Recognition of Patterns of Health Problems and Falls in the Elderly Using Data Mining

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Abstract. We present a generalized data mining approach to the detection of health problems and falls in the elderly for the purpose of prolonging their autonomous living. The input for the data mining algorithm is the output of the motion-capture system. The approach is general since it uses a k-nearest-neighbor algorithm and dynamic time warping with the time series of all the measurable joint angles for the attributes instead of a more specific approach with medically defined attributes. Even though the presented approach is more general and can be used to differentiate other types of activities or health problems, it achieves very high classification accuracies, similar to the more specific approaches described in the literature.

Keywords: health problems, activities, falls, elderly, machine learning, data mining.

1 Introduction

The number of elderly people in the developed countries is increasing [19], and they tend to lead isolated lives away from their offspring. In many cases they fear being unable to obtain help if they are injured or ill. In recent decades this fear has resulted in research attempts to find assistive technologies to make the living of elderly people easier and more independent. The aim of this study is to provide ambient assistive-living services to improve the quality of life of older adults living at home.

We propose a generalized approach to an intelligent care system to recognize a few of the most common and important health problems in the elderly, which can be detected by observing and analyzing the characteristics of their movement.

It is a two-step approach as shown in Figure 1. In the first step it classifies the person's activities into five activities, including two types of falls. These are: fall (F), unconscious fall (UF), walking (W), standing/sitting (SS), lying down/lying (L). In the second step it classifies classified walking instances from the first step into five different health states: one healthy (N) and four unhealthy. The types of abnormal health states are: hemiplegia (H), Parkinson's disease (P), pain in the leg (L), pain in the back (B).

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The movement of the user is captured with a motion-capture system, which consists of tags attached to the body, whose coordinates are acquired by sensors located in the apartment. The output time series of the coordinates are modeled with the proposed data-mining approach in order to recognize the specific activity or health problem. The architecture of the system is presented in Figure 1.

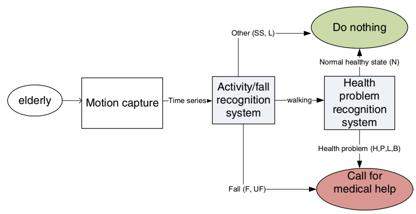

Fig. 1. Architecture of the system

In related studies the motion is normally captured with inertial sensors [18, 1], computer vision and also with a specific sensor for measuring the angle of joint deflection [15] or with electromyography [20]. In our study an infra-red (IR) sensor system with tags attached to the body [5] was used.

We do not only address the recognition of activities of daily living, such as walking, sitting, lying, etc. and the detection of falling, which has been addressed many times [3, 10], but also the recognition of health problems based on motion data.

Using a similar motion-capture system to that in our approach, the automatic distinction between health problems such as hemiplegia and diplegia is presented [9]. However, a much more common approach to the recognition of health problems is the capturing of movement that is later manually examined by medical experts [15, 4, 12]. Such an approach has a major drawback in comparison to ours, because it needs to be constantly monitored by medical professionals.

The paper [11] presented a review of assistive technologies for care of the elderly. The first technology consists of a set of alarm systems installed at people's homes. The system includes a device in the form of a mobile phone, a pendant or a chainlet that has an alarm button. They are used to alert and communicate with a control center. However, such devices are efficient only if the person recognizes the emergency and has the physical and mental capacity to press the alarm button. The second technology presented in [11] is video-monitoring. The problems of the presented solution are ethical issues, since elderly users do not want to be monitored by video [3]. Moreover, such an approach requires the constant attention of the emergency center. Miskelly [11] also presented a technology based on health monitors. The health monitor continuously monitors the pulse, skin temperature and movement. At the beginning of the system's use, the pattern for the user is learned. Afterwards, any deviations are detected and alarms are sent to the emergency center. Such a system detects collapses, faints, blackouts, etc.

