Emotion Capture among Real Couples in Everyday Life

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Abstract

Illness management among married adults is mainly shared with their spouses and it involves social support. Social support among couples has been shown to affect emotional well-being positively or negatively and result in healthier habits among diabetes patients. Hence, through automatic emotion recognition, we could have an assessment of the emotional well-being of couples which could inform the development and triggering of interventions to help couples better manage chronic diseases. We are developing an emotion recognition system to recognize the emotions of real couples in everyday life and in this paper, we describe our approach to collecting sensor and self-report emotion data among Swiss-based German-speaking couples in everyday life. We also discuss various aspects of the study such as our novel approach of triggering data collection based on detecting that the partners are close and speaking, the self-reports and multimodal data as well as privacy concerns with our method.

Author Keywords

Emotion; Couples; Multimodal Sensor Data; Smartwatch; Smartphone; Wearable Computing; Mobile Computing

CCS Concepts

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

Psychology;

Introduction

Evidence suggests that for married adults, illness management is mainly shared with their spouses and it involves social support [16, 12]. Social support among spouses is associated with healthier habits among diabetes patients [9] and has been shown to have positive or negative effects on emotional well-being [11, 6, 4]. Hence through emotion recognition, we could have an assessment of the emotional well-being of couples which could inform the development and triggering of interventions to help couples better manage chronic diseases. In effect, the development of a system for automatic recognition of couples' emotions could aid social psychology researchers to understand various dynamics of couples' relationships and their impact on well-being.

Currently, psychologists measure emotions through various self-reports such as the PANAS [18]. These self-reports are however not practical for continuous emotion measurement in everyday life because completing self-reports frequently will be obtrusive. Several works in the area of emotion recognition use data from actors reading texts in a specific emotional tone [10] or acting out dyadic interactions like couples [5]. It is not clear whether the algorithms developed using these data will work well for the use case of the naturalistic interactions of real couples.

We are developing an emotion recognition system to recognize the emotions of real couples in everyday life and in this paper, we describe our approach to collecting sensor and self-report emotion data among Swiss-based German-speaking couples in everyday life. We then discuss various aspects of the study such as our novel approach of triggering data collection based on detecting that the partners are close and speaking, the self-reports and multimodal data as well as privacy concerns with our method.

Data Collection

We are running a field study in which we collect sensor and self-report emotion data in the context of chronic disease management among couples. Specifically, we collect data for seven days from German-speaking couples in Switzerland in which one partner has type-2 diabetes [7]. We have collected data from eight (8) couples so far.

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 [2]. The DyMand system 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 emotions over the last 5 minutes using the Affective Slider [1] which assesses the valence and arousal dimensions of their emotions. We also record a 3-second video of their facial expression while they complete the self-report on the smartphone.

We trigger sensor data collection when the partners are close and speaking 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 [2]. 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 [3].

Discussion

Our hypothesis is that we are likely to collect high-quality sensor and self-report emotion 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 [8, 14], we use a novel method entailing triggering data collection after we detect that the partners are close and speaking. If none of these conditions are met in the hour, we do a backup recording by triggering data collection in the last 15 minutes of the hour. This approach has the potential to collect data that contain several conversation moments which would provide several data for developing the emotion recognition system. Other researchers can use our DyMand system for their data collection as the code is open source [2]. Additionally, the methods we use could also be used by other researchers to optimize the collection of sensor and self-report data among couples or other dyads in daily life.

We use the Affective Slider as opposed to other self-reports like the PANAS because it can be easily and quickly completed. Additionally, the valence and arousal dimensions based on Russell's circumplex model of emotions [15] can be used to place various emotions. Currently, we collect self-report emotion data on the smartphones which are given to the couples. It is possible to implement the Affective Slider on the smartwatch to ease the burden of completing the self-report and make the process quicker.

We collect multimodal sensor data using a smartwatch because previous works have shown that multimodal approaches to emotion recognition perform better than unimodal approaches [10]. Additionally, in an everyday life context, certain data modalities might not be available and hence, emotion recognition systems need to be developed that can perform well with subsets of these data modalities. Also, in the future, to aid in the recognition task, other sensor data about behavioral patterns could be collected such as phone unlock frequency, frequency of phone calls, messages sent, among others [17].

There are huge privacy concerns and ethical implications as sensitive data such as audio are collected frequently. We address these concerns by first subjecting our study protocol to review and resulting in approval by the ethics committee of the canton of Zurich. Also, we ensure that we collect a maximum of 5-minute of audio data per hour in order not to record a significant percentage of the couples' everyday life. Additionally, to protect the privacy of subjects not taking part in the study, we ask subjects to wear a tag we give to them indicating to others around them that they may be recorded. Finally, when the couples return the devices after the study, we give them the option to listen to the recorded audios and to request the deletion of any as they wish without any explanation. This approach has been used in other studies [13, 14].

