emphasis on finding audio-visual mutual behaviors that can be extracted automatically, with the vision of a real-time decision support tool. We introduce a dyadic negotiation dataset consisting of 42 face-to-face interactions and show experiments confirming the importance of multimodal and mutual behaviors.**

Keywords-negotiation; reaction prediction; multimodal; nonverbal; mutual behavior

I. INTRODUCTION

Negotiation is a complex and dynamic process in which two or more parties, often having non-identical preferences or agenda, attempt to reach agreement. Be it in our workplace or with our family or friends, negotiation comprises such a fundamental fabric of our everyday life that we sometimes engage in the act without even being consciously aware of it. It is then apparent that a real-time system that can automatically predict respondent reactions to negotiation offers will have substantial implications in our daily lives. For instance, such a system could function as a real-time decision support tool to directly help a person during a negotiation process or it could be useful in training a person to be a better negotiator.

Automatically predicting the respondent's reactions to offers during negotiation (i.e. whether the respondent will accept or reject an offer) is a challenging problem. Despite a long history of research on negotiation [6], much work is still needed in order to fully understand how people display various nonverbal behaviors in the context of negotiation. There has been very limited work that investigated nonverbal behaviors to build computational models, but recent progress in computer vision and audio signal processing technologies is enabling automatic extraction of various visual and acoustic behavioral cues without having to depend on costly and time-consuming manual annotations.

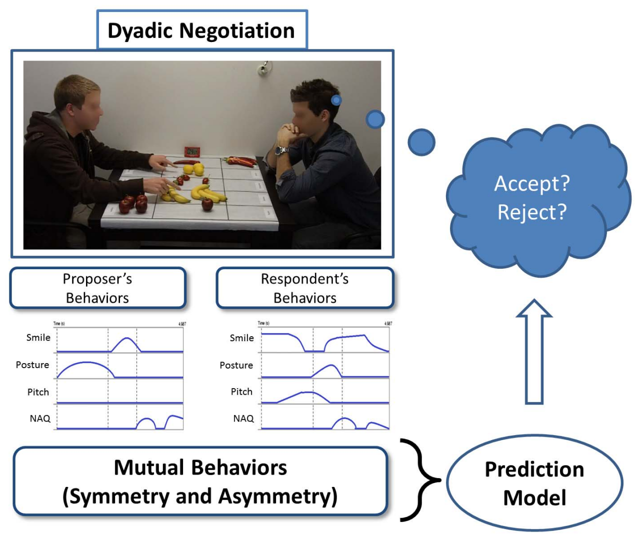

Figure 1. Overview of our approach to automatically predict respondent reactions to negotiation offers (acceptances or rejections) using mutual nonverbal behaviors.

In this paper, we show analysis of face-to-face dyadic negotiation sessions to investigate how people use nonverbal behaviors that could be predictive of respondent reactions to negotiation offers. Specifically, we focus on *mutual behaviors* which are defined as nonverbal characteristics that occur due to interactional influence, including behavioral symmetry and asymmetry between the two negotiators. We introduce computational descriptors for both visual and acoustic mutual behaviors. We hypothesize that mutual behaviors are important in the context of negotiation because people unconsciously engage in constant adaptation to others' behaviors during dyadic interaction, and this degree of coordination and behavioral matching (or mismatching) can hint at the overall atmosphere or rapport of the participants in the interaction. Moreover, we concentrate on finding such mutual behaviors that can be extracted automatically to explore the possibility of building an automatic system for predicting respondent reactions to negotiation offers.

The following section describes previous work in negotiation and computational prediction. In Section III, we

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present the theoretical background and mutual behaviors in dyadic interactions. Section IV describes the details of our acoustic and visual mutual behavior descriptors, and Section V describes the results of our experiments of building computational models for predicting respondent reactions to negotiation offers. We discuss our results in Section VI and conclude in Section VII.

II. Related Work

Negotiation has long been and still is an active topic of research, and the reader can find a brief history of the psychological study of negotiation in [6]. For researchers endorsing a traditional cognitive view, negotiation is essentially a decision-making process, the people involved dispassionate negotiators, and the outcome a result of dynamics governed by rational strategies. There are also researchers who put more emphasis on affective aspects [15]. Some have tried to understand the general role of affect in different stages of negotiation [5] while others have investigated the influence of mood [3][10], emotion [1][29], and personality [4]. In addition, researchers focusing on social contexts further deepen our understanding of negotiation dynamics [19][21].

