The potential of wearable technology for monitoring social interactions based on interpersonal synchrony

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ABSTRACT

Sensing data from wearables have been extensively evaluated for fitness tracking, health monitoring or rehabilitation of individuals. However, we believe that wearable sensing can go beyond the individual and offer insights into social dynamics and interactions with other users by considering multi-user data. In this work, we present a new approach to using wrist-worn wearables for social monitoring and the detection of social interaction features based on interpersonal synchrony - an approach transferable to smartwatches and fitness trackers. We build up on related work in the field of psychology and present a study where we collected wearable sensing data during a social event with 24 participants. Our preliminary results indicate differences in wearable sensing data during a social interaction between two people.

CCS CONCEPTS

• **Human-centered computing → Collaborative and social computing**; *Ubiquitous and mobile computing*;

KEYWORDS

wearable technology, social sensing, interpersonal synchrony

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1 INTRODUCTION

Recent developments in sensing technology and miniaturization of processors aided the development of ubiquitous and smart wearable devices in the form of fitness trackers and smartwatches. Those devices become ever more equipped with rich sensors, such as accelerometers, GPS, heart rate monitors, and even skin conductance measures. The main purpose of those sensors lies in personal health monitoring or fitness support; there is rich literature on the validity, suitability and acceptability of wearable technology in the fields of personal health informatics, behavior change, and medical support [12].

There has been little work on evaluating wearables beyond just a single person; e.g. a multi-user aggregate of sensing data to monitor social dynamics and interactions. Related literature in the fields of social and experimental psychology indicate that during social interactions, people tend to synchronize their movements, map each-others gestures, or even share the same heart rate and skin conductivity.

While the first works in investigating interpersonal synchrony used manual visual annotation tools, the availability of novel on-body sensing technologies such as the use of motion sensors (e.g. accelerometers), heart rate monitors (e.g. wearable ECG or optical sensors), or other physiological sensors (e.g. skin conductivity, skin temperature), provide unique opportunities to investigation this phenomenon in an automated way. The addition of wide-spread availability of sensing-rich wearables on the consumer market opens new possibilities for research and applications. Those potential application of wearable devices in detecting these synchronies and inferring social interactions, engagement, or emotional contagion could be:

- Providing feedback and monitoring during a conversation on how socially engaged all parties are.
- Developing novel research tools for larger scale in-the-wild studies from various disciplines such as behavioral or organizational research.
- Support for therapeutic sessions, where an increased synchrony of physiological measures has been shown to lead to increased perceived empathy and positive outcome [9].

In this paper, we propose leveraging data from wearables for social sensing based on interpersonal synchrony. We, furthermore, present some early results from a case study that we recently undertook in order to evaluate this approach in a social networking event. We believe this could be a first step in considering consumer wearable data for analyzing and quantifying social dynamics in

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large scale, real world scenarios, e.g. in planned events such as social gatherings, to aid bonding during family time, or to support therapy sessions.

2 BACKGROUND

Interpersonal, social interactions are characterized by complex dynamics, such as taking turns while talking, mirroring the opposites gestures, mannerisms and facial expressions of the opposite person. The effect of nonverbal behaviors or even physiological signals becoming more similar during interaction can be referred to as interpersonal synchrony [10]. From early age, synchrony is a part in social development; e.g. in facilitating the formation of a secure attachment between infants and care-giver [5]. In adult life, synchrony mainly functions as tools of rapport [15]. However, increased synchrony has also been shown to enhance cooperation between individuals [16], promote group bonding [14] or increase positive outcomes in therapy sessions [9]. Apart from the synchronization of body movements, physiological signals such as heart rate, skin conductivity and skin temperature have also shown to cooperate during interaction [11].

Interpersonal synchrony has been researched in various scenarios, including mother and child, therapist and patient, couples, teammates [11]. Research has also shown that interpersonal synchrony during interaction aids cooperation, supports social-cognition, and increases self-esteem [8, 17]. Common methods to detect synchrony between peoples' data, hereby, comprise correlation, spectral or recurrence analysis [3].

