Evaluating Daily Life Activity Using Smartphones as Novel Outcome Measure for Surgical Pain Therapy

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ABSTRACT

In this paper we investigate the potential of a smartphone to measure patients' changes in physical activity before and after a surgical pain relief intervention. Providing an objective intervention outcome measure to clinicians could enhance subjective assessments from patient questionnaires and contribute to optimal patient treatment. Thus, we show a proof of concept for our smartphone system providing physical activity from acceleration, barometer and location data to infer meaningful activity features that measure the intervention's outcome. In a case study, we monitored two patients carrying the smartphone 9 days before and another 9 days after a surgical intervention. Results indicate significant activity changes after intervention while the pain level decreased. Particularly physical activity in the home environment increased significantly for both patients where an averaged 98% increase in walking and a more than 150% gain in fast cadence was measured. Questionnaire assessed activity levels showed no meaningful correlations to activity measurements and turned out to be highly subjective.

Categories and Subject Descriptors

H.5.2 [**Information interfaces and presentation**]: Miscellaneous

General Terms

Design, Experimentation, Human Factors, Measurement.

Keywords

Activity monitoring, smartphone, pain patients, intervention.

1. INTRODUCTION

Chronic pain is a widespread and serious disease in our society. Around 20% of the world's adult population suffer from chronic pain [2]. Chronic pain occurs at different severity levels ranging from loss in quality of life (QoL) to bed-bound situations. While mild forms are often treated with medication, seriously affected pain patients need surgery. The *University Hospital Zurich* is applying an interventional pain therapy for patients seriously suffering from back and leg pain (Figure 1). A neuro-stimulator is implanted inside the body to stimulate nerves with electric pulses and therefore release pain. In a test phase, electrodes are implanted near the backbone to investigate success of the therapy (Figure 1b). The correct position of the electrodes is crucial to obtain pain-relieving stimulations. In case of at least 40% pain relief in daily life during the test phase, the neuro-stimulator is fully implanted inside the body (Figure 1c).

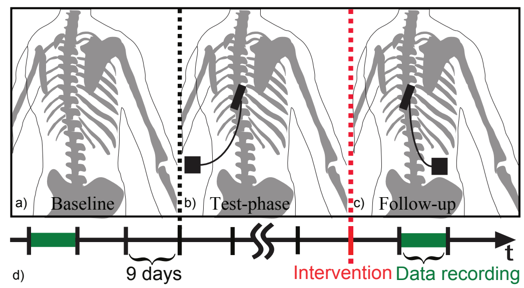

Figure 1: a) Patient with pain during baseline, b) in test phase, with test electrodes implanted but external neuro-stimulator, c) in follow-up with fully implanted system (after intervention), d) schedule for data recording.

The neuro-stimulator intervention is an invasive therapy and patients who undergo the implanting procedure are rare but heavily suffering from pain. To prevent therapy failure and unnecessary risk for patients an outcome measure during the test phase is crucial. Furthermore, doctors are highly interested in the outcome after full implantation (follow-up) to provide optimal after-treatment to patients. It is assumed that a release in pain results in a change in physical activity. Currently, outcome in test and follow-up phase is assessed using feedback from patients such as activity/pain diaries, functional disability and QoL questionnaires [4]. However, feedback from questionnaires is very subjective and therefore doctors look for an optimal outcome measure using non intrusive objective methods [3].

In pain patient monitoring the physical activity level is frequently assessed from accelerometers. Kop et al. [7] monitored the physical activity of Fibromyalgia pain patients using wrist-worn actigraphs, Ferriolli [6] investigated physical activity of cancer pain patients at different stages using an accelerometer worn at the thigh. Both studies reported a significant difference in physical activity of severe pain patients compared to healthy controls. Assessing the patient's activity from smartphones would not require further sensors such as actigraphs and even allow modalities beyond accelerometry thus leading to more comprehensive activity informa-

BODYNETS 2013, September 30-October 02, Boston, United States

DOI 10.4108/icst.bodynets.2013.253635

tion. Smartphone applications such as the HealthMate[1] track and visualize sleep and physical activity. The application BeWell [8] provides feedback to the user in terms of physical, social, and mental well-being based on physical activity, ambient sound and sleep.

