Activity Routine Discovery in Stroke Rehabilitation Patients without Data Annotation

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ABSTRACT
In this work, we investigated whether activity routines of stroke rehabilitation patients can be discovered from body-worn motion sensor data and without data annotation using topic modeling. Information about the activity routines performed by stroke patients during daily life could add valuable information to personal therapy goals. As topic model input, we used a set of activity primitives derived from upper and lower extremity motion sensor data. We monitored three stroke patients during their daily life in a day care center for 8 days each within 3 weeks. We achieved up to 88% accuracy for activity routine discovery for subject-dependent evaluations. Our discovery approach seems suitable for activity routine discovery in rehabilitation patients.

Categories and Subject Descriptors
H.5.2 [Information interfaces and presentation]: Miscellaneous

General Terms
Design, Experimentation, Human Factors, Measurement

1. INTRODUCTION
Stroke is considered to be the most leading cause of disability in the world, according to the WHO. To assess the physical impairment of stroke patients therapists use motor function tests, as the Fugl-Meyer Stroke and the Chedoke-McMaster Stroke Assessment [2, 3]. However, these clinical assessments can only be applied during therapy and do not provide information on patients’ activities and daily routines in daily life. Several approaches exist to implement objective activity measurements in daily life. Patel et al. estimated the total Functional Ability Scale score of patients from acceleration data [5]. Uswatte et al. used accelerometers at the wrists to infer the activity of the impaired arm [7]. While these approaches provide quantitative scores and activity measures, they do not yield insight in the type of activities and daily routines that patients performed. Nevertheless monitoring patients’ behavior and activity routines outside therapy could add valuable information on describing patient lifestyle and thus defining individual therapy goals.

Activity discovery has been proposed to identify daily routines, without previously trained classifiers. However, activity routine discovery needs to deal with variations in routine performance from day to day and between persons. A commonly considered approach to activity routine discovery is to compose routines from activity primitives. Activity primitives have a fine temporal granularity and can be recognized from on-body sensor data. Huynh et al. applied topic models to discover activity routines, such as lunch and office work from activity primitives [4]. They used activity primitives including desk activity and having lunch, which were classified using a previously trained Naïve Bayes model. These activity primitives were subsequently considered as input for the topic model. Since the activity primitives required a trained classifier, annotations of actual activity performances would be needed during the classifier training. In contrast, we investigate whether the activity routines of rehabilitation patients could be discovered from activity primitives without the need of trained classifiers. Our approach is based on person-independent body posture and activity features measured at the extremities.

In this work, we investigate a topic model-based activity routine discovery in rehabilitation patients using wearable motion sensors. Our approach does not require annotations for activity primitives and routines. In particular, the contributions of this paper are the following: (1) we show that activity routines can be discovered from a set of rule-based, person-independent activity primitives that do not require trained classifiers and activity annotations. (2) We ana-
lyzed the influence of the key topic model parameters document size, number of activity topics, and the hyperparameter $\alpha$, on the activity routine discovery performance. (3) We evaluated our approach with three stroke patients who were recorded in a day care center using wearable motion sensors during 8 days within 3 weeks.

2. METHODOLOGY

For activity routine discovery, we used a layered approach as illustrated in Figure 1a. Activity primitives were derived from sensor data according to a set of rules. Subsequently, the activity primitives were used as input for topic model based activity routine discovery. Activity topic activations (probabilities) were then mapped to distinct activity routines. The study recording process and the different layers of the discovery approach are detailed in the following.

2.1 Study Recordings

In our monitoring study, we included three male stroke patients, aged 47–57 years. The patients regularly visited the day care center of the Reha Rheinfelden rehabilitation center in Switzerland. Patients suffered from hemispheric stroke resulting in either left or right upper and lower extremity impairment. Two of three patients primarily used a wheelchair but were capable of short distance walking. Patients arrived in the day care center in the morning, followed their daily therapy schedule including lunch and resting phases and went home in the evening. In the morning, 6 Shimmer3 motion sensors were attached to each wrist, upper arm and upper leg as illustrated in Figure 1b and logged acceleration, gyroscope and magnetometer data at 50 Hz. Sensors were carried during the whole day (except for temporary removal during water therapy) and detached before patients left the day care center in the evening. The study was approved by the local Ethics committee.

