Classification of Daily Life Activities by Decision Level Fusion of Inertial Sensor Data

Dominik Schuldhaus
dominik.schuldhaus@cs.fau.de

Heike Leutheuser
heike.leutheuser@cs.fau.de

Bjoern M. Eskofier
bjoern.eskofier@cs.fau.de

Digital Sports Group, Pattern Recognition Lab, Department of Computer Science
University Erlangen-Nuremberg, Germany

ABSTRACT
The fusion of inertial sensor data is heavily used for the classification of daily life activities. The knowledge about the performed daily life activities is mandatory to give physically inactive people feedback about their individual quality of life.

In this paper, four inertial sensors were placed on wrist, chest, hip and ankle of 19 subjects, which had to perform seven daily life activities. Each sensor node separately performed preprocessing, feature extraction and classification. In the final step, the classifier decisions of the sensor nodes were fused and a single activity was predicted by majority voting.

The proposed classification system obtained an overall mean classification rate of 93.9 % and was robust against defect sensors. The system allows an easy integration of new sensors without retraining of the complete system, which is an advantage over commonly used feature level fusion approaches.

Categories and Subject Descriptors
I.5 [**Pattern Recognition**]: Applications

General Terms
Algorithms, Experiments

Keywords
Data Mining, Daily Life Activities, Decision Level Fusion, Inertial Sensors

1. INTRODUCTION
The World Health Organization states that the 4th leading risk factor for mortality is insufficient physical activity [13]. Approximately 3.2 million people of the world population die each year because of insufficient physical activity [13]. Several studies showed that physically active people have higher levels of health-related fitness and lower rates of various chronic diseases compared to physically inactive people [7]. It is assumed that the participation in 150 minutes of moderate physical activity per week reduces the risk of diabetes by 27 %, and the risk of breast and colon cancer by 21 % to 25 % [13].

Methods for assessing the individual daily life physical activity are of major interest in order to monitor the health status and to provide feedback about the individual quality of life. An overview of methods for the assessment of daily life activities is given for example in [12]. Here, self-reports provide the assessment of physical activity. However, self-reports induce problems with reliability, validity and sensitivity [8]. In recent years, small and light-weight wearable sensors like inertial measurement units were used to provide a reliable and objective measurement of physical activity. They are heavily applied in the field of classification of daily life activities, which is shown below.

In [1], five biaxial accelerometers were placed near the hip, wrist, arm, ankle and thigh. A decision tree classifier was applied to classify activities like walking, sitting or climbing stairs. An overall mean classification rate of 84 % was obtained. In [6], accelerometers were placed on the chest and wrist. An automatically generated decision tree was applied to classify activities like lying, rowing or Nordic walking. An overall mean classification rate of 86 % was obtained. In [5], two triaxial accelerometers were placed at the hip and wrist. A SVM-based system was applied to classify activities like vacuuming, treadmill running or cycling. An overall mean classification rate of 85.8 % was obtained. In [11], two inertial sensors consisting of a triaxial accelerometer and a triaxial gyroscope were placed on the right arm wrist and right foot. A SVM-based system was applied to classify activities like walking, standing or jogging. An overall mean classification rate of 91 % was obtained.

It was shown in [1, 6, 5, 11] that sensors on different body positions were needed to cover a wide range of activities that should be classified. Furthermore, feature level fusion was performed [4]. Here, features from different sensor signals are extracted and fused. The final decision of the classifier is based on the fused features. The problem of feature level fusion is described in the following section.

Networks of miniature body-worn sensors may suffer from interconnection failures, jitter in the sensor placement or defect sensors. Especially in the latter case, missing features

