User-friendly System for Recognition of Activities with an Accelerometer

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***Abstract*—Monitoring of a person's daily activities can provide valuable information for health care and prevention and can be an important supportive application in the field of ambient assisted living (AAL). The goals of this study are the classification of postures and activities using knowledge-based methods as well as the evaluation of the performance of these methods. The acceleration data are gained by a single tri-axial accelerometer, which is mounted on a specific position on the test subject. A data set for training and testing was gained by collecting data from subjects, who performed varying postures and activities. For these purposes, three different knowledge-based (decision tree and neural network) classification methods and a hybrid classifier were implemented, tested and evaluated. The results of the tests illustrated that the hybrid classifier performed best with an overall accuracy of 98.99%. The advantages of knowledge-based methods are the exchangeable knowledge base, which can be developed for different types of sensor positions and the state of health of the subject.**

I. INTRODUCTION

"If we could give every individual the right amount of nourishment and exercise, not too little and not too much, we would have found the safest way to health" [Hippocrates].
The ancient Greeks already knew how important a healthy and physical active lifestyle can be for the physical and mental health and wellness of a human. Living a healthy lifestyle[1] can be the best protection of personal health. Main behaviors of a healthy lifestyle are not smoking, eating a healthy diet, avoiding alcohol and enough physical activity.
One of the greatest health risk in modern Western society comes along with insufficient physical activity. Nearly two third of adults (aged 15 and older) in the European Union did not reach the recommended level of activity [2]. Too little or no activity causes approximately 600,000 deaths per year and results in a loss of 5.3 million years of healthy life due to premature mortality and disability per year [3]. A physical active lifestyle can not only prevent or inhibit the progress of diseases, it also supports improvement of physical fitness, muscular strength and the quality of life. In particular for older people regular and enough physical activity is important as it increases the potential for independent living. Of course not all diseases are preventable, but a large proportion of deaths can be avoided, particularly those from coronary heart disease and lung cancer. Scientific studies have identified certain types of behavior that contribute to the development of noncommunicable diseases and early death [4].
Based on these observations the monitoring of daily activities of a person can bring valuable information. The parameters of movement can provide information about health status, functional ability, effectiveness of rehabilitation, falling risks and other potential clinical data.
One possibility for the monitoring of daily physical activities is given by the use of an accelerometer which was also shown in previous studies [5]–[9]. An accelerometer can be directly mounted on a person's body and record accelerations which arise when a movement occurs. Based on acceleration data it is possible to classify and monitor movements of a person. The classification of human activities provides information about the daily behavior and energy expenditure of a person.
Previous studies [5]–[8] have developed activity recognition systems which used classical information-signal processing methods. These methods recognized the activities with a high accuracy if they were trained and personalized for the respective user. The training procedure comprises time-consuming practice of each classifiable activity for the user.
In this paper we present an activity classification system which adopts the advantages of knowledge-based methods. The user enters his/her characteristics (age group, gender, athleticism, etc.) and the system uses the data from the corresponding knowledge base to classify the activity. This approach enables the use of this system for each person with an high recognition accuracy without training the classification algorithm for each user.
The developed activity recognition system with knowledge-based methods offers a number of advantages. It is possible to use different acceleration sensors, or different sensor positions on the body (wrist, ankle, chest, etc.) or adapt the system to different areas of application (fitness center, at home, car, etc.) by changing the knowledge base without loose of recognition accuracy. These qualities vary the activity recognition system described in this paper from state of the art systems. Previous works [7], [10]–[14] also used knowledge based systems but focused on activity recognition systems which have to be trained for each user individually . In this work the system can be parameterized for different characteristics of the user (age group, gender, athleticism, etc.) whereby a high recognition accuracy is achieved.

[1] A healthy lifestyle is a way of living that lowers the risk of being seriously ill or dying early.

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TABLE I
SEVEN DIFFERENT POSTURES AND FOUR DIFFERENT ACTIVITIES CAN BE DETECTED WITH THE DEVELOPED ACTIVITY RECOGNITION SYSTEM.

