HEALTHRHYTHMS
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Automatic Detection of Social Rhythms in Bipolar Disorder via Smartphone

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MoodRhythm

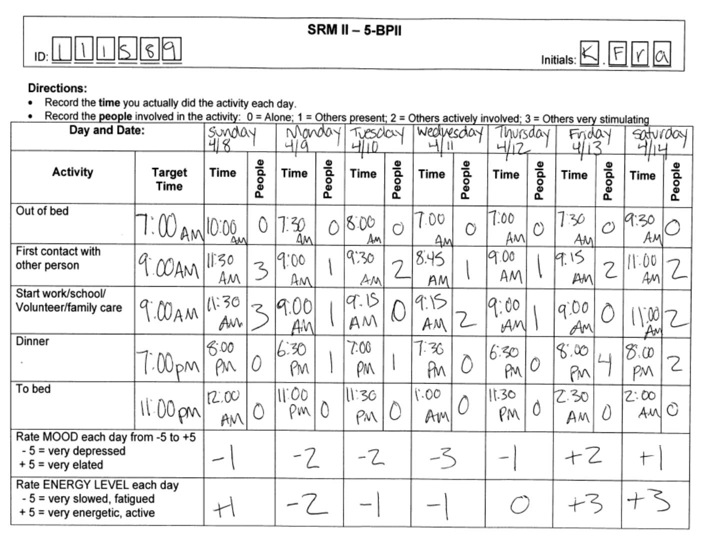
Abstract

Background: Substantial evidence indicates that greater regularity of daily routines is associated with improved outcomes in bipolar disorder. Indeed, stability of social rhythms is central to several forms of empirically-supported psychosocial treatment for bipolar disorders, including interpersonal and social rhythm therapy (IPSRT), family-focused treatment (FFT) and various cognitive-behavioral approaches. Ironically, when information about rhythmicity would be of greatest value to the clinician, patients are often unable or unwilling to complete self-reports of such data. To evaluate the feasibility of automatically estimating Social Rhythm Metric (SRM) scores, a clinically validated marker of stability of social routines, we assessed the relationship between self-reported SRM data and automatically sensed data from a smartphone app called MoodRhythm.

Methods: 7 patients with bipolar disorder used smartphones for 4 weeks that collected sensor data including accelerometer, microphone, location and communication information to infer behavioral and contextual patterns. Participants simultaneously completed SRM entries via the MoodRhythm app.

Results: We found that automated sensing can be used to infer SRM scores. Using location, distance traveled, conversation frequency, and non-stationary durations as inputs, our generalized model achieves root mean square error (RSME) of 1.40, a reasonable performance given the theoretical SRM score range of 0-7. Personalized models further improve performance with a mean RSME of .92. Classifiers using sensor streams can predict stable (> 3.5) vs. unstable (<3.5) states with high accuracy (precision=0.85; recall=0.86)

Conclusion: Automatic sensing is a feasible approach to inferring rhythmicity, a key marker of wellbeing in bipolar disorder. Automatically sensed smartphone data provide an excellent proxy for self-reported data on regularity of daily routines, offering novel opportunities for clinical intervention when it is most needed.


SRM II – 5-BPII

ID: 1 1 1 5 8 9 Initials: K . F r a

Directions:
- Record the time you actually did the activity each day.
- Record the people involved in the activity: 0 = Alone; 1 = Others present; 2 = Others actively involved; 3 = Others very stimulating

