Generalized approach to prolonging of autonomous living of elderly with semantic ambient media

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Abstract. This paper is presenting generalized approach to detection of health problems and falls of the elderly for the purpose of prolonging autonomous living of elderly using semantic ambient media. The movement of the user is captured with the motion capture system, which consists of the tags attached to the body, whose coordinates are acquired by the sensors situated in the apartment. Output time-series of coordinates are modeled with the proposed data mining approach in order to recognize the specific health problem or fall. The approach is general in a sense that it uses k-nearest neighbor algorithm and dynamic time warping with time-series of all measurable joint angles for the attributes instead of the more specific approach with medically defined attributes. It is two-step approach; in the first step it classifies person's activities into five activities including different types of falls. In the second step it classifies walking patterns into five different health states; one healthy and four unhealthy. Even though the new approach is more general and can be used to differentiate also from other types of activities or health problems, it achieves very high classification accuracies, similar to the more specific approach.

Keywords: Health problems detection, gait, machine learning, ambient media.

1 Introduction

The amount of elderly in the developed country is large and is increasing. Consequently the active population's capacity for taking care of its elderly members is decreasing [1].

We propose generalized approach to an intelligent and ubiquitous care system based on semantic ambient media for monitoring elderly in order to recognize a few of the most common and important health problems of the elderly, which can be detected by observing and analyzing the characteristics of their movement. It is two-step approach; in the first step it classifies person's activities into five activities including different types of falls. In the second step it classifies walking patterns into five different health states; one healthy and four unhealthy. The activities are: fall, unconscious fall, walking, standing/sitting, lying down/lying. Types of unhealthy walking are: hemiplegia (usually the result of stroke), Parkinson's disease, pain in the leg and pain in the back. The movement of the user is captured with the motion capture system, which consists of the tags attached to the body, whose coordinates are acquired by the sensors situated in the apartment. Output time-series of coordinates are modeled with the proposed data mining approach in order to recognize the specific health problem.

In the related work, motion capturing is usually done with inertial sensors [2, 5], computer vision and also with specific sensor for measurement of angle of joint deflection [3] or with electromyography [4]. For our study, the (infra-red) IR camera system with tags attached to the body [8] was used.

We do not address only the recognition of activities of daily living such as walking, sitting, lying, etc. and detection of falling, which has already been addressed [6, 10], but also recognition of health problems based on motion data.

Using similar motion capture system as in our approach the automatic distinguishing between health problems such as hemiplegia and diplegia is presented [9]. However, much more common approach to recognition of health problems is capturing of movement which is later examined by medical experts by hand [3, 7, 11]. Such approach has major drawback in comparison to ours, because it needs constant observation from the medical professionals.

The study [12] recognizes between the same five health states as presented paper but it is much more specific due to usage of 13 medically defined attributes.

2 Methods and experiments

In our experimental work we focused on analyzing the classification accuracies of model, built using the k-nearest neighbor machine learning algorithm and dynamic time warping for the similarity measure. The experimental classification accuracies were obtained using leave-one-out validation.

Table 1. Confusion matrix of k-nearest neighbor classifier, where F=fall, UF=unconscious fall, W=walking, SS=standing/sitting, L=lying down/lying. Numbers denote quantity of the classified examples.

		classified as				
		F	**UF**	**W**	**SS**	**L**
true class	**F**	30	0	0	0	0
	UF	0	30	0	0	0
	W	1	0	124	0	0
	SS	0	0	0	24	1
	L	0	3	1	0	26

The 10-fold cross-validation for 5-nearest neighbor classifier resulted in classification accuracy of 97.5 % and 97.6 % for activities and health problems, respectively.

Table 1 shows the confusion matrices, i.e. how many examples of a certain true class (in rows) are classified in one of possible five classes (in columns).

Table 2. Confusion matrix of k-nearest neighbor classifier, where H=hemiplegia, L=pain in the leg, N=normal (healthy) walking, P=Parkinson's disease and B=Pain in the back. Numbers denote quantity of the classified examples.

		classified as				
		H	**L**	**N**	**P**	**B**
true class	**H**	42	2	1	0	0
	L	0	25	0	0	0
	N	1	0	24	0	0
	P	0	0	0	25	0
	B	0	0	0	0	21

For the real world cases, we can use confusion matrices for three purposes:

- We can observe how many false positives (false alarms) can be expected using these classifiers. When in real world use the system would report false alarm, e.g., normal walking is classified as some health problem, ambulance could drive to pick up the elderly which would cause unnecessary costs
- We can see how many false negatives can be expected using these classifiers. False negatives could mean potentially risky situation for the elderly, as his/her health problem would not be recognized automatically
- We can identify between which health states (classes) the errors (misclassifications) occurs. Consequently, we can add additional features to help distinguish between those particular classes. The misclassifications happened very rarely.

The results show that in the proposed approach false positives/negatives are very rare, i.e., they would not cause much unnecessary ambulance costs. Since the method accurately classified most true health problems, it represents high confidence and safety for the potential use in elderly care.

3 Conclusion

This paper presented generalized approach to detecting of health problems and falls of the elderly for the purpose of prolonging autonomous living of elderly using semantic ambient media. It is general in a sense that it does not use specific medically inspired attributes but general approach of combined k-nearest neighbor algorithm with dynamic time warping. It is two-step approach; in first step it classifies person's activities into five activities including different types of falls. In the second step it classifies walking patterns into five different health states; one healthy and four unhealthy. Even though the new approach is more general and can be used also to classify other types of activities or health problems, it still achieves high classification accuracies, similar to the more specific approach.

Acknowledgements. Operation leading to this paper is partially financed by the European Union, European Social Fund. Author thanks Martin Tomšič, Bojan Nemec and Leon Žlajpah for their help with data acquisition, Anton Gradišek for lending his medical expertise and Blaž Strle for the discussion.

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