Towards a Wearable System for Assessing Couples' Dyadic Interactions in Daily Life

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ABSTRACT

Researchers are interested in understanding the dyadic interactions of couples as they relate to relationship quality and chronic disease management. Currently, ambulatory assessment of couples' interactions entail collecting data at random times in the day. There is no ubiquitous system that leverages the dyadic nature of couples' interactions (eg. collecting data when partners are interacting) and also performs real-time inference relevant for relationship quality and chronic disease management. In this work, we seek to develop a smartwatch system that can collect data about couples' dyadic interactions, and infer and track indicators of relationship quality and chronic disease management. We plan to collect data from couples in the field and use the data to develop methods to detect the indicators. Then, we plan to implement these methods as a smartwatch system and evaluate its performance in real-time and everyday life through another field study. Such a system can be used by social psychology researchers to understand the social dynamics of couples in everyday life and their impact on relationship quality, and also by health psychology researchers for developing and delivering behavioral interventions for couples who are managing chronic diseases.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**; • **Applied computing → Psychology**.

KEYWORDS

Wearable Computing; Smartwatches; Couples; Social Support; Mobile Health; Multimodal Fusion; Machine Learning; Deep Learning; CNN; BERT

ACM Reference Format:
George Boateng. 2020. Towards a Wearable System for Assessing Couples' Dyadic Interactions in Daily Life. In *Adjunct Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers (UbiComp/ISWC '20 Adjunct), September 12–16, 2020, Virtual Event, Mexico.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3410530.3414331

UbiComp/ISWC '20 Adjunct, September 12–16, 2020, Virtual Event, Mexico

ACM ISBN 978-1-4503-8076-8/20/09…$15.00
https://doi.org/10.1145/3410530.3414331

1 INTRODUCTION

Romantic relationships have powerful effects on people's mental and physical health (see e.g. [28] for an overview). For instance, conflicts and negative qualities of one's intimate relationship are associated prospectively with morbidity and mortality [19]. Relationships play a role in illness management as spouses share the responsibility [25, 30] and it involves social support and common dyadic coping (CDC). Social support entails providing resources to help a receiver cope in a time of need and can be emotional or instrumental [15]. CDC is the "we approach" to dealing with stressors in a couple's relationship [13] which is assessed objectively by counting first-person plural pronouns [29]. Spousal support and CDC in chronic disease management have been shown to have positive or negative effects on emotional well-being [14, 17], and result in healthier eating habits among diabetes patients [22]. Researchers are interested in understanding dyadic interactions in-situ, for example, in couples' management of diabetes in daily life [20] as it could inform behavioral interventions.

Smartwatches could be leveraged to collect data on couples' dyadic interactions and automatically infer various indicators of relationship quality and chronic disease management. Several features of smartwatches make them uniquely positioned for this task. Firstly, they are mostly with the wearer since they are worn in comparison with a smartphone which could be in various places like the pocket, bag, and just not in proximity to the user, or devices like Amazon Echo or Google Home which can only be in one place and not always around couples. Additionally, commercial smartwatches could be used to collect a wide variety of sensor data such as audio and heart rate (for emotion recognition), Bluetooth (for proximity detection), accelerometer, and gyroscope (for gestures and physical activity) and ambient light (to detect the context). These sensors together can be used to infer the mental health of individuals [3]. Our past work leveraged smartwatches for behavior recognition: eg. tracking stress [8] and physical activity [6, 7] and proposed to use them to collect voice activity information which could be used to monitor people's mental health [11]. Finally and importantly, smartwatches could be leveraged in novel ways to capture dyadic interactions of partners as we have done in our previous work (eg. triggering data collection when partners are close and speaking) [10].

This research work seeks to develop a smartwatch-based system that can collect data about couples' dyadic interactions, and infer and track indicators of relationship quality and chronic disease management. This system can be used by social psychology researchers to understand the social dynamics of couples in everyday life and their impact on relationship quality, and also by health psychology researchers for developing and delivering behavioral interventions for couples who are managing chronic diseases. Towards this end, we seek to answer the following research questions (RQs).

RQ1: *How effectively can a wearable system collect self-report and sensor data about couples' dyadic interactions in everyday life?* Some challenges to address entail designing a robust system that can collect significant amounts of self-report data and also high-quality multimodal sensor data from couples in their everyday life without increasing the burden of usage while addressing privacy concerns.

RQ2: *How effectively can a wearable system infer and track indicators of relationship quality and chronic disease management based on interactions?* Some indicators include emotional social support, CDC, conversation frequency and duration, physical closeness frequency and duration, conversations' emotional valence — positive or negative — (which we address separately in a different work [5, 12]). Some issues to address are which sensor data to use, features to extract, methods and machine learning algorithms to use, how to implement the methods to work in real-time, among others.

In the rest of this paper, we discuss related work in Section 2, methodology in Section 3, evaluation approach in Section 4, and results and expected contribution in Section 5.

