

Detection of Health Problems through Gait Patterns of Elderly

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Abstract. A system for automatic detection of health problems from gait patterns of elderly for the purpose of supporting their independent living is proposed in this paper. The gait of the user is captured with the motion capture system, which consists of tags attached to the body and sensors situated in the apartment. Position of the tags is acquired by the sensors and the resulting time series of position coordinates are analyzed with machine learning algorithms in order to identify the specific health problem. We propose novel features for training a machine learning classifier that classifies the user's gait into: i) normal, ii) with hemiplegia, iii) with Parkinson's disease, iv) with pain in the back and v) with pain in the leg. Results show that naive Bayes needs more tags and less noise to reach classification accuracy of 98 % than neural network for 99 %.

1 INTRODUCTION

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

Moreover, elderly want to live at their homes for as long as possible. When living alone, nobody could detect the potential health problem of the elderly. To overcome this problem, we propose system for automatic ubiquitous elderly health care, for which we developed accurate techniques for recognition of common health problems manifesting in gait of elderly. In case the system would recognize the health problem, it would automatically notify the physician and show him/her the explanation of the automatic diagnose in form of visualization of the kinematic model. Therefore, elderly would get constant health care at their homes and physicians would be less (over)occupied with work, however they would still have the possibility to confirm/reject automatic diagnose. In this case elderly would gain constant (ubiquitous) support, providing them more safety and confidence in living at their homes.

The target health problems for automatic recognition are: hemiplegia (usually the result of stroke), Parkinson's disease, pain in the leg and pain in the back. The gait of the user is captured with the motion capture system, which consists of the tags attached to the body. The position of the tags is acquired by the sensors situated in the apartment and the resulting time series of position

coordinates are analyzed with machine learning algorithms in order to recognize the specific health problem.

First objective of the research is to discover to what extent the automatic recognition of health problems with motion capture system is feasible. Second objective is to investigate the classification accuracy achievable using various numbers/placements of tags on the user's body and various amounts of noise in tag coordinates. Tag placement must achieve a trade-off between usability and technical requirements – the users prefer as few tags as possible, but too few tags cannot ensure sufficient accuracy. Both the finding regarding noise and tag placement can affect motion-capture system selection and further development and applications of care systems for elderly.

The paper is organized as follows. In Section 2 we present related work from the fields of movement recognition and sensor appliances used for the task of human behavior movement recognition. In Section 3 we propose our movement recognition system, which is based on the novel features which we describe in that section. We also define the machine learning setting, which we use for prediction of previously chosen health problems. In Section 4 we evaluate the performance of machine learning classifiers. In Section 5 we propose prototype application for the explanation of the interpreted health state. Section 6 concludes our paper and presents the potential further work in this field.

2 RELATED WORK

Motion capture. For the automatic recognition of the movement (gait) pattern, the movement must first be captured. For this purpose many types of motion capture devices exist. Widely used are inertial sensors composed of accelerometers or gyro sensors [2]-[4]. The second widely used approach uses video-image processing for the reconstruction of the human body movement [20], [23]. The third approach uses cameras in combination with tags attached to the body. Usually infra-red (IR) cameras are used and the body posture is reconstructed from the position of the retroreflective tags [12], as in our approach.

There also exist some specific measurement devices for the recognition of tremor – a symptom in Parkinson's disease, but not in hemiplegia, pain in the leg and pain in the back. Tremor can be acquired with variety of measuring approaches, including sensors for a measurement of the angle of the joint deflection in tremor-type joint movements [5] and with electromyography [6].

We did not address the recognition of the activities of daily living, such as walking, sitting, lying, etc., and the detection of falling, which has already been solved [9], [15]. We were focused on solv-

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ing a more challenging task, which is the recognition of gait-related health problems.

Recognition of health problems. In related work [10], [11], physicians and physical therapists usually diagnose health problems which manifest in gait just by manually observing the user's gait. If they cannot decide for certain diagnose easily, they can use semiautomatic approach. In this approach, they capture the movement using motion capture system and then they analyze it by manual observing the time series of the movement (such as time series of angles of legs, etc.).

They use the same procedure for pre-rehabilitation planning (e.g. physical therapy) and after- rehabilitation evaluation to calculate the difference in movement between those states. They also use some special medical tests, e.g., test for assessment of balance. However, none of those approaches can provide constant real-time observation of the elderly at home, for fast recognition of changes in movement (gait), indicating some health problem or progress in at home rehabilitation.

