Detecting gait-related health problems of the elderly using multidimensional dynamic time warping approach with semantic attributes

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Abstract We present a health-monitoring system based on the multidimensional dynamic time warping approach with semantic attributes for the detection of health problems in the elderly to prolong their autonomous living. The movement of the elderly user is captured with a motion-capture system that consists of body-worn tags, whose coordinates are acquired by sensors located in an apartment. The output time series of the coordinates are modeled with the proposed data-mining approach in order to recognize the specific health problem of an elderly person. This paper is an extension of our previous study, which proposed four data mining approaches to recognition of health problems, falls and activities of elderly from their motion patterns. The most successful of the four approaches is SMDTW (Multidimensional dynamic time-warping approach with semantic attributes), whose version is used and thoroughly analyzed in this paper. SMDTW is the modification of the DTW algorithm to use with the multidimensional time series with semantic attributes. To test the robustness of the SMDTW approach, this study calculates the DTW on the time series of various lengths. The semantic attributes presented here consist of the joint angles that are able to recognize many types of movement, e.g., health problems, falls and activities, in contrast to the more specific approaches with specific medically defined attributes from the literature. The k-nearest-neighbor classifier using SMDTW as a distance measure classifies movement of an elderly person into five different health states: one healthy and four unhealthy. Even though the new approach is more general and can be used to differentiate other types of activities or health problems, it achieves very high classification accuracy of 97.2%, comparable to the more specific approaches.
Keywords  Health-problems detection · Human-motion analysis · Gait analysis · Machine learning · Data mining · Temporal data mining · Time-series data mining · Human locomotion · Elderly care · Ambient assisted living · Ambient media · Ambient intelligence · Ubiquitous computing · Pervasive health

1 Introduction

The motivation for this research study is increasing rate of the elderly population in the developed countries [28]. They tend to lead isolated lives away from their offspring; however, 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 assisted-living services to improve the quality of life of older adults living at home.

An approach to an intelligent and ubiquitous 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, is presented in this paper. It classifies movement of an elderly person, captured with the motion-capture system, into five different health states: one healthy (N) and four unhealthy. The types of abnormal health states are:

- hemiplegia (usually the result of a stroke, H),
- Parkinson’s disease (P),
- pain in the leg (L),
- pain in the back (B).

This paper is an extension of our previous study [17], which proposed four data mining approaches to recognition of health problems, falls and activities of elderly from their motion patterns. The most successful of the four approaches is SMDTW (multidimensional dynamic time-warping approach with semantic attributes), whose version is intensively analyzed in this paper.

SMDTW is the modification of the DTW algorithm to use with the multidimensional time series and where the attributes are semantic and based on the medical knowledge. Moreover, it uses Sakoe-Chiba band for faster calculation of the DTW distance for the k-nearest-neighbor algorithm, which classifies walking patterns into 5 classes; i.e., into five health states.

The difference with [17] is, that in this paper only health problems are studied and only the infrared motion-capture system is used. Secondly, the leave-one-out evaluation is used as opposed to the SMDTW in [17], where the leave-one-person-out method is used. Thirdly, to test the robustness of the SMDTW approach, this study calculates the DTW on the time series of various lengths. Thus, for the dataset the original recordings of walking are used, which have lengths between 5 and 8 seconds. In the fourth place, the confusion matrix is calculated and based on it the robustness is evaluated through the number of false positives, false negatives and misclassifications. In the fifth place, the time series of two health states in the form of the calculated attributes are presented together with the discussion of the time series. Finally, the thorough discussion is provided, divided between “recognition results in comparison to the existing results in the field” and “comparison of the used motion-capture system to the new low-cost vision systems”.

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1.1 Relevance of the presented work for the semantic ambient media

Ambient-assisted living can be combined with intelligent systems into a new sub-area of semantic ambient media – *health-monitoring media* – which is the area of the presented paper. In line with the definition of media, the health-monitoring medium is a transmission tool used to deliver information (content) from a physical world to a digital world and vice versa. It uses sensors to capture data from the environment; i.e., body movement.