For recording days, activity routine annotations were extracted from the individual daily therapy schedule by assigning each therapy to one of the activity routines. Activity routines included cognitive training (covering training exercises on a computer or working sheet) socialising (active interaction with other people) motor training (therapies that involve physical motor function training exercises) medical fitness (intense physical training exercises) and rest/sleeping phases. Rest/sleeping phases were not specified in the therapy schedule but performed during breaks in the day care center. Thus, time and duration of rest/sleeping were added to the therapy schedule (hand written) by therapists and the study examinators. In total, we collected 137 hours of data, of which 100 hours were annotated. For each patient 8 days within 3 weeks were recorded. Depending on patients’ personal therapy schedule, only a subset of activity routines might be performed regularly. Table 2 shows the routines and number of repetitions recorded for each patient.

2.2 Activity Primitive Detector

In total, we derived 36 activity primitives from upper arm and lower arms and thigh-worn sensors. Activity primitives were described by binary decisions on particular arm and body postures as well as arm and leg movement as detailed in Table 1. We considered arm and leg activity including affected an non-affected extremities to be indicators for the physical activity of patients and thus relevant for activity routine discovery. We further distinguished between activity phases. In total, we collected 137 hours of data, of which 100 hours were annotated. For each patient 8 days within 3 weeks were recorded. Depending on patients’ personal therapy schedule, only a subset of activity routines might be performed regularly. Table 2 shows the routines and number of repetitions recorded for each patient.

2.3 Activity Topic Discovery and Mapping

We applied the Latent Dirichlet Allocation (LDA) topic model for activity topic discovery as suggested by [4]. In activity routine discovery the topic model is used to discover $K$ hidden activity topics in a corpus of segments. Each segment covers histograms over activity primitive sequences of a time segment $DS$ of a day. LDA assumes that for each segment $s$ there is an activity topic distributions $\theta_s$ which is derived from a Dirichlet distribution $\text{Dir}(\alpha)$ with the hyperparameter $\alpha$. While a high $\alpha$ value should favor all activity topics in a segment equally, small $\alpha$ would privilege one particular routine topic for one segment. When applying LDA to a corpus of segments a $K$-dimensional routine topic activation vector $\gamma_s$ is inferred from the activity primitive histogram of each segment $s$ based on the estimated distribution $\theta_s$. The normalized routine activation vector $\gamma_s$ describes the estimated occurrence ratio of each activity topic in a segment $s$. More detailed information on LDA can be found in [3]. As suggested by [4] the number of activity topics $K$ avail-

Table 2: Number of activity routine repetitions recorded for each patient in 8 days within 3 weeks.

<table>
<thead>
<tr>
<th></th>
<th>Patient 1</th>
<th>Patient 2</th>
<th>Patient 3</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cognitive training</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>Socialising</td>
<td>34</td>
<td>35</td>
<td>35</td>
<td>102</td>
</tr>
<tr>
<td>Motor training</td>
<td>31</td>
<td>32</td>
<td>34</td>
<td>97</td>
</tr>
<tr>
<td>Medical fitness</td>
<td>5</td>
<td>7</td>
<td>9</td>
<td>17</td>
</tr>
<tr>
<td>Rest/sleep</td>
<td>1</td>
<td>6</td>
<td>4</td>
<td>11</td>
</tr>
</tbody>
</table>

Figure 1: a) Overview of activity routine discovery approach: Activity primitives are detected from sensor data $S1$ – $S6$. Subsequently activity topics are discovered from activity primitives followed by kNN based mapping of activity topics to activity routines, b) sensor setup with affected arm left.
Table 1: Activity primitives (1)-(36) detected at the low-level activity primitive detector: The table shows feature window sizes/steps, thresholds of binary features $F_{Si}$ inferred from the 3-axis acceleration signal $acc_{xyz}$ and quaternions $(q_{Si}, q_{Sj})$ for sensors $Si, Sj \in \{S1, S2, \ldots, S6\}$ as well as detection logic for each activity primitive.

