Activity Patterns in Stroke Patients - Is There a Trend in Behaviour During Rehabilitation?

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Abstract. We describe stroke patients' activity patterns and trends based on motion data acquired during their stay in an ambulatory day-care centre. Our aim was to explore and quantify intensity and development in the patients' activity patterns as these may change during the rehabilitation process. We analyse motion data recordings from wearable inertial measurement units of eleven patients up to eleven days, totally 102 recording days. Using logic rules, we extract activity primitives, including affected arm move, sit, stand, walking, etc. from selected channels of the continuous median-filtered sensor data. Using relative duration of the activity primitives, we examine patient activity patterns regarding independence in mobility, distribution of walking over the days and trends in using the affected body side. Due to the heterogeneity of patients' behaviour, we focused on analysing patient-specific activity patterns. Our exploration showed that the rule-based activity primitive analysis is beneficial to understand individual patient activity.

Keywords: Activity primitives · Trend indication · Exploratory behaviour description · Rule base data extraction

1 Introduction

Wearable motion sensors have great potential for monitoring and continuous interpretation of stroke patient recovery process. In particular, in clinical settings research has shown that data from inertial motion sensors can be used to estimate the outcome of selected scales of standard clinical motor function assessments, such as the Wolf Motor Function Test (WMFT) [22]. Eventually, the interpretation of motion sensor data could complement the information from clinical assessments during times when patients are unsupervised, e.g. at home. However, assessing functional state outside of controlled clinical conditions is still an open challenge. While being successful, most approaches to estimate clinical outcome, focused on sub-scores of clinical assessments only. Thus, the estimation

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requires patients to perform certain exercises, some even require specific accessories. Consequently, there is currently no general solution on how rehabilitation progress could be interpreted remotely when patients have left the clinic.

As any rehabilitation training programmes aim at improving motor function, skills, and patient performance, changes in patient activity patterns are likely. For example, when a hemiparetic stroke patient relearns how to use the affected arm in daily activities, motion balance between affected and non-affected arms may change. Similarly, regaining motor capabilities may have an effect on behaviour and trends in activity patterns. For example, a patient could become more active and involved, thus walk more frequently. Detecting functional changes in patients requires long-term observation, across weeks or months. In contrast, many estimation approaches that focused on clinical assessments investigated momentary patient state, often recording individual exercises only (see related work for details). The heterogeneity of patient capabilities is large, often influenced by personal traits, mood, etc. Previous work of our group on discovering daily routines revealed that patients had widely varying routine patterns and shared only very few routines [18]. Moreover, daily routines, such as eating and socialising are rather abstract and may not reveal trends in activity patterns. Patients will cope differently with their individual limitation in motor capability. Therefore activities may be differently represented in motion sensor data and supervised recognition techniques would require large amounts of annotated motion data to derive statistical models. Due to cost and privacy concerns, annotating continuous day-long recordings across many rehabilitation days seems unfeasible.

In this work, we utilise a rule-based activity primitive detection approach to explore intensity and trends in activity patterns of hemiparetic stroke survivors during their rehabilitation programme. To derive activity primitives, we used conditions on features from individual motion sensor channels. Relative duration and ratios of the activity primitives are subsequently used to describe activity patterns among patients. We analysed motion data recordings of eleven stroke patients up to eleven days in a day-care centre using wearable inertial measurement units (IMUs). As patients attend to the day-care centre on selected days per week only, recording days spread over multiple weeks for each patient.

In particular this paper provides the following contributions:

1. We detail our construction of activity primitives from basic logic conditions and primitive ratios that were subsequently analysed to interpret activity pattern intensity and trends. Our approach utilises domain knowledge to derive the rule set, but remains user-independent.
2. We explore patient activity patterns in a dataset of day-long recordings in a day-care centre, where patients were not constrained in their activities, but had some scheduled training appointments. Study observers followed the patients on selected recording days to annotate and verify their behaviour. Our exploratory analysis considers independent mobility and duration of activity primitives, including sit, stand, walk, moving affected and non-affected arms and legs, as well as to analyse temporal changes in these activity patterns.

