Mobile Monitoring of Formal and Informal Social Interactions at Workplace

Aleksandar Matic
Telefonica Research*
Placa Ernest Lluch I Marti, 5
08019 Barcelona, Spain
amatic@tid.es

Venet Osmani
CREATE-NET
Via alla Cascata 56/D
38123 Povo, Trento, Italy
venet.osmani@create-net.org

Oscar Mayora-Ibarra
CREATE-NET
Via alla Cascata 56/D
38123 Povo, Trento, Italy
oscar.mayora@create-net.org

UbiComp '14, September 13 - 17 2014, Seattle, WA, USA
Copyright 2014 ACM 978-1-4503-3047-3/14/09…$15.00.
http://dx.doi.org/10.1145/2638728.2641287

*this work was done when the author was working at CREATE-NET

Abstract
This paper proposes using mobile technologies to provide an insight into social context at workplace. It provides takeaways for extracting features that are relevant for interpreting social context and types of social interactions, formal or informal. Our approach uses mobile phones and accelerometers to detect interpersonal spatial and speech related features, achieving accuracy of around 80% in classifying between formal and informal social interactions, based on the study of 53 social interactions. One of the potential impacts of this work is on studying communication channels to enable more efficient knowledge transfer between knowledge workers. There is an on-going debate in social sciences whether formal or informal social interactions foster productivity more. However, the consensus is that improving communication between workers requires deeper understanding of both formal and informal types of interactions.

Author Keywords
Mobile sensing; mobile applications; context aware computing; social interactions

ACM Classification Keywords

H.1.2. [Models and Principles]: User/Machine Systems – Human factors, Human information processing

Introduction

In 1995 Savage [1] described the future in which 2% of the working population will work on the land, 10% will work in industry and the rest will be knowledge workers. Although such future has not come true yet, the trends in previous years indicate that Savage's predictions were not random. According to the statistics in the US [2], knowledge workers already constitute 70% of the labour force. Whereas productivity of manual workers has been thoroughly investigated and a variety of strategies for its improvement have been proven, increasing productivity of knowledge workers represents a more complex objective and still little is known about the underlying principles. Mc. Dermott [3] estimated that 38% of time knowledge workers spend searching for information which is the fact that opens a promising avenue for investigation, namely how to improve ways of exchanging and distributing relevant information in order to save workers' time and consequently increase their productivity [4][5]. In this regard, various studies investigated methods for improving communication channels to enable more efficient knowledge exchange between employees as well as to boost their close collaboration and coordination. Most of the studies suggested the promotion of informal types of communication [6] since it has been found that such interactions play a crucial role in maintaining work and in achieving an overall success of a company. However, there are several studies which showed the opposite thus promoting formal over informal interactions as the way for an efficient knowledge transfer [7]. In the attempt to emphasize both, Krackhardt and Hanson described: "If the formal organization is the skeleton of a company, the informal is the central nervous system driving the collective thought processes, actions, and reactions of its business units" [8]. Ultimately, there is a general consensus that improving communication channels require a deeper understanding of both formal and informal types of interactions [6] [7] [9].

Despite the fact that enterprises were increasingly investing in projects designed to improve knowledge management, the lack of theoretical findings still limits significant discoveries in this field [10][5]. Difficulties in objectively measuring informal/formal networks is a key challenge towards making substantial steps in the efficient information transfer and consequently increase productivity in knowledge-driven communities [9]. Formal and informal communication networks have been investigated in the past using the standard interaction data collecting methods – engaging observers to take notes or through conducting self-reports. Such methods of reconstructing social interactions are error prone [11] and can even lead to contradictory results in this area [9]. This is attributed to the fact that periodical surveys fail in capturing temporal aspects i.e. they are prone to miss all the individual social interactions [12]. This is an important aspect considering the fact that social networks in companies are typically characterized by temporal changes.

Automatic data collection methods have shown huge potential to overcome the limitations of self-reporting methods in social sciences. However, the problem of analysing formal and informal structures in an automatic way, thus acquiring new theoretical findings

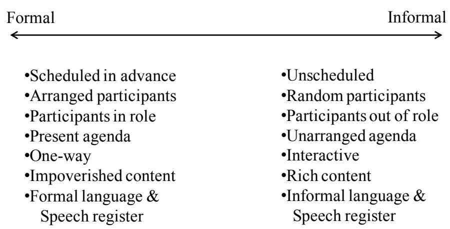

Figure 1: Formality Dimension of Communication [6]

about knowledge transfer [9] has not gained enough attention in social computing community. Analysis of social networks was extensively addressed by using MIT's Sociometer [13], [14], [15] and mobile phones [16] [17] focusing on mapping the structure of networks by inferring who and when interacted. Yet, the type of individual social interactions (informal vs formal) remained unknown, typically because of the content of the conversation was inaccessible due to privacy. Along this line, Do and Gatica-Perez [18] recognized the types of social interactions by analysing continuously sampled Bluetooth data. They performed longitudinal data analysis thus they did not focus on temporal aspects i.e. they did not detect social interactions that occur on a small spatio-temporal scale, rather providing an aggregated picture over longer time scale.