Then, the machine learning and data mining [10] are used to model the underlying processes that have generated the collected data. The models explain the data and they are used to recognize health problems of elderly, which is information delivered to a digital world. This information is transmitted back to a physical world through its representation to a user, i.e., presentation of the diagnosis to a medical expert.

1.2 Organization of the study

The presented study is organized as follows. Section 2 provides a review of the related work in the field, organized in the subsections. Section 3 presents implementation of the proposed system; from the system architecture, through the problem description, to the attributes and the methods used in the study. Section 4 describes the experiments and results; from the dataset to the insights into what caused misclassifications. Discussions about a) recognition results in comparison to the existing results in the field and b) comparison of the used motion-capture system to the new low-cost vision systems, are provided in Section 5. Section 6 concludes the study and provides ideas for further work.

2 Related work

The related work is split into subsections for better readability.

2.1 Motion capture

In related studies the motion is normally captured with inertial sensors [1, 25], computer vision and also with a specific sensor for measuring the angle of joint deflection [19] or with electromyography [29]. In our study an infra-red (IR) sensor system with tags attached to the body [6] was used.

2.2 Ambient intelligence systems

We do not 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, 12], but instead the recognition of health problems based on motion data, which represents bigger challenge.

The most common approach to the recognition of health problems is the capturing of movement that is manually examined by medical experts [4, 15, 19]. Such an approach has a major drawback in comparison to ours, because the movement needs to be constantly monitored by medical professionals.

Four examples of this type of approaches are illustrated in the following paragraphs; starting with [14], which presents 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 warden. When the warden is not available, the alert is sent to the 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 [14] is video-monitoring. The audio-video communication is done in real time over an ordinary telephone line. The video can be viewed on a monitor or domestic television. 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.

Rudel [20] proposed the architecture of a system that enables the control of users in their homes. It consists of three levels. The first level represents the ill people in their homes equipped with communication and measurement devices. The second level is the information and communication technology that enables the communication with the main server. The third level is the telemedicine center, including the duty operator, doctors and technical support, the center for the implementation of direct assistance at home, and the team of experts for implementing the telemedicine services. Such a system does not provide any automatic detection of unusual behavior but instead requires constant observation by the medical center.

Williams et al. [34] have shown that the ability to perform daily activities is reduced for people that have fallen several times and that this reduction can be detected using accelerometers. They tested elderly people that had not fallen and those that had fallen several times. All of them were asked to perform a predefined scenario, including sentence writing, object picking, etc. The accelerations differ significantly between the two groups of people during the test.

Significantly less common approach is a ubiquitous monitoring of an elderly at home with automatic recognition of health problems, which is also the goal of our study. The overview of this kind of approaches is started with the study of the recognition techniques for health problems such as hemiplegia and diplegia [11]. The paper proposes self-organizing maps algorithm using wavelet-transformed gait characteristics, such as walking speed and stride length, as attributes. The study of Lakany uses similar motion-capture system as our study but more tags and less noise, which makes it difficult to apply in practice. An example of the approach in [14] presented a technology based on health monitors. The health monitor is worn on the wrist and 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 of Miskelly [14] 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. [16] 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 user is located with a GPS, for when it is necessary to respond to alarms and to locate the user if he/she gets lost. The mobile module also provides bidirectional voice communication between the user and the call center in order to communicate critical information immediately.

2.3 User interfaces and interaction

Since user interfaces and interaction with the elderly are exceptionally important for the health monitoring systems, some works focused on this aspect are presented here.

Stojmenova et al. [23] presents another study, which provides call to the medical center or the relative in case of emergency without providing automatic recognition of health problems. Instead, it presents a novel design of interactive TV with the special graphical user interface for the elderly people offering to automatically remind them to take their medicines correctly and on time or to call a relative or a medical person in an emergency situation. Since the user interface was adapted for the elderly, the system is easy to use without previous training. For evaluating the interface, navigation and the general usability of the application, and hence the identification of key aspects that increase the adoption rate of assisted living applications among the target population, a methodology for a user evaluation study was designed and conducted in the paper.