2 Related Work

Wearable sensors, in particular IMUs, can continuously record motion data and have been applied in activity and movement analysis, including fall risk detection [7], stroke patient monitoring [4], and upper-body stability analysis during walking [9]. Several approaches exist that use wearable sensor data to evaluate functional ability in patients according to clinical scores. In contrast to therapists, who typically assess patient ability by visual inspection, wearable sensors could provide motion data in much finer resolution. Thus, wearable sensors may be beneficial for patients and therapists to determine and control near-term rehabilitation goals and can be deployed in unsupervised settings (e.g. at home). Wearable sensors have been used in clinical assessments including the Fugl-Meyer-Assessment (FMA) [6] and the Wolf Motor Function Test (WMFT) [22] to assess patient motor ability. To estimate the clinical scores from wearable sensor data, classification and regression techniques were applied to selected tasks of an assessments as described, for example, by Parnandi et al., Patel et al., and Knorr et al. [10,12,13].

Stroke patients often develop compensation strategies (e.g. shoulder and trunk rotations) to cope with functional limitations, thus influencing the original motion behaviour. Compensation strategies and limitations are discussed by Cirste et al., Bourbonnais et al., Di Fabio et al., and Murphy et al. [1,3,5,11]. Behaviour analysis of the elderly in smart homes was investigated to revel trends and changes in health and well-being by Suryadevara et al. and Rashidi et al. [14,20]. Ambient and motion detection sensors (e.g. attached to room heaters, toaster, bed, chair, and similar) were used to detect activities (e.g. sleeping, watching TV, and dining) for subsequent behaviour analysis. A multi modal identification and localisation approach for gesture and pose recognition in smart environments was proposed by Salah et al. [16]. Seiderer et al. explored the utilisation of a digital image frame for lifestyle intervention to improve well-being of older adults [17]. The sensors built into the image frame (e.g. distance sensors, light sensors, microphones, and cameras) were used for information or recommendations (e.g. to drink water, doing exercisers or remind about birthdays) to the user nearby. A sensor and vision based indoor application for elderly care was proposed by Tabar et al. [21]. The system was built from off-the-shelf devices under the constraints of size, cost, and power consumption. Robben et al. considered fall detection, position tracking, and posture classification as useful information for emergency service and a particular benefit of smart homes [15]. Behaviour interpretation of the elderly in the home environment to understand, anticipate, and respond to care needs was also described by Hine et al. [8].

We work focuses on stroke patients in an ambulatory care setting as an essential step towards home monitoring using wearable sensors. With the wearable sensors we can explore motion behaviour and trends in activities independent of the field of view of room-installed sensors, such as cameras or motion detectors.

3 Patient Study

3.1 Participants

Eleven hemiparetic stroke patients (6 males and 5 females) were included in our study. Patients were between 34 and 75 years. Inclusion criteria were: stroke or brain tumour extraction with subsequent upper and/or lower motor function deficits including wheelchair users. Exclusion criteria were: patients with further motor function impairments caused by additional neurological diseases other than stroke or brain tumour. Participants visited the ambulatory day-care centre of the Rehabilitation clinic Reha Rheinfelden, Switzerland. All included patients signed a consent form to participate in the study. This study was approved by the Swiss cantonal Ethics committee Aargau. Patient details are summarised in Table 1. The study dataset was previously used to investigate daily routine discovery as described by Seiter et al. [18].

Table 1. Overview of included patients. "Type" refers to type of locomotion (Wheelchair or Walker). "Duration" refers to total rehab duration in days. "Rec" refers to the number of recorded study days.