The example of the semiautomatic approach is also [23], where a system for long-term monitoring of the gait in Parkinson's disease is presented. The characteristics of every stride taken were acquired using a lightweight ankle-mounted sensor array that saved the data into a small pocket PC. In comparison to our approach, the described approach was meant for the monitoring of progress of Parkinson's disease for the known Parkinson's disease patient and was not used for the early automatic recognition of health problems.

The work [5] presents sensors for the measurement of the angle of joint deflection in tremor-type joint movements, which can also be used to assess Parkinson's disease. However, the sensor systems are too big and would prevent users from doing the activities of daily living if the systems were to be worn all day. Just like the system described previously it has major drawback in comparison to our approach, because the system cannot automatically recognize Parkinson's disease or any other health problem.

Using similar motion-capture system as that in our approach, the automatic distinguishing between health problems such as hemiplegia and diplegia is presented in [14]. A classification accuracy of 92.5 % was reported. This was achieved with Self-Organizing Maps, whose features were wavelet-transformed gait characteristics such as walking speed and stride length.

To present the motion recognition field more generally, also fall detection and activity recognition will be mentioned here. The works are broken down by the choice of motion capture system.

Fall detection and activity recognition using inertial sensors. Fall detection with accelerometers and gyro sensors [20] is quite common, particularly when using simple threshold algorithms [13], achieving classification accuracies close to 100 %. With a more advanced approach using the One-Class SVM machine learning algorithm whose features were accelerations, changes in acceleration etc., an accuracy of 96.7 % was reported [22].

Accelerometers can also be used for activity recognition. Five tri-axial accelerometers distinguished 30 physical activities of various intensities with an accuracy of 94.9 % with person-dependent training and 56.3 % with person-independent training [19]. This was achieved with C4.5 decision trees using various time- and frequency-domain features.

Fall detection and activity recognition from video. Fall detection and activity recognition from video are also quite common. In an example of fall detection [20], objects in the video

were first identified and then rules were applied to the aspect ratios of their bounding boxes, their horizontal and vertical gradients and angles, achieving an average accuracy of 83 %. In an example of activity recognition [23], ten states related to the activities of daily living were distinguished with an average accuracy of 74.1 %. This was achieved by first reconstructing the human body in the video and then matching its state against models defined using a specialized language.

Fall detection and activity recognition from video and tags. This work, using similar motion capture devices as ours [18], used 43 body tags sampled with 30 Hz to distinguish between seven activities related to military operations, reporting an accuracy of 76.9 %. This was achieved with the SVM machine learning algorithm whose features were the tag coordinates belonging to two postures separated by 1/3 of a second, reduced in number to 20 using Principal Component Analysis.

Another paper on activity recognition [17] used 41 body tags sampled with 120 Hz to distinguish between 21 dance gestures, reporting an accuracy of 99.3 %. The gestures were represented with Gaussian mixture models of joint angles. The high accuracy can in part be attributed to the high quality of the input data, the strictly defined gestures and the fact that testing was always done on the same dancer as the training.

Investigation of the optimal placement of motion capture devices. An important part of the research presented in this paper is the study of the impact of the placement of tags on the user's body and the amount of noise in tag coordinates on the classification accuracy. The closest work in this respect that we are aware of investigated the placement of accelerometers for fall detection [8], [13]. Their finding was that the head provides optimal accuracy, but is impractical, the wrist is not appropriate, and the waist is a good option.

3 METHODS AND MATERIALS

Targeted Health Problems. For the development of our health problem recognition system we focused on four health problems and normal walking as a reference in accordance with the suggestions received from the collaborating medical expert. The specific health problems for recognition were suggested based on the incidence in the elderly aged 65+, the medical significance and the feasibility of their recognition from the observed subjects' movements. The following four health problems were chosen as the most appropriate [10], [11]:

- Parkinson's disease,
- hemiplegia,
- pain in the leg and
- pain in the back.

Construction of the Features for Machine Learning. A physician usually diagnoses target health problems while observing a patient's gait (i.e. posture and the walking pattern). Since the gaits of patients with the observed four health problems and normal gait look similar to each other, a physician needs to pay attention to many details that need to be transformed into computable quantities. In practice, the observed five health states can be detected by the distinctive walking patterns [10], [11]. For the task of the automatic health- problem recognition we proposed and tested 13 features that are based on the tag locations, for 12 tags, placed on the shoulders, elbows, wrists, hips, knees and ankles of the elderly.