Vatavu [31] proposes a novel projection system instead of the physical television, which can be used for the graphical user interface for the elderly to communicate with the physician or family members or for projecting feedback to the elderly in case of the automatically controlled rehabilitation at home. The projection can be easily manipulated through the point & click interactions, which are natural to human perception and thus easy to use for the elderly. Another work of Vatavu [30] provides enhancement to human-human interaction which can be important tool for elderly people to improve their communication with younger generations that are used to the technology. Such system also provides stress-free introduction to the modern world of technology for the elderly, who often feel fear due to lack of experience with technology. The goal of the proposed system is to allow new modalities for self-expression as well as to enhance communication by displaying personal digital content in the form of “presence bubbles”.

2.4 Comparison to the currently presented study

The studies [5, 18] 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 semantic attributes based on the medical knowledge as presented in [17], which are more general than the attributes in [5, 18]. Thus, here used attributes may be without changing used also for the recognition of falls or activities, as shown in [17].

Here presented approach is the version of the SMDTW approach from Pogorelec and Gams [17], which uses the leave-one-out method of evaluation instead of the leave-one-person-out method used in [17]. Other differences between the approach in this paper and in [17] are already listed in Section 1. The study of Lakany [11] presents a technique to detect health problems such as hemiplegia and diplegia. It utilizes self-organizing maps with wavelet-transformed gait characteristics, such as walking speed and stride length as attributes. Although it uses similar motion-capture system to the one in our study, use of more tags and less noise may cause difficulties in practical applications.

The aim of this study is to realize an automatic classifier that is able to support the autonomous living of the elderly by detecting health problems that are recognizable through
movement. Earlier works (e.g., [8]) 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 health states by observing the time series of the movements of the users. Better movement-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.

3 Implementation

3.1 Architecture of the system

The architecture of the system is shown in Fig. 1. The movement of the user is captured with an IR 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 from motion capture system are 12 three-dimensional (3D) time series of the positions of body parts. Because the time course must be considered, they form a time series of a 36D attribute vector for each time instance of the series. This time series is transformed into a time series of 28D attribute vectors, which is fed into the k-nearest-neighbor classifier with SMDTW as a similarity measure that classifies the inputs into the five health states. If one of the health problem (H - hemiplegia, P - Parkinson’s disease, L - pain in the leg, B - pain in the back) is detected, the medical center is notified to initiate the communication with the elderly and intervene as necessary.

3.2 Targeted health problems for detection

All the health states 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, we focused on four health problems and normal walking as a reference [4]:

![Fig. 1 Architecture of the system. Meaning of the used letters: N—normal (healthy) state, H—hemiplegia, P—Parkinson’s disease, L—pain in the leg, B—pain in the back](image)
• Parkinson’s disease:

This is 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 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. The rate of the tremor is approximately 4–6 Hz. Since it is not seen in otherwise similar disorders, it can be used to help make a firm diagnosis, even when the other signs are absent. The rigidity is defined as a resistance (increased muscle tone) to passive movement; it affects mostly the neck, the torso and the knees.

• Hemiplegia:

This is a paralysis of the arm, leg and torso on the same side of the body. It is typically 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.

The affected leg is swung in a semi-circle from the hip with the pelvis tilted upward. The knee is hyperextended due to inappropriate quadriceps activity. The stiff knee inhibits the advancement of the leg and deprives the patient of shock-absorbing knee flexion during weight acceptance. The outer part of the foot slides on the floor. The arm is held flexed and close to the torso with minimum swing.

The compensatory movements of a hemiplegic patient include a decrease in walking velocity with a shorter duration of stance, decreased weight bearing, and an increased swing time for the affected leg. The unaffected leg has an increased stance time.

• Pain in the leg:

This resembles hemiplegia in that the step with one leg is different from the step with the other. In the elderly this usually means a pain in the hip or in the knee.