Day and Date:		Sunday 4/8		Monday 4/9		Tuesday 4/10		Wednesday 4/11		Thursday 4/12		Friday 4/13		Saturday 4/14	
Activity	Target Time	Time	People	Time	People	Time	People	Time	People	Time	People	Time	People	Time	People
Out of bed	7:00 AM	10:00 AM	0	7:30 AM	0	8:00 AM	0	7:00 AM	0	7:00 AM	0	7:30 AM	0	9:30 AM	0
First contact with other person	9:00AM	11:30 AM	3	9:00 AM	1	9:30 AM	2	8:45 AM	1	9:00 AM	1	9:15 AM	2	11:00 AM	2
Start work/school/ Volunteer/family care	9:00AM	11:30 AM	3	9:00 AM	1	9:15 AM	0	9:15 AM	2	9:00 AM	1	9:00 AM	0	11:00 AM	2
Dinner	7:00pm	8:00 PM	0	6:30 PM	1	7:00 PM	1	7:30 PM	0	6:30 PM	0	8:00 PM	4	8:00 PM	2
To bed	11:00pm	12:00 AM	0	11:00 PM	0	11:30 PM	0	1:00 AM	0	11:30 PM	0	2:30 AM	0	2:00 AM	0
Rate MOOD each day from -5 to +5 - 5 = very depressed + 5 = very elated		-1		-2		-2		-3		-1		+2		+1	
Rate ENERGY LEVEL each day - 5 = very slowed, fatigued + 5 = very energetic, active		+1		-2		-1		-1		0		+3		+3	

Figure 1: The Social Rhythm Metric (SRM)

Participant	Age	Gender	Diagnosis
1	30.1	Female	BP-I
2	59.2	Female	BP-II
3	48.5	Male	BP-II
4	31.3	Female	BP-II
5	35.8	Male	BP-NOS
6	32.7	Female	BP-II
7	27.5	Female	BP-II

Table 1. Demographic and clinical characteristics of study participants.

Objective

To evaluate the potential of using smartphone-based sensing to overcome the limitations of self-report in helping individuals with bipolar disorder maintain stable routines, we provided a customized smartphone app, MoodRhythm, to participants with a confirmed diagnosis of bipolar disorder, automatically collecting behavioral (e.g., speech, activity, sms and call log) and contextual data (e.g., location) for a period of 4 weeks. We employed machine learning techniques to model and predict markers of rhythmicity in the daily life of patients with bipolar disorder that have been shown to reduce the risk of relapse. To our knowledge, this is the first study that automatically infers social rhythm stability using smartphone sensor data.

Participants

Potential participants were identified through the Depression and Manic-Depression Prevention Program at Western Psychiatric Institute and Clinic. Study participants were required to already be participating in a treatment program at the clinic, able to provide informed consent, and have a confirmed diagnosis of bipolar disorder. Participants were excluded if they were unwilling or unable to comply with study procedures or had active suicidal ideation requiring inpatient or intensive outpatient management. Nine individuals (5 female, 4 male) consented to the study. One participant did not use the app and we were unable to retrieve another's sensor data, leaving 7 participants in the study (see Table 1). The research was approved by the University of Pittsburgh Institutional Review Board

Method

Each participant was given a Nexus 5 Android smartphone pre-loaded with our customized software and provided an explanation of how to use the different functions of the MoodRhythm app. MoodRhythm supports both self-rating and automatically-sensed data collection. It allows patients to track the timing of 5 core activities used in the paper version of the SRM-5: 1) **getting out of bed**, 2) **first contact** with another individual, 3) **starting their day** (i.e. work, school, childcare, etc., 4) having **dinner**, and 5) **going to bed**, as well as to add custom activities. The app also allows daily reporting of **mood** and **energy** on a -5 (very low) to +5 (very high) scale (See Figure 2).

The MoodRhythm App

MoodRhythym takes advantage of a variety of sensor data sources on the smartphone platform with the ultimate aim of inferring many of the activities included in the paper-based SRM. The platform continuously collects data from the phone's light sensor, accelerometers, and microphone, as well as communication patterns and information about phone usage events such as screen unlocks and battery charging state.

Human speech is captured by the microphone, which was activated every 2 minutes to capture ambient sound. If sound was detected, the microphone remained active. To filter out noise including speech from radio or TV, we use energy intensity and distribution entropy [6]. To protect privacy, the system does not record or transmit audio, but instead processes data in real-time to only extract and store features (i.e., spectral content and regularity, loudness) useful for detecting the presence of human voice but insufficient to reconstruct speech content [7]. Using these privacy-sensitive audio features and probabilistic inference techniques, it is possible to reliably estimate the number and duration of conversations in which an individual engages , and how much time a given individual speaks within a conversation , as well as speech rate and variations in pitch [7].