ID	Type	Gender	Age [a]	Duration [days]	Rec [days]	ID	Type	Gender	Age [a]	Duration [days]	Rec [days]
1	W'chair	m	57	79	11	7	W'chair	m	64	28	9
2	Walk	m	47	18	8	8	Walk	m	34	28	11
3	W'chair	m	53	77	10	9	Walk	f	72	30	7
4	Walk	f	52	16	7	10	W'chair	f	68	30	9
5	Walk	f	74	35	10	11	Walk	f	55	28	9
6	Walk	m	38	66	11						

3.2 Design

Patients received varying scheduled therapies and followed their individual routines for the remaining time at the ambulatory day-care centre. Visit frequency was two to three times per week. On selected recording days and in agreement with therapists and patients, patients were accompanied and observed by the study observer, up to eight hours per day. The study observer annotated patient activities using an Android based open-source smartphone framework CRNTC+ [19]. We defined a catalogue with activity primitives including, walking, walking stairs, sitting, etc. In addition, six activity routines (eating/leisure, cognitive training, medical fitness, kitchen work, motor training, and resting) were defined as reference for subsequent behaviour and trend description.

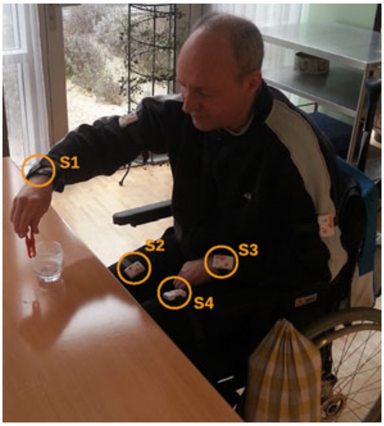

Fig. 1. Patient at the day-care centre marking his drinking glass with a clothes peg. The wearable sensors positions at the wrist and the upper legs that were considered in out analysis are highlighted (S1,...,S4).

3.3 Recording

Shimmer3 sensors [2] were used, providing three axial information from accelerometers, gyroscopes, and magnetometers. The sensors were configured to log acceleration (range $\pm$ 4 g) with a sampling frequency of 50 Hz to an SD card integrated into Shimmer3 sensors. Participants were greeted in the morning and got sensors attached on both wrists, upper arms, and upper legs. During special therapy sessions, e.g. lymph drainage, massages, or water therapy, sensors were temporary detached. Figure 1 shows the wrist and upper leg sensor positions considered in our analysis. At the end of each therapy day, the study observer detached all sensors and said goodbye to patients. In total, we recorded 102 days including 738 h of motion data.

4 Motion Data Analysis Procedure

For our exploratory behaviour and trend analysis, we extracted activity primitives from the wearable sensor data. In this section, we detail our rule-based approach to derive activity primitives and the comparison with ground truth.

4.1 Activity Primitive Extraction

We considered activity primitives for sit, stand, walk, and motions of the affected and non-affected arms and legs. Table 2 provides an overview on all activity primitives extracted.

Activity primitives were extracted from the accelerometer sensor data (wrist and upper leg sensors) by applying logic rules. Initially, time-domain features *mean* and *variance* were calculated from acceleration data, using 1 s windows. Subsequently, we applied a median filter to remove signal outliers. We derived the duration of each activity primitive to explore the motion behaviour and trends.

Table 2. Activity primitives considered for our analysis. For each activity primitive, logic operations (NOT (!), AND (&), Or (|)) were applied to acceleration sensor features (*mean* and *variance*). Sensor positions: RA (right arm), LA (left arm), RL (right leg), LL (left leg). Sensor axes: x,y, and z. Body sides: A = affected side, NA = non-affected side. Here AP1, AP2, and AP3 describe rules applied to RL.