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cause problems in the feature level fusion and affect the overall classification of daily life activities. Thus, the monitoring of the health status is affected. Another disadvantage of feature level fusion is the retraining of the complete classification system, when a new sensor is added, removed or placed at a different position. Since new and better sensors are frequently available on the market, the system should integrate them without much effort. In order to deal with defect sensors and a flexible adding of new sensors without retraining the complete system, decision level fusion can be performed [4].
Here, each sensor independently classifies the activity. The decisions of the sensors are fused and combined to get a final decision. Subsequently, two examples for decision level fusion approaches are described.
In [14], a meta-classifier was applied that fused the information of simple classifiers operating on 19 body-worn triaxial accelerometers. The sensor nodes were placed at regular intervals along the left and right arm. Each accelerometer axis was processed separately. For each activity class, one Hidden Markov Model (HMM) was defined and trained. The different HMMs were compared and the one, modeling best the features, indicated the class label. The decisions of all accelerometer axes were combined by a Bayes fusion algorithm. The approach was evaluated by recognizing a set of ten activities carried out by workers in the quality assurance checkpoint of a car assembly line. An average classification rate of 98 % was achieved.
In [15], data from two wearable inertial sensors attached on the foot and waist were used to classify activities like sitting, sitting-to-standing or walking upstairs. Each sensor consisted of a triaxial accelerometer and a triaxial gyroscope. Features were separately computed for foot and waist data and fed into two neural networks, each for one sensor. The decisions of the classifiers were combined by sensor fusion rules.
In [14] and [15], the applicability of decision level fusion of inertial sensor data for the classification of daily life activities was shown. However, only the sensor positions arm [14] and foot/waist [15] were considered.
Since for the discrimination of complex daily life activities more than two sensor positions have to be used [1], there is a major need for a system based on decision level fusion with a similar sensor setup as in [1].
Thus, the purpose of this paper was to perform decision level fusion for the classification of daily life activities using four sensor positions (wrist, chest, hip and ankle). Each sensor node consisted of a triaxial accelerometer and a triaxial gyroscope. For each sensor node, features were separately extracted. Each sensor node separately performed the classification of seven daily life activities. The decisions of the sensor nodes were fused by majority voting, in order to obtain a final decision. The system needs no complete retraining after adding new sensors and can deal with defect sensors.

2. METHODS

2.1 Data Acquisition

Four SHIMMER sensor nodes were used for the acquisition of inertial data [2]. Each sensor node consisted of a triaxial accelerometer and a triaxial gyroscope.
They were placed on the wrist, chest, hip and ankle (Fig. 1). These four positions were chosen due to previously published results [1, 6, 5, 11] and are motivated in the following section.
Sensors closely attached to the body's center of gravity like chest or hip are preferred [10]. In order to cover lower and upper extremities, one sensor node was placed on the wrist and on the ankle.
The range of the accelerometers was ± 6 g. The range of the gyroscopes was ± 500 °/s for the sensor nodes on the wrist, chest and hip and ± 2000 °/s for the sensor node on the ankle, since higher angular velocities were expected in the lower extremities. The sampling rate for all sensors was 204.8 Hz and the inertial data was stored on a SD-card.
A study with 19 healthy subjects (eight female and 11 male, age 26 ± 8 years, height 177 ± 11 cm, weight 75.2 ± 14.2 kg) was performed. All subjects gave written informed consent about their participation.
Before the data acquisition of the activities, the sensor nodes were put on a plate and an up-down movement was performed. This procedure allowed an offline synchronization of the four sensor nodes. The sensor nodes were then placed on the dedicated measurement positions and the data acquisition of the activities started.
Each subject had to perform three static activities (sitting, lying, standing) and one household activity (vacuuming) for one minute in a building of the university. Then, the subject had to walk 250 m to another building of the university. In this building, ascending stairs (until the third floor) and descending stairs were recorded. At the end, the subject had