Postures	Activities
Standing	Walking
Sitting	Running
Bending forward	Sitting down
Lying on the left	Standing up
Lying on the right	
Lying on the back	
Lying on the chest	

II. METHODS

An activity recognition system using knowledge-based methods was developed to detect different postures and activities based on acceleration data. The seven different postures and four different activities are part of the daily activities which are performed by healthy people every day. The seven varying postures and four different activities to be recognized are shown in Table I.
The activity recognition system consists of a signal preprocessing unit which performs filter operations and converts the received signal from the sensor into gravitational unit g. Then the preprocessed data are windowed and features of the acceleration data are extracted. Acceleration data have been gained from several subjects in a controlled laboratory environment. These data were used to build up a knowledge base for the different methods. The methods were tested in different settings to test the performance of activity recognition. In Figure 1 a principal schematic of the activity recognition system is shown. The activity recognition with knowledge-based methods differs compared to classical information-signal processing in the combination of the implicit model of the environment in which they are embedded and the information-processing function of interest. The knowledge-based methods allows the use of an exchangeable knowledge base. This knowledge base can be replaced, while the problem solving method remained the same.

A. Data Collection

Acceleration data have been collected from six normal, healthy volunteers (two female, four male, mean-age 28.7±2.8 years) in a controlled laboratory environment. The specified postures and movements were performed in a predefined sequence and period and supervised by a researcher. The researcher instructed the subject which posture or activity to perform over a predetermined period. The subjects were advised to perform the postures and activities as naturally as possibly. The data were timestamped and labeled with the number of the activity class between the start and stop time of the performance.
The test subjects wore the sensor board on the waist over the right leg. The sensor board was fixed with an elastic band with hook-and-loop fastener so that the sensor was not able to move strongly, when activities like walking and jogging were performed. No subject deemed the mounted sensor as distracting while they performed the activities. A sensor displacement could be eliminated due to the supervised mounting of the sensor.
The position was chosen because of the measurement range of the used accelerometer. The sensor can detect accelerations up to ±1.5 g. This limited the possible body positions where the sensor could be mounted. Previous studies indicate that at limb positions accelerations up to 12 g occur [15]. Positions with a high number of degrees of freedom were worse for the recognition of postures, due to the many possible changes of these body parts while retaining in the same posture. So only sensor positions close to the center of mass (COM) of the human body (pelvis area) are suitable.

B. Data Preprocessing

The acceleration signal is generated from the earth's gravity and the movement component, and is afflicted with noise. Not all information of the acceleration signal is necessary for the detection of activities and postures. The raw acceleration data with a sample frequency of 512 Hz does not contain necessary information in the frequencies above 20 Hz. In [16], it was shown that in gait 99% of the energy is contained below 15 Hz and in [5], it was stated that a 20 Hz sample frequency is required to asses daily physical activities. Hence, an elliptic low pass filter is used to eliminate the useless information in this frequency band. Elliptic filters are equiripple in both, the passband and stopband. They generally meet filter requirements with the lowest order of any filter type.
A sixth-order elliptic filter with a cutoff frequency at 15 Hz is employed to remove useless information. It is an IIR filter with 0.01 dB passband ripple and a stopband magnitude at

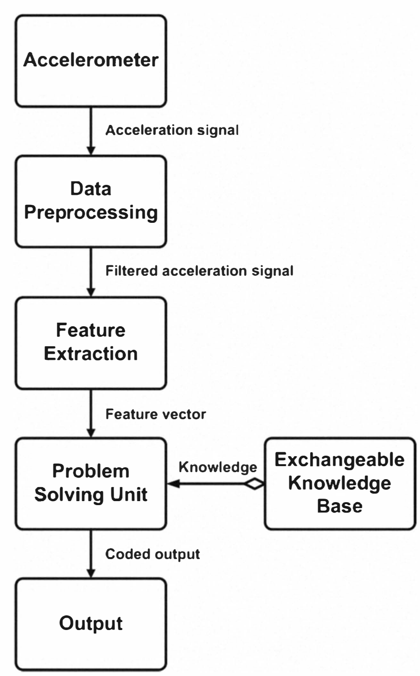

Fig. 1. Principal schematic of the activity recognition system.

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$-80\,\mathrm{dB}$. IIR filters have the advantage that they do not need many filter coefficients, but an infinite long impulse response is possible.
The acceleration signal consists of two components: gravity and acceleration due to body movement. For the recognition of activities with features of the acceleration signal, it is useful to extract the gravity component from the acceleration signal. The two components of the acceleration signal overlap in the frequency domain and cannot be completely separated by filtering. Most of the gravity component is found below $0.25\,\mathrm{Hz}$, so an elliptic IIR high pass filter with a cutoff frequency at $0.25\,\mathrm{Hz}$ was utilized for the separation of the gravity signal and the acceleration due to movement. It's an IIR filter with $0.01\,\mathrm{dB}$ passband ripple and a stopband magnitude at $-80\,\mathrm{dB}$.