In this paper we focus on the use of mobile technologies to infer the type (formal vs. informal) of on-going social interactions that occur on small spatio-temporal scale. We consider different categories of features related to nonverbal cues that characterize face-to-face conversations that are relevant for formal and informal interaction classification. We present the results of a feasibility study of inferring the types of social interactions relying on a mobile phone and an external accelerometer, which automatically detects speech activity and interpersonal spatial settings.

Monitoring setup

In our previous work [29] we presented a mobile platform for recognizing the occurrence of social interactions and discussed various trade-offs in automatic monitoring of face-to-face conversations. The platform consists of a mobile phone sensing system for inferring interpersonal distances (with a median accuracy of 50cm, relying on Received Signal Strength analysis of WiFi hotspot) and inferring relative body orientation (relying on phone's compass sensor). In addition, speech activity was detected using off-the-shelf accelerometer attached at the chest level to detect vibrations generated by vocal chords. Our goal was to address drawbacks of previous solutions that either i) require expensive infrastructures, constraining applications to pre-equipped rooms, or ii) involve specialised devices that are not available off-the-shelf, or iii) provide limited accuracy in gathering real-time data with spatial-temporal granularities, or iv) use microphone, whose activation raises privacy concerns in monitored subjects. For further details about our monitoring platform, please refer to [29].

Spatial and Speech Activity Features for Formal vs Informal Interaction Classification

Despite a common understanding of the distinction between formal and informal conversations, the difference between the two lacks a clear-cut definition. It also varies across different scientific disciplines. Considering our goal of identifying social contexts in the working environment, we relied on the distinctions provided in the field of social psychology. Referring to the social psychology literature, Kraut et al. [6] emphasized several variables for discriminating between formal and informal communications in the workplace – time scheduling, involved participants and their roles, agenda, content and language of the conversation (Figure 1). These variables provided a good foundation for designing the questionnaire to classify social encounters with respect to the level of their formality. In our work, we refer to this study as a guideline, both for annotating the ground-truth in the experiments and for identifying meaningful features for interpreting the social context.

Speech Activity Features

Several variables that indicate the differences between formal and informal interactions (Figure 1) are reflected through speech activity characteristics of the conversation, including the level of interaction/one-way-speech, richness of the content, speech register and the degree of language formality. Since acquiring the content of conversations would have raised privacy issues, we do not take the formality level of language and the spectrum of content in our consideration. As such, in our experiments, we do not use speech related features as we use an off-the-shelf accelerometer to detect speech activity. The level of interaction is estimated based on the amount of speaking for each participant, using accelerometer data. In particular, the distribution of the amount of speaking time for each participant is a suitable feature for the classification between formal and informal contexts. This provides a way to quantify the level of interactivity i.e. "One-way" vs. "Interactive" (Figure 1) as proposed in [6].

Furthermore, since dominance and status of participants in social interactions has been shown to be correlated with speech related cues (including speaking energy [19], speaking length and turns [20], and interruptions in conversation [21]) it can be speculated that the roles of participants (illustrated in Figure 1 by the variable "participants in role") is reflected through speech activity patterns. Jayogopi [22] extracted a number of features in order to estimate status and dominance in social interactions, including speaking energy, speaking length, number of speaking turns, turn duration, number of successful and unsuccessful interruptions, and several derived cues. The study demonstrated that the aforementioned nonverbal cues contribute to detection of the most dominant person and also group conversational context identification (regarding "competitive vs. cooperative" and "brainstorming vs. decision making" classifications). As speaking duration for each participant can be recognized using our accelerometer-based method, this allows the extraction of the two relevant features, namely speaking length index (analyzed in [22] for dominance recognition) and speaking length distribution index (analyzed in [22] for "competitive vs. cooperative" and "brainstorming vs. decision making" classifications). Speaking length index is calculated as the sum of total amount of time that each person spent speaking divided by the overall interaction duration. Speaking length distribution index was calculated applying the following algorithm:

1) Compose the vector A representing the levels of participation for each subject in the conversation with respect to the others, $t(i) / \Sigma_n t(i)$ where n is the number of subjects and $t(i)$ represents an amount of time that i-th subject was speaking during the overall duration of social interaction.