However, to our knowledge there are no studies available investigating objective measures to compare pain patients' activity before and after surgical intervention. To ensure optimal treatment, an objective quantification of the patients' physical activity changes after intervention is of great interest to doctors. Thus, in a case study we analyzed the potential of the smartphone to measure changes in physical activity of two pain patients undergoing a pain relief intervention. In our previous work [10], we explored the pain reduction effect in a first patient case and analysed activity feature changes in response to the intervention. We extend the investigation in this present work to two patient cases and provide a detailed analysis on activity feature changes to measure the outcome of the therapy. Furthermore, correlations between the patients' self-assessed physical activity and smartphone measurements as well as between pain level and activity are analyzed. The contributions in this paper are threefold:

1. We investigate activity changes of pain patients before and after a neuro-stimulator intervention.
2. We show a proof of concept for using a smartphone system to assess activity as outcome measure for a pain relief intervention including modalities beyond accelerometry.
3. We present and analyze the relevance of various features to reveal changes in activity before and after intervention as novel outcome measure for surgical pain therapy.

2. SYSTEM IMPLEMENTATION

2.1 Smartphone System

An overview of the smartphone based patient monitoring system we used is depicted in Figure 2. The Android application is based on the framework introduced in [5] and featured logging of raw data from all modalities, upload of data to a webserver and real-time visualization on a remote computer.

To ensure a data logging runtime across the whole day we used acceleration, barometer and GPS signals for inferring meaningful activity information combining physical activity with location. Acceleration and barometer data were resampled to a frequency of 30 Hz, for energy savings GPS updates were logged every 3 minutes and data was exclusively uploaded when the smartphone was plugged-in. Using the Sony Xperia Active smartphone a total battery life of around 17 hrs was achieved when logging data continuously. Sampling and data logging was started automatically when the charging cable was unplugged in the morning. Plugging-in the cable in the evening stopped data sampling, enabled data upload and triggered a questionnaire, assessing the time the patient spent away from home as well as the daily physical activity and pain level. The smartphone had only to be charged during night.

2.2 Features and Data Analysis

We considered the daily recording time (Trec), the ratio of walking (Walk), the time the patient walked at a certain speed (no cadence, low, medium, high), the number of steps (Ns) and the instances of climbing up stairs (Nst) to be indicators for the physical activity level of a patient. Furthermore, we assumed the total energy of the acceleration signals per day (AL) and the ratio patients spent in each intensity class (low, medium and high) to reveal activity intensity patterns across days. Changes of activity levels before and after intervention might depend on the location of the patient, e.g. when being away from home, activities might be more constrained due to commitments at work, whereas at home they might be more unlimited. Therefore, all features mentioned here were calculated for periods spent at home, away from home and overall (away+home). Furthermore, the number of location clusters a patient visited daily (Nc) and the number of transitions in between different clusters (Nct) might reveal new life style habits after intervention.

All features were calculated offline from the three axis acceleration signal $\mathrm{acc}_{x,y,z}$, the filtered and derivated barometer signal δp and the GPS data as defined in Table 1. Thresholds were extracted from the feature validation dataset described in the next section. Features were calculated per day, features in home environment were normed to the daily time spent home, features away respectively. On all features we performed a two-sample 1-tailed Student's t-test to reveal substantial changes in features before and after intervention. The two sample t-test performs a t-test of the null hypothesis, that data samples before and after intervention structure from normal distributions with equal mean against the alternative hypothesis that the mean before intervention is smaller (left-tailed) or greater (right-tailed). Normality of data distribution was verified by the Shapiro-Wilk test. The level of significance adopted was p=0.095 (weakly significant). To reveal correlations between activity features and the patients' questionnaire indications we cal-

[1] http://www.withings.com/en/app/healthmate

Figure 2: a) Patient monitoring system: Data is logged on a smartphone, uploaded to a webserver and stored in a database, enabling data visualization to doctors for analysis, b) experimental setup.

Table 1: Feature abbreviations, their definition and calculation to describe physical activity.

