Mobile Monitoring of Mood (MoMoMood) pilot: a multi-sensor digital phenotyping study

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Introduction

- Smartphones and other wearable and consumer devices have become " ubiquitous in the past decade.
- These devices (and the data collected from them) can be used in clinical " trials to study patients with mental disorders. These studies are commonly referred to as "digital phenotyping" studies.
- In the past years, many digital studies have shown that data gathered from " these digital devices exhibit correlations with the patient state (e.g. their mood).

Results

1. Normalized activity patterns of patients vs healthy controls based on data from three different sensors



The MoMoMood pilot study is a digital phenotyping study which " aims to study patients with major depressive disorder (MDD).

Study Design

Study participants: 14 outpatients diagnosed by SCID-I with MDD, under treatment at the start of the study at the Department of Psychiatry of the Helsinki University Hospitall. 22 healthy controls assessed with PHQ9

The study has two phases. The active phase lasts two weeks and passive phase lasts for as long as the study participant keeps the study app running on the phone (up to one year).

The study uses Niima study platform.

Participants fill out baseline questionnaires (including PHQ9). AWARE data collection app is installed on participants phones and they are given a bed sensor and an actigraphy device. They receive daily questions on the phone 5 times a day about their mood and sleep. At the end of the active phase they return the study devices and continue running the study app on their phone which collects passive data and sends it to the Niima server.



The figure above depicts the average normalized activity patterns of the two groups based on the data from Actiwatch II actigraphy device (AW), Bed sensor (BS) and mobile phone screen on events (Screen). Each data stream is indicative of one type of behavior of each group. In general we can see that the patient group have a more flat rhythm which means that there is less variation in their behavior throughout the day. For example, in BS curves we can see that there is less variation in the patient groups curve while the healthy group shows a bimodal behavior of in bed at night and not in bed during the day.

2. Classification of patients and healthy controls based on smartphone passive data

This figures depicts the study flow of MoMoMood pilot. All data is sent to Niima study platform servers. Data is hashed and anonymized and in some cases the resolution is lowered before being accessed by the researchers.

Objectives and Methods

MoMoMood pilot was mainly designed as a proof of concept and a feasibility study to prove that a larger study with this study design is feasible. Despite challenges (mostly due to technical issues of installing the app on participants personal phones) the study proved to be feasible with approximately ~75% of participants sending data to the server from all sensors at least for the duration of the active phase of the study. All participants returned the devices to the study staff intact at the end of the active phase.

We take data from three different sensors: smartphone, bed sensor, and actigraphy device and look at activity patterns based on these data. From smartphones we look at screen on events, which is a proxy of when the person is awake and is using the out phone. From the bed sensor we look at the patterns of the signal strength, which is highest when the person is moving in the bed or getting out of bed and is low when the person is idle in bed and close to zero when nobody is in bed. Data from the actigraphy devices is indicative of amount of physical movement and activity. For each person we add up all the events in the study period and normalize the whole pattern to one. This gives us an average of how the person's activity varies throughout the day. We average these patterns for each group (patients and controls).

	accuracy	accuracy	accuracy
Screen	0.9469	0.9136	0.9109
Location	0.9127	0.9420	0.8488
Communication	0.8495	0.8750	0.8667
Location and Communi-	0.8909	0.9275	0.8256
cation			
Screen and communica-	0.9469	0.9136	0.9208
tion			
Location and screen	0.9127	0.9565	0.8721
Location, screen and com-	0.9345	0.9565	0.8721
munication			

This table shows the classification accuracies for training, validation and test sets. The best accuracy is achieved by combining screen and communication data as the input for our LSTM model. Data used for this part of the analysis is only from weekends, which could be possibly responsible for the fact that adding the location features lowers the test accuracy.

Conclusion

- Digital phenotyping studies with various devices with patients with MDD and healthy controls in our study setting are feasible. Over this study and other test studies ~75% of participants successfully provide data from all devices at least for a few weeks.
- Looking at average activity patterns for patients and healthy controls across three different sensors and activity types we see that there is less variance in the activity rhythms of the patient group throughout the day, which indicates some level of activity also at night time.
- We train a Long Short Term Memory (LSTM) model to classify the study participants into two groups. This model only uses passive data from the smartphone as features. We use three sets of features: location, communication (based on calls and text messages) and screen on events to asess:

1) whether we can classify the study participants with high accuracy using these data 2) to find the data streams which are most informative in the classification task.

Training an LSTM model, we can see that patients and healthy controls can be classified with high accuracy on unseen test data. The highest accuracy in our dataset (when taking only data from weekends) comes from combined phone screen and communication features.

References

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