Activity primitive	Description of AP	Rules applied to extracted sensor data features
AP1	Sit	$RLaccy - RLaccz <= 0$
AP2	Stand	$RLaccy - RLaccz > 0$
AP3	Walk	$RLaccy - RLaccz > 0$ & $RLaccy_{var} > threshold$
AP4	Arm (A)	$!RA$ & LA *or* RA & $!LA$ on acc_{xyz}
AP5	Arm (NA)	$!RA$ & LA *or* RL & $!LL$ on acc_{xyz}
AP6	Leg (A)	$!RL$ &LL *or* RL & $!LL$ on acc_{xyz}
AP7	Leg (NA)	$!RL$ & LL *or* RL & $!LL$ on acc_{xyz}

4.2 Ground Truth Overlay

During the study at the day-care centre, study observers accompanied the patient on selected days to annotate activities. The annotation was not always possible, e.g., when only one observer was present while two or even three patients were recorded at the same day. Annotations were reviewed and revised where necessary after completion of the recording day to derive a ground truth for further analyses.

While our rule-based approach required setting thresholds, the threshold values were kept unchanged across all patients. Thus, the logic rules could be used independently of a patient and provide a basis for repeatable experiments. Thresholds were determined by visual inspection of motion acceleration data representations at each body part.

To inspect the extracted activity primitives, we divided the recording day into an hourly scale and compared primitives detection to the available ground truth. Figure 2 shows an example plot for the "Walk" activity primitive of one participant across eight recording days. Where available, we illustrated the ground truth and plotted the acceleration sensor variance for a leg.

5 Exploratory Results

5.1 Daily Analysis

Figure 2 shows the activity primitive "Walk" over the course of a day for Patient 2. Besides the ground truth, the walking moments detected using the logic rules, and the motion signals variance are shown. The illustration reveals the patient's mobility across the day regarding daytime and duration. Moreover, we concluded from the analysed data that the walking detection resembles well with the leg motion variance.

5.2 Difference Analysis

Differences between patients' motion duration are shown in Fig. 3 for all activity primitives. The activity primitives durations were normalised by deriving the ratio of the activity primitive duration per day divided by the corresponding recording time the day ($t_{norm} = \frac{t_{activity}}{t_{recduration}}$).

The boxplots represent then a comparison of the activity primitives for affected and non-affected body sides, sit to stand, and sit to walk. As Fig. 3 shows, the movement duration of the non-affected arm was longer than the duration of the affected arm, for all patients except for Patient 4. The "Leg" comparison plot shows the duration of the affected and the non-affected activity primitives. Similar to the comparison of the arm motion, we observed a lower activity duration of the affected leg compared with the non-affected leg.

Figure 3 furthermore shows "Sit" and "Stand" durations. The differences in the sit and stand durations could be an indication of the patients' ability to move. The duration varies more for Patient 1, 3, 4, 5, 7, and 10, than for Patients 2, 6, 8, and 9. Patient 11 is the only one, where the duration for standing was higher then the duration of sit.

We moreover compared the average motion duration of "Sit" and "Walk" of each patient during the rehabilitation at the day-care centre. "Sit" and "Walk" were highly correlated activity primitives ($r_{Pearson} = -0.806$), however the average duration of "Sit" is significantly higher than the average duration of "Walk" ($\rho = 0.0027$).

5.3 Trend Analysis

To further describe patient behaviour and analyse its relation to the recovery process, we investigated trends in in activity primitives. In Fig. 4 the normalised durations of the activity primitives describing motion of the affected and non-affected arms are illustrated. In addition to trend lines of the affected and non-affected arms, we calculated the ratio of the arm motion durations $R = \frac{affected}{non-affected}$. Figure 4 shows the computed ratio too. From the arm motion example, we observed a positive trend of the motion ratio of affected to non-affected body side for Patients 1, 2, 5, 6, 9, and 10. Negative ratio trends were observed for Patient 3, 4, 7, 8, and 11.

We calculated the first order polynomial fit coefficients (slope and offset of the trend line) of the activity primitive duration ratios for each patient. In Fig. 5 the calculated slope coefficients are illustrated as bars, indicating trends of the individual patient. For the trends of the arm motion (top left), sit/stand (bottom left), we observed a balanced between patients. Positive and negative trends occur almost evenly distributed among the patients. However, the leg movement ratio (eight positive and three negative) and the sit/walk ratio (two positive and seven negative) indicate clearer trend separability.