Feature	Description
Trec	Total recording time.
Nc	Number of location clusters visited; kmeans clustering on GPS data, fusion of cluster centers closer than 10m.
Nct	Number of transitions in between different location clusters.
AL	$\mathrm{IAA}_{\Delta t} = \int_0^{\Delta t} \mathrm{rect}(\mathrm{acc}_x)+\mathrm{rect}(\mathrm{acc}_y)+\mathrm{rect}(\mathrm{acc}_z)$ based on [1]; Δt=Trec, rect()=rectified signal.
I	Intensity. Number of intervals i within thresholds: min $<\mathrm{IAA}_{\Delta t_i} \leq$ max; $\forall i \mid \Delta t_i \in$ Trec (sliding window), $\Delta t_i =$ 30s.
Ilow	$0 < \mathrm{IAA}_{\Delta t_i} \leq 30$
Imed	$30 < \mathrm{IAA}_{\Delta t_i} \leq 110$.
Ihigh	$\mathrm{IAA}_{\Delta t_i} > 110$.
C	Cadence. Number of steps S within thresholds: min $< S \leq$ max. Step detection: $(\mathrm{acc}_x^2+\mathrm{acc}_y^2+\mathrm{acc}_z^2)^{\frac{1}{2}} > 0.3\,\frac{\mathrm{g}}{\mathrm{s}}$
nC	$\mathrm{S} < 20\,\frac{\mathrm{steps}}{\mathrm{min}}$
Clow	$20 < \mathrm{S} \leq 60\,\frac{\mathrm{steps}}{\mathrm{min}}$
Cmed	$60 < \mathrm{S} \leq 90\,\frac{\mathrm{steps}}{\mathrm{min}}$
Chigh	$\mathrm{S} > 90\,\frac{\mathrm{steps}}{\mathrm{min}}$
Ns	Number of steps.
Walk	Clow + Cmed + Chigh.
Nst	Number of instances climbing stairs; increased if $4.8 < \delta\mathrm{p} \leq 8.4\,\frac{\mathrm{m}}{\mathrm{min}}$

culated the Pearson correlation coefficient $\rho_{x/y}$ between two paired sequences of N data samples x_i and y_i, $i = 1, 2, ..N$.

3. EVALUATION STUDY

We monitored a 48 year old female and a 45 year old male patient, both undergoing a neuro-stimulator implantation (as detailed above). Patients had been suffering from intense leg and low back pain for more than 10 years. Interaction with patients took always place in close collaboration with doctors. Before the study, we informed the patients about the smartphone system and its usage. Furthermore, a validation dataset including 2 min of each *lying*, *sitting*, *walking* and *climbing stairs* was recorded.

During data recording patients were asked to carry the smartphone in a belt bag attached to the waist as shown in Figure 2b), whenever they were out of bed or water. Remote data access via webserver allowed us to monitor data collection and revealed daily measurement durations, whether the smartphone was carried at the body (from the acceleration signal's standard deviation) as well as the detection of operating errors by the user. During medical consultations patients received feedback regarding data collection. As depicted in Figure 1d) we monitored the patients for 9 consecutive days in baseline (before the intervention) and another 9 days during follow-up. Every evening patients completed a questionnaire on the smartphone. During medical consultations subsequently to baseline and follow-up patients completed an additional questionnaire. The questionnaire assessed whether the smartphone was worn during the whole day and carried in the bag-belt and whether any problems occurred operating the system during data recording.

4. RESULTS

In the following, we first verify the definition and thresholds of physical activity features. Subsequently, we compare activity level measurements to the patients' self-assessments and investigate correlations between pain and physical activity followed by a feature relevance analysis pre and post intervention.

4.1 Feature Validation

Applying feature calculation to the validation datasets of both patients, overall, we achieved 100% accuracy for the instance detection of climbing stairs (Nst) and 98% for walking (Walk). For stationary classes (lying, sitting) 100% was classified to be part of the low intensity class (Ilow) and cadence class nC. For movement classes (walking, climbing stairs) 100% was detected to be part of intensity class Imed, the assignment to the cadence classes followed a ratio of nC:Clow:Cmed:Chigh = 2:8:34:3. Thus, stationary classes were covered by low intensity and cadence (Ilow, nC), movement classes mainly by medium intensity and cadence (Imed, Cmed). High cadence/intensity classes (Chigh, Ihigh) did not occur in the validation dataset but could cover more intense movements. As features described the validation dataset reasonable we assumed feature calculation to be accurate.