Conclusion

In this work, we described our approach to collecting sensor and self-report emotion data from Swiss-based German-speaking couples in everyday life. We discussed various aspects of the study. First, we discussed the use of a novel approach of triggering data collection based on detecting that the partners are close and speaking rather than just randomly in the hour. Next, we discussed using a smartphone-based Affective Slider self-report because it is quick to complete. Then, we discussed collecting multimodal sensor data with a smartwatch because it could produce more accurate emotion recognition models. Finally, we discussed our approach to addressing privacy concerns such as giving subjects the option to request the deletion of any of their audio upon returning the devices.

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REFERENCES

[1] Alberto Betella and Paul FMJ Verschure. 2016. The affective slider: A digital self-assessment scale for the measurement of human emotions. *PloS one* 11, 2 (2016), e0148037.

[2] George Boateng, Prabhakaran Santhanam, Janina Lüscher, Urte Scholz, and Tobias Kowatsch. 2019a. Poster: DyMand–An Open-Source Mobile and Wearable System for Assessing Couples' Dyadic Management of Chronic Diseases. In *The 25th Annual International Conference on Mobile Computing and Networking*. 1–3.

[3] George Boateng, Prabhakaran Santhanam, Janina Lüscher, Urte Scholz, and Tobias Kowatsch. 2019b. VADLite: an open-source lightweight system for real-time voice activity detection on smartwatches. In *Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers*. 902–906.

[4] Niall Bolger and David Amarel. 2007. Effects of social support visibility on adjustment to stress: Experimental evidence. *Journal of personality and social psychology* 92, 3 (2007), 458.

[5] Carlos Busso, Murtaza Bulut, Chi-Chun Lee, Abe Kazemzadeh, Emily Mower, Samuel Kim, Jeannette N Chang, Sungbok Lee, and Shrikanth S Narayanan. 2008. IEMOCAP: Interactive emotional dyadic motion capture database. *Language resources and evaluation* 42, 4 (2008), 335.

[6] Masumi Iida, Mary Ann Parris Stephens, Karen S Rook, Melissa M Franks, and James K Salem. 2010. When the going gets tough, does support get going? Determinants of spousal support provision to type 2 diabetic patients. *Personality and Social Psychology Bulletin* 36, 6 (2010), 780–791.

[7] Janina Lüscher, Tobias Kowatsch, George Boateng, Prabhakaran Santhanam, Guy Bodenmann, and Urte Scholz. 2019. Social Support and Common Dyadic Coping in Couples' Dyadic Management of Type II Diabetes: Protocol for an Ambulatory Assessment Application. *JMIR research protocols* 8, 10 (2019), e13685.

[8] Matthias R Mehl, Megan L Robbins, and Fenne große Deters. 2012. Naturalistic observation of health-relevant social processes: The Electronically Activated Recorder (EAR) methodology in psychosomatics. *Psychosomatic Medicine* 74, 4 (2012), 410.

[9] Daisy Miller and J Lynne Brown. 2005. Marital interactions in the process of dietary change for type 2 diabetes. *Journal of Nutrition Education and Behavior* 37, 5 (2005), 226–234.

[10] Soujanya Poria, Erik Cambria, Rajiv Bajpai, and Amir Hussain. 2017. A review of affective computing: From unimodal analysis to multimodal fusion. *Information Fusion* 37 (2017), 98–125.

[11] Gabriele Prati and Luca Pietrantoni. 2010. The relation of perceived and received social support to mental health among first responders: a meta-analytic review. *Journal of Community Psychology* 38, 3 (2010), 403–417.

[12] Tuula-Maria Rintala, Pia Jaatinen, Eija Paavilainen, and Päivi Åstedt-Kurki. 2013. Interrelation between adult persons with diabetes and their family: a systematic review of the literature. *Journal of family nursing* 19, 1 (2013), 3–28.

[13] Megan L Robbins, Elizabeth S Focella, Shelley Kasle, Ana María López, Karen L Weihs, and Matthias R Mehl. 2011. Naturalistically observed swearing, emotional support, and depressive symptoms in women coping with illness. *Health Psychology* 30, 6 (2011), 789.

[14] Megan L Robbins, Ana María López, Karen L Weihs, and Matthias R Mehl. 2014. Cancer conversations in context: naturalistic observation of couples coping with breast cancer. *Journal of Family Psychology* 28, 3 (2014), 380.

[15] James A Russell. 1980. A circumplex model of affect. *Journal of personality and social psychology* 39, 6 (1980), 1161.

[16] Amber J Seidel, Melissa M Franks, Mary Ann Parris Stephens, and Karen S Rook. 2012. Spouse control and type 2 diabetes management: moderating effects of dyadic expectations for spouse involvement. *Family relations* 61, 4 (2012), 698–709.

[17] Mirjam Stieger, Marcia Nißen, Dominik Rüegger, Tobias Kowatsch, Christoph Flückiger, and Mathias Allemand. 2018. PEACH, a smartphone-and conversational agent-based coaching intervention for intentional personality change: study protocol of a randomized, wait-list controlled trial. *BMC psychology* 6, 1 (2018), 43.

[18] David Watson, Lee Anna Clark, and Auke Tellegen. 1988. Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of personality and social psychology* 54, 6 (1988), 1063.