The proposed features are listed as follows:

- Absolute difference between i) average distance between right elbow and right hip and ii) average distance between right wrist and left hip.
- Average angle of the right elbow.
- Quotient between maximal angle of the left knee and maximal angle of the right knee.
- Difference between maximal and minimal angle of the right knee.
- Difference between maximal and minimal height of the left shoulder.
- Difference between maximal and minimal height of the right shoulder.
- Quotient between i) difference between maximal and minimal height of left ankle and ii) maximal and minimal height of right ankle.
- Absolute difference between i) difference between maximal and minimal speed (magnitude of velocity) of the left ankle and ii) difference between maximal and minimal speed of the right ankle.
- Absolute difference between i) average distance between right shoulder and right elbow and ii) average distance between left shoulder and right wrist.
- Average speed (magnitude of velocity) of the right wrist.
- Frequency of angle of the right elbow passing average angle of the right elbow.
- Average angle between i) vector between right shoulder and right hip and ii) vector between right shoulder and right wrist.
- Difference between average height of the right shoulder and average height of the left shoulder.

The features for the identification of the chosen four health problems were designed with the help of a medical expert. They are afterwards used for modeling using the machine learning methods.

Modeling Target Health Problems using Machine Learning.

To construct a predictive model which can be subsequently used to automatically recognize health problems in the subjects yet to be observed (our first objective from the Introduction), we employed supervised learning methods from the field of machine learning (sub-field of the artificial intelligence field). In supervised learning, a training data set of already labeled subjects (i.e. classified into one of the target five classes) is used to construct a model, which is later used to predict the class of the subjects for which we wish to detect the health problem.

Our task was therefore to classify the recordings of walking into five classes: four with selected health problems (classes *hemiplegia*, *parkinson*, *pain-leg*, *pain-back*) and one without it (*normal*).

Data for the evaluation of the proposed approach was collected by recording the gaits of test subjects with particular walking patterns, of which each subject was recorded 4-5 times. The final data set of 141 recordings consisted of:

- 25 recordings of normal walking,
- 45 recordings of walking with hemiplegia,
- 25 recordings of walking with Parkinson's disease,
- 25 recordings of walking with a limp due to a pain in the leg,
- 21 recordings of walking with a limp due to a pain in the back.

The recordings consisted of the position coordinates for the 12 tags worn on the body, sampled with 60 Hz. The tag coordinates

were acquired with Smart IR motion capture system with 0.5 mm standard deviation of noise.

For each subject, the locations of the sensor tags were recorded in a session which lasted 5-8 seconds from which a vector of 13 proposed features was computed. These learning examples were labeled with the type of the representing health problem, yielding the final data on which the classifier was trained.

4 EXPERIMENTS AND RESULTS

In our experimental work we focused on analyzing the classification accuracies of model, built using the machine learning methods. The experimental classification accuracies were obtained using stratified 10-fold cross validation.

For testing, we used and compared the following machine learning algorithms [21]:

- naïve Bayes (NB) classifier: standard probabilistic classifier, no special parameters,
- neural network (NN): three-layered perceptron with 9 neurons in the hidden layer and the backpropagation learning rule using an adaptive gradient descent.

The 10-fold cross-validation resulted in classification accuracy of 97.2 % and 100 % for naïve Bayes and neural network classifier, respectively.

Table 1. Confusion matrices of matrices of naïve Bayes (left) and neural network classifier (right), 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				
true class		H	L	N	P	B
	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

		classified as				
true class		H	L	N	P	B
	H	45	0	0	0	0
	L	0	25	0	0	0
	N	0	0	25	0	0
	P	0	0	0	25	0
	B	0	0	0	0	21

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).

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. In case of naïve Bayes, normal walking was in 1 of 25 examples erroneously classified as hemiplegia.
- 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. In case of naïve Bayes, hemiplegia was in 1 of 45 examples erroneously classified as normal walking.
- 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.

4.1 Variation of noise

To test the robustness of the approach, we added Gaussian noise with varying standard deviation (and zero mean) to the raw coordinates. The standard deviation of noise was varied from 0 mm to 50 mm in steps of 5 mm.

