Real-time Schizophrenia Monitoring using Wearable Motion Sensitive Devices*

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Summary. Motor peculiarity is an integral part of the schizophrenia disorder, having various manifestations both throughout the phases of the disease, and as a response to treatment. The current subjective non-quantitative evaluation of these traits leads to multiple interpretations of phenomenology, which impairs the reliability and validity of psychiatric diagnosis. Our long-term objective is to quantitatively measure motor behavior in schizophrenia patients, and develop automatic tools and methods for patient monitoring and treatment adjustment. In the present study, wearable devices were distributed among 25 inpatients in the closed wards of a Mental Health Center. Motor activity was measured using embedded accelerometers, as well as light and temperature sensors. The devices were worn continuously by participants throughout the duration of the experiment, approximately one month. During this period participants were also clinically evaluated twice weekly, including patients' mental, motor, and neurological symptom severity. Medication regimes and outstanding events were also recorded by hospital staff. Below we discuss the general framework for monitoring psychiatric patients with wearable devices. We then present results showing correlations between features of activity in various daily time-windows, and measures derived from the psychiatrist's clinical assessment or abnormal events in the patients' routine.

1 Introduction

Clinical literature describes a wide range of motor pattern alternations, manifested in different phases of the schizophrenia disorder. Positive-signs schizophrenia patients are typically psychotic and disorganized, characterized mainly by positive symptoms (e.g. auditory hallucinations, delusions and

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paranoid thoughts). In clinical settings, these patients show involuntary movements, dyskinesia and catatonic symptoms [1]. In negative-signs schizophrenia, there is usually an observed motor retardation, psycho-motor poverty, decreased spontaneous movements, psycho-motor slowing and flattened affect [2, 3]. Some patients demonstrate both types simultaneously or during different phases of the illness.

Neurological Soft Symptoms (NSS) can manifest early and during the progression of the disorder, and include deficits in coordination, sensory integration, and sequential motor behaviors [4]. Medical treatment was found to improve some of the motor symptoms, including NSS, involuntary movement and dyskinesia [1]. These medications, however, may also introduce in chronic patients drug-induced movement disorders such as tremor dystonia, Parkinsonism (rigidity and bradykinesia), akathisia and tardive dyskinesia [5].

The diversity and specificity of motor symptoms throughout different phases of the disorder and as a response to drugs, makes them good candidates for patient monitoring and treatment outcome evaluation. Nonetheless, to date, these symptoms are evaluated in a descriptive non etiological manner based on subjective clinical scales such as the Unified Dyskinesia Rating Scale (UDysRS) [6] and the Unified Parkinson's Disease Rating Scale (MDS-UPDRS) [7]. The lack of objective, quantitative methods of measuring these symptoms, and the insufficient conceptual clarity around it, causes multiple interpretations of phenomenology, often entailing low reliability and validity of the diagnosis. In addition, symptom evaluation process requires expert staff and availability of resources, and it is not done frequently enough to capture delicate changes in patients' spontaneous and drug-induced conditions.

The last decade has seen a steep rise in the use of wearable devices in medical fields ranging from human physiology [8] to movement disorders [9,10] and mental health [11]. Accelerometers and gyroscopes, which are commonly embedded in smart-watches and other wearable devices, are now used to assess mobility, recognize activity, and context. In a clinical setting, these sensors may be used in order to detect change in high-level movement parameters, track their dynamics and correlate them with mental state.

The objective of the current study is to develop and evaluate a framework, where wearable devices are used to facilitate continuous motor deficits monitoring in schizophrenia patients in a natural setting. This is an important step towards a detailed automatic evaluation system of symptom severity in schizophrenia. Such a system has a great potential to help understand this illusive disease. An additional goal would be to help with the overwhelming need for detection and characterization of sub-types of the disease towards a better understanding of underlying causes, and the development of better and more personalized treatment.

Fig. 1. Raw data as recorded by the smart-watches, including tri-axial accelerometer (top panel), light sensor (middle), and temperature (bottom). This plot shows data from a single patient, recorded on 28 Jan, 2017 at 5:00-5:05pm. Only accelerometer data was used for further analysis.

2 Methods

2.1 Participants and clinical evaluation

Twenty seven inpatients from the closed wards at Shaar-Meashe MHC participated in the study after signing appropriate Helsinki legal consents. Most participants (21/27) were diagnosed with schizophrenia according to the DSM-5, 3 with paranoid schizophrenia, 2 with schizoaffective disorder, and one with psychotic state cannabinoids. Participants' age varied from 21 to 58 (mean of 37.48), with course of illness varying from 0 (first hospitalization) up to 37 years (mean of 16.9 years). Two of the patients dropped out of the study after less than a day due to lack of cooperation. The rest (25 patients) were followed for a period of three weeks on average (6-52 days).