Another presented technology is the group of fall detectors. They measure the accelerations of the person using tags worn around the waist or the upper chest. If the accelerations exceed a threshold during a time period, an alarm is raised and sent to the community alarm service. Bourke et al. [2] presented the acceleration data produced during the activities of daily living and when a person falls. The data was acquired by monitoring young subjects performing simulated falls. In addition, elderly people performed the activities of daily living. Then, by defining the appropriate threshold it is possible to distinguish between the accelerations during falls and the accelerations produced during the normal activities of daily living. In this way accelerometers with a threshold can be used to monitor elderly people and recognize falls. However, threshold-based algorithms produce mistakes, for instance, quickly standing up from or sitting down on a chair could result in crossing the threshold, which is erroneously recognized as a fall.

Perolle et al. [13] described an elderly-care system that consists of a mobile module worn by the user all the time that is able to locate the user, detect falls and monitor the user's activity. In addition, this device is connected to a call center, where the data is collected, analyzed, and emergency situations are managed. The mobile module is worn on a belt. It produces an alarm, provides the possibility to cancel it, shows the battery status, etc. In addition, it monitors the user activity and gives it three classifications: low, medium and high. Once a day, the data is sent to the call center for analysis.

The studies [14, 21] differentiate between the same five health states as presented in this study, but are more specific due to the use of 13 medically defined attributes. The currently presented study instead uses very general attributes of the angles between body parts, allowing the system to use the same attributes and the same classification methods for differentiating between five activities and between five health states.

The aim of this study is to realize an automatic classifier that is able to support the autonomous living of the elderly by detecting falls and health problems that are recognizable through movement. Earlier works (e.g., [7]) describe machine-learning techniques employed to analyze activities based on the static positions and recognized postures of the users. Although these kinds of approaches can leverage a wealth of machine-learning techniques, they fail to take into account the dynamics of the movement. The present work has instead the aim to recognize movements by observing the time series of the movements of the users. Better activity-recognition performance can be achieved by using pattern-matching techniques, which take into account all of the sensors' readings, in parallel, considering their time course.

2 Materials and Methods

2.1 Targeted Activities and Health Problems for Detection

The proposed system uses a two-step approach for the recognition of important situations. All the situations that we are recognizing were suggested by the collaborating medical expert on the basis of occurrence in the elderly aged over 65, the medical significance and the feasibility of their recognition from movements. Thus, in the first step we are recognizing five activities: accidental fall, unconscious fall, walking, standing/sitting, lying down/lying. We are focusing on differentiating between "accidental fall" and "unconscious fall":

- **Accidental fall:** as the name suggests it happens due to an accident. The types of accidental falls are, e.g., stumbling and slipping. If the person does not hurt him/herself after it, he/she does not need medical attention.
- **Unconscious fall:** this happens due to an illness or a short loss of consciousness. In most cases the person who falls in this way needs medical attention.

The other three activities of interest are common activities at home, also known as the activities of daily living (ADL).

In the second step we focused on four health problems and normal walking as a reference in accordance with the suggestions received from the collaborating medical expert. The following four health problems were chosen as the most appropriate [4]:

- **Parkinson's disease:** a degenerative disease of the brain (central nervous system) that often impairs motor skills, speech, and other functions. The symptoms are frequently tremor, rigidity and postural instability. The rate of the tremor is approximately 4–6 Hz. The tremor is present when the involved part(s), usually the arms or neck, are at rest. It is absent or diminished with sleep, sedation, and when performing skilled acts.
- **Hemiplegia:** is the paralysis of the arm, leg and torso on the same side of the body. It is usually the result of a stroke, although diseases affecting the spinal cord and the brain are also capable of producing this state. The paralysis hampers movement, especially walking, and can thus cause falls.
- **Pain in the leg:** resembles hemiplegia in that the step with one leg is different from the step with the other. In the elderly this usually means pain in the hip or in the knee.
- **Pain in the back:** this is similar to hemiplegia and pain in the leg in terms of the inequality of steps; however, the inequality is not as pronounced as in walking with pain in the leg.

