Walking in Sync: Two is Company, Three's a Crowd

Kleomenis Katevas, Hamed Haddadi, Laurissa Tokarchuk
Cognitive Science Research Group
Queen Mary University of London, UK
name.surname@qmul.ac.uk

Richard G. Clegg
Department of Computing
Imperial College, London, UK
richard@richardclegg.org

ABSTRACT

Eventual gait synchronization between two individuals while walking and talking with each other has been shown to be an indicator of agreeableness and companionship. The inferred physical signal from this subconscious phenomenon can potentially be an indicator of cooperation or relation between two individuals. In this paper we investigate this effect, and whether having a third person actively engaging in the same act or conversation can reduce this synchronization level. Using high frequency accelerometer data from a dedicated smartphone app, we perform a number of controlled experiments on a number of individuals in different group configuration. Our results bring an interesting insight: it is the *non-verbal social signals* such as the *gaze*, *head orientation* and *gestures* that is the key factor in synchronization, not necessarily the number or configuration of the walkers. These early results can lead us on detecting relationships between individuals or detecting the group formation and numbers for crowd-sensing applications when only partial data is available.

Categories and Subject Descriptors

Human-centered computing [**Ubiquitous and mobile computing**]: Empirical studies in ubiquitous and mobile computing

General Terms

Experimentation, Human Factors, Measurement

Keywords

Mobile Sensing, Crowd Sensing, Gait Analysis, Accelerometer

1. INTRODUCTION

It is well known that crowds have several common behavioral patterns. For example, pedestrians inside a crowd tend to move together as a unit; with group members walking at the same speed, following the same trajectories and quickly reform after they become separated [2].

An interesting phenomenon in small groups is the synchronization of stepping that often occurs in people walking side by side. This mutual engagement can either occur intentionally (e.g. a public procession that occurs by imitation) or unintentionally when that happens subconsciously, a behavior known in psychology as "mirroring" [3]. Previous studies suggest that the reason behind an unintentional sync in walking is that they share a common feeling of unity and close relationship [8].

In most cases, a group walk also includes engagement with a conversation. People tend to look at each other while walking, interact with gestures and at the same time have a turn-taking conversation. According to Moussaid *et al.* [11], group members usually have a V-shaped walking formation that facilitates social interactions between members. According to Battersby *et al.* [1], gaze and head orientation becomes problematic in conversations between more than two participants. The reason is that the gaze can only focus on a single person at a time, especially when the participants are walking side by side. We believe that these non-verbal social signals influence the walking patterns and synchronization of these walking groups.

Modern technology such as mobile sensing can be used to explore these kinds of group behaviors. Accelerometer sensors such as the ones embedded in modern smartphones can be used to analyze the walking patterns of people engaged in a conversation.

In this paper we focus not only on the physical act of walking, but on specific gait analysis and walk synchronization. We use high-quality 3-axis accelerometer data at a minimum sampling rate of 90Hz in order to accurately capture the gait synchronization between two individuals, in addition to studying the effect of the third person on the synchronization. This is important for crowd-sensing and potentially security applications in scenarios which we are exploring in the continuation in this work. Our findings also empirically support those of Richardson *et al.* [13] and Shockley *et al.* [15], who have used posture sway to understand the interpersonal coordination in the context of a cooperative verbal task, showing that *conversation* is responsible for such coordinations. The way in which a conversation potentially causes locomotion coordination amongst two individuals remains debated amongst scholars.

2. RELATED WORK

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
WPA'15, May 22, 2015, Florence, Italy.
Copyright © 2015 ACM 978-1-4503-3498-3/15/05 ...$15.00.
DOI: http://dx.doi.org/10.1145/2753497.2753502.

Due to importance of movement coordination in interpersonal communication, there have been a vast number of studies in this space by different methods such as observational studies or use of video-based gait analysis. Analysis of walk synchronization has been of interest in psychology [13, 4] and robotics [10], as well as for behavioral analysis of individuals [12]. In the latter study, paired individuals were observed to have synchronous walking rhythm and gait while having a phone conversation. However they have utilized speech data and vertical oscillation of the device.