C. Feature Extraction

The raw acceleration data are not used for the classification, but instead application specific features were computed to summarize and extract important details from the data. All features were extracted from the preprocessed acceleration data using a window size of 1024 samples and 50% overlap between the consecutive windows. Feature extraction with those overlap has demonstrated success in previous works ([10], [17]). At a sampling frequency of 512 Hz, each window represents data for two seconds.
Features are calculated from the time as well as the frequency domain. To calculate the frequency domain features a FFT is used. These features are listed in Table II and are described in detail below.

- Minimum Peak (smallest value of the filtered acceleration signal in the window)
- Maximum Peak (largest value of the filtered acceleration signal in the window)
- Signal magnitude area (SMA): The SMA is a suitable measure for distinguishing between activity and rest using triaxial accelerometer signals [9], [11], [12]. It is equal to the sum of the acceleration magnitude summations over three axes (x_i, y_i, z_i) of each window and normalized

TABLE II
LIST OF FEATURES, WHICH ARE EXTRACTED FROM THE ACCELERATION SIGNAL.

Features	Domain
Minimum peak	Time
Maximum peak	Time
SMA	Time
Tilt angle ρ	Time
Tilt angle ϕ	Time
Tilt angle θ	Time
Correlation between x- and y-axis	Time
Correlation between x- and z-axis	Time
Correlation between y- and z-axis	Time
Energy	Frequency
Spectral Entropy	Frequency

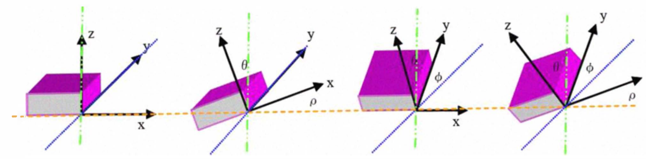

Fig. 2. Tilt angles of a triaxial accelerometer. The green dotted line denotes the direction of the earth's gravity [19].

by the window length w [18]. For the calculation of the SMA the filtered acceleration signal is used:

$$SMA = \frac{1}{w}\left(\sum_{i=1}^{w}|x_i| + \sum_{i=1}^{w}|y_i| + \sum_{i=1}^{w}|z_i|\right). \quad (1)$$

- Tilt angle: In order to define the angles of the accelerometer in three dimensions the pitch, roll and theta angles are sensed using all three outputs of the accelerometer. Pitch (ρ) is defined as the angle of the X-axis relative to ground. Roll (ϕ) is defined as the angle of the Y-axis relative to the ground. Theta (θ) is the angle of the Z-axis relative to gravity [19]:

$$\rho = \arctan\frac{x_i}{y_i^2 + z_i^2}, \quad (2)$$

$$\phi = \arctan\frac{y_i}{x_i^2 + z_i^2}, \quad (3)$$

$$\theta = \arctan\frac{\sqrt{x_i^2 + y_i^2}}{z_i}. \quad (4)$$

- Correlation between axes: The correlation among the axes is calculated for each pair of axes as the ratio of the covariance and the product of the standard deviations. Each correlation value is calculated from the filtered acceleration signal. The correlation between two variables X on the x-axis and Y on the y-axis, with standard deviations σ_X and σ_Y is defined as

$$correlation(X,Y) = \frac{cov(X,Y)}{\sigma_X \sigma_Y}. \quad (5)$$

This feature is useful for the discrimination between activities that involve translation in just one dimension.
- Energy: Energy is the sum of the magnitudes of squared discrete FFT components of the signal in a window.

$$Energy = \frac{\sum_{i=1}^{W}|F_i|^2}{|W|} \quad (6)$$

where F_i is the ith FFT component of the window, $|F_i|$ is the magnitude of F_i and $|W|$ is the window length. The energy can be used to discriminate sedentary activities from moderate and vigorous activities. Due to visibility of the periodicity of the acceleration data in the frequency domain, the energy feature is to capture data periodicity [14].