The affective and social perspectives of negotiation give intuitions that nonverbal behaviors can give clues to the ongoing state of a negotiation process. Although negotiation research abounds in literature, there is still limited work that investigated nonverbal behaviors in the context of negotiation, let alone computational models. Probably a research problem that is most analogous to our line of research was explored in [14] where the authors simulated an employment negotiation scenario and found that certain speech features within the first five minutes of negotiation were predictive of the overall negotiation outcome in the end. Whereas previous works were mainly on predicting the overall negotiation outcomes in the end, our focus is on making immediate predictions of respondent reactions to offers (acceptances or rejections) for individual proposals made during negotiation. In our previous work [25], we created manual annotations to explore various multimodal factors (including nonverbal behaviors) for respondent reaction prediction, and the results served as a proof-of-concept to show that such prediction is possible within reasonable accuracy. In this paper, we put our focus on automatic analysis of mutual behaviors for respondent reaction prediction.

III. Mutual Behavioral Factors in Dyadic Interaction

Extensive research shows that we have a tendency to match our behaviors to our interactional partners in various ways [22], and it is described with many terms in the literature including behavior matching, imitation, mimicry, synchrony, or chameleon effect. The changes in our behaviors often occur unconsciously and in many different channels of communication from facial expressions to speech patterns [12][13][22]. Such behavioral characteristics are parts of what we broadly refer to as mutual behaviors in this paper, which are not only limited to behavior symmetry but span more to also include any nonverbal characteristics that occur due to interactional influence, including behavior asymmetry.

Mutual behaviors are important in the context of negotiation because much evidence exists to show that they are related to social rapport. In general, people simply seem to get along better when their behaviors are well coordinated [8], and it is shown that displaying similar behaviors helps with the smoothness of interactions and also builds a feeling of liking or positivity between interactional partners [12][13]. The phenomenon is so prevalent that even computer agents that mimic human interactional partners are seen with a more positive feeling than non-mimicking agents [2]. Moreover, studies [7][18] show that observable nonverbal cues can be indicative of rapport, suggesting that it is possible to detect and gauge rapport between interactional partners, which in turn can be used to assess the status of a negotiation process.

More specifically, Bernieri et al. [7] studied observable nonverbal cues that were indicative of rapport in two different contexts of adversarial and cooperative settings, and the list of behaviors included gestures, posture shifts, proximity, back-channel responses, eye contact, and forward lean. Tickle-Degnen et al. [28], who described rapport in terms of three components of mutual attentiveness, positivity and coordination, also studied several nonverbal cues associated with rapport that included a similar set of behaviors.

Mutual behaviors that hint at rapport can also reside at the speech level. People are known to imitate various acoustic characteristics of interactional partners including accents, pauses, speech rate, and tone of voice [22]. Some researchers focus more on the smoothness of turn taking, which are usually measured with simultaneous speech, mutual silences, and interruptions [8].

IV. Mutual Behavior Descriptors

In creating computational descriptors of mutual behaviors, we considered the following three main aspects: behavioral symmetry / asymmetry, time dependency (short-term and long-term), and automatic extraction.

Although past research principally focused on symmetric mutual behaviors, such as social rapport and behavior matching (see Section III), we note that much information can also reside in asymmetric mutual behaviors, such as opposite postures, in the context of our negotiation problem. For behavioral symmetry, we considered the similarity of behavioral patterns of the two negotiators. And for behavioral asymmetry, we considered behavioral patterns of one negotiator that contrasted with the other negotiator's.

- *Behavioral symmetry*: These mutual behavior descriptors are designed to model similarity and synchrony in the negotiators' behaviors. For example, mutual gaze or reciprocal smiles can show a general feeling of rapport and connection. We expect to see these more often in cooperative settings.