Use of accelerometer data for gait analysis has recently been of interest due to availability of high-frequency 3-axis accelerometers in smartphones and wearables. Roggen *et al.* [14] used on-body accelerometer sensors placed on people hips in order to classify people walking independently, in a group, or in two and three subgroups. Marin-Perianu *et al.* [9], in a similar research, used accelerometer sensors to identify people walking as a group. In a more advanced research, Kjærgaard *et al.* [7] used sensor fusion techniques of accelerometer, magnetometer and WiFi sensors to recognize pedestrian flocks using smartphone devices with an accuracy of up to 87 percent. Finally, Garcia-Ceja *et al.* [5] have used low-frequency accelerometer (5Hz) and WiFi data to detect when two individual are walking at the same time.

3. ANALYZING PEDESTRIAN FLOCKS

This study aims to analyze the walking behavior of pedestrians existing in a group of two or three people. It will focus on the synchronization behavior that occurs when a group of people is engaged in their walking activity.

This section starts with a description of CrowdSense, the mobile application developed for the purpose of this research, as well as for a series of future studies. It continues with a detailed description of the experiment including the materials used, the participants, the experimental design and the procedure followed.

3.1 CrowdSense

CrowdSense is an Android application based on the continuous sensing library Sensing Kit [6], a cross-platform library for iOS and Android platforms. It supports several Sensor Modules of SensingKit library, when these are available and supported by the device. It can be run in all Android smartphones with version Jelly Bean (v4.1) or greater. The application runs as a background service, collects the sensor data and save them into the device's memory in CSV format.

Table 1 shows the SensingKit Sensor Modules supported in CrowdSense at this moment, as well as the system requirements.

3.2 Materials

We installed CrowdSense in three Samsung Galaxy S2 Android smartphones. All devices have been updated to the latest Android version officially supported by the manufacturer. We configured CrowdSense to only record Accelerometer sensor data at the fastest sampling rate possible. A short audio sample of 10 seconds has also been recorded and used to synchronize the sensor data between the three devices. Table 2 shows the three smartphones used in this experiment, with the average sampling rate for capturing Accelerometer data.

Table 1: CrowdSense Sensor Modules

Sensor Module	System Requirement
Accelerometer	Android Jelly Bean (v4.1)
Gravity	Android Jelly Bean (v4.1)
Linear acceleration	Android Jelly Bean (v4.1)
Gyroscope	Android Jelly Bean (v4.1)
Rotation	Android Jelly Bean (v4.1)
Magnetometer	Android Jelly Bean (v4.1)
Ambient Temperature	Android Jelly Bean (v4.1)
Step Detector	Android KitKat (v4.4)
Step Counter	Android KitKat (v4.4)
Light	Android Jelly Bean (v4.1)
Location	Google Play Services
Activity	Google Play Services
Battery	Android Jelly Bean (v4.1)
Screen Status	Android Jelly Bean (v4.1)
Audio Recorder	Android Jelly Bean (v4.1)
Audio Level	Android Jelly Bean (v4.1)

Table 3: Demographic information

Participant	Gender	Height	Weight
P1	Male	1.80m	75kg
P2	Male	1.72m	76kg
P3	Male	1.86m	89kg

3.3 Participants

The experiment involved the recruitment of three participants (P1, P2 and P3). The participants were students from Queen Mary University of London and had no previous experience with the current study.

The following Table (Table 3) shows the demographic information of the recruited participants.

3.4 Experimental Design

As stated above, this experiment focuses on the syncing behavior of people walking in groups of two (Scenario 1) and three people (Scenario 2). For that reason, the participants have been assigned to the groups listed in Table 4, following a Within Subject experimental design. The idea behind this separation is that in Scenario 2, Scenario 1 should be repeated with another participant injected between the initial group (Participant 3).

3.5 Procedure

The experiment took place in the Mile End Park, an open and usually not crowded park close to Queen Mary University of London. All three participants were informed that this experiment will aim to understand the walking behavior of people and received a short demonstration of CrowdSense application. Finally each participant did a short walk, with the mobile device placed on the left pocket.

