Estimating Physical Ability of Stroke Patients without Specific Tests

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ABSTRACT

We estimate the Extended Barthel Index (EBI) in patients after stroke using inertial sensor measurements acquired during daily activity, rather than specific assessments. The EBI is a standard clinical assessment showing patient independence in handling everyday tasks. Our work aims at providing a continuous ability estimate for patients and therapists that could be used without expert supervision. We extract nine activity primitives (AP), including sitting, standing, transition, etc. from the continuous sensor data using basic rules that do not require data-based training. Using the relative duration of activity primitives, we evaluate the EBI score estimation using two regression methods: Generalised Linear Models (GLM) and Support-Vector Regression (SVR). We evaluated our approaches in full-day study recordings from 11 stroke patients with totally 102 days in ambulatory rehabilitation in a day-care centre. Our results show that EBI can be estimated from the activity primitives with approximately 12% relative error on average for all study participants using SVR. Our results indicate that EBI can be estimated in daily life activity, thus supporting patients and therapists in tracking rehab progress.

Author Keywords

Wearable sensor; Stroke; Assessment; EBI estimation

ACM Classification Keywords

I.5.m. Pattern Recognition: Miscellaneous

1. INTRODUCTION

Wearable sensor can monitor movement and assist during exercising of patients, while providing feedback to wearer and therapist [4, 5]. Body-worn sensors allow therapists to assess functional ability of patients during specific exercises or tests [2]. Eventually, the sensor-based motion analysis could supplement therapeutic assessments with measured data, speed-up repeated assessments, and provide feedback and guidance to the patient. Some lab-based studies have shown that features from wearable sensor data are related to the scores of therapeutic patient assessments (for example, for stroke patients [4]); however, most investigations considered therapist-supervised conditions and particular exercises only. Reproducing clinical tests could be difficult for patients without guidance. After returning from hospital care for a stroke or other disabling event, patients could benefit from wearable systems that could provide regular feedback. Similarly, therapists could better understand physical ability trends of patients from everyday measurements.

Assessing physical ability beyond simplistic activity intensity metrics, as pedometers provide, is a challenging topic. Typically, there is no supervision and thus no annotated data available that could help to interpret patient activities. Moreover, patients cope and recover differently and thus will likely render generalised multi-user models unreliable. Unsupervised pattern analysis and physical ability estimation has rarely been applied to patient state. Similarly, specific tests and assessments are most often used for estimating patient independence as opposed to everyday, day-long activity recordings.

In this paper, we investigate the feasibility of estimating the Extended Barthel Index (EBI) from daily activity recordings in stroke survivors using wearable motion sensors. The EBI is a standard clinical assessment that measures how independent patients can handle everyday life and is thus particularly suited for estimating patient ability trends in uncontrolled settings. Our approach builds on extracting activity primitives (AP) that frequently occur in daily life, including sitting, standing, transitions, moving affected side limbs, etc. from wearable inertial sensors. To obtain the APs, we used general rules that rely on coarse information about the sensor position and therefore do not require training or any adaptation to a recorded dataset. Our hypothesis is that the occurrence of APs in daily life reflect patient capabilities so that the patient's EBI score can be estimated from it.

In particular, this paper provides the following contributions:

1. We present our AP extraction method that does not require supervised information about a patient's behaviour. Based on features of the recorded motion sensor data from different body positions, logic rules were designed that represent basic motion and posture-related to patient activities. Subsequently, regression models were used to estimate EBI. We consider in this work Generalised Linear Models (GLM) and Support-Vector Regression (SVR).

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2. We evaluate our EBI-estimation approach in a dataset of day-long activity recordings of 11 stroke survivors for 102 recording days. Patients wore inertial motion sensors attached to wrists and thighs and followed their regular routine of daily activities at the day-care centre, including socialising, playing table games, resting, and varying therapy sessions.