<table>
<thead>
<tr>
<th>Activity Primitives</th>
<th>Window</th>
<th>Binary Feature</th>
<th>Detection Logic</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) activity both arms, (2) activity affected arm, (3) activity non-affected arm, (4) no arm activity</td>
<td>1s/1s</td>
<td>$F = 1 \land</td>
<td>acc_{xyz}</td>
</tr>
<tr>
<td>(5) activity both legs, (6) activity affected leg, (7) activity non-affected leg, (8) no leg activity</td>
<td>1s/1s</td>
<td>$F = 1 \land</td>
<td>acc_{xyz}</td>
</tr>
<tr>
<td>Peak in low frequency band: (9) both arms, (10) affected arm, (11) non-affected arm, (12) none</td>
<td>5s/1s</td>
<td>$F = 1 \land \max{FFT(acc_{xyz})} \in [0.2, 2.5]$Hz</td>
<td>(9) $F_{S2} \land F_{S5}$, (10) $F_{S9} \land F_{S5}$, (11) $F_{S7} \land F_{S5}$, (12) $F_{S3} \land F_{S5}$</td>
</tr>
<tr>
<td>Peak in low frequency band: (13) both legs, (14) affected leg, (15) non-affected leg, (16) none</td>
<td>5s/1s</td>
<td>$F = 1 \land \max{FFT(acc_{xyz})} \in [0.2, 2.5]$Hz</td>
<td>(13) $F_{S2} \land F_{S6}$, (14) $F_{S9} \land F_{S6}$, (15) $F_{S7} \land F_{S6}$, (16) $F_{S3} \land F_{S6}$</td>
</tr>
<tr>
<td>(17) body movement, (18) no body movement</td>
<td>120s/1s</td>
<td>$F = 1 \land \max{</td>
<td>acc_{xyz}</td>
</tr>
<tr>
<td>(19) stand, (20) sit</td>
<td>1s/1s</td>
<td>$F = 1 \land \mu(</td>
<td>acc_{xyz}</td>
</tr>
<tr>
<td>Wrist orientation affected arm (21) horizontal, (22) vertical, (23)-(24) non-affected arm analogue</td>
<td>1s/1s</td>
<td>$F = 1 \land \mu(</td>
<td>acc_{xyz}</td>
</tr>
<tr>
<td>Arm posture affected arm (25) adducted, (26) 90° angle, (27) stretched, (28)-(30) non-affected arm analogue</td>
<td>1s/1s</td>
<td>$F = 1 \land \arccos(</td>
<td>q_{Si}, q_{Sj}</td>
</tr>
<tr>
<td>Lower arm orientation affected arm (31) down, (32) horizontal, (33) up, (34)-(36) non-affected arm analogue</td>
<td>1s/1s</td>
<td>$F = 1 \land \arctan2(acc_{xyz},</td>
<td>acc_{xyz}</td>
</tr>
</tbody>
</table>

Table: Activity primitives (1)-(36) detected at the low-level activity primitive detector: The table shows feature window sizes/steps, thresholds of binary features $F_{Si}$ inferred from the 3-axis acceleration signal $acc_{xyz}$ and quaternions $(q_{Si}, q_{Sj})$ for sensors $Si, Sj \in \{S1, S2, \ldots, S6\}$ as well as detection logic for each activity primitive.

4. Implementation

To evaluate the topic model we used the LDA implementation of [1], which includes an iterative optimization for topic model parameters $\alpha, \theta$ regarding model likelihood. The initial hyperparameter $\alpha$ was set to $\alpha = 0.01$ as suggested by [4]. Activity primitive segments were formed of segment size $DS$ with a segment step $DW = 0.1 \cdot DS$. We applied the Borda Count ranking method to the topic activations $\gamma_{Si}$ of all segments $s$ covering the same $DW$ time slot. We investigated subject-dependent leave-one-day-out cross-validation and subject-adapted leave-one-day-out cross-validation, which involved topic model and kNN model estimation on all patients’ data except for the left-out day. For the evaluation analysis we only evaluated activity routines counting at least 3 repetitions in the dataset resulting in 3, 4, 5 and 5 activity routines for patient 1, 2, 3 and subject-adapted analysis (Table 2). For each topic model estimation we performed 3 iterations and chose the one with the highest likelihood. As evaluation measure we used the averaged class-specific accuracy of activity routine predictions on activity routine annotations. Because of random topic model internal parameter initialization we investigated mean and standard deviation across 5 independent topic model runs. We further investigated the influence of the hyperparameter alpha on the discovery performance. Thus, we evaluated fixed alpha values beyond the suggested default setting 50/$K$ [6].