In order to facilitate their conversation during the walk, we asked every group to decide on a preferred conversational topic, chosen from a list of 25 subjects. This also helped the

Table 4: Groups Configuration

Scenario	Group	Participants
S1	G1	P1, P2
S2	G2	P1, P3, P2

Table 2: Device Specification

Participant	Type	Op. System	Sampling Mean (SD)
P1	Samsung Galaxy S2	Jelly Bean 4.1.2	91.93Hz (2.15)
P2	Samsung Galaxy S2	Jelly Bean 4.1.2	90.90Hz (2.37)
P3	Samsung Galaxy S2	Jelly Bean 4.1.2	91.64Hz (2.23)

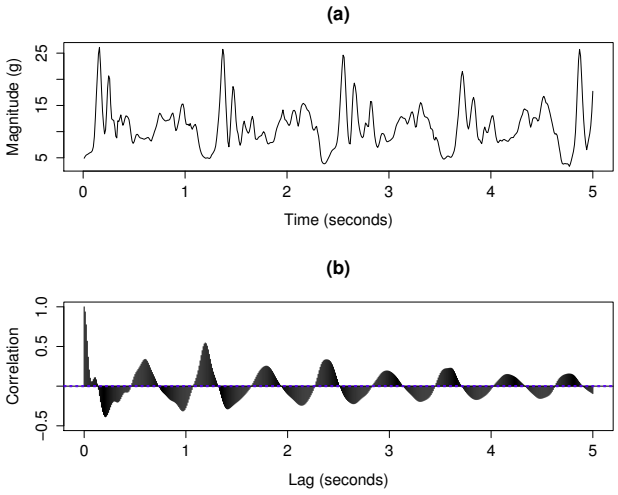

Figure 1: Acceleration Magnitude of 5 sec (a) and Autocorrelation (b) of Participant 1 in Scenario 1. The dotted blue lines are a 95% confidence interval.

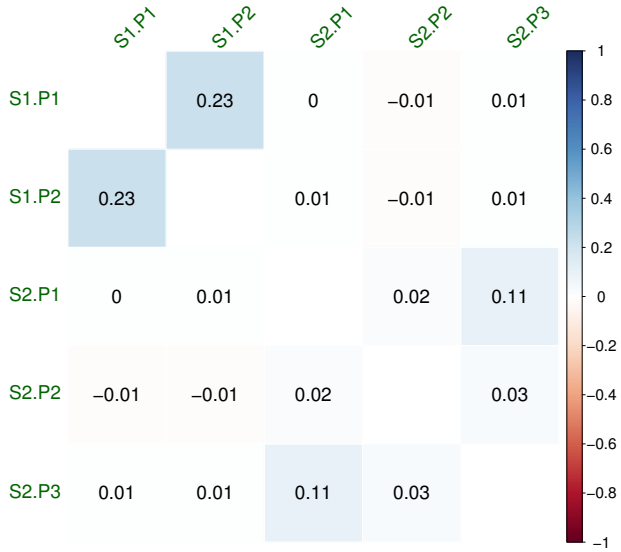

Figure 2: Pearson Correlation matrix of all 5 datasets, visualized as a heat map plot.

group to concentrate on the conversation and not on their walking activity.

The two groups walked for 12 minutes in the park. The researcher was observing the group from a distance of approximately five meters while keeping notes using a voice recorder.

4. RESULTS AND DISCUSSION

Before starting the data analysis, we synchronized all data using the audio sample described previously in section 3. Using this technique, we had an accuracy of ±50ms. Table 2 shows the Mean and Standard Deviation (SD) of the sampling rate of the three devices when using the accelerometer sensor. Since a smartphone is not a real-time system, the requested sampling rate (fastest in our case) is only a suggestion to the system, with the actual rate being rather unstable. Thus, we interpolated the data to 100Hz using a linear interpolation method. Finally, we calculated the magnitude (resultant acceleration) of the 3-axis accelerometer sensor using the formula $\sqrt{x^2 + y^2 + z^2}$.

Figure 1a shows a five second period of walking activity, performed by P1. In this periodic signal, the high peaks represent the acceleration produced by the left leg while doing one step (x = 16, 137, 255 and 372) whereas the lower acceleration peaks are from the stride while the other leg is doing another step. The duration of every step (produced by the same foot) can be calculated from the distance between two high-peaks (1.21 sec). This repeated pattern is also visible in the autocorrelation analysis of the complete walk, as shown in Figure 1b. The figure indicates that the walking rhythm is a periodic pattern with features that reflect on the walking activity of the individual.

