From self-reporting to monitoring for improved migraine management

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***Abstract*—Migraine affects around 18% of the population and is considered one of the most disabling conditions with a great socio-economic impact. Many therapeutic decisions in the management of migraine patients are almost entirely dependent on the patient's accurate recollection of headache events and associated circumstances that have occurred between visits. Therefore, today's solutions to improve the traditional interview at each physician visit exist of self-reporting systems, either paper-based or using one of the available smartphone apps. This way, patients manually record clinical and related events on the day they occur, such that possible headache triggers in the lifestyle of the patient can be discussed. However, self-reporting all lifestyle events is cumbersome and subjective. To overcome these issues, we have developed mBrain, a migraine app that automatically records activities, sleeping behavior and stress. mBrain also allows patients to record their personal feelings, migraine attacks and medication intake on a day-to-day basis. This way, mBrain enables a shift from sporadic self-reporting towards continuous and objective monitoring. To further optimize the migraine management, we also designed a dashboard for clinicians that uses semantic reasoning. The dashboard visualizes the optimal information to treat the patient without requiring any configuration. This allows physicians to have a more detailed and objective view on the patient, relevant clinical events, and the patient's response to the treatment, thus aiding physicians with posing pertinent questions. The time physicians used to spend on uncovering the relevant history from the memory of the patients can now be used to diagnose the patients more quickly and optimize their treatments, paving the path towards improved migraine management and personalized migraine therapies.**

***Keywords*—headache disorders, migraine, mobile health, mobile app, dashboard, remote monitoring**

I. Introduction

Headache disorders are characterized by recurrent headache and are frequently experienced by many people [1]. The World Health Organization (WHO) estimated in 2016 that approximately 50% of all people had suffered at least once from a headache disorder in the previous year [2].

Migraine is a highly prevalent primary headache disorder. It affects around 18% of the world-wide population and is therefore considered one of the most disabling conditions with a large socio-economic impact [3]. According to the International Classification of Headache Disorders, 3rd edition (ICHD-3) [4], migraine is mainly characterized by disabling headache attacks lasting 4 to 72 hours when they are untreated or unsuccessfully treated. Typical associated symptoms are hypersensitivity to light, hypersensitivity to sound, nausea and/or vomiting. Other typical characteristics of the headache are its unilateral location, pulsating quality, moderate or severe intensity, and/or that the pain is aggravated by routine physical activity. Often, only a subset of the symptoms is associated, as migraine attacks have a high intra-individual heterogeneity.

Because of the high prevalence of primary headache disorders like migraine, it is important to accurately classify headache attacks, diagnose patients with the correct disorder, and perform a continuous follow-up during the management of their disorder [5, 6]. Today, no biological markers exist to reliably perform these tasks. Hence, in current clinical practice, the main assessment tool still is a traditional patient-physician interview. These sporadic interviews take place during patient consultations and provide historical information about their headache attacks and associated properties. This information is entirely self-reported by

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patients. In order to better recall headache information during these interviews, patients can rely on paper diaries or mobile applications like Migraine Buddy which allow them to manually record all clinical and related contextual lifestyle events [7]. These alternatives try to make headache follow-up a more continuous process, but still have remaining issues that make them not yet sufficient. Self-reporting all headache attacks and lifestyle events is cumbersome, time-consuming and subjective by nature. No headache follow-up solution already exists that relies next to self-reported information on objective physiological data and contextual information [7].

II. mBrain

To overcome the issues associated with current intermittent headache follow-up that is entirely based on sporadic self-reporting, we have created mBrain [8]. mBrain is an explorative, observational research study that introduces the continuous, objective and semi-autonomous monitoring of primary headache disorder patients based on physiological and contextual data. To achieve this, we have developed the mBrain app. This is a headache app that automatically records activities, sleeping behavior and stress of patients. To accomplish this, participants of the mBrain study are equipped with a wearable device, i.e., the Empatica E4, which measures physiological data and acceleration [9]. In-house designed machine learning algorithms use this automatically collected data to record these different events, and present them in the mBrain app. In addition, mBrain participants can use the mBrain app to document the relevant properties and associated symptoms and triggers of their headache attacks, their personal feelings, and medication and food intake on a day-to-day basis. Moreover, the mBrain app also allows collecting data from different smartphone sensors to be used in the data analysis. To further optimize headache management, we have designed a dashboard for clinicians that visualizes the optimal information needed to treat the patient, without requiring any configuration by the clinician. Through semantic reasoning, the dashboard constructs an objective and detailed view for every patient on relevant clinical events and how the patient responds to his or her treatment.