2 RELATED WORK

Various smartphone-based apps have been developed for ambulatory data collection by psychologists. One popular one is the Electronic Activated Recorder (EAR) which has been used for several studies [21, 26] and has been used for collection audio data in various couples' interactions such as couples managing breast cancer[18, 27]. The EAR triggers data collection at random times in the day and collects snippets of ambient sound (e.g. 30 seconds) which are later transcribed and coded. The EAR does not collect self-report data. On the other hand, a mobile and wearable system was used to collect data for conflict detection among couples [31]. Similar to the EAR, sensor data, and additionally, self-report data were collected at random times in the day. Another work [24] used a digital recorder for a whole-day recording of couples managing cancer.

Despite these advances in the ambulatory assessment of couples' interactions, there are still gaps. Firstly, the random triggering of data collection does not take advantage of the dyadic nature of couples interactions (eg. collection of data when partners are interacting) and could miss key conversations. The EAR collects only audio and does not leverage other sensor data or self-reports. The all-day recording of [24] has significant privacy concerns. Also, [31] focuses on conflict detection which is only one component relevant for relationship quality. Finally, these works also do not implement a ubiquitous system for real-time inference and consequently do not address the turn-taking actions of couples' interactions. Hence, there is currently no ubiquitous system that leverages the dyadic nature of couples' interaction for data collection and also performs real-time inference relevant for relationship quality and chronic disease management.

3 METHODOLOGY

To answer our research questions, our plan is to implement the following approach:

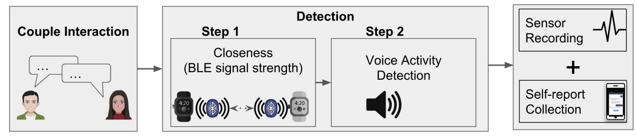

Figure 1: Overview of the DyMand system

(1) Develop mobile and wearable apps and then collect multimodal sensor and self-report data about couples' dyadic interaction in everyday life
(2) Develop methods for detection of indicators of relationship quality and chronic disease management using the collected data
(3) Develop a smartwatch system that automatically infers and tracks indicators of couples' relationship quality and chronic disease management

3.1 Overview of System

We propose to develop a smartwatch system consisting of two components: data collection and inference. The data collection component would trigger the collection of sensor data and self-report data (which is filled on a smartphone). This data would be stored for later analysis by, for example, psychologists or used by the inference component. The inference component would use the data to perform real-time detection and tracking of the indicators of relationship quality and chronic disease management.

3.2 Data Collection

Our first study evaluates the data collection component of the system in the context of couples managing a chronic disease. We are currently running a Dyadic Management of Diabetes (DyMand) study in Switzerland with German-speaking couples in which one partner has type 2 diabetes. We plan to collect data from 180 couples (N=180; n=360) but we have collected data from ten (10) couples so far [20]. We collect data from the field for 7 days. Each partner is given a smartwatch and smartphone running the DyMand system, a novel open-source mobile and wearable system that we developed for ambulatory assessment of couples' chronic disease management Figure 1 [10]. The DyMand system corresponds to the data collection component of our proposed system and triggers the collection of sensor and self-report data for 5 minutes each hour during the hours that subjects pick. We collect the following sensor data from the smartwatch: audio, heart rate, accelerometer, gyroscope, Bluetooth low energy (BLE) signal strength between watches, and ambient light. After the sensor data collection, a self-report is triggered on the smartphone that asks about social support, CDC, and emotions (using the Affective Slider, a digital affect measuring tool that measures the valence and arousal dimensions of their emotions [4]) over the last 5 minutes. We also record a 3-second video of their facial expression while they complete the self-report on the smartphone. Additionally, at the end of the day, we trigger the Affective Slider, and also a short form of the PANAS self-report [32] for the couples to report their emotions over the whole day as well as another self-report that asks about health behavior.

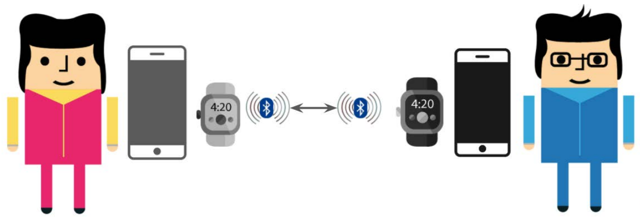

Figure 2: Closeness and Speaking Detection

Our hypothesis is that we are likely to collect relevant and high-quality sensor and self-report data during times that the partners are interacting. Hence, rather than trigger data collection at some random times in the hour which is the standard approach [21, 27], we use a novel method entailing triggering data collection after we detect that the partners are close and speaking (Figure 2). We do this in two steps. First, we determine closeness using the BLE signal strength between the smartwatches. We check if the signal strength is within a certain threshold, which corresponds to a distance estimate [11]. Then, we determine if the partners are speaking by using a voice activity detection (VAD) machine learning model that classifies speech versus non-speech, which we developed and implemented to run in real-time on the smartwatch [10]. In the case in which this condition is not met in the hour, we do a backup recording in the last 15 minutes of the hour. The detection of the frequency and duration of conversations and physical closeness is an extension of this novel triggering method.

