Multimodal Indoor Social Interaction Sensing and Real-time Feedback for Behavioural Intervention

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ABSTRACT

Social interactions play an important role in people's personal as well as working life. Interactions come in various forms, identifiable mainly by duration and proximity. The ability to detect and distinguish interactions can often shed light over worktask performance, epidemic spreading, personal relationship development, use of space and more. Questionnaires and direct observations have often been used as mechanisms to identify interactions, however, these are either very expensive in terms of staff time, yield very coarse grained information or do not scale. Technology has started cutting costs by allowing automatic detection, however precise interaction identification often requires individuals to wear custom hardware. The aim of my work is to exploit the capabilities of off-the-shelf wearable devices (i.e. smart watches and fitness trackers) to build a social interactions sensing platform which offers accuracy and scalability. To this end, non-verbal behaviours, such as, body language, will be considered in addition to the occurrence of the interactions (individuals involved, duration and location) with the objective of providing unobtrusive real-time feedback.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Design; Deployment; Evaluation.

Keywords

Mobile sensing; Wearables; Social interactions; Real-time feedback.

1. MOTIVATION AND CHALLENGES

Research has shown that in-person social interactions play a significant role in different contexts. In the workplace, serendipitous interactions between members of different groups have been demonstrated to be a key factor for team coordination, cohesiveness and productivity [14, 7, 20]. Architects have studied how to increase this sort of unplanned interactions by changing the layout and design of physical spaces. Informal and high-traffic spaces such as coffee areas and photocopiers have been proven to encourage inter-group serendipitous meetings and their location inside a building is crucial [6, 24, 12]. Another research area that benefits from tracking face-to-face interactions is epidemiology. Several studies and deployments have been conducted in order to develop an understanding of disease spreading [26].

Sociologists, architects and health researchers have suffered from a crucial limitation: the lack of reliable and scalable means of tracking social interactions. These phenomena have been mainly studied so far using ethnographic research techniques which involve participant observations or self reports and surveys. However, observations are not cost effective because they require long hours of monitoring and cannot be applied for long sessions. Surveys scale better but could provide data with a lower resolution as people are not good at remembering the interactions they had throughout the day [23]. Moreover, these two approaches are subject to biases as participants could adapt their behaviour because they are aware they are being observed [25] or because they prefer to provide socially desirable responses [4]. Several technologies have been proposed to overcome these issues but the automated and accurate measurement of human interactions is still lagging behind. The main shortcomings regard the accuracy and resolution of the produced data. For example, many systems use Bluetooth transceivers included in modern smartphones to detect proximity but they are usually power hungry and do not offer fine spatial and temporal granularity [1, 8, 15, 26]. Other systems, are able to provide better accuracy, but rely on dedicated hardware and require the instrumentation of the building which complicates their widespread adoption [5, 10, 13]. Additionally, it is important to keep in mind that the results provided by these technologies are based on probabilities and are far from the perfection: for example, Choudhury reported that the Sociometric Badges developed at MIT can correctly identify interactions 87% of the time [10].

In this area, it is possible to identify two main research challenges. Firstly, the scalability and reliability of the system are critical aspects. The possibility to collect longitudinal fine grained data can provide important insights on how human relations evolve over time and on changes in organisational structures. Efforts need to be focused on making the technology easy to deploy and accurate in order to guar-

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antee a large adoption and collect rich data that could serve for a better understanding of social interaction dynamics.

Secondly, many of these technologies focus only on capturing the occurrences of the interactions, i.e., the beginning, the end and in some cases the location. However, interesting and useful insights can be gathered by analysing an interaction while it is happening. For example, non-verbal behaviours, such as facial expressions, gestures, body language or the way we speak, have an important role during interactions to communicate attitudes and emotions [21, 9]. While some works have addressed the analysis of speech-related non-verbal signals in real environments [19], very little knowledge is available for other aspects like body language and gestures in realistic settings [11]. The challenge in this case would be to explore technologies and techniques to capture and analyse these signals accurately without increasing the burden on the user and provide feedback to promote behavioural change.