As a preprocessing step, a Kalman filter was used to smooth the potentially unrealistic difference between the positions of two consecutive time samples, caused by the addition of Gaussian noise to the captured positions [16]. The classification accuracies the classifiers, modeled on noisy data, are shown in Table 2.

Table 2. Classification accuracies (CA in [%]) of the naive Bayes (second row) and neural network machines classifier (third row) built on data with added noise. The table cells contain the classification accuracy and the significance level of the two-tailed paired t-test which was performed between the cross-validation folds of the initial setting (0 mm noise) and the corresponding amount of noise denoted by the table column. Dark shading denotes the experiments in which the classification accuracy significantly changed ($\alpha < 0.05$).

Noise [mm]	0	5	10	15	20	25	30	35	40	45	50
CA (NB)	97.2	97.9 $\alpha = 0.608$	98.6 $\alpha = 0.168$	97.2 $\alpha = 0.999$	95.7 $\alpha = 0.443$	95.7 $\alpha = 0.443$	96.5 $\alpha = 0.654$	95.7 $\alpha = 0.343$	93.6 $\alpha = 0.096$	92.2 $\alpha = 0.045$	92.2 $\alpha = 0.068$
CA (NN)	100.0	99.3 $\alpha = 0.343$	99.3 $\alpha = 0.343$	97.2 $\alpha = 0.037$	100.0 $\alpha = 0.999$	98.6 $\alpha = 0.168$	98.6 $\alpha = 0.168$	94.3 $\alpha = 0.022$	95.0 $\alpha = 0.045$	92.9 $\alpha = 0.064$	94.3 $\alpha = 0.011$

Table 2 shows the results of varying the amount of standard deviation of noise in the range 0 – 50 mm. The results indicate that only significant decrease in classification accuracy happened at 45 mm for naive Bayes and at 15, 35, 40 and 50 mm for support neural network. Neural network manages to retain its performance longer while increasing the data noise.

Even with the highest amount of noise added, the classification accuracies of both classifiers were much higher than the accuracy of the majority class classifier with classification accuracy of 31.9 %. Majority class classifier defines the lowest acceptable classification accuracy, which can be trivially achieved by classifying all examples into the majority class, i.e., class with the largest number of training examples. Therefore, the models are robust to the addition of the noise.

4.2 Reduction of the number of tags

Since wearing the full complement of 12 tags may be annoying to the user, we investigated ways to reduce the number of tags. We started with all 12 tags and removed them in the order that retained the largest number of the features when decreasing the number of tags by one. Consequently, the “best” tag placement for each number of the 12 tags was obtained. The classification accuracies for the best tag placements for various numbers of tags and without addition of noise are shown in Table 3.

The results show that decreasing the number of tags results in the decrease of classifier’s performance. From Table 3 we can observe that 6 is the smallest number of tags for which the performance of classifiers is insignificantly different compared to the initial setting.

For recognizing target health states, the positions of tags from the most to the least appropriate are: shoulder, wrist, elbow, hip, ankle and knee.

Table 3. The classification accuracies achieved with the best tag placements for each number of tags. The table cells contain the classification accuracy and the significance level of the two-tailed paired t-test which was performed between the initial setting (12 tags) and the corresponding number of tags. Dark shading denotes the experiments in which the classification accuracy decreased significantly ($\alpha < 0.05$).

Nr. of tags	12	11	10	9	8	7	6	5	4	3	2	1
CA (NB)	97.2	97.9 $\alpha = 0.343$	98.6 $\alpha = 0.168$	97.9 $\alpha = 0.343$	97.2 $\alpha = 0.999$	92.9 $\alpha = 0.052$	96.5 $\alpha = 0.591$	93.6 $\alpha = 0.052$	92.9 $\alpha = 0.195$	83.0 $\alpha = 0.001$	68.8 $\alpha = 0.001$	50.4 $\alpha = 0.001$
CA (NN)	100.0	98.6 $\alpha = 0.168$	99.3 $\alpha = 0.343$	99.3 $\alpha = 0.343$	99.3 $\alpha = 0.343$	97.2 $\alpha = 0.106$	99.3 $\alpha = 0.343$	93.6 $\alpha = 0.030$	88.7 $\alpha = 0.004$	80.9 $\alpha = 0.001$	68.1 $\alpha = 0.001$	44.7 $\alpha = 0.001$

4.3 Dependence of the classification accuracy on the tag placement and noise level

Besides experimenting with tag placement, for every placement we also varied the standard deviation of noise from 0 to 50 mm. Figure 1 and Figure 2 show the dependence of the classification accuracy (CA) on the tag placement and the noise level. We can observe a variation of the noise in the standard deviation from 0 to 50 mm on horizontal axis and the best tag placement for each number of tags from 12 to 1 tag on the vertical axis. Each curve of different color and shape (e.g. dotted, dashed) connects points of the particular classification accuracy.