Activity is captured by the smartphone accelerometer that detects movement. The system generates and stores physical activity status (i.e., active vs. sedentary). For **location** detection, we used the Android location service, which combines Global Position System (GPS), Wi-Fi and cellular data to provide location estimates. MoodRhythm also collects **communication patterns** including SMS and call logs. The sensor data are stored in the smartphone and securely transmitted to our remote study server periodically. The impact of MoodRhythm on battery life is reasonable, with 16 hours of continuous sensing after a full recharge.

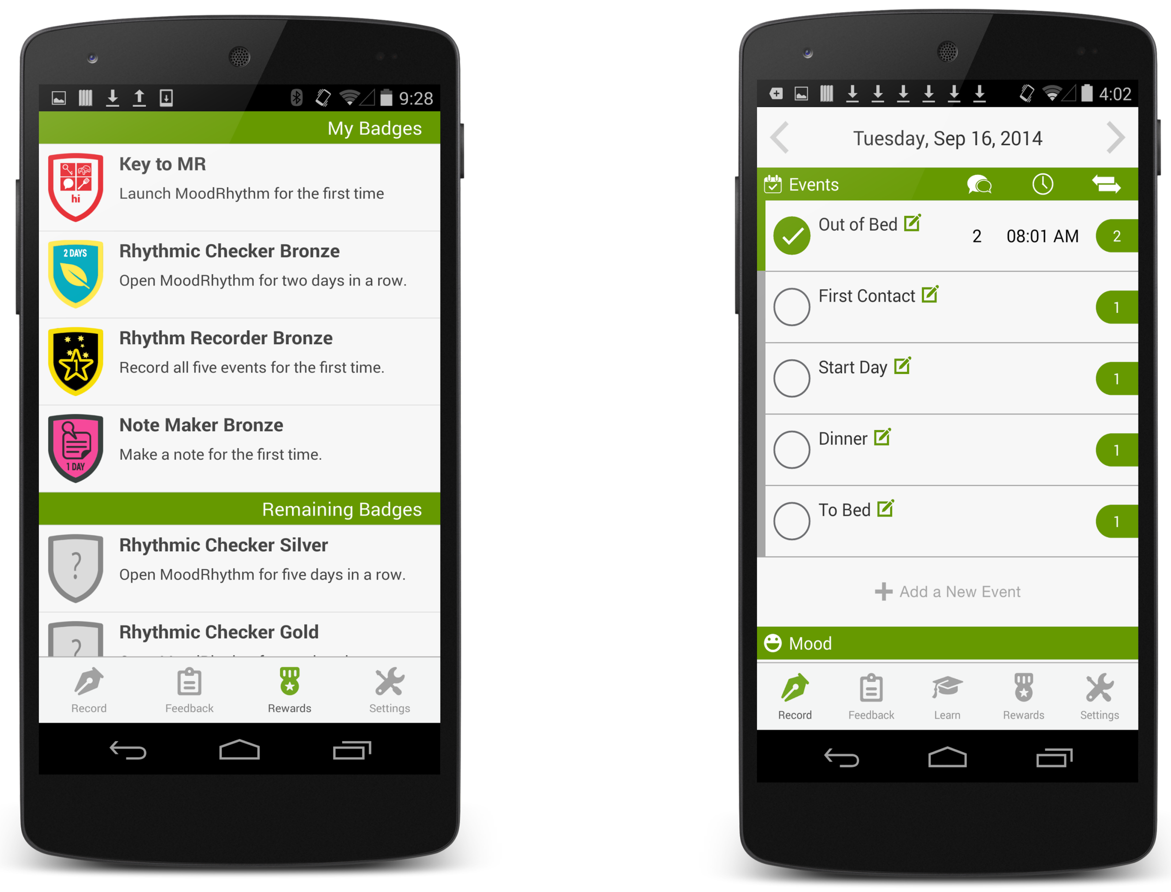


Figure 2: Screens from the MoodRhythm app used by study participants.