mBrain extends traditional self-reporting headache management systems with the continuous monitoring of lifestyle events through the automatic collection of objective physiological data, and a dynamic dashboard to visualize important treatment information to clinicians. Participants of the mBrain study are equipped for three months with the Empatica E4 wearable and the mBrain app installed on their smartphone. This way, physiological and contextual data is collected from the different sources and analyzed. The main research question of the mBrain study is whether this approach allows generating more useful insights to improve the diagnosis, follow-up, treatment and general management of primary headache disorder patients, and how these insights can be optimally presented to clinicians in a dashboard.

III. Related work

In migraine management, the use of a paper-based medical diary is already common practice to provide relevant data to health professionals. However, there is a substantial discrepancy between patients' reports on triggers and objective clinical data [10].

As an alternative to paper-based solutions, existing digital solutions further assist headache patients in their headache management. In general, much research has been done in recent years to introduce telemedicine in headache disorder management [11]. More concretely, one study showed how a diagnostic headache diary can be combined with clinical interviews to optimize the diagnosis of headache disorders [12]. Another study investigated how headache applications have helped patients in controlling their usage of acute medication, which is important since overuse may lead to chronic headache disorders [13].

Many existing digital solutions are commercially available smartphone apps that assist headache patients in self-reporting headache attacks and related contextual lifestyle events [14]. Examples are Migraine Buddy [15], My Cluster Headache [16] and Migraine Manager [17]. Most of these apps are limited to self-reporting only. They often exhibit usability issues and are not personalized to the patient [14]. Nevertheless, studies have shown their usefulness in improving headache management, and the interaction between patient and physician [18, 19]. Some apps do include some form of automatic event detection along with self-reporting features, like the sleep detection in Migraine Buddy, but this is always very limited and almost never linked with the patient’s physiology [18, 20]. In addition, clinical safety and privacy preservation are important factors that are often unaddressed in commercial solutions [20, 21].

Limited work exists on migraine management using wearable sensors. In their work, Siirtola et al. present how migraine days can be predicted based on physiological data collected only during the night [22]. The results however show low performance and highlight that the methodology does not allow for building user-independent models. In the work of Pagán et al., the time of a migraine attack is predicted, but the evaluation is limited to two subjects only and the monitoring kit is inadequate for 24/7 monitoring [23]. Both works are limited to predicting attacks, are not tested in real-life and do not give patient and/or physician additional insights into what triggered the attacks, or how the patient’s migraine should be managed. In general, some other studies also refer to the possible benefits of including wearable devices for migraine management [11, 24].

IV. mBrain components

In this section, the various mBrain components are discussed in more detail.

A. *Machine learning model for activity recognition*

The activity recognition model uses the triaxial accelerometer signal from the Empatica E4 and its Euclidean Norm (EN) derivation. As a first step, a band-pass filter is applied to the signals and their derivations. Next on, the filtered output is scaled to represent values in the range of the earth’s gravity acceleration (g). Afterwards, the data is segmented into windows of 15 s with 50% overlap on which time-domain and spectral features are extracted. Finally, the features are standardized by removing the mean and scaling to unit variance.

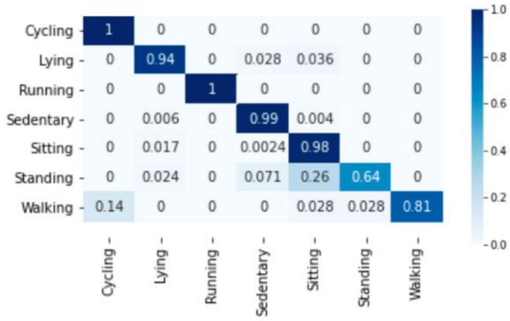

Figure 1: Activity recognition confusion matrix on mBrain data.