The study was conducted in natural settings, where patients were *not* required to change any personal or medical procedure. In addition to routine reports by nurses and physicians, every patient underwent an additional evaluation by a trained psychiatrist twice a week. The procedure included medication monitoring (type, dosage and frequency), as well as clinical evaluation of positive and negative symptom severity (PANSS [12]) and neurological symptoms severity (NES [13]).

All procedures performed in the study were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

2.2 Data Acquisition

At study onset, each participant was given a smart-watch (GeneActiv[5]). The devices included tri-axial accelerometers, light, and temperature sensors, the

[5] https://www.geneactiv.org/

high frequency output ($50Hz$) of which was stored on memory cards embedded in the device (see Fig. 1). Data was collected by the aforementioned smart watches worn continuously by patients throughout the experiment (for a total of 489 days of data from 25 patients). The devices were placed and removed by the medical staff, and the content of the memory card was uploaded to a central storage location upon termination of the experiment for further analysis.

In order to reduce noise introduced by the variability in patient activity due to external circumstances rather than mental state, weekends were excluded from the study; our analysis focused on fixed time windows with regular departmental daily activity: Occupational therapy time slots (10am-11am), lunch (12pm-1pm), and indoor free time (4pm-5pm). In addition, we calculated full day features (6am-10pm) and used night time features (10pm-6am) to evaluate sleep quality.

2.3 Features

Features were computed on the basis of the accelerometer readings, analyzed in 1 minute windows (see Table 1 and Fig. 2). Light and temperature data were not used for the analysis. The point-wise sum of values and sum of square values of the tri-axial accelerometer measurements (Energy Square and Energy Sum respectively) were averaged over 1 minute intervals. The variance of the sum of squares (Energy Variance) was also computed over the same window. Stepping behavior (Step Detector) was detected as large maxima of the smoothed square norm of the point-wise acceleration. Overall Dynamic Body Acceleration (ODBA), a measure of energy expenditure, was computed as the mean norm of the accelerometer signal after application of a high-pass filter.

Table 1. List of features calculated on the basis of the tri-axial Accelerometers. Average and variance was calculated on a 1 minute time window.

Feature	Description
Step Detector	Simple count of the number of steps per minute
Energy Square	Averaged sum of point-wise square acceleration
Energy Sum	Averaged sum of point-wise acceleration
Energy Variance	Variance of point-wise square acceleration
ODBA	Mean norm of a high-passed version of acceleration

2.4 Clinical Assessments

The 30-item scale for positive and negative symptom assessment (PANSS) was reduced to the following 5 literature-based factors: Positive, Negative, Disorganized/Concrete, Excited and Depressed. The dimensionality reduction

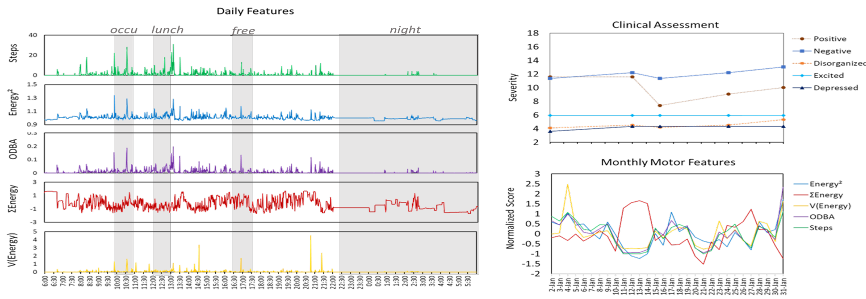

Fig. 2. The daily features of a single subject (left): gray areas indicate the time windows used for aggregated feature calculation. Monthly follow-up of a single patient (right): top panel shows the clinical five-factor PANSS score given by a trained psychiatrist on a bi-weekly basis; bottom panel shows the aggregated features calculated based on the different time windows.

was done according to the consensus model suggested by Wallwork et al. [14], based on 25 previously published models and refined with confirmatory factor analysis (CFA).

The negative and positive factors had low between-factor correlation ($R = 0.399$), indicating good separation of the symptomatology space. As expected, the positive factor was in high correlation with the mean of all positive PANSS items ($R = .944$), and likewise the negative factor was in high correlation with the mean of all negative PANSS items ($R = .972$).

3 Results

We investigated two distinct ways by which wearable devices can be used for patient monitoring, in order to assist physicians in understanding the state of a patient. The first aspect of monitoring relates to the automatic assessment of a patient's condition, in order to provide automated, continuous, and objective measures of mental state. To this end we investigated the correlation between the computed measures and assessments by physicians, as described in Section 3.1. The second aspect of monitoring relates to the detection of change (or anomalous behavior patterns) which warrants additional attention from the medical staff, as described in Section 3.2.