Results

Over the four-week study, participants recorded an average of 36.5 (SD: 11.17) energy ratings, 46.12 (SD: 12.71) mood ratings, and 144.43 (SD: 43.1) SRM event entries. Sensor data indicated an overall distance traveled per day of 8.34 km (SD: 13.34). The ratio of sedentary to active time per day was 2.09. Participants were around human speech 3.25 hours (SD: 3.67) a day. As shown in Table 2, the trend of self-assessed energy scores correlates significantly with sensor streams. Self-reported mood is weakly correlated with conversation ($r = 0.16$, $p = 0.06$) and non-sedentary duration ($r = 0.15$, $p = 0.08$).

We used the sensed data to build a statistical inference and prediction model using machine learning techniques. For this study, patient-reported SRM scores represented ground-truth, with the goal of developing a predictive model that can infer the SRM score from smartphone-based sensor data. Specifically, we used the number of location clusters, distance traveled, frequency of conversation inferred from audio data, and duration of non-sedentary activity calculated over each day as inputs to the model (i.e. feature set). We selected these features as good indicators of social and physical functioning.

Given the high granularity of our sensed data, we calculated SRM scores using a rolling 7-day window. The value of the SRM score ranges from a theoretical 0 to a theoretical 7, with higher values indicating greater rhythmicity. Using 10-fold cross-validation, we found that the average root mean square error (RMSE) is only 1.40, indicating that our model achieves reasonably good accuracy. Models trained separately on each individual significantly improved performance, with a mean RMSE of 0.92. In addition to SRM **scores**, we focused on inferring **social rhythm stability status** from sensor data. Based on a large (n=1249) study of a representative healthy population [8] in which the mean SRM score was ~3.5, we considered an SRM score <3.5 as an unstable state and a score ≥3.5 as indicative of a stable state. We used a Support Vector Machine (SVM) for prediction of stability status. Over 10-fold cross-validation, our model achieved high performance with a precision score of 0.85 and recall score of 0.86.

Finally, we used recursive feature elimination (RFE) [9] to assess the importance of specific parameters in predicting SRM stability from sensor data. As shown in Table 3, in our dataset the most important features for prediction are the location cluster and total distance traveled over a day

Sensor Stream	Correlation with Self-reported Energy
Number of Location Clusters	0.31***
Distance Traveled	0.23**
Conversation Frequency	0.25**
Non sedentary duration	0.39***
	**p <0.01; ***p <0.001

Table 2. Correlation between sensor stream and trend of self-reported energy scores computed as rolling average over 7 days.

Feature	Ranking	Weight
Distance Traveled	1st	1.56×10^{-2}
Location Cluster	2nd	3.27×10^{-3}
Non-sedentary duration	3rd	-3.79×10^{-4}
Conversation frequency	4th	7.69×10^{-5}

Table 3. Ranking of feature importance for social rhythm stability status using recursive feature elimination (RFE) and weights assigned to features in a support vector machine using linear kernel.

Study Limitations

- Small study population
- Data collected over only four weeks
- Sensor data accuracy dependent on participants carrying the phone
- Participants used study phones rather than their own devices

Summary

We investigated the feasibility of automated assessment of SRM score — a clinically validated marker of stability in patients with bipolar disorder — using sensor data streams from MoodRhythm, a smartphone app. Employing statistical learning techniques, we found that smartphone sensor data can be used to distinguish between stable and unstable states (precision=0.85 and recall=0.86). The confidence score associated with the output also indicates that the model is quite robust.

Given that maintaining stability in daily routines can significantly reduce risk of relapse in individuals with bipolar disorder [3], being able to automatically assess rhythmicity without requiring active user engagement could have considerable clinical utility. In particular, this approach could help to overcome issues with existing paper-and-pencil based clinical tools by substantially lowering user burden associated with manual tracking and by providing data when patients are in clinical states least likely to be associated with adherence to self-report data collection.

Because automatic sensing can result in much more granular and wide-ranging data than manual and subjective tracking, this approach could be extended to an early warning system for relapse detection. Such a system could open up novel ways to provide interventions — enabling preemptive care at the right moment and the right place based on subtle, but crucial clues to inform clinical decisions on individualized treatment course.

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