The activity recognition model employs Gradient Boosted Trees (i.e., CatBoost) on an internal collected dataset to discern six different activities, i.e., Sitting, Standing, Lying Down, Walking, Running and Cycling [25]. As the signals are divided into windows of 15 s with 50% overlap, a prediction is obtained every 7.5 s (i.e., eight predictions per minute). These predictions are aggregated per minute by selecting the class with the highest mean probability for that minute. Majority voting from five aggregated individual minute predictions then determines the prediction on a five-minute level.

In Figure 1, the normalized confusion matrix of the validation results on mBrain patient data is shown. The least performing class is standing, which is often mistaken for sitting. This can be explained by the fact that there is often no difference in the freedom of movement or position of the arms/hands while both sitting or standing. Moreover, as sitting is the majority class, the model is biased towards it and thus predicts some standing as sitting. There are also some cases in which walking is mistaken for cycling. This usually happens when a person is pushing something, e.g., a bike, a supermarket cart, a stroller. The misprediction is caused by the presence of wrist-vibrations, similar to the ones which are observed while biking.

B. Algorithm for sleep quality monitoring

A sleep detection algorithm was designed to determine sleep patterns based on the wearable data. To do so, the activity index, defined as the square root of the mean variance over a rolling window of 10 minutes, was calculated directly using the raw accelerometer data [26]. Afterwards, this index is filtered with a band-pass filter and scaled to a range from 0 to 1. The more active a user was at a given moment in time, the higher this activity index is.

While sleeping, the activity index will be lower compared to periods in which the participant is awake, as shown in Figure 2. To define the threshold, a sleep and rest state detection methodology was designed based on a heuristic model around the automatic scoring algorithm of Cole, R.J.

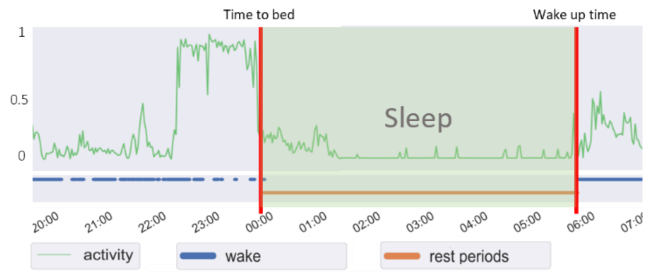

Figure 2: Detection of sleep patterns using the activity index.

et al. [27]. The algorithm defines a score based on the activity index, indicating how certain these values are associated with an awake or rest period. Combining all these scores reveals the sleep pattern.

C. Machine learning model for stress detection

Prior research highlighted relationships between (the relief of) stress and migraine attacks [28]. This research focused on self-reported (daily) stress and did not take physiology into account. One of the main objectives of the mBrain study is to investigate the potential of current wearable-based solutions for ambulatory stress detection, both at an acute and chronic level.

To do so, a data-driven acute stress model was constructed for the Empatica E4. This model uses the Empatica's skin conductance, inter-beat-interval (IBI), skin temperature, and movement data. The stress model is trained on two datasets; an in-house ambulatory dataset using self-reports as ground-truth, and WESAD [29], a dataset of 15 participants in which stress was induced using the Trier Social Stress Test [30]. A real-time prediction pipeline was built with tsflex [31].

The acute stress model predicts a stress probability for each minute. A stress event will be shown in the mBrain app's timeline if at least three consecutive stress probabilities exceed the threshold of 50%. Non-stressed events are shown if consecutive probabilities do not meet this threshold. Users can interact with stress events by either confirming, removing, or re-labeling them. Moreover, after stress-event interactions, users will be asked whether they have some time to fill in a short questionnaire that queries the causes of the (non-)stressed period.

Currently, there is no chronic stress model as there was no data to construct it. However, the mBrain study queries with an evening questionnaire the participants basic psychological needs [32], daily mood [33] and perceived stress level [34]. This paves the path towards investigating chronic stress modeling with retrospective data analysis.