The higher correlation between two participants implies that their steps are also synchronized. Bivariate correlations of the acceleration signals between the participants in Scenario 1 show a positive correlation (Pearson Correlation = 0.23, $p < 0.01$). Similar but smaller correlations exist when comparing the signals of Group B: 0.02 ($p < 0.01$) for P1 and P2, 0.11 ($p < 0.01$) for P1 and P3, and 0.03 ($p < 0.01$) for M2 and M3. The effect can be visually identified in the following heat map plot (Figure 2) that presents the combinations of all bivariate correlations between the recorded data. In the same plot, the irrelevance of the data between different walks is clearly visible (e.g. P1 of Scenario 1 with P1 of Scenario 2).

Similar correlation values can be identified in Figure 3, where we performed a cross-correlation with a maximum lag of 1 second. The maximum correlation between P1 and P2 in Scenario 1 (Figure 3a) is 0.24 at lag = 0.01s, higher than all correlation between participants in Scenario 2 (Figure 3b, c and d). Smaller positive correlations appear in Scenario 2, with 0.05 at lag = -0.6s (P1 and P2), 0.08 at lag = -0.14s (P2 and P3), and 0.13 at lag = -0.03 (P1 and P3). This indicates that the two participants in Scenario 1 have the highest correlation and with the minimum lag in their stepping (lag = 0.01s). Since both analyses P1 × P2 and P2 × P3 show much smaller correlation and high lag in the sync, we can assume that P2 is the least synchronized person of the group.