4.2 Self-Assessment versus Measurement

In total 474 hrs of data were recorded during 16 days for patient 1 and 18 days for patient 2. Patient 2 did not complete one questionnaire and one recording day was missed because of wrong system operation by patient 2. On average patients used the application 14.0 hrs/day. Figure 3 depicts measured and questionnaire assessed activity levels. For patient 1 we measured a weak correlation of questionnaire assessed and measured activity ($\rho_{AL/ALq} = 0.44$). The qualitative trend, i.e. increases or decreases in AL and ALq compared to the previous day, are consistent for measurements and self-estimation, except for day 8 in baseline and day 5 in follow-up (increase in activity measured but self-estimated decrease). However, absolute values were indicated differently in comparison to measurements: e.g. day 1 and 4 in follow-up show the same perceived activity level but day 4 measures 2.5 times the activity level of day 1. Contrary to patient 1, data of patient 2 indicated no correlation ($\rho_{AL/ALq} = 0.02$) between the physical activity level in the questionnaire (ALq) and the activity measurements (AL). In baseline patient 2 indicated a 27% increase in activity (ALq) between day 1 and day 2 but an inverse trend (-43%) was measured (AL). Furthermore, average questionnaire activity levels (ALq) in follow-up were 75% lower than in baseline whereas measurements (AL) increased by 10% in the same time. Either the patient perceived activity levels in baseline differently than in follow-up or had difficulties in consistently ranking activity levels (ALq) on the scale.

4.3 Pain Level versus Physical Activity Level

A decrease in pain (PLq) was expected to result in an increase in physical activity (AL). For patient 1, measurements confirmed this assumption: An average 12% decrease in pain level (PLq) resulted in 20% increase in physical activity (AL) (Figure 3). For patient 2, we observed a similar trend: A mean 40% decrease in pain level (PLq) in follow-up resulted in a 10% increase in physical activity (AL). However, neither for patient 1 nor for patient 2 meaningful correlations ($\rho_{f_i/PLq} > 0.8$) or anti-correlations ($\rho_{f_i/PLq} < -0.8$) were found between pain level and features f_i. All features showed only weak correlations $\rho_{f_i/PLq} < 0.5$.

4.4 Feature Changes

Figure 4 depicts mean percentage changes of features in follow-up, averaged for both patients. We measured decreases for all features describing inactivity (e.g. nC, Ilow). Increases were observed for activity intense features (AL, Ns, Cmed, Chigh, Ihigh, Walk, Nst) in home environment, away from home and overall, except for the activity level away (AL away). Generally, activity increases in home environment were much higher (e.g. AL: +54%) compared to away (-15%) and overall features (+15%). Considering these gains and the patients' statements always having worn the smartphone being out of bed or water, we measured increased physical activity in follow-up.

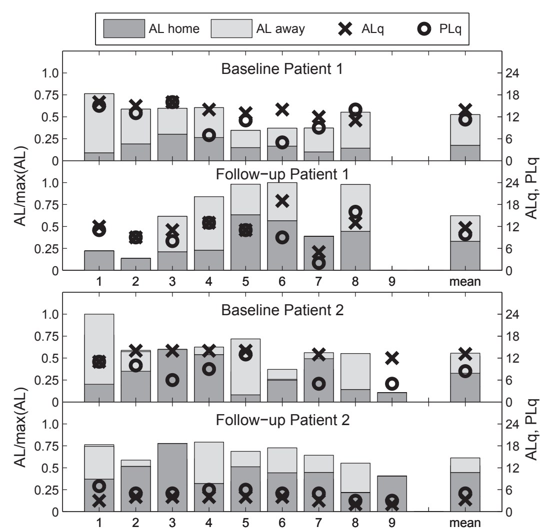

Figure 3: Comparison of measurements and questionnaire: daily activity level (AL) measured at home and away, activity (ALq) and pain level (PLq) from questionnaires in baseline and follow-up for both patients.