D. mBrain mobile app for user behavior monitoring

The mobile mBrain application consists of several pages that allow users to collect wearable and smartphone data and monitor their behavior. The main functionalities of this application include data collection, event registration, timeline of events, daily records and daily questionnaires.

Via the application, the user can access the data collection page, which is hosted inside a native Android app. From this page, the user can connect an Empatica E4 wearable device with the smartphone via BLE to start the real-time streaming of wearable data to the smartphone. In addition, once this page is opened, several services are automatically started, collecting smartphone sensor and application data.

The mBrain app allows the user to keep track of headache attacks and contextual events such as activities, sleeping periods, stress periods and medicine intakes. These events are chronologically listed in the user's timeline. On the one hand, the timeline includes the output of the data-driven models, i.e., predicted activities, sleeping periods and stress periods, together with relevant predicted metrics. Users can interact

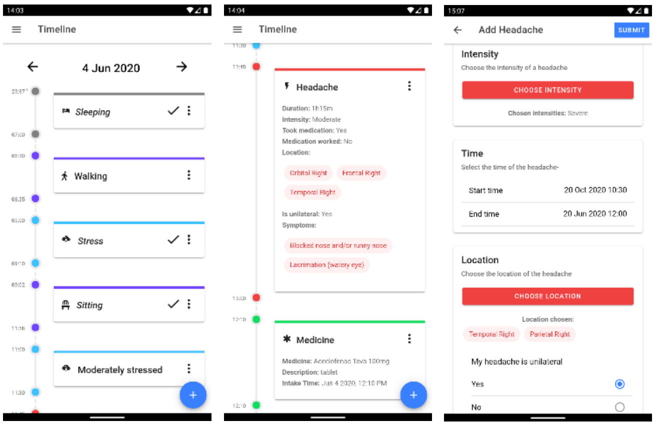

Figure 3: Screenshots of the mBrain app (left & mid: timeline of events; right: headache attack registration).

with these events by either confirming or correcting them, enabling future development of more-performant algorithms using retrospective analysis. On the other hand, events can be manually registered as well. In practice, this is mainly done for headache attacks and medicine intakes. For the registration of headache attacks, relevant properties (e.g., pain intensity, location, associated symptoms) are requested in accordance with ICHD-3 [4]. Screenshots of the timeline and headache registration are shown in Figure 3.

The mBrain app also keeps track of other contextual user data on a day-to-day basis through daily records. This includes the user's food intake, emotional mood, and a general stress level. Moreover, two daily questionnaires can be filled in by the user every morning and evening. These questionnaires query for the user's headache and stress anticipation, mood, sleep and stress perception.

E. Dynamic dashboard for clinicians

To summarize and present the collected metrics (e.g., activities, sleep quality, stress level, medicine intake) at the click of a button to the physician, IDLab's Dynamic Dashboard [35] has been enhanced with mBrain related visualizations. These visualizations have been designed and selected in collaboration with participating clinicians during our study. The semantic reasoning within the dashboard enables the dynamic addition of visualization-widgets for newly captured metrics. Through the semantic description of both the data (i.e., the available sensors and the metrics they observe) and the visualizations (i.e., the types of data they can visualize), the dashboard is able to reason which visualizations are most relevant to the clinician given the specific patient. The dashboard ontology used for these semantic descriptions is based on the Resource Description Framework (RDF) [36] and the Sensor, Observation, Sample and Actuator (SOSA) ontology [37].

To gain insights in the collected data of a patient, the most relevant patient data must first be selected. Next on, aggregations of related metrics must be created and finally, the best visualization option must be chosen from a plethora of supported visualizations. This process requires expert knowledge of the available data and the visualization tool that is used. The dynamic character of the dashboard relieves the user of this task by automating this process and immediately presenting a dashboard for a given patient with no configuration needed, as shown in Figure 4.

V. Discussion

Headache medicine nowadays is largely performed by history taking and clinical examination of patients with headache disorders. Measurements of the physiological components of headache attacks are currently underused during routine clinical visits.

Our understanding of the biology of the disorders is that fluctuations in biological systems involved in stress, sleep or activity may trigger headache attacks or influence the course of the disorders [38]. By using physiological measurements from wearable devices combined with the computational power of data-driven algorithms, our research groups hypothesize that these inputs may provide valuable information on the nature of individual headache attacks on a personal level.