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- Spectral entropy: The spectral entropy $S_N(f_1, f_2)$ represents the normalized sum of PSD values of the frequency band f_1 to f_2

$$S_N(f_1, f_2) = \frac{-\sum_{f_i=f_1}^{f_2} P(f_i) \log P(f_i)}{log(N[f_1, f_2])}, \qquad (7)$$

where $P(f_i)$ is the power spectral density value of the frequency f_i. The PSD values are normalized so that their sum in the band $[f_1, f_2]$ is 1. $N[f_1, f_2]$ is the number of frequency components in the corresponding band in PSD [20].

D. Knowledge-based Methods

Different knowledge-based methods have been implemented to recognize the seven postures and the four activities. To create a knowledge base, the acquired acceleration data were used with the same principal process for each knowledge base (see Figure 3). The acceleration data were labeled with the posture or activity code, which included the a priori knowledge corresponding to the activity. An acceleration data were preprocessed with the filters described in section II-B and the features (see section II-C) were extracted from the windowed (1024 samples with 512 samples overlap) preprocessed acceleration data. These labeled feature sets were used to train the classification methods and to generate the knowledge base. The designs of the knowledge bases are specified in the descriptions of the implemented knowledge-based methods below.
Two different types of knowledge-based methods are used to recognize the postures and activities denoted above (see Table I). Also, a hybrid classifier is described which uses two different classifiers; one to recognize the postures and another for the recognition of activities. The structure and parameters of these methods are described in this section.

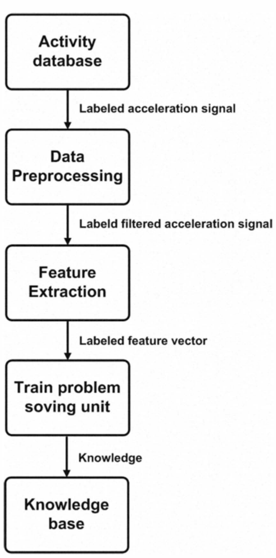

Fig. 3. Principal process of creating a knowledge base for knowledge-based methods for the purpose of posture and activity recognition.

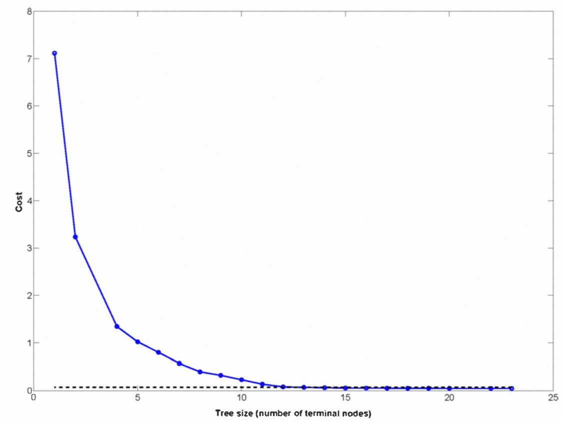

Fig. 4. Cost of nodes of the decision tree. The cost of a node is the mean squared error over the observations in that node.

1) Decision Tree: It is natural and intuitive to classify a pattern through a sequence of questions, in which the next question asked depends on the answer to the current question. Such a sequence of questions is displayed in a directed decision tree, where by convention the first or root node is displayed at the top, connected by successive links or branches to other nodes. These are similarly connected until the reach of a leaf node, which has no further links [21].
Time domain and frequency domain features are used to generate the decision tree:

- SMA,
- the angles ρ, ϕ and θ,
- the correlation between three axes,
- minimum and maximum of the acceleration of the x-axis

and from the frequency domain:

- energy,
- spectral entropy of the frequency band at 0 to 10 Hz.

In Figure 4 the cost of the nodes of the tree are shown. The cost of a node is the mean squared error over the observations in that node. Cost is a vector of cost values for each subtree in the optimal pruning sequence for the tree. The resubstitution cost is based on the same sample that was used to create the original tree, so it underestimates the likely cost of applying the tree to new data. Figure 4 shows that at least 12 nodes are necessary to generate a correctly working decision tree.
The decision tree is a rule-based knowledge-based method and generates decision rules to classify between seven postures and four activities. The binary tree compares a feature value with a generated threshold in each node and either to the next left or right node dependent on the result of the parent node. The structure of the tree and the thresholds of the nodes are the knowledge base of the decision tree and are generated with the training's acceleration data. The leaf nodes denote the seven postures and four activities. When the features are calculated, the rules generated from the decision tree are checked and result in the recognized posture or activity.

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2) Neural Network: The structure of the used neural network consists of an input layer, four hidden layers and an output layer. The neural network is a feed-forward network with sigmoid functions as the activation functions in the hidden and output neurons.