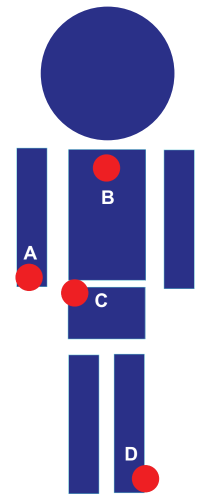
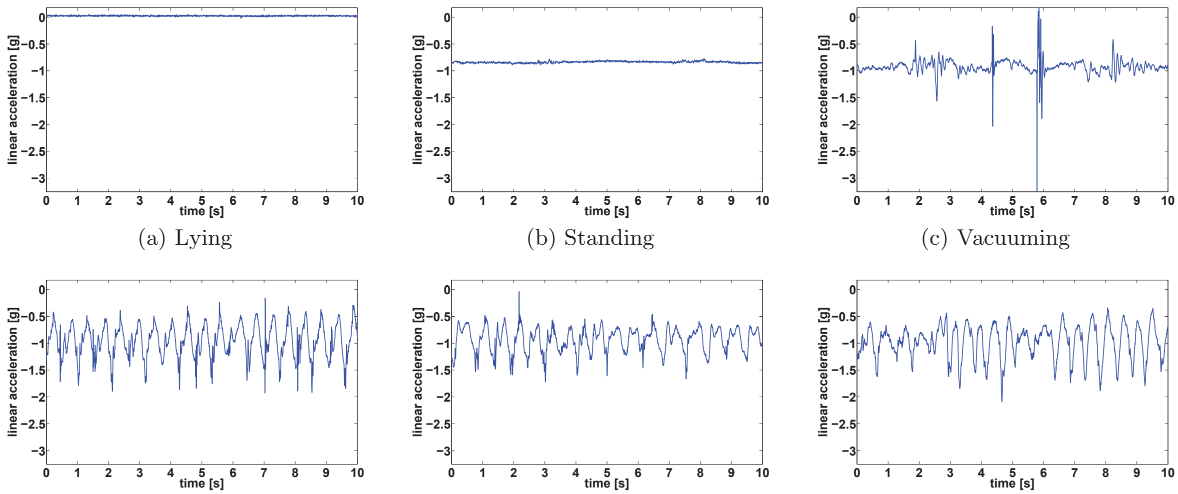


Figure 1: Sensor placement: A (wrist), B (chest), C (hip) and D (ankle).

Table 1: List of performed activities and abbreviations.

Activity	Abbreviation
Sitting	SI
Lying	LY
Standing	ST
Vacuuming	VC
Walking	WK
Ascending stairs	AS
Descending stairs	DS



(a) Lying (b) Standing (c) Vacuuming

(d) Walking (e) Ascending stairs (f) Descending stairs

Figure 2: Linear acceleration in vertical direction of the hip sensor for the activities lying, standing, vacuuming, walking, ascending stairs and descending stairs.

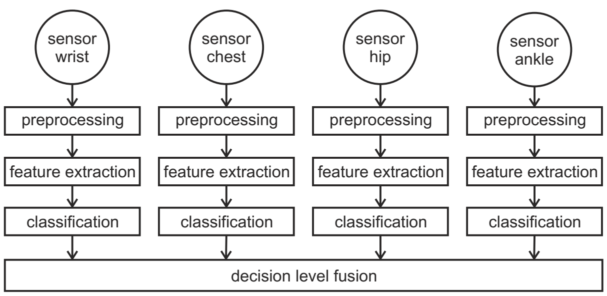


Figure 3: Proposed classification system.

to walk back to the first building. The duration of the activities walking, ascending stairs and descending stairs varied between the subjects due to different self-imposed speed levels. The list of performed activities and the used abbreviations are summarized in Table 1.
A researcher accompanied the subject during the whole data acquisition and labeled the start and end of each activity by an Android based labeling app.
As an example, Fig. 2 shows the linear acceleration in vertical direction of the hip sensor for the activities lying, standing, vacuuming, walking, ascending stairs and descending stairs.

2.2 Proposed classification system

The proposed classification system is depicted in Fig. 3. Each of the four sensor nodes separately performed preprocessing, feature extraction and classification. In the final step, the classifier decisions of the sensor nodes were fused and a single activity was predicted. In the following section, the details are described.

2.2.1 Preprocessing

The inertial data of the four sensor nodes were synchronized. Therefore, the previously mentioned up-down movement was considered, which caused a peak in the vertical acceleration signal of all four sensor nodes. The corresponding point in time constituted the common start point of all sensor nodes. Furthermore, the sensor data was labeled regarding the associated activity. Further processing of the acquired inertial data was performed in sliding windows with 50 % overlap, which was also proposed in [1]. The width of the window was set to five seconds.