2. RELATED WORK

Several approaches exist to estimate clinical scores based on wearable sensor data. Clinical assessments as the Wolf Motor Function Test (WMFT) or the Fugl-Meyer-Assessment (FMA) were used, as they focus on patients functional abilities. Since WMFT and FMA use coarse quantitative scales to assess recovery progress, their interpretation as a trend measure is limited. Wearable sensors permits fine-scaled and continuous measurements, which is beneficial for patients and therapists for determining near-term rehab goals tailored to patient needs. We focus on EBI estimation since it allows us to assess patient capability in free living as explained in Section 4. *Iosa et al.* [1] showed how upper body acceleration, gait stability and walking speed correlate with clinical scores including the original Barthel Index (BI), but no estimation algorithms were implemented. Actual estimation algorithms of clinical scores were often implemented using classification or regression techniques, where the proposed approaches mainly focus on task-subsets of the complete assessments. Classification was described in Parnandi and Mataric [3], where a Naive Bayes classifier estimated the functional ability score (FAS) based on statistical features extracted from a wrist worn inertial measurement unit (IMU) of one post-stroke participant. The authors reported a RMSE of 0.4472 compared to the therapists assessed score. *Patel et al.* [4] used classification in combination with regression to estimate the FAS from accelerometers placed on several body locations (index finger, thumb, hand, forearm, upper arm and trunk). A *Random Forest* regression algorithm estimated the total FAS from a subset of tasks for 24 stroke patients with a deviation of 2.43 points to the therapists' assessed score. A multiple linear regression method was implemented by *Knorr et al.* [2] to estimate differences across eight patients using the FMA and data from three accelerometer sensors. Results support the hypothesis that wearable sensors capture characteristics (e.g. jerk in motion) associated with functional limitations caused by stroke. Pooled regression was applied by *Strohrmann et al.* [6] to assess changes in motion capacity while performing defined motor tasks (e.g. the Nine Hole Peg Test, open and close a bottle, turn around cards, and similar). In the study, 10 defined motor tasks were weekly performed by 4 children (2 girls; 2 diagnosed with cerebral palsy and 2 with stroke, on average 10.5 years) and motion recorded with 10 full IMUs including 3-axial acceleration, gyroscope and magnetometer sensors. Features included task completion time, movement intensity variation, and the dominant frequency were extracted and compared to the clinically assessed score (mean RMSE was 0.15, mean r-correlation was 0.86). The evaluation of specific metrics to describe simulated daily-life arm movement performances related to the upper FMA part was the focus of *van Meulen et al.* [7]. The authors suggested that their metrics can be used to objectively assess the performance in a daily-life setting by a body worn sensing system. In contrast, our work aims at estimating EBI from activities performed during the day without following a strict test protocol.

3. EBI ESTIMATION APPROACH

Our approach combines rule-based unsupervised AP extraction from acceleration sensors with subsequent regression models to estimate EBIs. Here we describe the AP extraction considering wrist and upper leg sensor locations and introduce the regression methods applied.

Rule based AP extraction: APs were extracted from features of acceleration sensor data using logic rules. We extracted characteristic APs that potentially describe patients' behaviour related to rehabilitation progress. Affected and non-affected body side motion was considered separately to assess side differences specifically for hemi-paretic stroke patients. Usually patients' affected body side is paralysed and thus mostly inactive, while the non-affected side is actively used. In four APs we covered movement on affected and non-affected arms and legs. The APs *sit, stand,* and *transition* reflect patients' mobility, thus these APs serve as indicators of independence. Thresholds for the logic rules were determined by considering the basic movement representation in acceleration data at each body position and by visual inspection. Table 1 summarises all nine APs considered in this work.

Table 1. Activity primitives (AP) used in this work. Each AP is described by logic operations (NOT (!), AND (&), OR (|)), applied to acceleration sensor features (*mean, 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.

AP #	AP Description	Rules applied to extracted sensor data features
AP1	Sit	$RL_{accy} - RL_{accz} <= 0$
AP2	Stand	$RL_{accy} - RL_{accz} > 0$
AP3	Transition (sit to stand, stand to sit)	$RL_{accy} > 1 \vert RL_{accy} < -1$ & $RL_{accz} > 3 \vert RL_{accz} < -2$
AP4	Arm (A)	$!RA$ & LA or RA & $!LA$ on acc_{xyz}
AP5	Arm (NA)	$!RA$ & LA or RL & $!LL$ on acc_{xyz}
AP6	Both arm move.	RA & LA on acc_{xyz}
AP7	Leg (A)	$!RL$ &LL or RL & $!LL$ on acc_{xyz}
AP8	Leg (NA)	$!RL$ & LL or RL & $!LL$ on acc_{xyz}
AP9	Both leg move.	RL & LL on acc_{xyz}

EBI estimation: EBI were estimated using regression methods. In particular, we used Generalised Linear Models (GLM) and Support-Vector Regression (SVR). Duration of all APs were derived for each recording day and normalised by the total recording time of the recording day: $t_{Norm} = \frac{t_{primitive}}{t_{recording}}$. By normalising duration, APs become independent of recording time variations and can be compared as relative time spent for an AP across all recording days. The resulting relative AP duration for all primitives were then used as input for the regression analysis. We used a leave-one-out cross-validation method to estimate EBIs for each patient. To avoid over-fitting due to small number of observation samples (i.e. recording days), we considered a subset of five APs for the final regression model. While five APs was an arbitrary choice, the limit reflected the available data and potential correlation among APs. To evaluate the best AP combination, we applied an exhaustive search over all APs (AP1, . . . , AP9).