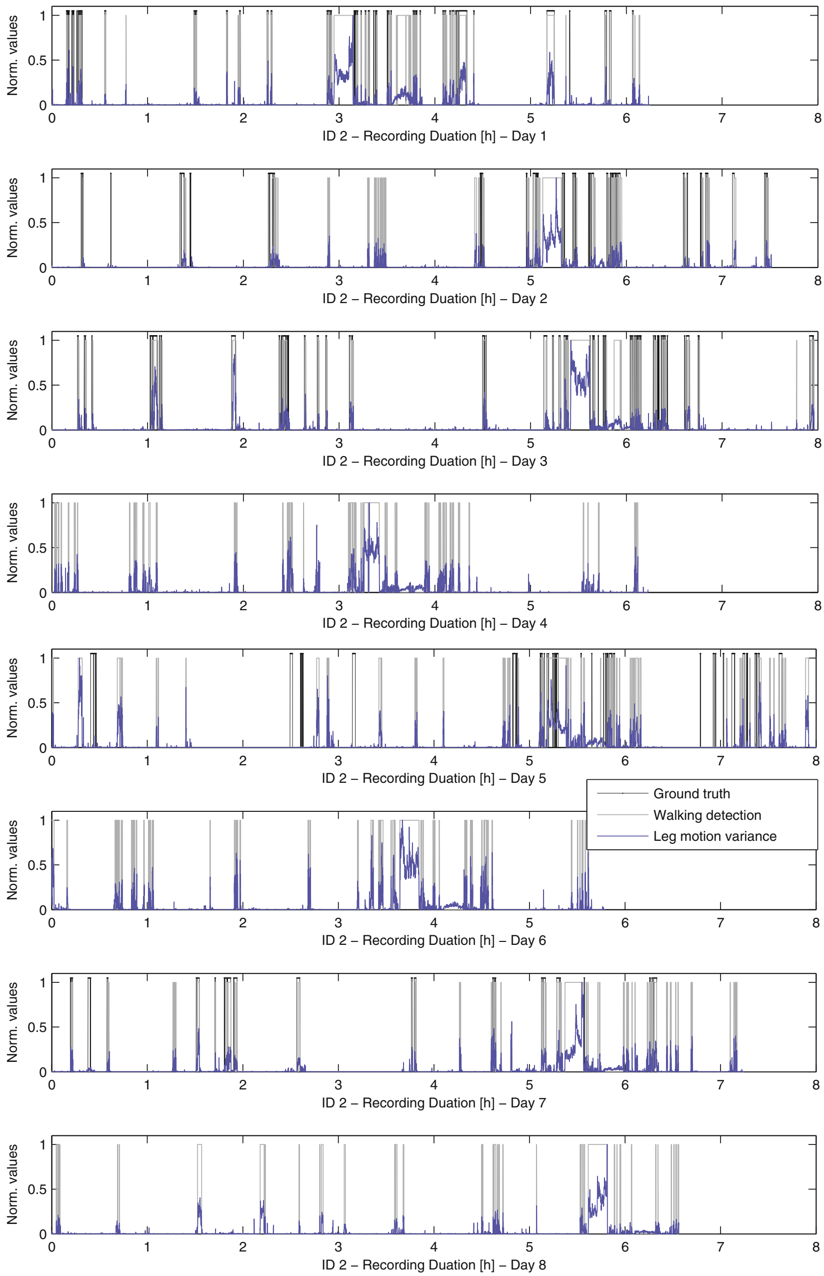

Fig. 2. Walking behaviour pattern for Patient 2 during the rehabilitation at the day-care centre. The ground truth was available at days 1, 2, 3, 5, and 7. Variance of the affected leg acceleration signal is illustrated. Variance over a thresholds was considered to be walking.