A person with such a problem typically steps slowly on the affected leg, leans the torso laterally to the side of the affected leg, trying not to put too much weight on it, steps quickly on the unaffected leg and moves the torso back to the vertical position. Leaning the torso from the vertical position means that one shoulder is lowered in comparison to the other, and later returned to the normal position. In addition, the knee is bent when stepping on the affected leg.

• Pain in the back:

This is also similar to hemiplegia and pain in the leg in the inequality of steps; however, the inequality is not as pronounced as in hemiplegia and pain in the leg.

Like with a pain in the leg, it causes a lateral deviation of the torso, but this deviation is largely constant. In order to minimize the pain, the affected person usually supports his/her back with the arm(s).

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

3.3 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 60 Hz, as
shown in Fig. 2. The tag coordinates were acquired with a Smart IR motion-capture system [6] 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 at time t
- 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.

3.4 Dynamic time warping

Dynamic time warping (DTW) is a robust technique to measure the “distance” between two time series [9, 26]. The two time series are aligned through the minimization of some distance measure. The DTW achieves an optimal alignment (minimum distance warp path) 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, as it is shown in this paper. Figure 3 shows examples of two time series and the value alignment (matching) between them for the Euclidean distance (top) and the DTW similarity measure (bottom).

The time series in Fig. 3 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.
Many attempts to speed up DTWs have been proposed [22]; 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 [21] and Itakura Parallelogram [7].

3.5 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. The name of the modified approach is SMDTW we proposed it in [17].

Multidimensional time warping is very rarely implemented in the existing studies. One example of it is [27]; however, comparing to ours it does not use the Sakoe-Chiba Band for a faster calculation of the DTW.

In comparison to the more specific approaches such as [18], we aimed at algorithm useful for several tasks of movement recognition, e.g., for activity- or fall recognition in addition to the health-problem recognition. Therefore, we designed attributes as the angles between adjacent body parts, where the angles between body parts that rotate in more than one direction are expressed with the quaternions $q$ (four-dimensional angle representation) in comparison to the simple angles $\alpha$ (one-dimensional angle representation). The used semantic attributes, which together build a 28-dimensional (28D) attribute vector, are listed here:

- $q^t_{SL}$ and $q^t_{SR}$ … left and right shoulder angles with respect to the upper torso at the time $t$ (2*4D)
- $q^t_{HL}$ and $q^t_{HR}$ … left and right hip angles with respect to the lower torso (2*4D)
- $q^t_{TU}$ and $q^t_{TL}$ … the angle (orientation) of the upper and of the lower torso (2*4D)
- $\alpha'_{EL}, \alpha'_{ER}, \alpha'_{KL}$ and $\alpha'_{KR}$... left and right elbow angles, left and right knee angles (4*1D).

The proposed algorithm can be represented with the following instructions:

1) Select one measurement.
2) Create a time series of N-dimensional attribute vectors through calculating from the raw sensor data according to the instructions (result is a time series of a 28D vector of attribute values for each time instance of the series).
3) To align train and test time series, compute a matrix of local distances $d(i,j)$ in which each element $(i,j)$ represents the local distance between the $i$-th point of the train and $j$-th point of the test time series.
4) Let $L_{js}$ be a train attribute vector element and $T_{is}$ be a test attribute vector element, where $1 \leq s \leq N$ ($N=28$ for 28 dimensions) is the considered attribute. Calculate the local distance as:
   \[
   d_{Euc}(i, j) = \sqrt{\sum_{s=1}^{N} (L_{js} - T_{is})^2}.
   \]
5) From the matrix of local distances $d$, calculate the matrix of global distances $D$ between two time series using the Sakoe-Chiba band constraint.
6) Save the value of the minimum global distance between two time series, found in the last column and row $D(r_L, c_L)$, as the DTW value.
7) Use the DTW value for similarity measure for k-nearest neighbor classifier.
4 Experiments and results

4.1 Dataset and experiments

The dataset for the recognition of health problems using data mining [10] was collected by recording the walking patterns of 9 test subjects, of which 4 had hemiplegia (3 subjects had right and 1 had left hemiplegia) and 5 subjects who were healthy. Each subject was recorded 4–5 times. Because the test subjects with other target health problems were unavailable for the study, some of the data were acquired artificially under the supervision of an expert physician. These data were captured by recording healthy test subjects who were imitating particular health problems by following the physician's instructions. The final data set of 141 recordings consisted of recordings of walking: 25 of a normal (healthy) person, 45 with hemiplegia, 25 with Parkinson’s disease, 25 with a limp due to a pain in the leg, and 21 with a limp due to a pain in the back.