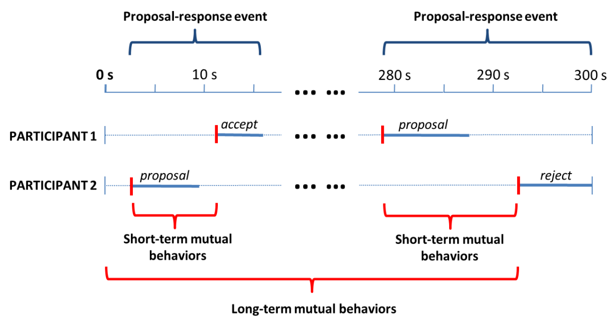

Figure 2. An illustration of the proposal-response event and different time windows from where mutual behavior descriptors were extracted.

- *Behavioral asymmetry*: These mutual behavior descriptors are designed to model unilateral behaviors or behavioral patterns that contrast each other's. For example, if only one of the two participants is smiling or if they show opposite body postures, these are possible signs of disengagement and competition.

Furthermore, since negotiation is an ongoing process in which participants constantly adapt themselves to each other, assessing both short-term and long-term behaviors provides a deeper understanding of the current state of negotiation on which to base predictions of future actions (Fig. 2). For this purpose, we defined a *proposal-response event* as an utterance made with a clear offer related to negotiating the items and followed by a clear utterance of acceptance or rejection (Fig. 2). For the short-term time window, we explored mutual behaviors within the boundary of each *proposal-response event*, while cumulative history of behaviors was explored in the long-term time window.

- *Long-term behavior*: These mutual behaviors descriptors are designed to model the social engagement and rapport that is created over a longer period of time. For example, a continuous mutual gaze is often correlated with high rapport, which in turn can be correlated with successful collaboration.
- *Short-term behavior*: These mutual behavior descriptors are designed to model recent momentum of the negotiation. For example, the negotiation momentum could change rapidly because of cheating or mockeries, and the short-term mutual behaviors are designed to quickly adapt.

Finally, we concentrated only on nonverbal behaviors that could be automatically extracted and that mutually occurred between the proposer and the respondent simultaneously. That is, in extracting automatic mutual behavior descriptors, we derived each by considering jointly nonverbal behaviors of both the proposer and the respondent occurring at the same time, and none of our descriptors was derived from nonverbal behaviors of just one party in the interaction.

A. Visual Mutual Behaviors

In order to automatically extract visual mutual behavior descriptors, we used a commercial software [24] that detects a person's face from frame to frame in a video and outputs various low-level and high-level facial features. Below is a list of mutual behavior descriptors that were extracted for each participant per negotiation session. Each visual descriptor listed below was smoothed with a linear filter, and each descriptor, except for smile, was converted into a binary descriptor using an empirically-determined threshold point:

- *Smile*: Used to indicate if the person is displaying positive affect with a smile.
- *Leaning posture*: Used to indicate if the person is showing a forward or a backward lean (posture); approximated with face length and face size.
- *Head gaze*: Used to indicate if the face is directed downward (toward the table).
- *Eye gaze*: Used to indicate if the gaze is directed downward (toward the table).

For each *proposal-response event*, the visual descriptors above were extracted from 2 different time windows: within the short-term time window (from the start of the proposal until the start of the response) and within the long-term time window (from the start of the interaction until the start of the response) as shown in Fig. 2. Then, for each time window, symmetric mutual behavior descriptors were computed with Pearson's correlation coefficient for each descriptor between the two participants in each dyadic session. The difference in the mean values and the difference in the standard deviation values were computed for asymmetric descriptors.

B. Acoustic Mutual Behaviors

The following acoustic mutual behavior descriptors were extracted at 100 Hz for each participant per *proposal-response event* only within the long-term time windows since the amount of time was often too short to compute meaningful descriptors within the short-term time windows:

- *Voice quality – peak slope*: Used to indicate breathiness or tenseness of the voice. Values closer to zero are considered as more tense [20][26].
- *Voice quality – normalized amplitude quotient (NAQ)*: Another feature for the tenseness of the voice [26].
- *Pitch (f0)*: The base frequency of the speech signal. It is the frequency the vocal folds are vibrating during voiced speech segments. We utilized the method introduced in [16] in this work.
- *Energy*: Used to indicate the loudness and intensity of the voice.
- *Energy slope*: Extracted as the absolute value of the first derivative of the energy. High slope values indicate stronger changes in the energy and low values higher monotonicity of the energy.
- *Spectral stationarity*: A measure that captures the fluctuations and changes in the voice signal. High