The classification into five activities and into five health problems was made using the k-nearest-neighbor machine-learning algorithm and dynamic time warping for the similarity measure.

2.2 Attributes for Data Mining

The recordings consisted of the position coordinates for the 12 tags that were worn on the shoulders, the elbows, the wrists, the hips, the knees and the ankles, sampled at 10 Hz. The tag coordinates were acquired with a Smart IR motion-capture system with a 0.5-mm standard deviation of noise.

From the motion-capture system we obtain the position of each tag in x-y-z coordinates. Achieving the appropriate representation of the user's behavior activity was a challenging part of our research. The behavior needs to be represented by simple and general attributes, so that the classifier using these attributes will also be general and work well on behaviors that are different from those in our recordings. It is not difficult to design attributes specific to our recordings; such attributes would work well on them. However, since our recordings captured only a small part of the whole range of human behavior, overly specific attributes would likely fail on general behavior.

Considering the above mentioned, we designed attributes such as the angles between adjacent body parts: left and right shoulder angles with respect to the upper torso, left and right hip angles with respect to the lower torso, the angle (orientation) of the upper and of the lower torso, left and right elbow angles, left and right knee angles. The angles between body parts that rotate in more than one direction are expressed with quaternions.

2.3 Dynamic Time Warping

We will present dynamic time warping (DTW) as a robust technique to measure the "distance" between two time series [8]. Dynamic Time Warping aligns two time series in such a way that some distance measure is minimized (usually the Euclidean distance is used). Optimal alignment (minimum distance warp path) is obtained by allowing the assignment of multiple successive values of one time series to a single value of the other time series and therefore the DTW can also be calculated on time series of different lengths.

The time series have similar shapes, but are not aligned in time. While the Euclidean distance measure does not align the time series, the DTW does address the problem of time difference. By using DTW an optimal alignment is found among several different warp paths. This can be easily represented if two time series $A = (a_1, a_2, ..., a_n)$ and $B = (b_1, b_2, ..., b_m)$, $a_i, b_j \in R$ are arranged to form a n-by-m grid. Each grid point corresponds to an alignment between the elements $a_i \in A$ and $b_j \in B$. A warp path $W = w_1, w_2, ..., w_k, ...w_K$ is a sequence of grid points where each w_k corresponds to a point $(i, j)_k$ – the warp path W maps elements of sequences A and B.

From all possible warp paths the DTW finds the optimal one [22]:

$$DTW(A,B) = \min_W \left[\sum_{k=1}^{K} d(w_k) \right]$$

The $d(wk)$ is the distance between the elements of the time series.

The purpose of DTW is to find the minimum distance warp path between two time series. Dynamic programming can be used for this task. Instead of solving the entire problem all at once, solutions to sub-problems (sub-series) are found and used to repeatedly find the solution to a slightly larger problem. Let $DTW(A, B)$ be the distance of the optimal warp path between time series $A = (a_1, a_2, ..., a_n)$ and $B = (b_1, b_2, ..., b_m)$ and let $D(i, j) = DTW(A', B')$ be the distance of the optimal warp path between the prefixes of the time series A and B:

$$D(0,0) = 0$$
$$A' = (a_1, a_2, ..., a_i), B' = (b_1, b_2, ..., b_j)$$
$$0 \le i \le n, 0 \le j \le m$$

DTW(A, B) can be calculated using the following recursive equations:

$$D(0,0) = 0$$
$$D(i, j) = \min(D(i-1, j), D(i, j-1), D(i-1, j-1))$$
$$+d(a_i, b_j),$$

The distance between two values of the two time series (e.g. the Euclidean distance) is $d(a_i, b_j)$. The most common way of calculating *DTW(A, B)* is to construct a $n*m$ cost matrix M, where each cell corresponds to the distance of the minimum distance warp path between the prefixes of the time series *A* and *B*:

$$M(i, j) = D(i, j)$$
$$1 \le i \le n, 1 \le j \le m$$

Procedure starts by calculating all the fields with small indexes and then progressively continues to calculate the fields with higher indexes:

```
for i = 1...n
  for j = 1...m
    M(i,j) = min(M(i-1,j), M(i,j-1), M(i,j)) +
dst(ai,bj )
```

The value in the cell of a matrix *M* with the highest indexes *M(n,m)* is the distance corresponding to the minimum distance warp path. A minimum distance warp path can be obtained by following cells with the smallest values from *M(n,m)* to *M(1, 1)*.

