Towards Real World Activity Recognition from Wearable Devices

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***Abstract*—Supporting people in everyday life, be it lifestyle improvement or health care, requires the recognition of their activities. For that purpose, researches typically focus on wearable devices to recognize physical human activities like walking whereas smart environments are commonly the base for the recognition of activities of daily living. However, in many interesting scenarios the recognition of physical activities is often insufficient whereas most smart environment works are restricted to a specific area or one single person. Moreover, the recognition of outdoor activities of daily living gets significantly less attention. In our work, we focus on a real world activity recognition scenario, thus, practical application including environmental impact. In this context, we rely on wearable devices to recognize the physical activities but want to deduce the actual task, i.e., activity of daily living by relying on background and context related information using Markov logic as a probabilistic model. This should enable that the recognition is not restricted to a specific area and that even a smart environment could be more flexible concerning the number of sensors and people. Consequently, a more complete recognition of the daily routine is possible which in turn allows to perform behavior analyses.**

I. Introduction

For more than a decade, researchers have focused on Human Activity Recognition by relying on inertial sensors and have revealed significant insights. However, many existing studies on the subject are conducted in a highly controlled environment. The recent development and expansion of smart devices like phones, glasses, watches, and bands have caused more and more researches to shift their focus from the proof of concept to real world applications. These include health care services for elders but also just lifestyle improvement. As a consequence, the shift goes along with new and undressed problems. For instance, considering machine learning based approaches, so far, researchers mainly focused on subject-specific classifiers. Hence, training and testing data belong to the same person. This is not feasible in a health care scenario, i.e., patients are often unable to collect and label required data. Besides, to assume that their physical movement behavior does never change is also a simplification. In addition, many interesting scenarios require the recognition of activities on a higher level of abstraction (e.g. taking medicine) but usually researchers focus on rather basic activities such as walking. Indeed, the recognized physical activities can be considered as low-level activities where background and context related information may enable to abstract the required higher-level activities (*sitting* vs. *eating*). However, especially the latter has got too little attention.

II. Research Issue

Our aim is to develop robust activity recognition methods based on wearable device sensors that generate high quality results in a real world setting. More precisely, we focus on supporting and observing especially elders in everyday activities where a high degree of accuracy is mandatory. In contrast to most existing works, we focus on recognizing physical human activities but also to deduce the actual performed high-level task also referred to as Activity of Daily Living (ADL). In this context, ADLs embody a fusion and interpretation of single physical human activities, also known as locomotions, related to the current environment and situation. For that purpose, we focus on the following key research issues:

1) *Physical Human Activity Recognition:* As wearable devices are not fixed to a specific on-body position and also flexibility in their movement, the research question is how to reliable recognize the physical movement in everyday life. This includes also the possibility to use labeled sensor data across people, to have a classification model immediately at hand.
2) *Activities of Daily Living:* The identification of relations between and the nature of high-level activities but also availability and coherence of context related information concerning probabilistic modeling are the subjects of research.

III. Research Summary

In the following, we summarize our works which we already published [1], [2] but also works that are under construction [3], [4]. In this context, we outline our progress over the problem and insights gained during our investigation. Due to lack of space, we also incorporate related works.

A. Physical Human Activity Recognition

As a first step, we focused on position-aware activity recognition because commonly it is up to the user where the device is carried. Researchers stated that the on-body position information is essential concerning the recognition rate but the recognition and influence of this was only limited investigated [5]. Therefore, we examined [1] its real world feasibility by considering all relevant on-body positions and common physical activities. For that purpose, we focused on a subject-specific scenario and a single accelerometer and relied on a large self-created realistic data set[1]. Considering a sliding

[1]http://sensor.informatik.uni-mannheim.de

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windows approach and a wide-range of supervised classification techniques, our results show that we were able to achieve an F-measure of 89% concerning the position recognition while this information improved the activity recognition rate by +4% (84%). Focusing on the individual on-body positions strikes that there is no best device position but it depends on the performed activity which is most suitable.

The main drawbacks of a subject-specific activity recognition approach are the collecting and labeling effort and thus that a classification model is not available at hand. As an approach to that problem, researches mainly focused on leave-one-subject-out, i.e., create a classification model on all data expect the target person [6]. However, different movement patterns of, e.g. children and elders, for the same physical activity can lead to worse recognition rates. Indeed, some works hypothesize that physical characteristics (e.g., weight) could be reliable indicators to form groups of people [6]. Thus, we investigated this hypothesis to clarify the performance and feasibility [3]. The results of our experiments showed on one hand that abstract physical characteristics of subjects enable us to build meaningful cross-subjects models where on the other hand a leave-one-subject-out model only covered the dominate behavior across all subjects. Considering the most reliable device position, the group based approach was able to achieve a recognition rate of 79%. Besides, an interesting insight was that the noise which results from the slight movements of the device (e.g., trouser pocket) was handled by a subject-specific approach because it was consistent but not across subjects.

To improve the recognition rate of a cross-subjects activity recognition model, we shifted our focus to personalization by online and active machine learning. Indeed, this idea is not new but so far researchers mainly focused on incremental learning, parameter adaption, or just retraining to personalize the model. Due to our preceding results, we focused on an online version of the random forest classifier [4]. The online mode enables to continuously update an existing model without keeping already seen data available. Further, new information can be more weighted than older, thus, current behavior is more important than older ones. In this context, we applied active learning, i.e., queried the user regarding the most uncertain classifications. Our results show that the personalized cross-subjects models achieve an F-Measure of 84% while dynamic activities which are normally of higher interest are recognized with 87%. More important, the user's effort that goes along with personalization is less than for a subject-specific approach. The benefits for the user make an application in a real situation more feasible.

B. Activities of Daily Living

So far, we have only considered rather basic activities like walking and running. Many interesting scenarios, however, require the recognition of activities on a higher level of abstraction. We expect that this will require the use of background knowledge about the nature of and relations between high level activities. Considering also context related information (e.g., location, heart rate) should enable to recognize certain activities like *going to work* or *preparing meal* but also detect abnormal behavior, e.g., lying in the kitchen. Indeed, it is not feasible to enumerate all sequences of actions but semantic relations may allow to derive complex ADLs.

As a first step, we focused on a smart-home environment where we relied on ontological and probabilistic reasoning to perform unsupervised recognition of interleaved ADLs [2]. The results of our experiments showed on one hand that a Markov logic network is a suitable way to model constraints and relations like duration, dependencies, and patterns of activities but also that an ontological model could be a promising approach to model environment-independent conditions which can be considered in the probabilistic model. On the negative side, the knowledge engineering effort that goes along with this approach can be high but manual modeling would be unfeasible in a realistic scenario. As a next step, we want to investigate once the physical activity is recognized to what extent this information can reduce the considered sensors of but also the dependency on a specific smart environment.

IV. Conclusion

Trying to recognize high level activities in a more realistic open world setting will come with significant challenges both with respect to acquiring background knowledge and developing robust recognition methods. Thus, after successfully recognizing common physical human activities and personalize recognition models in a real world setting, we focus now on the feasibility to derive and recognize high level activities even outside of a smart-home environment where we want to rely on Markov Logic as a probabilistic framework. The succeeding step would be to analyze and interpret the daily routine of the user, i.e., creating a personal process model would allow to perform behavior analyses and conformance checking [7].

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