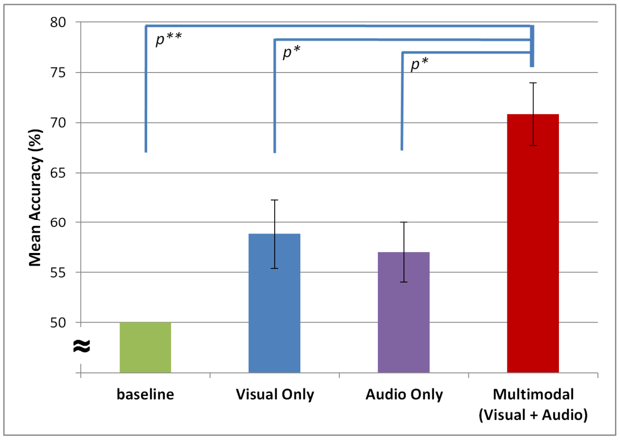

Figure 3. The mean accuracies for predicting respondent reactions to negotiation offers using descriptors from different modalities (performance differences shown only between the multimodal predictor and others). The results are statistically significant at $p^* < 0.05$ and $p^{**} < 0.01$. Error bars show standard errors.

values indicate a stable vocal tract and little change in the speech (e.g. during hesitation or sustained elongated vowels) indicating higher monotonicity [17][27].

For each *proposal-response event*, the acoustic descriptors extracted for each participant within the long-term time windows were used to compute a correlation value between the participants using a time-aligned moving average (sliding window) technique [30], which were used as symmetric mutual behavior descriptors. In addition, for asymmetric mutual behavior descriptors, the difference in the mean values and the difference in the standard deviation values between the two participants were also computed for each descriptor within the same time windows.

V. EXPERIMENTS

For this paper, our primary research hypothesis was the following:

- *H1*: Computational descriptors of acoustic and visual mutual behaviors can predict respondent reactions during dyadic negotiation.

If this primary hypothesis end up being true, we suspect that it is due to the mutual behavior descriptors capturing the overall nature (or rapport) of the interaction itself (i.e. whether the interactional partners were having a smoother and more cooperative interaction or a tougher and more competitive interaction). Based on this observation, we added a secondary research hypothesis:

- *H2*: Computational descriptors of mutual behaviors that are predictive of respondent reactions are also useful for determining whether the nature of a negotiation session is cooperative or competitive.

TABLE I. PREDICTION OF RESPONDENT REACTIONS TO NEGOTIATION OFFERS

	Accuracy	p-value
Baseline	50.0 %	p < 0.0001
Acoustic	57.0 %	0.0143
Visual	58.9 %	0.0124
Multimodal	70.8 %	-

A. Dyadic Negotiation Dataset

A dataset of dyadic negotiation sessions was collected in order to understand how people negotiate with various incentive scenarios. In total, 84 undergraduate business-major students (40 males and 44 females) participated in 42 dyadic negotiation sessions, of which one dyad was discarded because the participants deviated from the experimental procedure. Each session involved same-sex participants in each dyad to control for the influence of gender. In addition, negotiators in each dyad were instructed to adopt only one of three motivational orientations that derived from the monetary incentive associated with the negotiation task: cooperative (maximize joint outcomes), individualistic (maximize own outcomes), and competitive (maximize own outcomes relative to the other's outcomes). Out of 42 sessions, 13 were cooperative, 13 individualistic, and 16 competitive. Negotiators in each dyad received the same motivational instruction and were aware that the other was so instructed. A total of 3 cameras were placed unobtrusively to record a near-frontal view of each negotiator, as well as an overall side view of the interaction.

In each session, two participants sat face-to-face across each other at opposite ends of a table, on which several types of plastic fruits or vegetables were placed. The participants were randomly assigned to represent one of two different restaurants, which had different pay-off matrices associated with the items on the table. Each participant knew only the pay-off matrix of his/her assigned restaurant, and the participants had 12 minutes to negotiate on how to distribute the items on the table. As an incentive, each participant could receive up to $50 depending on the final points earned for his/her restaurant.