In this work, we focus on utilizing a wrist-worn device equipped with a 3-axis accelerometer, an optical heart rate, as well as skin conductance and skin temperature sensors. This is similar to the setup often found in consumer wearable technology, such as the Apple Watch, Microsoft Band or Fitbit. Our approach could be applicable to real-world, long-term scenarios where people use their own wearable devices during studies, for self-tracking or professional monitoring of their social interaction with other people.

3 STUDY DESCRIPTION

To evaluate our hypothesis, we performed a case study on investigating interpersonal synchrony in sensing signals from a mobile phone and wearable wristband during natural social interactions. We recruited 24 participants for this ethics board approved study. Participants were hereby briefed that we collect sensing data from the phone and wearable to investigate the data during social interaction. They were not aware that we looked at interpersonal synchrony in particular to avoid any unconscious bias. These participants were invited to take part at a social networking event taking place in an open, event-friendly space of our institution. During this event, the participants were equipped with E4 wristbands [4] and instructed to install a SensingKit-based [6] app for recording mobile sensor data while the phone was placed in their pocket. The event space was video (but not audio) monitored for later manual ground truth annotation on the social interactions.

We collected data about the participants personality using the *Big-5 Inventory* [13] and *Empathy Quotient* [7] questionnaire to investigate confounding factors. Each participant was asked about their relationship, sympathy and closeness [1] towards each other participant. This task was performed before and after the experiment, in order to identify if people becoming closer during the experiment is related to a higher synchrony during interactions. Mood changes were recorded throughout the social networking event by using the *Self-Assessment-Manikin* [2] and *Positive and Negative Affect Scale* (PANAS) [18], in order to investigate the coordination of perceived affects after an interaction.

This study setup allowed the data collection in a natural setting, which differed from many related studies which used for example special tasks such as walking side-by-side, dancing, or interacting in a controlled lab setting.

Table 1: Mean and standard deviation of wearable sensor features during interaction and non-interaction. The features were calculated per 10 second time window for each participant pair. Features include the max and mean of the cross-correlation function (ccf) and the distance of the measures (absolute difference) between the participant pairs' data

		mean (SD)	
		interacting	non-interacting
Skin Cond.	max of ccf	1.44 (4.5)	0.96 (2.5)
	mean of ccf	1.33 (4.27)	0.86 (2.28)
	distance	1.17 (1.34)	1.27(1.47)
Heart Rate	max of ccf	7642.06 (1736.35)	7616.81 (1633.71)
	mean of ccf	7532.32 (1708.41)	7505.16 (1603.91)
	distance	14.02 (12.57)	14.23 (12.36)
Skin Temp.	max of ccf	1169.15 (128.76)	1179.59 (131.13)
	mean of ccf	1164.55 (125.98)	1174.78 (128.95)
	distance	3.14 (2.4)	3.22 (2.24)

4 PRELIMINARY RESULTS

Preliminary analysis of similarities in the collected wearable sensing data during interactions revealed that mean cross-correlation coefficients of the skin conductance, heart rate were larger between interacting persons than non-interacting pseudo-pairs. Further, we could observe a lower distance of mean heart rate, skin temperature and skin conductance measures between two interacting people vs non-interacting pseudo-pairs (Table 1). This indicates a higher synchrony and coordination when people are interacting. In our ongoing analysis, we are applying appropriate data filtering mechanisms, spectral analysis, Cross-Recurrence Quantification Analysis, and machine learning.

5 DISCUSSION AND FUTURE DIRECTION

We hope that with the proposed study we can show that wrist-worn sensing technology, like accelerometers or heart rate sensors available in most common smartwatches and fitness trackers, can provide useful sensing data to detect characteristics of social interaction between individuals based on interpersonal synchrony. Being able to detect those synchronies and hence infer characteristics of an interaction or interpersonal relationship can be the first step towards novel wearable applications in social-mediating technology, self-care apps or mental health applications.

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