Importance of Personalized Health-Care Models: A Case Study in Activity Recognition

Article *in* Studies in Health Technology and Informatics · January 2018

Importance of personalized health-care models: a case study in activity recognition

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Abstract. Novel information and communication technologies create possibilities to change the future of health care. Ambient Assisted Living (AAL) is seen as a promising supplement of the current care models. The main goal of AAL solutions is to apply ambient intelligence technologies to enable elderly people to continue to live in their preferred environments. Applying trained models from health data is challenging because the personalized environments could differ significantly than the ones which provided training data. This paper investigates the effects on activity recognition accuracy using single accelerometer of personalized models compared to models built on general population. In addition, we propose a collaborative filtering based approach which provides balance between fully personalized models and generic models. The results show that the accuracy could be improved to 95% with fully personalized models, and up to 91.6% with collaborative filtering based models, which is significantly better than common models that exhibit accuracy of 85.1%. The collaborative filtering approach seems to provide highly personalized models with substantial accuracy, while overcoming the cold start problem that is common for fully personalized models.

Keywords. personalized health-care, activity recognition, activity of daily living, ADL

1. Introduction

The recent advances in the communication and computer technologies, have allowed the development of patient-centric pervasive environments that enable monitoring of patients in real-time and access to patient's information on demand from any location [1],[2]. The need for the development of such pervasive environments has introduced the concept of Ambient Assisted Living (AAL), which strives to improve the quality of life of patients and maintain their independence [3].

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This work was partially financed by the Faculty of Computer Science and Engineering at the Sts. Cyril and Methodius University, Skopje, Macedonia and in part by the networking activities provided by the ICT COST Action IC1303 AAPELE. We also acknowledge the support of Microsoft Azure for Research through a grant providing computational resources for this work.

One of the main challenges for AAL systems is the increased number of sensory inputs and the increased volumes of data that need to be processed. A method for detection of several activities of daily living (ADL) based on non-intrusive sensors was proposed and evaluated in [4], obtaining very high accuracy. The study presented in [5] evaluates importance of accelerometer placement for posture recognition and fall detection. Embracing the spread of smart devices with integrated accelerometers, [6] evaluates how accurately can wrist devices recognize daily activities and falls. The methods presented in [7] and in [8] facilitate automation of the process of feature extraction and selection from arbitrary time series data, and could be useful to come up with lightweight and powerful models with the least possible sensors. According to [8], such generic methods can be applied even on data that is collected under field conditions with approximately self-labeled data by participants.

However, AAL Systems should not be limited to sensory data, but should also include online data from the users, such as social networks, and also integrate data from health records and different medical devices. The integration of these multiple sources of data would enable a more comprehensive view on healthcare data [9].

In this paper we investigate the effects on activity recognition accuracy using single accelerometer of personalized models compared to models built on larger population. Inspired by [9], we evaluate the possibility to detect groups of similar patients by collaborative filtering methods for which we have historic labeled data, and then to use these models for patients for which we do not have labeled data.

2. Methods

2.1. Data processing

The data sources used for AAL systems consist of many different kinds of sensors. Given that the methodology for automated feature engineering and selection proposed [7] and [8] have been proven to work even under field conditions with multiple devices, we have also applied it for the feature engineering and selection in this paper.

2.2. Generic models

The generic models use all available labeled data from other users, excluding the data of the users on which the model is evaluated. For this purpose, we have used leave-one-subject-out cross-validation, as the most common method for activity recognition with small number of subjects [6].

2.3. Personalized models

In contrast to generic models, personal models use historic data from the same user from an earlier time period to learn from, and then newer data for evaluation. This allows building of a separate prediction model for each user. The main challenge with such models is deployment on new users for which there is no historic labeled data, *i.e.* cold start problem.

2.4. Collaborative filtering models

These models use collaborative filtering to find similar users for which a common model is built and then applied for new users. Note that, for new users the labelled data is not required because using various metrics with the unlabeled data, such as correlation, clustering, etc., a cluster or group of similar users can be determined. Consequently, the model of the group is used for classifying actions of new users of the same group. In real integrated systems where all historic electronic health records are available, similarity between users can be determined using various demographics, such as: age, gender, health state, disease history, *etc*. However, to the best of our knowledge there are no publicly available datasets that have both EHR and activity recognition data, *e.g.* from accelerometers.

Therefore, in this study we have used a clustering approach based on the accelerometer data. Similar to the approach presented in [10], we calculate various descriptive statistics from time and frequency domain (after computing FFT) from the first 10 minutes of recording for each user. Then, we cluster the data from all other users except from the user on which we are evaluating (*i.e.* leave-one-subject out) into 3 clusters, which we think is reasonable number considering that there are only 15 subjects in total. For each user, once his cluster is determined, the classification model for his cluster is used to recognize the activities.

3. Case study

To evaluate the proposed methodology, we have used a publicly available dataset for activity recognition, which is extensively described in [11] and [12]. We have selected this particular dataset because the actions that are analyzed are realistic and important in an AAL application. Additionally, what is interesting about this dataset is that using only one accelerometer some actions can be recognized with over 94% accuracy. The best accuracy obtained for the three approaches is listed as follows: **personal models 94.9%, collaborative filtering-based models: 91.4% and generic models: 85.1%.**

The performance of the personal and generic models is in line with the findings of the original study [12], albeit our approach uses generic framework for feature engineering and selection [7] and [8] that yielded merely 20 features, as opposed to their specialized approach for this dataset. However, the main benefit is using a collaborative filtering approach that makes it possible to apply the model on new users without significant degradation of performance compared to the fully personal models.

Table 1. Confusion matrix of Random Forest with 1000 trees, where each value is the percentage of all instances and all values add up to 100%, based on collaborative filtering. Total accuracy 91.6% (sum of all values in the diagonal).

	Predicted				
Actual	**WorkPC**	**Stand**	**Walk**	**Stairs**	**StandTalk**
WorkPC	27.8%	0.7%	0.2%	0.0%	0.9%
Stand	0.3%	4.8%	1.0%	0.3%	1.9%
Walk	0.0%	0.5%	20.3%	0.2%	0.1%
Stairs	0.0%	0.4%	0.3%	1.6%	0.0%
StandTalk	0.1%	1.4%	0.2%	0.0%	37.1%

In order to evaluate the class discernibility, we have analyzed the confusion matrices of the classifiers based on collaborative filtering. As the dataset is highly unbalanced, it is expected that for the less frequent classes the performance to be worse, as shown in Table 1.

4. Conclusion

This paper investigated the effects on activity recognition accuracy using single accelerometer of personalized models compared to models built on general population. We evaluated the feasibility of detecting similar users by collaborative filtering methods for which we have historic labeled data, and then using these models for new users. We have shown that generic models can achieve an accuracy of about 85%, whereas personal models built only on user's own historic data can have an accuracy of about 95%. The proposed collaborative filtering method, which first determines the groups of users similar to the current user and then uses their data to build prediction model for the current user, yielded accuracy of about 91.6%. This increase of accuracy over the general models is substantial. This seems as a promising research direction, especially as more and more initiatives are active for utilizing EHR for machine-learning based processing.

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