B. Respondent Reaction Annotations

A total of 253 *proposal-response events* were identified, out of which 190 were accepted proposals and 63 were rejected proposals. In addition, speaker diarization was performed with manual annotations, but we note that this step could have been done automatically with close-talk microphones equipped for both participants. For each negotiation session, all the events of proposal-response pairs were identified using ELAN software [9].

C. Prediction Model and Experimental Methodology

For the prediction models, support vector machine (SVM) classifiers with linear kernel were trained and tested [11]. A subset of candidate mutual behavior descriptors were first selected based on their prediction performances as

TABLE II. TOP MUTUAL BEHAVIOR DESCRIPTORS SELECTED FOR PREDICTING RESPONDENT REACTIONS TO NEGOTIATION OFFERS

Mutual Behavior Descriptors		Time Dependency
Visual	Symmety - smile	short-term
	Symmetry - posture	
	Symmetry - head gaze	long-term
	Symmetry - eye gaze	
	Asymmetry - head gaze	
	Asymmetry - eye gaze	
Acoustic	Asymmetry - voice pitch	
	Asymmetry - voice quality (NAQ)	
	Asymmetry - spectral stationarity	

individual descriptors in each modality (visual and acoustic), and then an exhaustive feature selection was performed to identify top mutual behavior descriptors.

Using the final descriptor set, 4-fold testing hold-out validation was performed with 1 hold-out fold for validation to find the optimal parameters using a grid-search technique and another hold-out fold for testing. In order to make balanced sample sets for predictor (classifier) training and testing, all of the 63 samples of the rejected proposal-response events were combined with 63 randomly selected samples of the accepted events (making the baseline prediction at 50%), and 3 such randomly balanced sets were created. Each randomly balanced set was again randomly separated into 4 folds with almost an equal number of accept and reject samples. All the prediction results were averaged over 12 test results (3 sets × 4-fold cross-validation). It is worth noting that none of the folds contained samples from the same negotiation session. In other words, the 4 folds were created such that they were all session-independent to one another.

To test for our second hypothesis, we also investigated to what extent the prediction accuracies were due to the mutual behavior descriptors' capturing the different conditions of the negotiation sessions, specifically between the cooperative and competitive conditions. Using the final descriptor set from the respondent reaction predictor, another classifier was trained and tested in order to classify each negotiation session between the cooperative and competitive conditions. The samples were also randomly balanced with 13 cooperative sessions and 13 competitive sessions (making the baseline classification at 50%), and similar feature selection technique and 13-fold cross validation with 1 hold-out fold for testing were performed.

VI. RESULTS AND DISCUSSIONS

All the results have the baseline prediction/classification rate of 50% since all the samples were trained and tested using randomly balanced sample sets.

A. *Predicting Respondent Reactions to Negotiation Offers*

For the prediction of respondent reactions to negotiation offers, a multimodal predictor using mutual behavior descriptors selected from both visual and acoustic channels performed best at the prediction rate of 70.8%, which we

TABLE III. CLASSIFICATION OF NEGOTIATION SESSION TYPES (COOPERATIVE VS. COMPETITIVE)

	Accuracy	p-value
Baseline	50.0 %	0.0057
Acoustic	59.0 %	0.3599
Visual	65.4 %	1.0000
Multimodal	65.4 %	-

believe to be a reasonable prediction rate to confirm our first hypothesis (*H1*). The prediction made using only visual descriptors performed at 58.9% and with only acoustic descriptors at 57.0% (Fig. 3 and Table I). Paired-sample t-tests showed the multimodal predictor's performance to be better with a statistical significance at $p < 0.05$ compared to the prediction performances using only visual descriptors or only acoustic descriptors alone.

B. *Predictive Mutual Behavior Descriptors*

Top mutual behavior descriptors selected for predicting respondent reactions are shown in Table II. When comparing these top descriptors for accepted and rejected proposals, we observed the following general trend for all 4 symmetry descriptors (smile, posture, head gaze and eye gaze): higher symmetry for accepted proposals. This is most likely due to a higher degree of rapport between negotiators when proposals are accepted. Asymmetric gaze descriptors (both eye and head gaze) showed predictive power in our prediction task, most likely helping with the identification of rejected proposals. We see a similar phenomenon for all 3 top audio descriptors: voice pitch, voice quality (NAQ), and spectral stationarity.