The input vector of the neural network consists of the feature set generated from the acceleration signal. The m neurons (hyperplanes) of a hidden layer maps the D-dimensional input space (feature vector) onto the vertices of a unit side hypercube in the m-dimensional space. The first layer of neurons divides the input D-dimensional space into a polyhedral set, which are formed by hyperplane intersections. The second hidden layer forms regions whereby each neuron of the second layer realizes a hyperplane that leaves only one of the vertices of the hyperplane on one side of the region. The neurons of the output layer form the output classes [22].

In our case, the knowledge base are the weights and biases of the neural network which haven been generated with the backpropagation algorithm. This knowledge base is exchangeable and does not affect the structure of the network. The backpropagation learning updates the network weights and biases in the direction in which the performance decreases most rapidly [23]. When the network is generated, the unknown weights are initialized randomly with small values. After the initialization, the gradient terms are computed backwards, starting with the weights of the last layer and then moving towards the first layer. Now the weights are updated and this procedure is repeated until the termination procedure is met [22]. As a termination procedure the mean squared error was used which calculates the mean squared difference between actual response $\widehat{y}_m$ of the actual output neuron m and the desired response y_m for all layer N:

$$
\begin{aligned}
J &= \sum_{i=1}^{N} E(i) \qquad (8)\\
, E(i) &= \sum_{i=1}^{k} e_m^2(i) = \sum_{i=1}^{k} (y_m(i) - \widehat{y}_m(i))^2\\
&, i = 1, ..., N,
\end{aligned}
$$

where $J(w)$ is the quadratic cost function, e_m is the difference error between the actual and desired output, and $E(i)$ is the squared error of the i^{th} layer.

Important is the size of the network. The neural network has to be large enough to learn what makes data of the same class similar and data from different classes dissimilar. But it has also to be small enough not to be able to learn underlying differences between the data of the same class. This would lead to the so called overfitting [22]. For the choice of the network size, the pruning technique is selected. This technique starts from a large network and then removes weights and/or neurons iteratively, according to a specific criterion [22]. This criterion is satisfied, when the sum of squared errors is relatively constant over several iterations.

The coding of the output of the neural network denotes the recognized posture or activity. So each output neuron indicates a different posture or activity and the output of the activated output neuron is 1 while all others have the output value 0.

3) Hybrid Classifier: In order to reduce the size of the neural network for recognizing postures and activities, a hybrid classifier was developed. Network size involves (in the case of layered neural network architectures) the number of layers in a network, the number of nodes per layer, and the number of connections. In general, the neural network size affects network complexity, and learning time, but most importantly, it affects the generalization capabilities of network; that is, its ability to produce accurate results on patterns outside its training set. [24].

The hybrid classifier consists of two phases: pre-classifier construction phase and static/dynamic classifier construction phase. The objective of the pre-classifier is to distinguish between static activities (postures) and dynamic activities.

The pre-classifier is simple thresholding method of the feature SMA. The SMA is equal to the sum of the acceleration magnitude summations over three axes of each window and normalized by the window length [18]. In many previous studies SMA was used to distinguish between active and passive activities [11], [12], [18]. The SMA has a high information content about the activity level of a subject. Dynamic activities have a SMA over 0.2 while the SMA value of postures is mostly below 0.015.

After pre-classification the actual activity is either static (inactive, posture) or dynamic (active). If it is determined to be inactive, the static feature subset is calculated. This feature subset consists of the three tilt angles ρ, ϕ and θ. This feature subset is the input vector for the *static neural network*. The *static neural network* is a feed-forward network with log-sigmoid activation functions. The network has two hidden layers with four neurons in the first hidden layer and seven neurons in the second hidden layer, and uses the backpropagation algorithm for learning. The output classes of the network are seven different postures (see Table I).

If the output of the pre-classifier shows that the actual acceleration window determines an activity, the dynamic feature subset is generated. The dynamic feature subset consists of time domain features:

- SMA,
- the angle ρ, ϕ and θ,
- the correlation between three axes,
- minimum and maximum of the acceleration of the x-axis

and of the frequency domain features:

- energy,
- spectral entropy of the frequency band at 0 to 10 Hz.

For the classification of the dynamic activities a feed-forward neural network with backpropagation learning is also used. The neural network for classifying activities also has two hidden layers, whereby the first hidden layer consists of 14 neurons and the second hidden layer has eleven neurons. The dynamic feature subset is the input vector of the network and four different activities are distinguished (see Table I).