Figure 1 illustrates that naive Bayes classifier never exceeded classification accuracy of 99 %. It (nearly) reached the classification accuracy of 98 % with 10-12 tags and 0-5 mm noise. At least 8 tags with 0-35 mm noise and precisely 6 tags with 0-40 mm noise were required to surpass the 95 % accuracy limit. At least 3 tags with 0-10 mm noise, 4 tags with 15-40 mm noise and 5 tags with 45-50 mm noise were needed to achieve the classification accuracy of over 80 %.

The neural network classifier in Figure 2 needed only 8 tags with noise 0-20 mm to reach the classification accuracy of over 99 %; however, we can observe significant decrease of accuracy for 15 mm noise. Reaching an accuracy of over 90 % was provided using 5 tags for 0-45 mm noise and 8 tags for 50 mm noise.

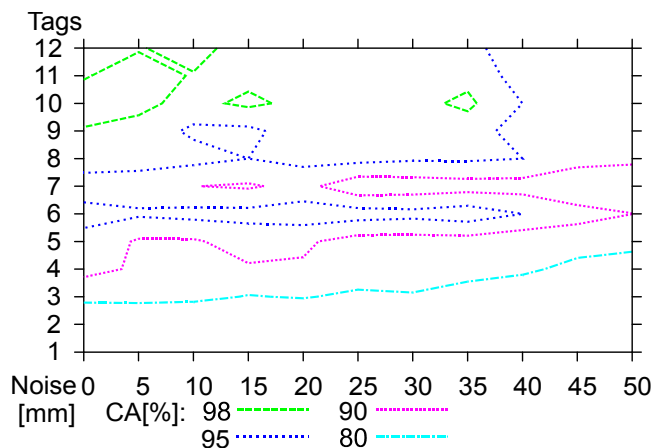


Figure 1. Classification accuracy with respect to the number of tags and the noise level for the recognition of the target health problems using the naive Bayes classifier.

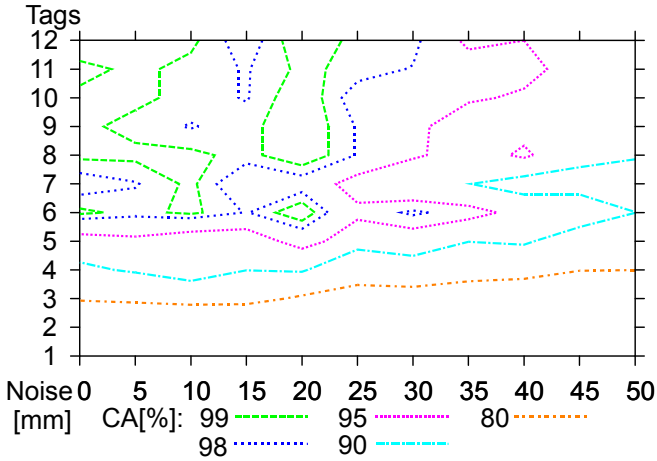


Figure 2. Classification accuracy with respect to the number of tags and the noise level for the recognition of the target health problems using the neural network classifier.

Although the classification accuracies of the neural network classifier are overall better than of naive Bayes, naive Bayes has important advantage in interpretability of the predictions. In case the system recognizes some health state it explains the reasons for classification to the physician.

5 EXPLANATION OF THE DETECTION

Because it is very important for the physician to obtain an explanation for the interpreted health state, we also paid a lot of attention to it and developed a control-panel prototype, which is intended to be used by physicians (Figure 3).

In the middle of the prototype screen, there is visualization of the kinematic model of the elderly moving through the room. In the upper-right-hand corner there are controls for saving and loading the captured movement. Underneath there are the time series of the calculated angles.