C. *Classification of Negotiation Cooperation vs. Competition*

We then investigated to what extent the prediction performance was due to the descriptors capturing the different conditions of the negotiation sessions, specifically between the cooperative and competitive conditions. Using the same mutual behavior descriptors from the respondent reaction predictor experiment (shown in Table II), the best classification rate that could be achieved for condition classification was 65.4% (Table III), which was relatively lower compared to our respondent reaction prediction accuracy but still significantly higher than the baseline model. This result indicates that the descriptors that were useful for the reaction prediction were also helpful in determining the type of negotiation sessions (*H2*). The result also suggests that the performance of our respondent reaction predictors could be partially due to the mutual behavior descriptors' having captured the nature of the negotiation sessions (the overall atmosphere of cooperation or competitiveness).

VII. CONCLUSIONS AND FUTURE WORK

In this paper, we presented our experimental results showing that we could predict respondent reactions to negotiation offers (whether the respondent will accept or reject an offer) with reasonable accuracy using mutual behavior descriptors, which were extracted from mutual nonverbal behaviors in both acoustic and visual channels between the two negotiators in a dyad. In particular, we focused on descriptors that could be automatically extracted, and our results show that machine analysis of human negotiation has potential to add fundamental insight into how people negotiate and possibly provide automatic, practical tools to benefit human negotiators. For future work, more automatic features could be explored including non-mutual behaviors [25]. Also, we plan to investigate how humans perform for the same prediction problem and compare with our automatic approach.

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REFERENCES

[1] K. Allred, J. Mallozzi, F. Matsui, and C. Raia, "The influence of anger and compassion on negotiation performance," Organ. Behav. Hum. Dec., vol. 70 (3), Jun. 1997, pp. 175-187.

[2] J. Bailenson and N. Yee, "Digital chameleons: Automatic assimilation of nonverbal gestures in immersive virtual environments," Psychological Science, vol. 16 (10), Oct. 2005, pp. 814-819.

[3] R. Baron, "Environmentally induced positive affect: Its impact on self-efficacy, task performance, negotiation, and conflict," J. Appl. Soc. Psychol., vol. 20 (5), Mar. 1990, pp. 368-384.

[4] B. Barry and R. Friedman, "Bargainer characteristics in distributive and integrative negotiation," J. Pers. Soc. Psychol., vol. 74 (2), 1998, pp. 345-359.

[5] B. Barry and R. Oliver, "Affect in dyadic negotiation: A model and propositions," Organ. Behav. Hum. Dec., vol. 67 (2), Aug. 1996, pp. 127-143.

[6] D. Pruitt, "A history of social conflict and negotiation research," in Handbok of the History of Social Psychology, A. Kruglanski and W. Stroebe, Eds. Psychology Press, New York, 2012, pp. 431-452.

[7] F. Bernieri, J. Gillis, J. Davis, and J. Grahe, "Dyad rapport and the accuracy of its judgment across situations: A lens model analysis," J. Pers. Soc. Psychol., vol. 71 (1), Jul. 1996, pp. 110-129.

[8] F. Bernieri and R. Rosenthal, "Interpersonal coordination: Behavior matching and interactional synchrony," in Fundamentals of Nonverbal Behavior, R. Feldman and B. Rime, Eds. Cambridge University Press, New York, 1991, pp. 401-432.

[9] H. Brugman and A. Russel, "Annotating multimedia / multi-modal resources with ELAN," The 4th Int'l Conf. on Language Resources and Evaluation (LREC 04), 2004, pp. 2065-2068.

[10] P. Carnevale and A. Isen, "The influence of positive affect and visual access on the discovery of integrative solutions in bilateral negotiation," Organ. Behav. Hum. Dec., vol. 37 (1), Feb. 1986, pp. 1-13.