2) Using Bhattacharyya distance [24], compare vector A with the uniform vector which is of the same dimension n being constituted of values 1/n.

This method yields a value between 0 and 1 for each social interaction, where 0 corresponds to the social interaction where all participants have spoken an equal amount of time while 1 corresponds to a conversation in which solely one participant was talking. Speaking length distribution index reflects the level of interactivity in a social interaction, represented in Figure 1 by the variable “one-way” vs “Interactive”, which characterizes the difference between formal and informal context.

Spatial Features

The main postulates of the proxemics study [25] suggest that people unconsciously organize the space around them, corresponding to different degrees of intimacy. Colloquial knowledge suggests that having a chat with a close friend and talking to the boss differ in spatial settings conventions i.e. interpersonal distance is affected by level of formality in social interaction. According to social psychology, the formality is bounded with roles and hierarchies among participants [6] (in Figure 1 described with the variable “participants in/out of role”) which is further mirrored in spatial arrangements. The matching between social relations and the spatial formations in social interactions was also investigated using a computer vision system for estimating distances between subjects, confirming a strong positive correlation [26]. Therefore, we selected interpersonal distance as a classification feature in the attempt to classify between formal and informal social context.

In addition, our monitoring platform provides measures of relative body orientation and its standard deviation (which represents an index of stable relative body position between participants) which, in our previous study [27], demonstrated high predictive power of detecting the occurrence of social interactions. Since, relative body orientation has been used to describe the immediacy of interaction, subject’s attitude or similar phenomena in social interactions [28], we hypothesised that body orientation related cues (namely relative body orientation and its standard deviation) also correlate with the level of formality, having included it in our classification analysis.

Overview of the Classification Problem – Temporal and Cumulative Features

Interpersonal distance, relative body orientation and its standard deviation are captured in temporal scale, (every 10 seconds) during an ongoing social interaction, and will be referred to as *temporal* features. These *temporal* features are calculated for each pair of subjects that participate in the same social interaction. In contrast, speaking length and speaking length distribution indices result in one value that characterizes the completed social interaction, which will be referred to as *cumulative* features. Unlike *temporal* features that refer to pairs of subjects in conversation, *cumulative* features describe the entire group behaviour during a face-to-face encounter.

Furthermore, we also analysed location and duration of conversation, *attributes* that can be assigned to each concluded social interaction and we combined them with the *cumulative* features in order to improve classification accuracy. Location is expressed as an index representing the probability of informal social interaction occurrence calculated solely based on the experience from the experiments (for instance, if 4 formal and 6 informal social interactions occurred in a building hall, this location is assigned with a value of 0.6). Location was automatically detected using the mobile phone. Duration refers to the number of minutes from initiating until concluding the conversation. It is important to consider that duration and location of formal and informal social interactions

Interpersonal distance	d
Relative body orientation	α
SD of relative body orientation	σ
Speaking length index	SLI
Speaking length distribution index	SLDI
Duration of social encounter	DUR
Location index	LOCIN

Table 1: Summarized Features for Formal vs Informal

are strongly dependent on various parameters including layout of a building or workers' routines. The goal of including these two attributes in the analysis of formal versus informal context classification was to investigate whether a heuristic-based approach can contribute to the classification model built for a particular workplace.

The summary of the *attributes* (highlighted with grey colour) and the *temporal*/*cumulative* features which are evaluated regarding formal and informal social interaction classification is given in Table 1 with corresponding denotations.

Experimental setup and interaction data

Establishing ground-truth

The questionnaire that we used to infer the ground-truth (formal or informal interaction) was designed according to the instructions provided by Kraut et al. [6] which categorized the context relying mostly on the degree to which the conversation was scheduled. The four categories for assessing the degree of preplanning conversation include: a) scheduled (previously scheduled/arranged interaction), b) intended (there was one initiator prompting other subject for the conversation), c) opportunistic (one participant planned to talk with another and took the advantage to have a conversation), d) spontaneous (there were no previous plans for the conversation). Each participant responded independently and the conversation was characterized with the least spontaneous answer following the order of scheduled < intended < opportunistic < spontaneous (for instance, if one reported opportunistic and another scheduled, the conversation was categorized as scheduled). The questionnaire used in our experiments included: demographic information, topic of conversation (work related, non-work related), frequency of the communication between participants (every day, several times a week, once a week or less), period that participants knew each other (less than 3 months, between 3 months and one year, more than one year), and subjective description of the conversation (formal, informal). In several cases when answers by different subjects were not in concordance, single social interaction was assigned with the least reported value in terms of selecting the smallest reported frequency of communication, the smallest reported amount of time that subjects knew each other, the most formal reported context and the least formal topic of conversation.