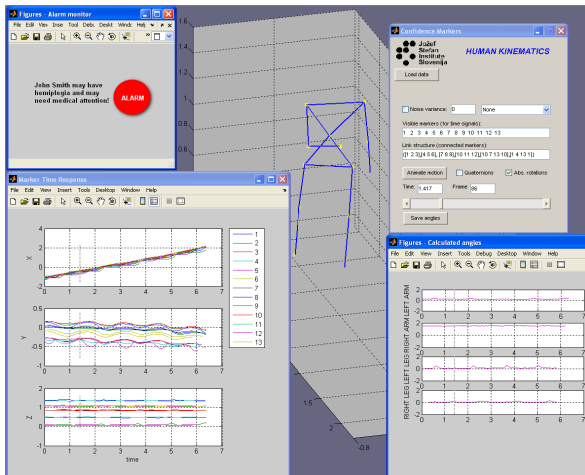


Figure 3. Panel prototype for the explanation of the interpreted health state

In the lower-left-hand corner the time series of the x, y and z positions are shown for all 13 tags (the 13th tag is calculated from the positions of the nearest tags). When the health problem is recognized, the red alarm button appears in the left upper-left-hand corner with the necessary description of the recognized case for the

relatives and for the medical center that has the control panel.

6 CONCLUSION

A system for detection of health problems through gait patterns of elderly to support their independent living is proposed in this paper. Time series of the detected positions of the body parts from the motion-capture system are transformed into a form for supervised machine learning methods using novel features for recognition of health problems. Although the automatic recognition of health problems is rarely addressed in research, our results are promising.

First objective of the research was to discover to what extent the automatic recognition of health problems with motion capture system is feasible. The results show that in the initial setting (no noise, all tags) naive Bayes and neural network algorithm achieved an average classification accuracy of 97.2 % and 100 %, respectively. This is much higher than the 31.9 % of the reference majority class; consequently, achieved classification accuracies are high. In the experimental results of initial setting, there were a few false positives/negatives, thus they would not cause much unnecessary ambulance costs in implementation of our approach in practice. Since the system accurately classified the most true health problems, it represents high confidence and safety for the elderly in the potential use in elderly care. Therefore, the automatic recognition of health problems with motion capture system is feasible to a high extent.

Second objective was to investigate the classification accuracy achievable using machine learning approach and various numbers/placements of tags on the user's body and various amounts of noise in tag coordinates. Tag placement must achieve a trade-off between usability and technical requirements – the users prefer as few tags as possible, but too few tags cannot ensure sufficient accuracy. Both the finding regarding noise and tag placement can affect motion-capture system selection and further development and applications of care systems for elderly.

The results of varying the amount of noise indicate that only significant decrease in classification accuracy happened at 45 mm for naive Bayes and already at 15 mm for neural network. Naive Bayes manage to retain their performance longer than neural network while increasing the data noise. The approach is therefore robust to the addition of the noise. The results of decreasing the number of tags show that it causes the decreasing of classifier's performance. Six is the smallest number of tags for which the classification accuracies of classifiers are insignificantly different compared to the initial one.

The results of investigation of the dependence of the classification accuracy on the tag placement and noise level show that neural network was much more accurate since it reached classification accuracy of over 99 % with only 8 tags with 0-20 mm noise, but naive Bayes was able to reach only 95 %. However, naive Bayes has important advantage over neural network, since the results of its classification are easily interpretable, i.e., if in practice the system would recognize some health state, the physician could check, why the system thinks it is certain health state.

Because it is very important for the physician to obtain an explanation for the interpreted health state, we also paid a lot of attention to it and developed a control-panel prototype for the explanation of the interpreted health state, which is intended to be

used by physicians. When the health problem is recognized, the alarm button appears with the necessary description of the recognized case for the relatives and for the medical center that has the control panel.

For future work, we can modify the proposed system to be used also for automatic evaluation of rehabilitation process (e.g. after stroke) at home.

ACKNOWLEDGEMENTS

This work is partially financed by the European Union, the European Social Fund. The author thanks Matjaž Gams for advising the PhD research, partially reported in this paper. He also thanks Martin Tomšič, Bojan Nemec and Leon Žlajpah for their help with data acquisition, Anton Gradišek for his medical expertise and Zoran Bosnić and Mitja Luštrek for helpful discussions.

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