[11] C.-C. Chang and C.-J. Lin, "LIBSVM: A library for Support Vector Machines," ACM Transactions on Intelligent Systems and Technology, vol. 2 (3), Apr. 2011, 27:1-27:27.

[12] T. Chartrand and J. Bargh, "The chameleon effect: The perception-behavior link and social interaction," J. Pers. Soc. Psychol., vol. 76 (6), 1999, pp. 893-910.

[13] T. Chartrand, W. Maddux, and J. Lakin, "Beyond the perception-behavior link: The ubiquitous utility and motivational moderators of nonconscious mimicry," in The New Unconscious, R. Hassin, J. Uleman, and J. Bargh, Eds. Oxford University Press, New York, 2005, pp. 334-361.

[14] J. Curhan and A. Pentland, "Thin slices of negotiation: Predicting outcomes from conversational dynamics within the first 5 minutes," J. Appl. Soc. Psychol., vol. 92 (3), 2007, pp. 802-811.

[15] D. Druckman and M. Olekalns, "Emotions in negotiation," Group Decision and Negotiation, vol. 17 (1), Jan. 2008, pp. 1-11.

[16] T. Drugman and A. Abeer, "Joint robust voicing detection and pitch estimation based on residual harmonics," The 12th Annual Conference of the International Speech Communication Association (Interspeech 11), 2011, pp. 28-31.

[17] S. Finkelstein, S. Scherer, A. Ogan, L.-P. Morency, and J. Cassell, "Investigating the influence of virtual peers as dialect models on students' prosodic inventory," Proceedings of Workshop on Child, Computer and Interaction (WOCCI 12), 2012.

[18] J. Grahe and F. Bernieri, "The importance of nonverbal cues in judging rapport," J. Nonverbal Behav., vol. 23 (4), Dec. 1999, pp. 253-269.

[19] L. Greenhalgh and D. Chapman, "Negotiator relationships: Construct measurement and demonstration of their impact on the process and outcomes of negotiation," Group Decis. Negot., vol. 7 (6), Nov. 1998, pp. 465-489.

[20] J. Kane and C. Gobl, "Identifying regions of non-modal phonation using features of the wavelet transform," The 12th Annual Conference of the International Speech Communication Association (Interspeech 11), 2011, pp. 177-180.

[21] R. Kramer and D. Messick, Negotiation as a Social Process. Thousand Oaks, CA, US: Sage Publications, Inc., 1995.

[22] M. Louwerse, R. Dale, E. Bard, and P. Jeuniaux, "Behavior matching in multimodal communication is synchronized," Cognitive Science, vol. 36 (8), Nov./Dec. 2012, pp. 1404-1426.

[23] A. Mehrabian, Nonverbal Communication. Aldine/Atherton, Chicago, 2007.

[24] OKAO Vision. http://www.omron.com/r_d/coretech/vision/okao.html

[25] S. Park, J. Gratch, and L.-P. Morency, "I already know your answer: Using nonverbal behaviors to predict immediate outcomes in a dyadic negotiation," The 14th ACM Int'l Conf. on Multimodal Interaction (ICMI 12), Oct. 2012, pp.19-22.

[26] S. Scherer, J. Kane, C. Gobl, and F. Schwenker, "Investigating fuzzy-input fuzzy-output Support Vector Machines for robust voice quality classification," Computer Speech and Language, vol. 27 (1), Jan. 2013, pp. 263-287.

[27] S. Scherer, N. Weibel, L.-P. Morency, and S. Oviatt, "Multimodal prediction of expertise and leadership in learning groups," The 1st Int'l Workshop on Multimodal Learning Analytics (MLA 12), 2012.

[28] L. Tickle-Degnen and R. Rosenthal, "The nature of rapport and its nonverbal correlates," Psychol. Inq., vol. 1 (4), 1990, pp. 285-293.

[29] G. Van Kleef, C. De Dreu, and A. Manstead, "The interpersonal effects of emotions in negotiations," J. Pers. Soc. Psychol., vol. 87 (4), 2004, pp. 510-528.

[30] B. Vaughan, "Prosodic synchrony in cooperative task-based dialogues: A measure of agreement and disagreement," The 12th Annual Conf. of the International Speech Communication Association (Interspeech 11), 2011, pp. 1865-1868.