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As described in section II-D2, the size of network is important for the performance of the neural network. The best size for both networks (postures, activities) is computed with the pruning technique. These technique starts from a large network and then weights and/or removes neurons iteratively, according to a specific criterion [22]. This criterion is satisfied, when the sum of squared errors is relatively constant over several iterations.
The coding of the output of the neural network denotes the recognized posture or activity. So each output neuron indicates a different posture or activity and the output of activated output neuron is one while all others have the output value zero.

III. Results

For the evaluation the parameters true positive tp, false negative fn, true negative tn and false positive fp were collected from the activity recognition output. From these parameters the sensitivity (Eqn. 9), the specificity (Eqn. 10) and the overall accuracy (Eqn. 11) are calculated. The overall accuracy is defined as the sum of true positives and true negatives divided by the total number of examples.

$$sensitivity = \frac{tp}{tp + fn} \tag{9}$$

$$specificity = \frac{tn}{tn + fp} \tag{10}$$

$$overall\ accuracy = \frac{tp + tn}{Total\ number\ of\ examples} \tag{11}$$

The classifiers were trained and validated with the data acquired from six subjects. The classifiers were trained with these data and for the tests of the classifiers the same data were 4-fold cross validated. For the tests the acquired data were randomly divided into four disjoint subsets of equal size. All classifiers used in this work were run on four different settings:

- *User-specific*: Data from a single subject are used for training and testing of classifiers. This setting was used to detect systematic errors in algorithms [25].
- *Gender-specific*: Data only from one gender are used for training and testing of classifiers.
- *Gender-leave-one-out*: Data from only one gender are used for training and data from other gender are used for testing the classifiers.
- *Leave-one-out*: Data from multiple subjects from one gender are used for training and data from another subject with the same gender are used for testing of classifiers.

The overall accuracy of the different classifiers for the four different settings are illustrated in Table III.
The decision tree performed best in the user-specific setting with an overall accuracy of 99.71% and second best in the only-male setting. In the leave-one-out setting the hybrid classifier showed the best performance with an overall accuracy of 99.95%. Neural network and hybrid classifier performed with a high accuracy in all settings.

TABLE III
Overall accuracy (in percentage) of activity recognition of the classifiers with the sensor at the waist.

Classifier	User-specific	Leave-one-out	Gender-specific	Gender-leave-one-out
Decision tree	99.71	88.62	99.84	90.35
Neural Network	99.52	97.79	99.55	91.55
Hybrid classifier	99.63	98.99	99.95	95.05

TABLE IV
Summary of decision tree results in percentage using gender specific leave one out training and with the sensor positioned on the waist.

Activity	Sensitivity	Specificity
Stand	99.07	96.02
Sit	86.75	97.52
Bend	89.57	93.79
Lie left	96.91	99.51
Lie right	99.93	99.94
Lie face up	99.89	99.96
Lie face down	94.59	99.12
Walk	93.09	99.20
Run	97.44	99.35
Sit down	62.12	98.64
Stand up	74.71	98.87

The results also show that classifiers performed worst in gender-leave-one-out setting. With knowledge-based methods it is possible to exchange the knowledge base without changing classifier structure; thus, a knowledge base for each gender brings a good perfomance of the method. The use of knowledge-based methods for activity recognition allows the generation of different knowledge bases. In [26], it was noted that for example in walking and running the styles depend on the person's physique, purpose of walk, type of footwear, physical health, emotional state and gender. With a large number of different test persons it is possible to create knowledge bases, which take some of the characteristics in account. These characteristics can be gender, age, athleticism, height, weight and body mass index. These selectable characteristics could improve the recognition accuracies, as seen in the gender-specific setting. The overall accuracy of decision tree, neural network and hybrid classifier are above 99.5%, when the knowledge base was generated from gender specific data and the methods tested with data from the same gender. With test data from the other gender the overall accuracy obviously decreased.
The more important parameters of classifier performance are the sensitivity and the specificity. These parameters were calculated from tests with the leave-one-out setting for all eleven activities and illustrate the recognition performance of the classifiers for all postures and activities.
The sensitivity and the specificity of the decision tree with leave-one-out setting are shown in Table IV.
Decision tree recognized the standing and lying postures

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with a high sensitivity and the lying postures with a high specificity. Sitting and bending forward recognition showed a lower sensitivity and were wrongly detected as standing or lying face down respectively. The worst results are shown in recognition of sitting down and standing up. The sensitivity of the classifiers detecting siting down and standing up shows that a third of sitting down and a fourth of standing up were wrongly classified.