Table 2. Study data with anonymous patient ID, EBI at entry and resignation of the rehab period (EBI in/out), type of locomotion (W'chair/Walker), total rehab duration, and number of recorded days.

ID	EBI in/out	Type	Duration [days]	Rec [days]	ID	EBI in/out	Type	Duration [days]	Rec [days]
1	51/59	W'chair	79	11	7	56/59	W'chair	28	9
2	63/64	Walk	18	8	8	64/64	Walk	28	11
3	51/61	W'chair	77	10	9	48/48	Walk	30	7
4	60/61	Walk	16	7	10	48/57	W'chair	30	9
5	50/57	Walk	35	10	11	57/57	Walk	28	9
6	64/64	Walk	66	11					

For GLM, we used the Matlab Statistics Toolbox implementation. SVR analysis was implemented using the ISIS support vector machine toolbox. For SVR, we used a radial basis function (RBF) kernel and quadratic loss function.

4. EVALUATION

Participants: Our study included 11 patients (6 males and 5 females) between 34 and 75 years that fulfilled the inclusion criteria: stroke or brain tumour extraction with subsequent upper and/or lower extremity motor function deficits and a signed consent form. Seven patients were able to walk and four required a wheelchair. Patient details, including EBIs are listed in Table 2.

Study design: The participants visited the day-care centre (Reha Rheinfelden, Switzerland) for scheduled ambulatory therapies on 2 to 3 days per week, for up to 8 hours per day, and across 79 days, during our recording period. Patients were accompanied by study examiners, annotating activities with a smartphone app, based on an activity catalogue including the APs. After the recordings, annotations were time-synchronised with the sensor recordings time. EBI scores were determined by therapists for each patient at the beginning and end of the patients' ambulatory rehabilitation, according to the assessment guidelines. The EBI involves assessing patient behaviour while performing daily activities including drinking, grooming, and walking, with points (0 = patient needs full support, 4 = no support needed). Therapists derived a total score indicating the ability to live independently with a potential maximum of 64 points.

Data recording: Patients' movements were recorded using six Shimmer3 inertial sensors attached with velcro straps to the participants wrists, upper arms, and upper legs, as illustrated in Figure1. The sensors were set to sample at 50 Hz and stored acceleration, gyroscope, and magnetometer data to the sensor's internal SD-card. To limit complexity of the EBI estimation, we considered in this work wrist and upper leg acceleration sensors only. After arriving at the day-care centre in the morning, patients were greeted and sensors attached. Sensors were removed before patients left to return home. During the day, sensors were only temporary removed during water therapies. In total, we recorded during 102 days, 738 h of motion data.

Performance evaluation: For both algorithms (GLM and SVR) we evaluated the performance in a leave-one-out 11-fold cross-validation. In each validation fold, data for one recording day was left out of the training set and used for testing. The root-mean-square error (RMSE) was computed between the estimated and therapist-assessed EBI. For this

Figure 1. Patient at the day-care centre wearing the sensor setup while performing a drinking gesture. Sensor positions at the wrist and upper leg are indicated (S1, . . . , S4).

analysis, EBI scores were linearly distributed over recording days. Finally, resulting RMSE from all folds were averaged. In addition, we normalised RMSE by the change in EBI between entry and resignation (rRMSE) to illustrate the estimation performance on a percent metric.

$$RMSE=\sqrt{\frac{\sum_i^N \left(EBI(i)_{ref}-EBI(i)_{est}\right)^2}{N}} \qquad rRMSE=\frac{RMSE}{EBI_{max}-EBI_{min}}$$

5. RESULTS

We initially investigated the APs' relative share in the recording, thus determining how much time every patient spent for each AP. As an example, Figure 2 shows the normalised duration of the AP stand of a regular wheelchair user. From the normalised duration we could derive information about the motion behaviour and analyse differences in upper and lower extremities as well as between affected and non-affected sides. If a patient moved the affected side more frequently we would also observe an increased duration in the corresponding AP, which could potentially indicate recovery trends.

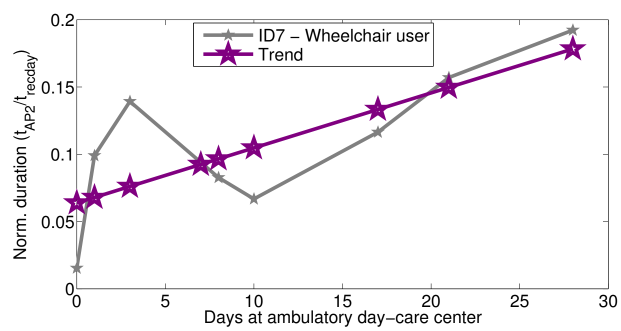

Figure 2. Stand behaviour during 28 days of rehab for patient 2. A first order regression fit illustrates the AP trend indicating the recovery process.