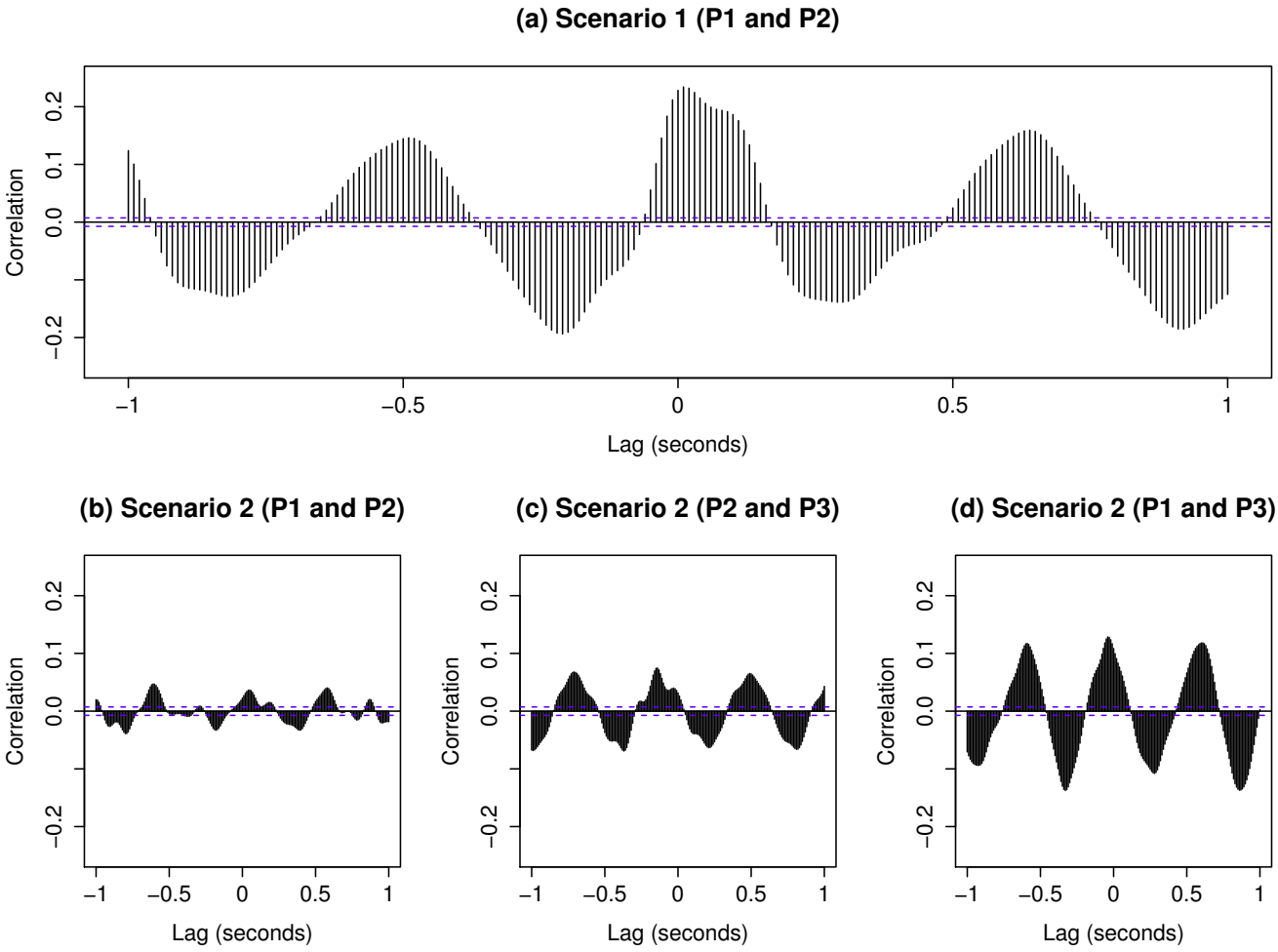

Figure 3: Cross-correlation analysis of Scenario 1 (a) - 2 people walking, and Scenario 2 (b, c, d) - 3 people walking in a park for 12 minutes. The dotted blue lines are a 95% confidence interval.

The same synchronization was observed visually by the researcher in Group A during the experiment, but only in cases were two of the people were discussing together while the other was not paying attention to the conversation. A likely explanation of this correlation is the engagement of the conversation that affects the participants to synchronize their steps unconsciously. According to Lakens and Stel "*The tendency to synchronize movement rhythms has been theorized to play an important role in the formation of a social unit*" [8]. When three people are walking together, the conversation is taking place in turns between two people, changing their gaze so that each person looks at each other. This influences their walking, making their steps to correlate again in each turn and break the synchronization between the participants of the past turn.

This effect is also clear in Figure 4, where the correlation for every second is plotted for both Scenario 1 and Scenario 2. In Figure 4a, the two people are not synchronized at windows 1 to 27, but becomes in sync after window 28. In Figure 4b it is obvious that there is a weaker synchronization between the people in the group. There are moments that P1 and P2 are in sync (window 12 - 19) and only a few moments that all three people look synchronized.

5. CONCLUSIONS AND FUTURE WORK

Interpersonal communication through voice, gestures, and gait is an essential part of the human evolution. Through analyses of subconscious actions such as gait synchronization and gestures, it is possible to infer rich information about individuals' relationships. Availability of highly sensitive smartphones enables us to capture these interactions with high accuracy.

In this paper we analyzed the accelerometer data from individuals walking in different formations, while having conversations in groups of two or three. We have recorded and processed high frequency data from the gait motions and have cross correlated these data. From our results, we have empirically confirmed previously published observatory studies: the non-verbal social signals such as the gaze, head orientation and gestures between individuals plays a significant factor in gait synchronization between two individuals walking together. A third person being involved in this for-

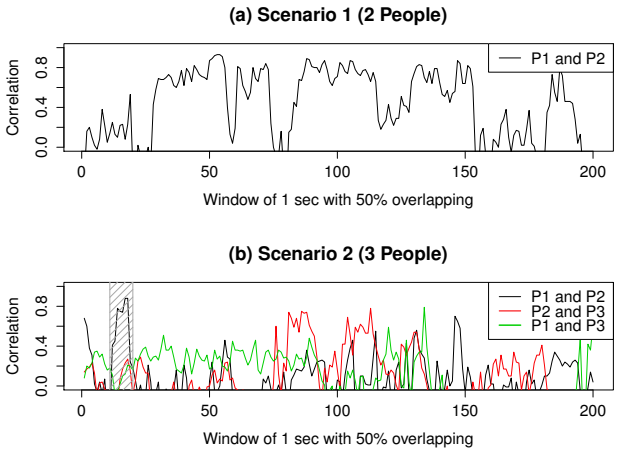

Figure 4: Pearson Correlation applied to windows of 1 sec (with 50% overlap) for Scenario 1 (a) and Scenario 2 (b).

mation can distort the synchronization, unless they are not actively engaged in the conversation between a pair.