Not only measurements but also communication of different metrics to physicians for routine clinical practice are important and should not be underestimated. Therefore, a dedicated dashboard for clinicians should always be part of this set-up and be customizable to the needs of the individual physicians and patients.

The efforts presented above rely on dedicated knowledge-driven multidisciplinary collaboration by physicians,

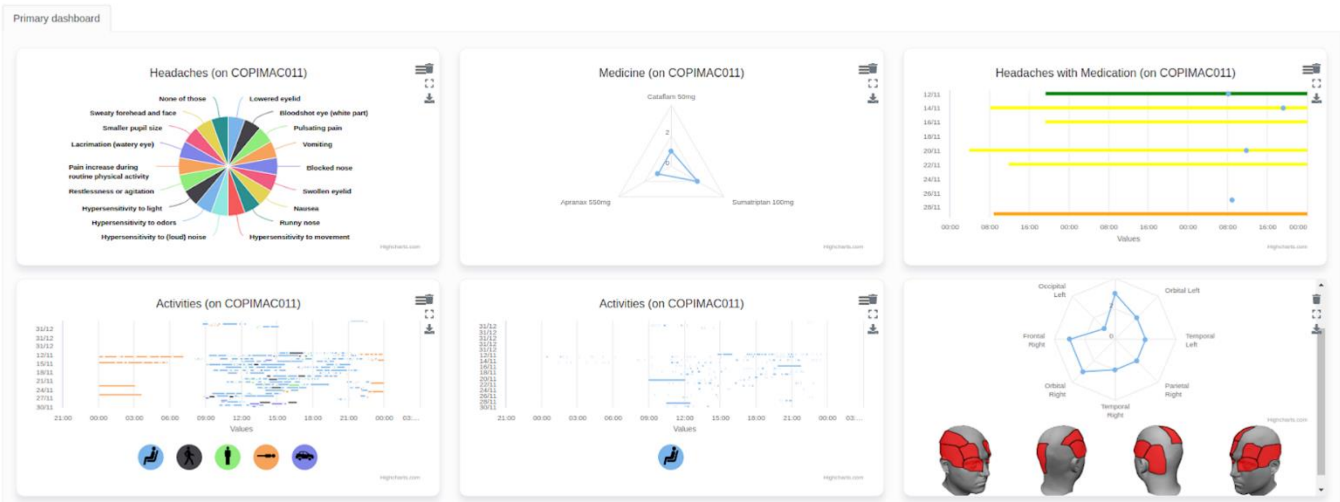

Figure 4: Dynamic dashboard for clinicians, visualizing all the collected data for a specific patient.

engineers and computer scientists. Feedback by participants in the study helps to learn the research team to adapt new strategies to collect the most valuable information from conscious and subconscious registrations of applications and wearables. By doing so, this research will help create new low-level feature extraction methods for continuous follow-up of headache disorders by new technological advancements for the benefit of both patients and headache physicians.

VI. Conclusion

This paper has presented mBrain, a research study that introduces the continuous, objective, and semi-autonomous monitoring of primary headache disorder patients based on objective physiological and contextual data. This way, mBrain tries to improve on current headache diagnosis and follow-up that is solely based on subjective self-reported data intermittently discussed orally between patient and physician. The study includes the mBrain app to collect all data, data-driven algorithms to predict a patient's lifestyle events including activities, sleeping behavior and stress, and a dynamic dashboard for clinicians visualizing all relevant information for each patient. By collecting data, analyzing it, and presenting the relevant information on a silver platter via the dashboard, physicians might combine and correlate the visualized info to derive new insights that might have been missed before. This way, time that they used to spend on uncovering relevant history from the patient's self-reports is now used to diagnose patients' headache attacks and disorder more efficiently and correctly, and to optimize their treatments. First results do prove that extending traditional self-reporting headache management systems with the continuous monitoring of lifestyle events allows to generate more insights and optimize headache diagnosis and follow-up. This opens the path towards further improvement in migraine management, including personalized migraine therapies as well as the automatic detection of relevant events such as headache triggers.

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