In Table V the sensitivity and specificity of the recognized postures and activities with the neural network and leave-one-out setting are represented. With the neural network, sitting and bending forward showed a better sensitivity and specificity, but lying face up with a sensitivity of 85.67% was wrongly recognized as bending forward or sitting.

As with decision trees the neural network showed a low sensitivity in recognizing sitting down and standing up. Standing up was wrongly recognized as standing or sitting. The recognition sensitivity of sitting down and standing up showed a very low sensitivity of particulary in one person, whereas in testing with data from the other subjects a sensitivity of more than 85%.

The hybrid classifier showed the best performance in recognizing the the activities standing up and sitting down in leave-one-out setting (see Table VI).

Sitting down was recognized with a sensitivity of 78.67% and standing up with 80%. But the hybrid classifier lacked in recognizing standing, lying face up and lying face down. The tests with one person showed a very low sensitivity of only 35% in recognizing standing, whereby standing was recognized as sitting.

Overall, the hybrid classifier and the neural network performed best in recognition of postures and activities. When recognizing activities with the hybrid classifier, standing is confused with sitting and lie face down with bending forward, respectively. For the purpose of posture and activity recognition with a single accelerometer, the results recommended the neural network and hybrid classifier as knowledge-based methods.

TABLE V
SUMMARY OF NEURAL NETWORK RESULTS IN PERCENTAGE USING GENDER SPECIFIC LEAVE ONE OUT TRAINING AND WITH THE SENSOR POSITIONED ON THE WAIST.

Activity	Sensitivity	Specificity
Stand	98.67	97.67
Sit	96.00	99.67
Bend	91.67	98.33
Lie left	97.67	99.72
Lie right	99.33	99.86
Lie face up	85.67	99.23
Lie face down	95.67	99.57
Walk	98.67	99.86
Run	98.33	99.63
Sit down	63.67	99.14
Stand up	75.33	99.33

TABLE VI
SUMMARY OF HYBRID CLASSIFIER RESULTS IN PERCENTAGE USING GENDER SPECIFIC LEAVE ONE OUT TRAINING AND WITH THE SENSOR POSITIONED ON THE WAIST.

Activity	Sensitivity	Specificity
Stand	77.00	99.67
Sit	99.91	96.33
Bend	99.87	99.97
Lie left	97.00	99.00
Lie right	99.93	99.98
Lie face up	83.33	98.33
Lie face down	84.67	99.97
Walk	99.33	99.67
Run	99.97	99.99
Sit down	78.67	99.67
Stand up	80.00	98.33

IV. CONCLUSION

In this work knowledge-based methods were evaluated and implemented to detect discrete activities with an acceleration sensor. Contrary to classical information-signal processing, knowledge-based methods separate between the representation of knowledge from regarding problems (knowledge base) and the processing of the knowledge (knowledge processing).

The developed system collected data from a single accelerometer, preprocessed the acceleration signal and extracted characteristic features from the signal. The extracted features were from both, the time and frequency domain and were calculated over a defined time window of two seconds.

Three different knowledge-based methods were developed to recognize seven different postures and four different activities. Data were collected from 6 persons, who wore a sensor at the waist above the right leg.

The collected data from accelerometer at the waist position were used to train and verify the knowledge-based methods for the evaluation of the classifiers. For the training and testing different settings, cross-validated data were used. In the evaluation of the knowledge-based methods, using the leave-one-out setting, it was found out that hybrid classifier performed best. The neural network showed slightly lower sensitivity and specificity rates than the hybrid classifier, while the decision tree performed the worst.

Based upon training and testing of the classifiers with the different settings, it can be concluded, that the classifiers trained and tested with gender-specific data performed with larger sensitivity and specificity rates than classifiers trained with data sets from a specific gender and tested with data sets from another gender. With knowledge-based methods it is possible to exchange the knowledge base without adapting the classifier structure.

In summary, this primary study with only six persons showed that posture and activity recognition with a single accelerometer can be performed with a high sensitivity and specificity rate when the sensor is positioned near the center of mass on the human body. Knowledge-based methods facilitate the

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use of activity recognition systems because the training of the methods for each single user is not longer required.

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