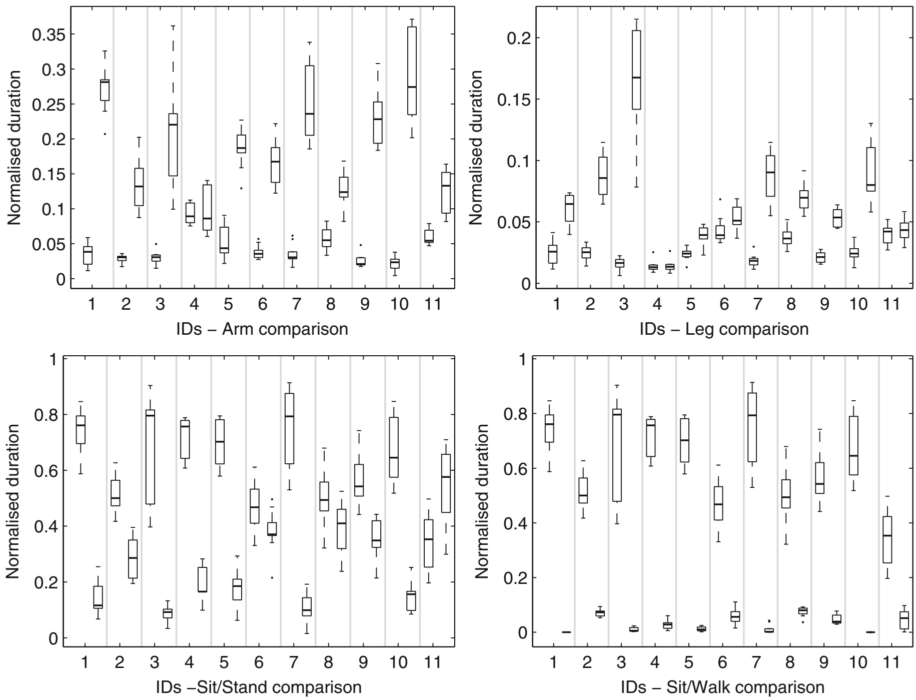

Fig. 3. Activity primitives "Sit", "Stand", "Walk", as well as arm and leg motion of the affected and non-affected side for each patient. The boxplots indicate the normalised durations of each activity primitive detection during the rehabilitation at the day-care centre. The activity primitives are considered here to describe the patients' motion behaviour.

6 Discussion

Combining context information (e.g. therapy schedule, therapy type, and expert knowledge) with wearable sensor data could provide information beyond the possible observation by therapists, thus applicable in unsupervised environments (e.g. at home). The present work is a step towards unsupervised monitoring, where the emphasis is on generic activity representation, instead of abstract daily routines. We investigated the motion patterns under the hypothesis that a patient's motor development should be observable in basic motion and trends across a rehabilitation stay. Our analysis results partially confirm the assumed positive trends, however do show negative trends too.

It is clear that the motion variability between stroke survivors is large due to various confounding factors that could not be completely assessed in the presented study. It is nevertheless interesting to observe that the generic rules to extract activity primitives and the duration analysis confirm clear trends, either positive or negative. The implementation of linear regression models for trend exploration was motivated by the limited amount of observations available.