There are significant ethical and privacy concerns of such a system and study since we collect audio which is sensitive data, and more so in the context of couples' interactions in which there is likely to be speech which could be about private topics. We address these concerns in detail in our previous works [9, 11] but in summary, we take several measures as follows (1) our study has ethical approval by the ethics committee of the canton of Zurich (2) we collect a maximum of 5-minute of audio per hour (3) we ask subjects to wear a tag that we give them to indicate to others that recording may be happening and (4) after subjects return their devices, we give them the option to listen to and request the deletion of any audio samples without any explanation. We believe these measures are adequate to safeguard the privacy of study subjects and others not taking part in the study.

3.3 Data Processing and Analysis

We will preprocess the sensor data into a form for easy data analysis. For the audio data, we will remove nonvocal segments (e.g. silence and noise portions), filter, downsample, and reduce the background noise. We will perform speaker diarization to annotate the segments of the audio corresponding to the speech of each partner. We will also annotate any segments of the audio corresponding to various nonverbal vocalizations such as laughs, sighs, and also background context e.g. TV, audio, indoors, outdoors, etc. This speech processing pipeline is important for the detection of conversation sessions. We will also transcribe the audio in order to use the content of the speech for example, for inferring emotional social support (e.g. checking if encouraging words are used) and CDC (eg. checking the use "we" pronoun). The speaker diarization, annotation, and transcriptions will be done manually to ensure high data quality and then we will develop automated tools to do same for the real-time recognition. Audio samples that are found to be too noisy to be useful will not be used for data analysis. Other sensor data such as accelerometer and gyroscope data will be filtered and downsampled. Heart rate data will be processed to remove samples that were collected when there was no or poor contact with the skin since the smartwatch provides that data.

Next, to perform the detection, we will extract various features from the sensor data modalities, explore transfer learning, for example, use pretrained models like YAMNet [2] which is a pretrained acoustic convolutional neural network model (CNN), German BERT [1] which is a pretrained language model based on Bidirectional Encoder Representations from Transformers (BERT) [16] and use traditional machine learning algorithms (eg. random forest, support vector machines) and deep learning algorithms (eg. convolutional neural networks, recurrent neural networks). We will explore multimodal fusion using different combinations of modalities at the feature level, the decision level, model level, or some hybrid approach [23].

4 EVALUATION APPROACH

We plan to train models to detect the presence or absence of emotional social support, CDC, and conversation for all 5-minute sessions collected from the field study. We will use as ground truth, the responses from the couples. Hence, the machine learning problem will be framed as a binary classification task for each of the 3 indicators. We will perform an evaluation using accuracy, confusion matrices, and leave-one-couple-out cross-validation which has been used as a robust evaluation approach in couples' conflict detection [31] and emotion recognition [12]. We will compare the performance between using manually and automatically annotated data.

We will then pick the best performing models, optimize them to run in real-time, and implement them as part of the inference component for real-time inference and tracking of the indicators. We will then run another user study similar to the current study to evaluate the performance of the system in daily life among couples. The system will trigger data collection when an interaction is detected like the previous study. We will additionally for evaluation purposes trigger at some random times also. After 5 minutes of data collection, subjects will be asked to respond to self-reports about the presence or absence of the indicators. These will be compared with the system's predictions to evaluate its accuracy.

5 RESULTS AND EXPECTED CONTRIBUTIONS

We have developed the data collection component of our proposed system: the DyMand system along with a smartwatch-based, light-weight VAD system for sensor and self-report data collection [10, 11]. The DyMand system uses a novel method of data collection: triggering data collection when partners' are interacting (i.e., detects closeness and speaking) which is a key part of the whole system. The remaining work is to use the data from the ongoing study to develop machine learning models for recognition of emotional social support, CDC, and conversation. Then we will develop and evaluate the inference component of the smartwatch system consisting of those models and the tracking of the frequency and duration of conversations and physical closeness.

The potential contribution of this work is a smartwatch system that can be used for (1) collection of sensor and self-report data about couples' dyadic interactions in daily life, and (2) inferring and tracking indicators of couples' relationship quality and chronic disease management: emotional social support, CDC, conversations, and physical closeness. The system could be extended to infer other behavioral dynamics relevant for relationship quality and chronic disease management which are not included in this work. This smartwatch system can be used by social psychology researchers to understand the social dynamics of couples (and potentially other dyadic relationships) in everyday life and their impact on relationship quality, and also by health psychology researchers for developing and delivering behavioral interventions for couples who are managing chronic diseases.

6 BIBLIOGRAPHY

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ACKNOWLEDGMENTS

I'm grateful to my research advisors, Prof. Dr. Tobias Kowatsch, and Prof. Dr. Elgar Fleisch. Also, I thank my research collaborators and lab colleagues for their contributions and assistance in this research work. This research is partially funded by the Swiss National Science Foundation (CR12I1_166348/1).

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