For each subject, the locations of the sensor tags were captured in a session that lasted 5–8 s. A multidimensional time series of the 36D vectors of the captured positions was transformed into a multidimensional time series of a 28D vector of attribute values for each time instance of the series. Each transformed time series was labeled with the type of the represented health state, yielding the final data on which the classifier was trained.

In Figs. 4 and 5 we can see the comparison of the recorded walking between a person with hemiplegia and a healthy person. The measurements are presented in the form of the calculated angle attributes with the following meanings corresponding to the subfigures:

1) left arm:
   a) $q.s$, $q.x$, $q.y$ and $q.z$ are the four dimensions of the quaternions of the left shoulder angles
   b) $f_i$ is the one-dimensional angle of the left elbow
2) right arm:
   a) $q.s$, $q.x$, $q.y$ and $q.z$ are the four dimensions of the quaternions of the right shoulder angles
   b) $f_i$ is the one-dimensional angle of the right elbow
3) left leg:
   a) $q.s$, $q.x$, $q.y$ and $q.z$ are the four dimensions of the quaternions of the left hip angles
   b) $f_i$ is the one-dimensional angle of the left knee
4) right leg:
   a) $q.s$, $q.x$, $q.y$ and $q.z$ are the four dimensions of the quaternions of the right hip angles
   b) $f_i$ is the one-dimensional angle of the right knee
5) upper torso:
   a) $q.s$, $q.x$, $q.y$ and $q.z$ are the four dimensions of the quaternions of the angle (orientation) of the upper torso
6) lower torso:
   a) $q.s$, $q.x$, $q.y$ and $q.z$ are the four dimensions of the quaternions of the angle (orientation) of the lower torso.

We can clearly observe the paralysis of the arm. For the hemiplegic person $f_i$ angle of the right elbow has a constant value around 1.5 in comparison to the sinusoidal shape of the
angle of the left elbow with the range from 0.2 to 0.4. In the case of healthy individual, the angles of both arms have sinusoidal shapes ranging from 0.2 to 0.4 and are symmetric. Moreover, the paralysis of the arm is evident also in the quaternions of the shoulder angles, where sinusoidal shape of both shoulders and symmetry is observable only in the case of a healthy individual.

The most evident is the paralysis of the leg in a hemiplegic patient. In the case of the healthy person, both the left and right knee angles resemble sinusoidal curve and they are symmetric with the sinus of one knee shifted for a half of the period against the other. While the left knee of the hemiplegic patient to some extent resembles sinusoidal shape, a sinusoidal pattern is not present in the case of the right knee. The reason for the paralysis of both the arm and leg on the same side is the nature of the hemiplegia, which paralyses one side of the body. The observations about the knee angles hold also for the quaternions of the hip angles. While the quaternions are not easily interpretable by human observations, they are preferred for the computer analysis since they do not suffer from singularity, as opposed to the Euler angles.

![Recorded walking pattern of a person with hemiplegia](image)

*Fig. 4* Recorded walking pattern of a person with hemiplegia
For the comparison of the hemiplegic and normal gait, angles of the lower and upper torso do not contain valuable information, but are presented here only to show all the calculated attributes. They are important for instance to differentiate these two health states from the pain in the back; however, in order to maintain the paper concise, the other figures are not shown.

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 k-nearest-neighbor classifier based on the DTW distance measure to design the algorithm as a health-problems 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).

Fig. 5 Recorded walking pattern of a healthy person
4.2 Results

The leave-one-out method of evaluation for the 5-nearest-neighbor classifier resulted in a classification accuracy of 97.2%. In other words, 97.2% of the recordings were correctly classified into one of the five health states.