Opportunistic and spontaneous meetings were always subjectively described as informal while scheduled ones were described as formal conversation, being in accordance with the distinctions between formal and informal context provided in [6]. Although the literature categorises intended meetings as informal, the participants were mostly reporting formal contexts as their subjective description. In these cases, the topic determined the formality: work-related was formal, otherwise the conversation was categorised as informal. Formal conversation was not affected by the frequency of interaction and the degree of familiarity between subjects. In other words, subjects were interacting formally, regardless of how long they knew each other. On the other hand, informal interactions were mostly occurring among subjects that knew each other better.

Experimental scenarios

The first experimental scenario was performed at several locations, including three meeting rooms, three offices, three coffee rooms, two balconies and an entrance hall, all environments with dimensions that did not physically confine subjects thus not affecting interpersonal distances. At randomly determined times, we interrupted face-to-face interactions that were about to occur or were already initiated by explaining to subjects that the investigation is on social interactions phenomena which does not require recording audio data. Afterwards, participants were provided with the equipment for monitoring (accelerometer for speech activity detection and smart phones that were sampling orientation and WiFi hotspot signal for distance [29]). In most cases, subjects accepted participation in experiments, however some refused wearing the accelerometer due to inconvenience of mounting it on the chest. They were given a case to carry the phone on the right hip thus the position of the phone with respect to the body was directly known. Once the social interactions ended, participants were asked to fill out a short check-box questionnaire (previously described) in order to infer whether the conversation was formal or informal. Overall, there were 30 face-to-face interactions collected, 21 informal (duration of 9±5 minutes) and 9 formal (duration 21±9minutes), which included participation of 50 subjects (33 males/17 females, with an age of 32.7±6.6 years). Wi-Fi and orientation were sampled with 1Hz and interpersonal distance / relative body orientation were estimated for each time frame of 10 seconds. In this experimental scenario, only 2 formal and 4 informal interactions were monitored through sensing modalities, the accelerometer and mobile phone.

In the second experimental scenario, we recruited four subjects that shared the same office (3 males and 1 female, 29.0±1.4 years) for 7 working days. Each day (typically between 11h and 17h) they were carrying the monitoring equipment that included both speech and spatial settings detection. Participants were asked to fill-out the questionnaire after every meeting they had only with monitored subjects which resulted in 7 formal and 16 informal meetings with duration of 25±8 minutes and 8±7 minutes respectively.

Overall, we analysed 53 meetings (37 informal and 16 formal) monitored with mobile phones phone (providing spatial arrangement detection), out of which 20 informal and 9 informal were monitored with both sensing modalities (speech activity and spatial settings recognition).

Formal Vs Informal Interaction Classification Based on Cumulative features

Speaking activity features were extracted using accelerometer-based approach while the duration of meetings was calculated directly. Location at the room level was detected using Wi-Fi fingerprinting method (fingerprints were previously captured in the locations of interest) or it was directly observed (which was feasible in the first experimental scenario). The predictive power of the cumulative features and attributes in classifying the social contexts is assessed using 10-fold cross validation and the results are presented in Table 2. The accuracy corresponds to the percentage of correctly classified social interactions ("*Overall*" column). As the sample was not balanced (20 informal and 9 formal interactions), Table 2 shows also the percentages of correctly classified formal interaction ("*formal*" column) and correctly classified informal interactions ("*informal*" column) separately. We used SVM and Naïve Bayes (KDE) methods. The former only slightly outperformed the latter thus for the

Feature	Overall	Formal	Informal
SLI	55%	44%	60%
SLDI	66%	67%	68%
SLI+SLDI	66%	78%	60%
SLI+DUR	72%	78%	65%
SLI+LOC	66%	78%	60%
SLDI+DUR	76%	78%	70%
SLDI+LOC	72%	89%	65%
SLI+LOC+DUR	69%	78%	65%
SLDI+LOC+DUR	79%	89%	75%

Table 2. Formal vs Informal Classification (Cumulative Features)

simplicity reasons we present only SVM results in Table 2.