Many attempts to speed up DTWs have been proposed [17]; these can be categorized as constraints. Constraints limit the minimum distance warp path search space by reducing the allowed warp along the time axis. The two most commonly used constraints are the Sakoe-Chiba Band [16] and Itakura Parallelogram [6].

2.4 Modification of the Algorithm for Multidimensional Classification

The DTW algorithm commonly described in the literature is suitable for aligning one-dimensional time series. This work employed a modification of the DTW, which makes it suitable for multidimensional classification.

First, each time point of the captured time series consisting of the positions of the 12 tags coming out of the motion-capture system is transformed into angle attribute space, as defined before. The classification is then performed in the transformed space.

To align an input recording with a template recording (on which the classifier was trained), we first have to compute the matrix of local distances, *d(i,j)*, in which each element *(i, j)* represents the local distance between the *i*-th time point of the template and the input at the time *j*. Let C_{js} be a generic attribute-vector element relative to a template recording, and Q_{is} be the attribute-vector element relative to a new input recording to recognize, where $1 \le s \le N$ is the considered attribute.

For the definition of distance the Euclidean distance was used, defined as follows:

$$d_{Euc} = \sqrt{\sum_{s=1}^{N} \left(C_{js} - Q_{is}\right)^2}$$

The value of the minimum global distance for the complete alignment of the DTW procedure, i.e., the final algorithm output, is found in the last column and row, *D(Tr, Tr)*. The optimal alignment can also be efficiently found by back tracing through the matrix: the alignment path starts from *D(Tr, Tr)*, then it proceeds, at each step, by selecting the cell that contains the minimum cumulative distance between those cells allowed by the alignment path constraints until *D(1, 1)* is reached.

3 Experiments and Results

The DTW algorithm attempts to stretch and compress an input time series in order to minimize a suitably chosen distance measure from a given template. We used a nearest-neighbor classifier based on this distance measure to design the algorithm as a fall detector and a disease classifier. The classification process considers one input time series, comparing it with the whole set of templates, computing the minimum global distance for each alignment and assuming that the input recording is in the same class of the template with which the alignment gives the smallest minimum global distance (analogous to instance-based learning).

The proposed algorithms were tested with the methodology and the data set described in the study. The 10-fold cross-validation for the 5-nearest-neighbor classifier resulted in a classification accuracy of 97.5 % and 97.6 % for the 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 five possible classes (in columns). The results show that in the proposed approach false positives/negatives are very rare, i.e., they would not cause many unnecessary ambulance costs. Since the method accurately classified most real health problems, it represents high confidence and safety for its potential use in the care of the elderly.

Table 1. Confusion matrices of k-nearest-neighbor classifier, where in a) F=fall, UF= unconscious fall, W=walking, SS=standing/sitting, L=lying down/lying, and in b) H=hemiplegia, L=pain in the leg, N=normal (healthy) walking, P=Parkinson's disease and B=Pain in the back. Numbers denote the 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	1	1
	SS	0	0	0	24	1
	L	0	3	1	0	26

		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

4 Conclusion

This study presented a generalized approach to the discovery of the patterns of health problems and falls in the elderly. It is general in the sense that it does not use specific medically defined attributes but the general approach of a combined k-nearest-neighbor algorithm with multidimensional dynamic time warping. It is a two-step approach. In the first step it classifies the 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 also be used to classify other types of activities or health problems, it still achieves high classification accuracies, similar to the more specific kind of approach.

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