3. RESULTS

3.1 Activity Routine Discovery

Figure 2 shows the averaged class-specific accuracies for subject-dependent and subject-adapted evaluation for different segment sizes $DS$ and number of activity topics $K$. Using our layered discovery approach the activity routines of rehabilitation patients were discovered with up to 88% accuracy for patients 1 and 2 and about 75% for patient 3. The evaluation included activity routines as specified in Section 2.4. With increasing number of topics, accuracies even increased for all patients. For all patients, the highest accuracies could be achieved at a segment size of $DS = 20$ min. At comparable parameters for subject-dependent models (segment size of $DS = 20$ min and $K = 2M$) we achieved 78% accuracy for patient 1 ($K = 6$) and 3 ($K = 10$) and 88% for patient 2 ($K = 8$). Patient 2 was not using a wheelchair and the recordings showed larger variability in activity primitives across the activity routines, which could explain the overall higher accuracy obtained for this patient. We even yielded 71% accuracy for subject-adapted evaluation including all activity routine data (also routines with less than 3 repetitions per patient, Table 2).

![Figure 2: Averaged class specific accuracies and standard deviation for varying segment size $DS$ and number of activity topics $K$ for subject-dependent (patients 1, 2 and 3) and subject-adapted (all patients) evaluation.](image-url)
Figure 3: a) Confusion matrices for subject-dependent (patients 1, 2, 3) and subject-adapted (all patients) evaluation showing patient specific activity routine classes. Activity routines are clearly separable from activity primitives based on therapeutic relevant parameters, b) averaged class specific accuracies for different topic model hyperparameters $\alpha$ and number of topics $K$. The hyperparameter does not influence the discovery accuracy of the approach as variations are small and within the standard deviation of 5%.

Figure 3b shows discovery performances across different $\alpha$ values exemplary for patient 3. The parameter rarely has an influence on the accuracy as variations are small and within the accuracy’s standard deviation (Figure 2). This trend is similar for all 3 patients. Thus, routine topic activations $\gamma$ inferred from activity primitives seem to be discriminative, independent of $\alpha$. Having discriminative routine topic activations the kNN (used for mapping and performance evaluation) yields high accuracies. However, when targeting activity routine discovery favored and thus clear activated activity topics (small $\alpha$ values) per segment could make routine topic and activity routine mapping more evident. The investigation this hypothesis an alternative to kNn for performance evaluation should be analyzed in future work.

Figure 3a depicts the confusion matrices for subject-dependent and subject-adapted evaluations. Using the layered discovery approach all activity routine patterns were clearly separable for each patient. Furthermore, few confusions for the subject-adapted analysis suggest activity routine patterns to be similar across patients. The 6% decrease in averaged accuracy compared to subject-dependent analysis (Figure 2) results from increasing confusions for cognitive training and socialising. Reasons might be highly patient dependent execution of the activity routine cognitive training and few activity routine repetitions (total= 9, Table 2). Overall high accuracies show that it is possible to discover activity routines of stroke patients from sensor data using topic modeling. The topic model discovered meaningful activity routine patterns from activity primitive derived from upper and lower extremity activity and body and arm postures.

4. CONCLUSION
In this paper, we investigated activity routine discovery of rehabilitation patients from sensor data using topic modeling. We achieved accuracies between 78% and 88% for all subject-dependent evaluations when considering activity routines including socialising, cognitive training, medical fitness, motor training and rest/sleeping phases. These results indicate that our approach can be suitable for the discovery of activity routines that rehabilitation patients perform during a day in the day care center. The topic model parameter investigation showed that with increasing number of activity topics, accuracy increased for all subject. While the optimal accuracy was found for a segment size of $DS = 20$ min, the hyperparameter $\alpha$ did not influence accuracy. High discovery accuracies suggest that the activity routines show characteristic patterns regarding the derived set of activity primitives which was based on arm and leg movement as well as arm and body postures for both, affected and non-affected body side. Thus, activity routine discovery does not require complex activity primitives detected from trained classifiers. Furthermore, the subject-adapted investigation showed, that activity routine patterns seem to be highly similar across all three stroke patients. In future work, we plan to validate our approach by extending the study to more patients.

5. ACKNOWLEDGMENTS
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6. REFERENCES