According to our results, Speaking Length Index (SLI) was not shown to be a discriminating feature between formal and informal context providing the accuracy of only 55% (a random guess would provide the accuracy of 50%). By combining SLI with the location or duration of meetings, the accuracy increased by up to 10%. As expected considering social psychology literature, Speaking Length Distribution Index (SLDI) that reflects the variable "one-way/interactive" (Figure 1) was more indicative for the classification. This suggests that in informal social interactions participants spent more balanced amount of time talking than in the case of formal context. When SLDI was combined with the location and/or duration of social interactions, the accuracy increased to 79%, while the fusion of SLI and SLDI improved only the detection of formal interactions.

Knowledge of location and duration improved the classification accuracy of selected cumulative features. These two attributes can be automatically extracted using the proposed mobile sensing modalities, however they require heuristics building, thus applicable in specific location only.

Speaking Length Index, which represents the proportion of time used by all the participants together during the duration of a social encounter was not shown to be discriminative. Speaking Length Distribution Index, which is reported in the literature to be very effective for estimating the most dominant person, demonstrated a moderate accuracy in classifying between formal and informal context – being successful in 66% of cases. The best accuracy of 79% was achieved when combining SLDI with both location and duration of social interactions. This indicates that speaking activity related cues, extracted using solely an off-the-shelf accelerometer, can distinguish between formal and informal interaction context.

Formal vs Informal Interaction Classification based on Temporal features

Whereas *cumulative* features refer to the group characteristics of an interaction, *temporal* features can be calculated for each pair of subjects during an ongoing social interaction. We calculated temporal features every 10 seconds; this time-frame duration was indicated by Groh et al [23] to be appropriate for capturing dynamic changes in social interactions. In order to assess the predictive power of interpersonal distance, relative body orientation and standard deviation of relative body orientation, we analysed these features for all the pairs of participants in the labelled social interactions. The accuracy was evaluated through 10-fold cross validation where the training set never included data samples acquired from the same social interaction (such as the other involved subjects) or from the same subjects (such as the data from the other social encounters) so as to not bias the result. The classification results (Table 3) demonstrate that interpersonal distance and standard deviation of relative body orientation are relevant features to infer the type of face-to-face communication, providing maximal accuracy of 81%. Unlike relative body orientation, computing standard deviation of orientation does not require the phone to be at a known place on the body thus allowing for an unobtrusive monitoring of subjects.

Feature vector	Naïve Bayes (KDE)	SVM
(d, α)	67%	68%
(d, α, σ)	76%	78%
(d, σ)	78%	81%

Table 3 Formal Vs Informal Classification (Temporal Features)

Conclusion

This paper discussed the possibilities of using mobile sensing modalities for automatic classification of formal and informal types of social interactions. We relied on the social psychology literature for the guidelines in identifying nonverbal cues that are meaningful and informative for interpreting the social context. In particular, we selected a set of spatial and speech related features for the classification between formal and informal social interactions. Our evaluation demonstrated high predictive power (up to 81%) of spatial settings parameters that were extracted solely by using mobile phone sensing. When combining speech activity features with location or duration of a social interaction, the accuracy increases to 79%, indicating that in specific applications speaking activity related cues extracted by using solely an off-the-shelf accelerometer can distinguish between formal and informal interaction context.

Acknowledgements

This work was partially supported by EIT ICT Labs.

References

[1] C. Savage, Fifth Generation Management, Second Edition: Dynamic Teaming, Virtual Enterprising and Knowledge Networking. Butterworth-Heinemann, 1996.

[2] U. M. Apte and H. K. Nath, "Size, structure and growth of the U.S. information economy.," in Managing in the in- formation economy. Springer, Heidelberg, pp 1–28, Springer, Heidelberg, 2007, pp. 1–28.

[3] M. Mcdermott, "Knowledge Workers: You can gauge their effectiveness," Leadersh. Excell., vol. 22, 2005.

[4] R. Cross, A. Parker, and L. Sasson, Networks in the knowledge economy. Oxford University Press, Oxford, 2003.

[5] S. Aral, E. Brynjolfsson, and M. Van Alstyne, "Information, technology and information worker productivity: task level evidence," in Proceedings of the 27th annual international conference on information systems, 2006.

[6] R. E. Kraut, R. S. Fish, R. W. Root, and B. L. Chalfonte, "Informal communication in organizations: Form, function, and technology," in Human reactions to technology: Claremont symposium on applied social psychology, 1990.