2. RESEARCH OBJECTIVES

The objective of my research is to *investigate new methodologies to efficiently and accurately monitor and model social interactions and their non-verbal signals in order to provide real-time feedback for behavioural intervention.* In particular the following three broad topics will be investigated more deeply:

Investigation of new sensing modalities for detecting social interactions. Several approaches have been devised to monitor face-to-face interactions but a truly accurate and scalable solution has not been produced yet. On the one hand, systems based on commodity hardware such as smartphones benefit from the fact that users can use their own devices making the system more comfortable and easy to use. The downside of this approach is that usually the accuracy and the granularity of the collected data is not enough for detailed analysis [1, 8, 15, 26]. On the other hand, systems built on top of custom designed devices have the advantage of being able to capture fine grained data but suffer from the usability point of view. In fact, they require the user to carry an additional device which could be obtrusive, easy to forget and make the user feeling observed [5, 10, 13]. One of the goals of my research would be to explore the capabilities of commercially available wearable devices (i.e. smart watches) to understand if they can be used to make the face-to-face interaction monitoring efficient and as effortless as installing an app. Secondly, new sensors and technologies would be investigated in order to augment modern wearables to improve the accuracy of interaction sensing.

Measurement of non-verbal behaviours of social interactions. Detecting precisely when interactions happen is only part of a more comprehensive study about social interactions. When people interact, the verbal part of the communication (speaking to each other), is not the only modality used. Other non-verbal channels, such as body language, facial expressions or characteristics of the speech, are combined to influence the conversation and its participants [18, 17, 9]. This means that increasing the awareness about a person's non-verbal behaviour could be beneficial for her because she could improve her outcome in certain situations which involve interpersonal interactions (e.g., during job interviews and relations with colleagues and managers). However, in order to gain this level of awareness, an automatic system that recognises and tracks one's body language is needed.

So far, non-verbal dimensions have been studied in very specific contexts reproduced in the lab (e.g. job interviews or public speeches) and with the use of cameras which limits the flexibility of the system [3, 11]. The objective of my work would be to research new ways to detect and measure non-verbal behaviours during daily social interactions, with focus on postures and body language. The capabilities of accelerometers, gyroscopes, pressure and stretch sensors will be analysed to develop a new wearable device which would allow continuous body posture monitoring during an interaction.

Exploration of real-time feedback mechanisms for social intervention. The offline analysis of large amount of data is used to inform people about their habits allowing them to change behaviour accordingly. This has been a common practice in social science where the results of a study change, eventually, people's behaviour a long time after the study has been conducted. With technology, however, the intervention could be shifted to a previous moment, when the user needs it the most, during the data collection phase. Modern devices are becoming in fact smaller and more powerful with each generation and new ways of presenting information to the user are flourishing (e.g., vibration [22, 2], thermal [22] and electrical muscle stimulation [16]). In particular, for social interactions the need to change the behaviour quickly is important because, has mentioned in the previous paragraph, our non-verbal communication behaviour impacts the outcome of the interaction. Therefore, the possibility to learn about one's body language and be discreetly advised, in order to assume the ideal behaviour, has the potential to improve social interactions. In light of this, the aim of the present work is to study in deep how to provide real-time feedback to the user about her non-verbal communication behaviours.

Important aspects such as the best form of feedback and the best moment in time to provide it to the user will be investigated in a challenging environment, as the social sphere of a person is. In fact, I envision to provide real-time feedback during social interactions but this poses a big challenge that is to provide rich information without disturbing the person and his interlocutors. Wearable devices seem to offer a promising mean to achieve this because they have the advantage of being always in contact with the user's skin, so they will be the preferred platform for the intended investigation.

3. PRELIMINARY RESULTS

The first technology that I decided to explore for interaction sensing is Bluetooth Low Energy (BLE). This technology has been chosen because it is employed in all currently available wearable devices making it particularly suitable for the intent of simplifying the platform deployment. Moreover, as a short range low-power radio, it offers several transmit power levels which make it ideal for fine-grained interaction sensing by periodically transmitting and listening for beacons without draining the battery too quickly. To evaluate its capabilities I built a prototype wearable platform based on Nordic's nRF51822 SoC[1] which can sense proxim-

[1] https://www.nordicsemi.com/eng/Products/Bluetooth-Smart-Bluetooth-low-energy/nRF51822

ity between devices and detect the coarse location by using static beacons in the environment. The performance of the platform has been analysed through several benchmarks and a week long study with six users in a real work environment. The platform is able to capture short lived interactions (e.g. individuals passing by in a hallway or an individual stopping by an office entrance for a quick question) as well as long ones with a temporal granularity of three seconds up to a distance of 2.5 meters.

Currently, work in progress is a bigger deployment in a workplace with about 35 employees for a period of one month. The larger scale of the study opens improvement prospects for the platform. First, the long duration of the study and the impossibility of being present on site every day imposes the necessity to have a reliable platform. Second, improvements on evaluation and ground truth collection techniques are foreseen in order to make the system less susceptible to false positives. In addition, a larger number of participants will enable me to collect more data and begin to explore the patterns of human interactions more closely.

4. REFERENCES

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