For the detailed analysis of the results, confusion matrix will be used. It is presented in Table 1 and it shows how many examples of a certain true class (in rows) are classified in one of five possible classes (in columns).

For the recognition of health problems, the confusion matrix can be used for an estimation of the:

1) **False positives (false alarms):** When the system would report a false alarm in the real world, e.g., classifying the normal walking as a health problem, an ambulance would erroneously drive to pick up the elderly person, which would result in unnecessary costs. The following false positives were observed in the experiments:

   - normal walking was classified as hemiplegia in 1 out of 25 examples. False positives are shaded with green in Tables 1 and 2.

2) **False negatives:** False negatives could mean a potentially risky situation for the elderly person, as his/her health problem would not be recognized automatically. The experiments resulted in the following false negatives:

   - hemiplegia was classified as normal walking in 1 out of 45 examples. False negatives are shaded with red in Tables 1 and 2.

3) **Errors (misclassifications):** They denote a wrong classification. The following misclassifications were detected:


| true class | classified as | row sum |
|------------|--------------|---------|
| H | 93.3 | 4.4 | 2.2 | 0.0 | 0.0 | 100.0 |
| L | 0.0 | 100.0 | 0.0 | 0.0 | 0.0 | 100.0 |
| N | 4.0 | 0.0 | 96.0 | 0.0 | 0.0 | 100.0 |
| P | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 100.0 |
| B | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 100.0 |
hemiplegia was in 2 out of 45 examples erroneously classified as pain in the leg. Misclassifications are shaded with blue in Tables 1 and 2.

To be able to represent false positives/negatives and errors relative to the examples of each class, we divided each cell of each row (each row is representing one true class) of the confusion matrix from Table 1, by the sum of all examples in that row and multiplied with 100 to provide representation in per cents. The results are shown in Table 2. From Table 2 and Fig. 6 (which is a graphical representation of the confusion matrix from Table 2) it is evident that the amounts of false positives, negatives and errors are very low.

The results show that in the analyzed approach false positives are rare, i.e., the unnecessary ambulance intervention would be very unlikely. Moreover, it is observable that probability of false negatives or misclassifications is also very low, thus a health problem would be most probably differentiated from the healthy state and from the other health problems.

Consequently, the approach represents high confidence and safety for potential use in elderly care.

4.3 Insights into what causes classification errors

After reviewing the literature and discussing with the collaborating medical expert, we were informed that it is difficult to distinguish between the selected five health states, if the system is not taking enough symptoms into account. The example is differentiation between pain in the leg and hemiplegia since both are characterised by the asymmetry of the steps with left and right leg. To avoid this issue, the system must take into account also other symptoms, such as

![Fig. 6 Confusion matrix from Table 2 in a graphical form. The graphical representation in a form of 3D bars clearly illustrates the ratio between the false negatives/false positives/misclassifications and the correct classifications]
paralysis, which appears only in hemiplegia. All health problems can be also mistaken with the healthy state, if some symptoms are not expressed. Therefore the system must observe many characteristics that the probability of mistakes is decreased to minimum.

For the reason of keeping the errors at minimum, we used multidimensional dynamic time warping, where the time series from 12 tags transformed into angle attribute space, were warped in order to achieve the best classification. Thus, the most of the available information was used.

5 Discussion

5.1 Recognition results in comparison to the existing results in the field

In the presented study, 97.2% of the recordings were correctly classified into one of the five health states, which is a high rate of correct classification. Since there are not many related works automatically recognizing the health problems from the gait patterns, the comparison is rather short.