3.1 Movement patterns and mental state

In order to investigate the correspondence between patterns of movement and mental state, *multiple correlation analysis* was computed between activity related features (described in Section 2.2) and PANSS factors. Results (Table 2) indicate the predictive benefit of the computed activity-related features with respect to the PANSS factors. When separately considering features computed in each of the time-windows, it is evident that different time windows provide varying predictive value for the 5 different PANSS factors.

Table 2. Percent Explained Variance based on *Multiple Correlation* between computed features in each of the 5 time-windows and each of the 5 PANSS factors. (See Section 2.2 for time-window specifications.)

	free	lunch	occu	day	night	all
Positive Factor	16.30%	11.14%	12.31%	19.80%	5.21%	53.77%
Negative Factor	19.74%	3.15%	2.06%	18.36%	9.77%	55.50%
Disorganized/Concrete Factor	22.73%	0.50%	15.13%	13.42%	5.82%	64.81%
Excited Factor	23.79%	8.75%	15.08%	10.35%	12.70%	57.10%
Depressed Factor	31.01%	9.23%	8.94%	5.78%	6.39%	58.33%

Specifically, the Depressed Factor is described relatively well using features from the *free time* window, with 31.01% explained variance, while all other time-windows are below 10%. Both Positive and Negative factors are described well using features from the *free time* as well as *all day* time-windows. The remaining factors are again best described using *free time*. Overall, the *free time* window is the single most effective window, presumably since it imposes less structure on the movement of the subjects, allowing for the manifestation of the underlying mental state. In all cases, combining all time windows (rightmost column in Table 2) leads to substantially higher explained variance, compared to any of the individual windows.

Interestingly, looking at individual variable correlations we see that step count during *free time* was positively correlated with positive, disorganized and exited factor ($R = 0.37, 0.37$ and 0.31 respectively), but not with the negative and depressed factors. In addition, patients who had higher scores in disorganized and exited factors tended to have lower Energy scores during occupational time ($R = -0.28$ for Energy Sum and -0.22 for Energy Variance). This may indicate some motor retardation which is manifested only in non-walking time.

3.2 Continuous Monitoring

Our measures can be used to track changes in the patient's condition as compared to some established normal baseline, and may identify external events which are correlated with the departure from normality. Fig. 3 demonstrates such a case: daily *step counts* of a patient dramatically increased 5-fold, at the same time as a significant change in medication dosage was introduced. Whether the change in medication *caused* the rise in movement propensity or they were both triggered by a change in mental state, this observation points to the relevance of monitoring macro movement patterns as part of routine patient monitoring.

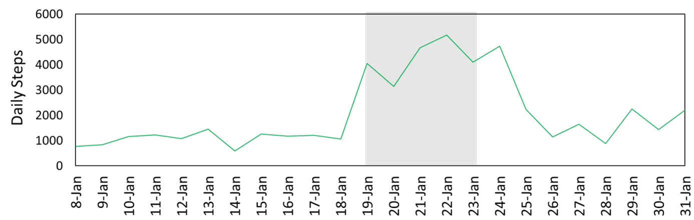

Fig. 3. Mean *daily steps* of a single subject. The gray area corresponds to a short-lasting change in medication regime.

4 Conclusions

We describe a study designed to evaluate the utility of wearable devices fitted with accelerometer, light, and temperature sensors, for the monitoring of schizophrenia patients in a closed ward mental health institution. Initial results show correlations between features of activity in various daily time-windows, and factors derived from the PANSS assessment.

Results indicate that movement features during free time are the most indicative of mental state. This finding is somewhat counter-intuitive, since the more structured activity during occupational therapy or lunch was expected to highlight differences in the state of patients. However, our results clearly show that the behavior of individuals when left to their own devices is better correlated with the PANSS factors.

These findings point to the possibility of automatically and continuously tracking Schizophrenia related symptoms and patient state in a natural setting hospital environment.The benefits of such a tracking system are twofold; first, the continuous tracking will assist physicians in understanding the state of a patient on an on-going basis, as opposed to specific points in time, when assessed by the doctor. Second, long term monitoring of a large number of patients will produce data allowing us to develop objective measures of motor aspects of the illness, and facilitate a more personalized, objective, and data driven approach which is much needed in the field of mental health.

Future work will focus on measuring the utility of this approach as an augmentation tool from a physicians perspective on the one hand, and the ability to predict physician assessments for automation of diagnosis on the other.

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