Feature selection: The exhaustive feature search was restricted to a maximum of 5 APs to avoid over-fitting. Figure 3 shows the selection count of all APs for the SVR algorithm with the best average performance. Here, SVR was applied for each patient and the number of selection summed. The activity primitives AP3, AP7, AP8, and AP9 were selected most often.

We investigated estimation performances in relation to the number of APs used and compared mean rRMSE between

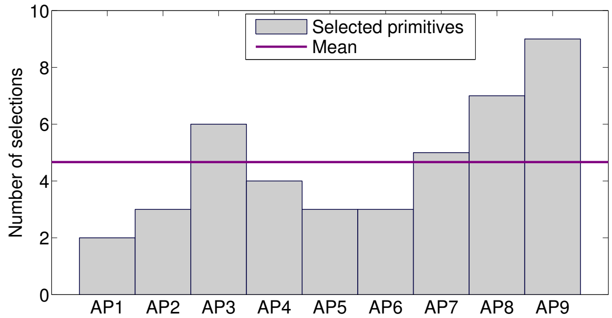

Figure 3. Selection count of the activity primitives AP1, ..., AP9. An exhaustive search was applied to select max. five APs using the SVR algorithm performance as objective function. The analysis was performed for each patient and selection results summed.

GLM and SVR. Figure 4 shows the results of a parameter sweep with a leave-one-out cross validation. A benchmark regression was derived by applying GLM on randomly selected feature values (uniformly distributed). The benchmark yielded an rRMSE of more than 25 % on average. Both, SVR and GLM perform significantly better than random chance (benchmark regression): one sided t-Test (α = 0.01), SVR (p = 0.0005) and GLM (p = 0.0014). We concluded that the acceleration data and the extracted APs provide appropriate useful information to estimate the EBI. With more than two and less than six APs, SVR outperforms GLM.

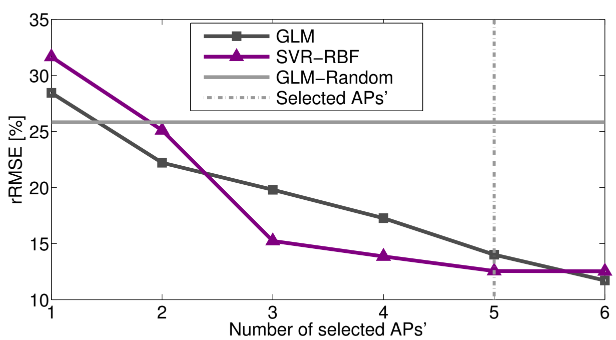

Figure 4. Parameter sweep over the number of selected APs. With two or more APs, SVR and GLM outperform the benchmark regression shown as straight line at about 25 % rRMSE. Further analysis was performed with five selected APs.

Error analysis: The RMSE and rRMSE of EBI estimations compared to the EBI assessed by therapists are summarised in Table 3. The SVR method (mean rRMSE = 12.56 %) outperformed GLM (mean rRMSE = 14.02 %). With both regression methods we observe outliers (rRMSE values above 20 %) for ID2, ID3, ID5, ID6, and ID11.

6. CONCLUSION AND FURTHER WORK

In this work we showed that rule-based AP extraction combined with regression algorithms can be used to estimate EBI. An EBI estimation from wearable sensor data is of particular interest for therapists and patients to determine and track near-term rehab goals continuously. Our result indicates that the patients' capabilities can be estimated from APs with an average RMSE below one EBI point. The error rate seems well in the range of EBI assessment variation. In further work we seek to extend the set of APs, including higher level activities like eating or drinking, to quantify motion.

Table 3. GLM and SVR performance evaluation results regarding RMSE and rRMSE for all participants with five selected APs.

ID	GLM		SVR	
	RMSE	rRMSE [%]	RMSE	rRMSE [%]
1	1.167	14.59	0.547	6.84
2	0.298	29.81	0.112	11.22
3	2.411	24.11	2.736	27.36
4	0.007	0.66	0.138	13.76
5	1.403	20.04	1.162	16.60
6	0.019	19.49	0.020	20.06
7	0.104	3.47	0.135	4.50
8	0.013	12.90	0.014	14.05
9	0.001	0.92	0.002	2.39
10	0.643	7.14	0.832	9.25
11	0.021	21.04	0.012	12.13
mean	0.553	14.02	0.519	12.56

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