Here presented approach is a version of the SMDTW approach from Pogorelc and Gams [17], which uses the leave-one-out method of evaluation instead of the leave-one-person-out method used in [17]. The SMDTW approach in [17] achieved slightly lower classification accuracy than the one presented here, namely 96.6%. The approach in [17] uses the leave-one-person-out evaluation, which does not contain the training examples of the same person as the testing is performed on, thus resulting in slightly lower accuracy. Moreover, the dataset in [17] consists of the examples of 1 s, while the one presented here consists of the examples of the original length of the recordings (5-8 s). The study presented in [17] suggests and analyzes also three other approaches to recognizing health problems, resulting in lower accuracies; namely 63.1% for CML, 77.3% for MDTW and 95.0% for SCML. Other comparable studies are the studies [5, 18], which 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 semantic attributes of the angles between body parts, which are general enough to allow the system to use the same attributes and the same classification methods for differentiating between health states and other types of movement.

The study [18] achieved comparable classification accuracies with various classifiers; ranging from 90.1% with decision trees, through 97.2% with naive Bayes, 97.9% with support vector machines and 99.3% with random forest, to 100% with neural network and k-nearest neighbour. The work presented in [5], which used only the data acquired artificially under the supervision of an expert physician, reports classification accuracy of over 99% using support vector machines.

The automatic distinguishing between health problems such as hemiplegia and diplegia with a classification accuracy of 92.5% is presented in [11]. This was achieved with self-organizing maps, whose features were wavelet-transformed gait characteristics, such as walking speed and stride length. The study used similar motion-capture system as the approach presented in this paper but more tags and less noise, which makes it difficult to apply in real cases.

5.2 Comparison of the used motion-capture system to the new low-cost vision systems

The alternative to the motion-capture system used in this study are also inexpensive depth camera systems such as the Microsoft Kinect [13].
In the study by Stone et al. [24] Kinect was investigated for passive gait assessment in home environments. Similarly as in our work, it is used to assess risk of falling, along with detecting the early onset of illness and functional decline of elderly. The use of the Kinect for obtaining measurements of temporal and spatial gait parameters is evaluated against an existing web-camera based system, along with a Vicon marker-based motion capture system (as the Smart system we used) for ground truth. In the study, techniques for extracting gait parameters from the Kinect data are described, as well as the potential advantages of the Kinect over the web-camera system for passive, in-home gait assessment.

In comparison to our work Kinect has an advantage that no additional equipment is necessary for the user to wear. However, systems like Kinect are not accurate enough to detect the details, which separate our chosen health states.

Moreover, Kinect can also be used for enhancing interaction, e.g. interaction between elderly and physician, relatives or friends. An example of using Kinect for enhancing interaction is the study of Radu-Daniel Vatavu [32] introducing a novel concept (nomadic gestures) for reusing a set of user-defined gesture commands in the context of interacting with ambient systems. Nomadic gestures are saved on each user’s personal mobile device and are uploaded to the ambient system prior to interaction. The interface employs the users’ own sets of gestures with their own preferred function associations.

Even though the depth-camera systems like Kinect lack the accuracy to separate our chosen health states, they may separate some simpler movements as shown in the related work. Since our previous work has already shown that the SMDTW approach can be used with different motion-capture systems and for recognizing various types of movements, such as health problems, activities and falls, we can assume that the combination of Kinect and SMDTW is suitable for recognition of various movement-related data.

6 Conclusion

This study presented an ambient-assisted-living solution to the recognition of health problems in the elderly to prolong the autonomous living of the elderly using a data-mining approach.

The approach is based on the SMDTW approach, which we proposed before and consists of the k-nearest-neighbor algorithm and multidimensional dynamic time-warping. It classifies walking patterns into five different health states: one healthy and four unhealthy.

It uses semantic attributes based on the medical knowledge, but they are general enough, to be able to recognize other types of movement such as falls and activities, as shown in our previous paper. Despite the generality of attributes, it still achieves high classification accuracy of 97.2 %, similar to the more specific kind of approaches from the literature.

In future work, the system could be tested on other types of health problems or similar movements, since the proposed approach is general and should work well on them. A modification of the proposed recognition system could also be used for an automatic evaluation of the rehabilitation process (e.g., after a stroke) at home. The important problems of rapid aging of a population could be softened if the approach proposed in this paper or in related work were to be transferred into practice. More extensive group of elderly with the health problems could also be tested.
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