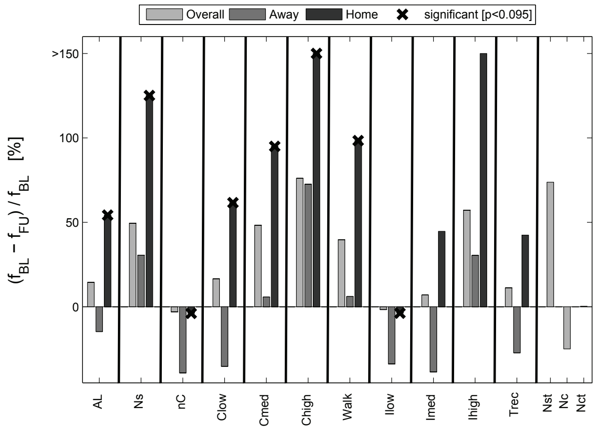

Figure 4: Mean percentage changes of features in follow-up f_{FU} towards the same feature in baseline f_{BL} at home, away from home and overall (away + home). Values are averaged over both subjects' feature changes. Changes showing statistical significance for both patients are highlighted.

Figure 4 points out averaged feature changes after intervention but does not provide an insight in the ratio of different walking speeds (nC:Clow:Cmed:Chigh) for each patient. The ratio of all cadence classes is illustrated in Figure 5a) and b) for patients 1 and 2. For patient 1, all movement cadence classes (Clow, Cmed, Chigh) increased in follow up in each scenario, home, away and overall. Not only the total amount of walking increased in follow-up but most of the time when walking, fast walking (Chigh) was performed when being away from home while in baseline slow and medium walking (Clow, Cmed) were predominant. For patient 2, the ratio of walking (all cadence speeds Clow+Cmed+Chigh) increased at home, but did not change when patient 2 was away after intervention. Away, the increase in fast walking (Chigh) compensated the decrease in low speed walking (Clow).

We found 8 feature changes being significant for both patients as highlighted in figure 4: The activity level home (Al home), number of steps walked at home (Ns home), all cadence classes (nC home, Clow home, Cmed home, Chigh home) and the low intensity class Imed home. Thus, feature analysis particularly pointed out increased physical activity in home environment.

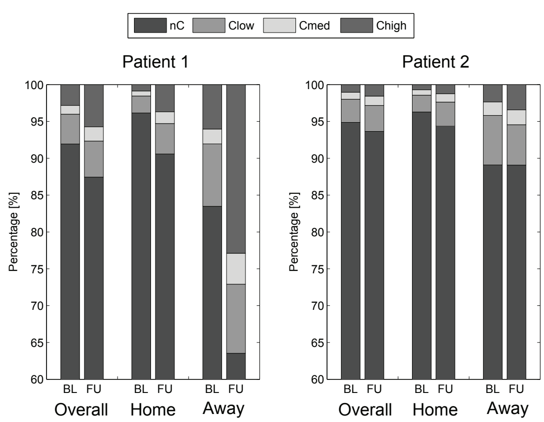

Figure 5: Mean percentages of time spent in each cadence class nC, Clow, Cmed and Chigh in baseline (BL) and follow-up (FU). Percentages are in % per day for BL and FU overall, in % of time spent home for BL and FU home and in % of time spent away for BL and FU away.

5. CONCLUSION

In this paper, we investigated the usage of a smartphone for monitoring physical activity in daily life to infer meaningful activity features as novel outcome measure after a pain relief intervention. In a case study, two pain patients were monitored in their daily life during two phases of the pain therapy, baseline and follow-up. While the patients' perceived pain levels decreased in follow-up, we found an increase (20% patient 1, 10% patient 2) in the physical activity level. However, no strong correlations between activity features and pain level were found on a daily basis. Thus, a decrease in pain resulted into an increase in physical activity during different phases, but not on the daily level. Furthermore, questionnaire assessed activity levels turned out to be highly subjective and showed no strong consistency to activity measurements as also reported in [9]. We conclude that activity questionnaires may not provide valid measurements to clinicians.

Looking at the patients' life styles, the release in pain did not result in more diverse location visits as the number of location clusters did not change. However, for both patients, we found statistically significant increases in activity after intervention. In this study, the smartphone's location information contributed strongly to provide meaningful activity measures. Only features describing physical activity at home increased significantly for both patients, such as the number of steps walked at home (+128%), while changes in features overall and away from home were smaller for both patients and only significant for patient 1. We conclude that smartphone based activity monitoring has the potential to provide objective intervention outcome to clinicians while not obstructing patients in their daily life activities. In the next step, we plan to validate our approach in a more extensive study. Furthermore, assessing social activities using sound could provide meaningful pain relief indicators.

6. ACKNOWLEDGEMENTS

This work was supported by the EU Marie Curie Network iCareNet under grant number 264738.

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