[7] R. Aalbers, O. Koppius, and W. Dolfsma, "On and off the beaten path: Transferring knowledge through formal and informal networks," Circ. Electron. Work. Pap. Ser., 2006.

[8] D. Krackhardt and J. R. Hanson, "Informal networks: the company behind the charts," Harv. Bus. Rev., vol. 74, no. 4, pp. 104–111, 1993.

[9] K. Fischbach, P. a. Gloor, and D. Schoder, "Analysis of Informal Communication Networks – A Case Study," Bus. Inf. Syst. Eng., vol. 1, no. 2, pp. 140–149, Dec. 2008.

[10] [M. ME, "What makes information workers productive," MIT Sloan Manag. Rev., vol. 49, no. 2, pp. 16–17, 2008.

[11] R. A. Hannemann and M. Riddle, Introduction to social network methods. University of California, Riverside, 2005.

[12] [B. P and H. DA, "Ties, leaders, and time in teams – strong inference about net-work structure's effects on team viability and performance," Acad. Manag. J., vol. 49, no. 1, pp. 49–68, 2006.

[13] T. Choudhury, "Sensing and modeling human networks," Massachusetts Institute of Technology, 2004.

[14] D. Olguin Olguin, B. N. Waber, T. Kim, A. Mohan, K. Ara, and A. Pentland, "Sensible organizations: technology and methodology for automatically measuring organizational behavior.," IEEE Trans. Syst.

Man. Cybern. B. Cybern., vol. 39, no. 1, pp. 43–55, Feb. 2009.

[15] N. Eagle, A. S. Pentland, and D. Lazer, "Inferring friendship network structure by using mobile phone data.," Proc. Natl. Acad. Sci. U. S. A., vol. 106, no. 36, pp. 15274–8, Sep. 2009.

[16] N. Eagle, A. S. Pentland, and D. Lazer, "Inferring social network structure using mobile phone data," Proc. Natl. Acad. Sci., vol. 106, no. 6, pp. 15274–15278, 2009.

[17] D. Wyatt, T. Choudhury, J. Keller, and J. Bilmes, "Inferring Colocation and Conversation Networks from Privacy-sensitive Audio with Implications for Computational Social Science," in ACM Transactions on Intelligent Systems ans Technology, 2010.

[18] T. M. T. Do and D. Gatica-Perez, "GroupUs: Smartphone proximity data and human interaction type mining," in 5th annual International Symposium on Wearable Computers, 2011, no. 2.

[19] D. N. E. and J. K. Burgoon, "Perceptions of power and interactional dominance in inter- personal relationships.," J. Soc. Pers. Relat., vol. 22, no. 2, pp. 207–233, 2005.

[20] M. Schmid Mast, "Dominance as expressed and inferred through speaking time: a meta- analysis," Hum. Commun. Res., vol. 28, no. 3, pp. 420–450, 2002.

[21] L. (1989). Brody, C. and Smith-Lovin, "Interruptions in group discussions: The effects of gender and group composition," Am. Sociol. Rev., vol. 54, no. 3, pp. 424–435, 1989.

[22] D. B. Jayagopi, "Computational modeling of face-to-face social interaction using nonverbal behavioral cues," Lausanne, EPFL, 2011.

[23] G. Groh, A. Lehmann, and M. De Souza, "Mobile Detection of Social Situations with Turn Taking Patterns," in WAC2011, 2011.

[24] A. Bhattacharyya, "On a measure of divergence between two statistical populations defined by their probability distributions," Bull. Calcutta Math. Soc., vol. 35, pp. 99–109, 1943.

[25] E. Hall, The hidden dimnesion. New York: Double Day Anchor Books, 1966.

[26] G. Paggetti, A. Vinciarelli, I. Italiano, and G. It, "Towards computational proxemics : inferring social relations from interpersonal distances," in IEEE International Conference on Social Computing, 2011.

[27] A. Matic, V. Osmani, A. Maxhuni, and O. Mayora, "Multi-Modal Mobile Sensing of Social Interactions," in 6th International Conference on Pervasive Computing Technologies for Healthcare, May 21-24, San Diego, California, USA, 2012.

[28] A. Mehrabian, "Some referents and measures of nonverbal behavlor," Behav. Res. Methods Instrum., vol. 1, no. 6, pp. 203–207, 1969.

[29] A. Matic, V. Osmani, and O. Mayora-Ibarra, "Trade-offs in Monitoring Social Interactions," IEEE Communications Magazine, Vol 51, Issue 7, 2013.