Our results and methodology can have a number of benefits for different disciplines. They can be beneficial for scientists studying human interaction, or for organizations interested in crowd sensing, or inferring individuals relationships. To continue this work we will explore the power of cross-correlation for detecting hidden individuals. This could be in a crowd or people accompanying the walkers. We will also look at situations where only partial data (for example from only some of the group) is available, as well as. Finally, we will investigate the required resolution of the data, as well as the benefit of complementing the accelerometer and gyroscope data with data from other sensors.

6. ACKNOWLEDGMENTS

The authors wish to thank the participants in the trial. This work is supported by funding from the UK Defense Science and Technology Laboratory.

7. REFERENCES

[1] S. A. Battersby and P. G. Healey. Head and hand movements in the orchestration of dialogue. In *Proceedings of the 32nd Annual Conference of the Cognitive Science Society*. Cognitive Science Society, 2010.

[2] R. Challenger, C. W. Clegg, and M. A. Robinson. Understanding Crowd Behaviours: Practical Guidance and Lessons Identified, Mar. 2010.

[3] T. L. Chartrand and J. A. Bargh. The chameleon effect: The perception–behavior link and social interaction. *Journal of personality and social psychology*, 76(6):893, 1999.

[4] T. L. Chartrand and J. A. Bargh. The chameleon effect: The perception-behavior link and social interaction. *Journal of Personality and Social Psychology*, 76(6):893–910, 1999.

[5] E. Garcia-Ceja, V. Osmani, A. Maxhuni, and O. Mayora. Detecting walking in synchrony through smartphone accelerometer and wi-fi traces. In E. Aarts, B. de Ruyter, P. Markopoulos, E. van Loenen, R. Wichert, B. Schouten, J. Terken, R. Van Kranenburg, E. Den Ouden, and G. O'Hare, editors, *Ambient Intelligence*, volume 8850 of *Lecture Notes in Computer Science*, pages 33–46. Springer International Publishing, 2014.

[6] K. Katevas, H. Haddadi, and L. Tokarchuk. Poster: Sensingkit: A multi-platform mobile sensing framework for large-scale experiments. In *Proceedings of the 20th Annual International Conference on Mobile Computing and Networking*, MobiCom '14, pages 375–378, New York, NY, USA, 2014. ACM.

[7] M. B. Kjærgaard, M. Wirz, D. Roggen, and G. Tröster. Detecting pedestrian flocks by fusion of multi-modal sensors in mobile phones. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, UbiComp '12, pages 240–249, New York, NY, USA, 2012. ACM.

[8] D. Lakens and M. Stel. If they move in sync, they must feel in sync: Movement synchrony leads to attributions of rapport and entitativity. *Social Cognition*, 29(1):1–14, 2011.

[9] R. Marin-Perianu, M. Marin-Perianu, P. Havinga, and H. Scholten. Movement-based group awareness with wireless sensor networks. In A. LaMarca, M. Langheinrich, and K. Truong, editors, *Pervasive Computing*, volume 4480 of *Lecture Notes in Computer Science*, pages 298–315. Springer Berlin Heidelberg, 2007.

[10] Y. Miyake. Interpersonal synchronization of body motion and the walk-mate walking support robot. *Robotics, IEEE Transactions on*, 25(3):638–644, June 2009.

[11] M. Moussaïd, N. Perozo, S. Garnier, D. Helbing, and G. Theraulaz. The walking behaviour of pedestrian social groups and its impact on crowd dynamics. *PloS one*, 5(4):e10047, 2010.

[12] R. Murray-Smith, A. Ramsay, S. Garrod, M. Jackson, and B. Musizza. Gait alignment in mobile phone conversations. In *Proceedings of the 9th International Conference on Human Computer Interaction with Mobile Devices and Services*, MobileHCI '07, pages 214–221, New York, NY, USA, 2007. ACM.

[13] M. J. Richardson, K. L. Marsh, and R. Schmidt. Effects of visual and verbal interaction on unintentional interpersonal coordination. *Journal of Experimental Psychology: Human Perception and Performance*, 31(1):62, 2005.

[14] D. Roggen, M. Wirz, D. Helbing, and G. Tröster. Recognition of crowd behavior from mobile sensors with pattern analysis and graph clustering methods. *Networks and Heterogeneous Media*, 2011.

[15] K. Shockley, M.-V. Santana, and C. A. Fowler. Mutual interpersonal postural constraints are involved in cooperative conversation. *Journal of Experimental Psychology: Human Perception and Performance*, 29(2):326, 2003.