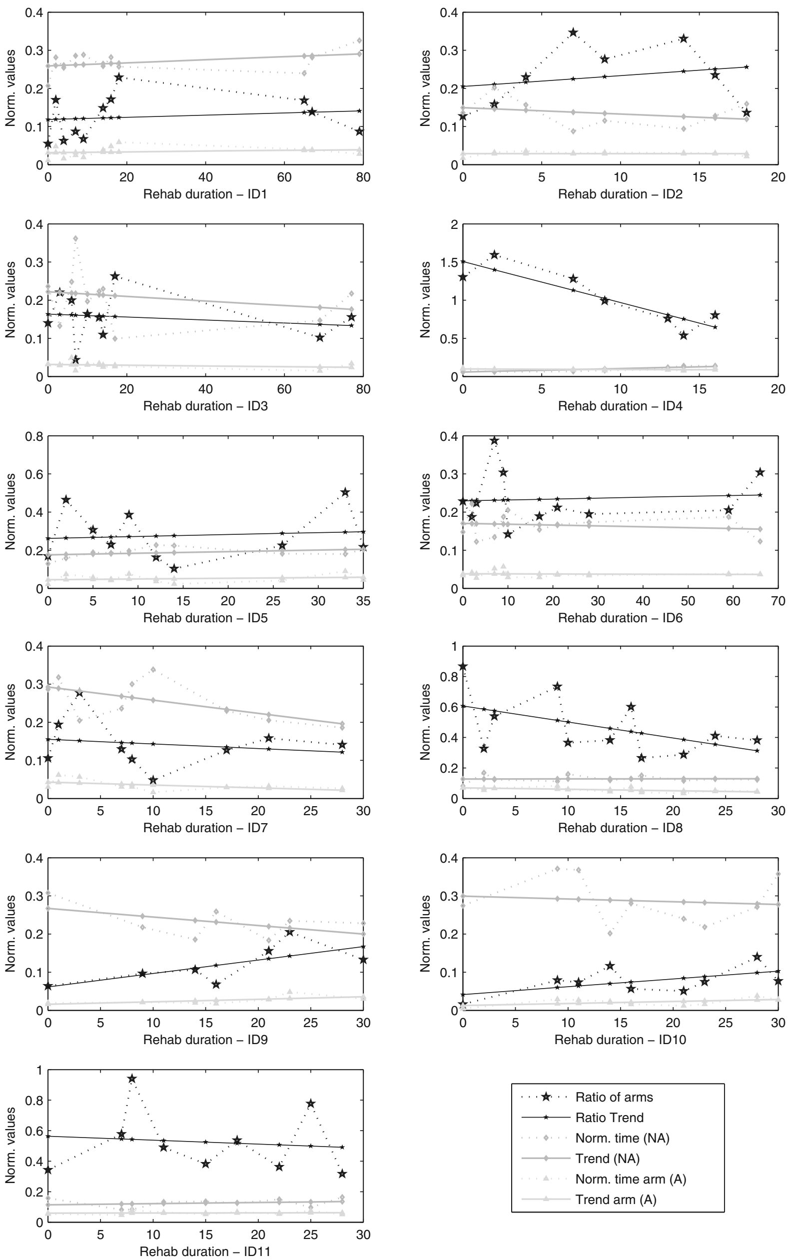

Fig. 4. Arm motion duration of the affected (A) and non-affected arm (NA) of each patient. In addition, a ratio of the arm motion duration and trends are plotted against the rehabilitation stay at day-care centre. The used marker indicate recording days. The vertical axis represent the normalised arm motion duration. Normalisation was done again by total daily recording duration.

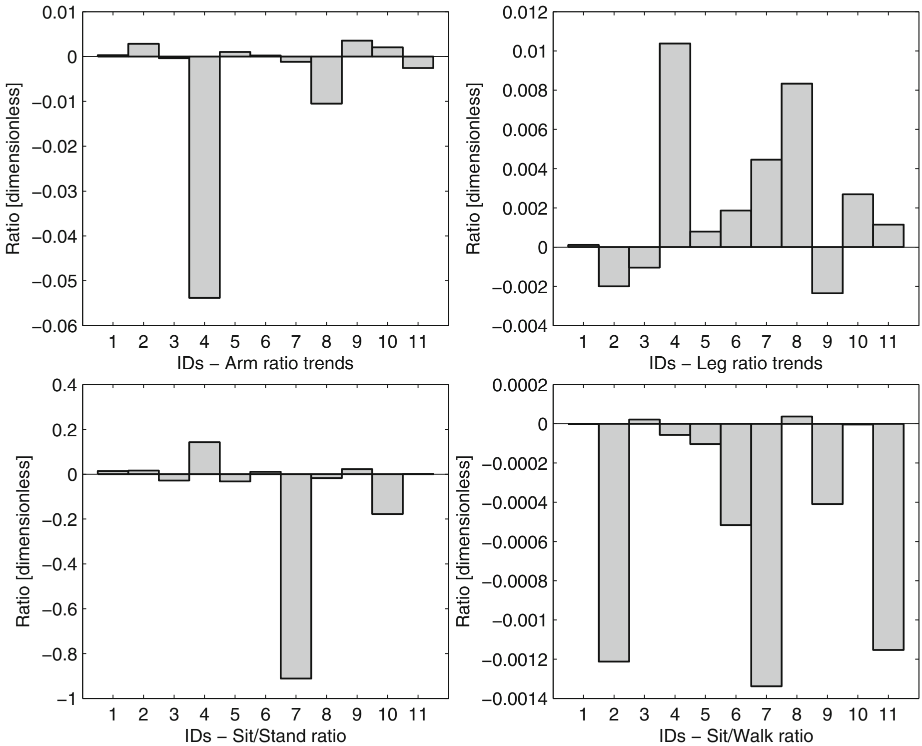

Fig. 5. Slope coefficients of the activity primitive duration ratios. The bar charts illustrate trends of each patient. Wide variations can be observed between patients and considered activity primitives. For the arm ratio trends, 6 out of 11 patients showed an upward trend. For the leg ratio, 8 show an upward trend. For sit to stand ratio, 6 patient show an upward trend and for sit to walk ratio, 2 patients show an upward trend. Both patients showing the upward trend in the sit to walk analysis were wheelchair users. For Patient 1 (w'chair user) no walking was indicated by the detection rules.

Although a big dataset including 102 days was recorded, the patient variability is large and prohibitive to pooling patient data.

Context information could add beneficial information to interpret individual behaviour. By extending the inertial sensor set with light, temperature, vital signs, or acoustic sensors, a patient's situation could be better interpreted. Light and temperature sensors provide information about location (e.g. in the house or outside), microphones could indicate leisure behaviour (e.g. watching TV or listening to music), and optical wrist worn sensor could monitor heart rate variability. The fusion of different modalities might also decrease the amount of sensors required to extract relevant context information.

We received positive feedback from the participants of the clinical study in the day-care centre. In informal conversations, patients did not complain regarding the wearing comfort of the sensors. Thus we assume that a similar sensor set-up could be successfully applied in fully unsupervised monitoring too. Our experience in the day-care centre and from conversations with patients suggest that an easy and quickly attachable, waterproofed, and unobtrusive set of sensors are important requirements for long-term, power optimised, recordings.

7 Conclusion

In this work, we explored patient behaviour represented as motion patterns. We modelled motion patterns in activity primitives and analysed trends and variation of the activity primitives among study participants. Our rule based data extraction is beneficial to understand individual patients, thus provide information to evaluate the patients' motion behaviour.

We conclude that our generic rule-based activity primitive extraction from wearable sensor data has the potential to interpret stroke patients' behaviour and recovery trends. Our approach is also applicable for the elderly, thus an alternative to ambient sensors or vision systems used in home environments. Our activity primitive detection rules were implemented to derive basic motion patterns including sit, stand, and walk, thus apply in the same way to fully unsupervised monitoring applications with a low number of wearable sensors.

8 Further Work

In further work we aim to describe patients' behaviour in even more detail by using postures and orientations calculated from IMUs. Orientation and posture information of extremities could permit us a description of range of motions (e.g. to assess reaching tasks) or to estimate angles between extremities (e.g. lower and upper arm). Quantified information are required to compare the affected and non-affected body side, to identify compensation strategies, and could be used to tailor rehabilitation exercises to individual patients. In further research, we furthermore aim to reduce the amount of sensors or integrate them, e.g. in garments, which decreases the burden on wearers.

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