2.2.2 Feature extraction

Six features were computed for each sliding window in each of the three accelerometer and gyroscope axes. In order to extract information about the range of the signal amplitudes, the minimum and maximum of the amplitudes were computed. In order to extract information about the statistics of the signal amplitudes, the mean, variance, skewness and kurtosis of the amplitudes were computed. The six features are listed in Table 2. In total, this resulted in 36 features per sensor node.

2.2.3 Classification

Since there is no single classifier that is suitable for all classification tasks [3], the following classifiers were compared: de-

Table 2: List of features computed for each axis.

Name	Description
MIN	minimum of amplitudes
MAX	maximum of amplitudes
MEA	mean of amplitudes
VAR	variance of amplitudes
SKW	skewness of amplitudes
KUR	kurtosis of amplitudes

Table 3: Overall mean classification rates (in percent) of all classifiers regarding sensor nodes wrist, chest, hip and ankle (best classifiers in bold).

	C45	kNN	NaiveBayes	RandomForest	SVM
WR	74.5	76.1	65.0	**80.7**	80.5
CH	84.7	84.8	81.5	88.3	**89.6**
HP	85.7	85.4	73.4	**91.3**	90.9
AK	86.6	89.7	87.9	**91.1**	89.0

Table 4: Mean class dependent classification rates (in percent) of the best classifier regarding sensor nodes wrist, chest, hip and ankle (best classification rates in bold).

	WR	CH	HP	AK
SI	84.7	77.7	**92.1**	70.5
LY	84.6	**99.8**	89.0	99.3
ST	78.4	89.1	**94.2**	83.5
VC	89.4	93.5	**97.2**	97.2
WK	95.6	93.8	97.2	**98.7**
AS	58.9	82.2	84.6	**95.2**
DS	73.1	91.2	85.1	**93.6**

Table 5: Mean class dependent classification rates and overall mean classification rate of decision level fusion (classification rates in percent).

	Classification rate
Sitting	95.1
Lying	99.8
Standing	93.7
Vacuuming	98.8
Walking	99.1
Ascending stairs	81.8
Descending stairs	88.8
Mean	93.9

cision tree (C4.5), k-Nearest Neighbor (kNN), Naive Bayes (NB), Random Forest (RF) and Support Vector Machine (SVM) with linear kernel [9, 3]. In the case of kNN, k was set to three. The cost parameter of the SVM classifier was set to one. For performance assessment, the mean class dependent classification rate and the overall mean classification rate were computed with a leave-one-subject-out procedure. For further processing, the best classifier of each sensor node was considered.

2.2.4 Decision level fusion

The classifier decisions of the four sensor nodes were fused and a majority vote was applied, in order to obtain the final decision. In the case of an equal distribution of the predicted classes in the majority vote, the activity was chosen which first appeared in Table 1.
In order to evaluate the sensitivity of the proposed classification system regarding defect sensors, the number of sensors used in the decision level fusion was varied from one to four. In each case, the classification rate for all combinatorial possibilities were computed and averaged regarding the number of combinations, since it was not known before which of the four sensor nodes were defect.

Table 6: Confusion matrix of the proposed classification system. Rows and columns coincide with the true and predicted activities, respectively. Each entry represents the number of class-dependent decisions. One decision decision corresponds to one five second sliding window.

	SI	LY	ST	VC	WK	AS	DS
SI	**410**	6	11	1	3	0	0
LY	1	**434**	0	0	0	0	0
ST	25	0	**403**	1	1	0	0
VC	0	0	5	**427**	0	0	0
WK	0	0	1	11	**1997**	3	3
AS	0	0	0	0	53	**239**	0
DS	0	0	0	2	25	1	**221**

Table 7: Overall mean classification rates (in percent) with varying number of used sensors.

	1	2	3	4
Classification rate	88.2	85.4	94.6	93.9

3. RESULTS

Table 3 shows the overall mean classification rates of all classifiers regarding sensor nodes wrist (WR), chest (CH), hip (HP) and ankle (AK). The best classifier was the Random Forest for the sensor nodes wrist, hip and ankle. For the sensor node chest, the SVM was slightly better than the Random Forest.
Table 4 shows the mean class dependent classification rates of the best classifier regarding each sensor node.
Table 5 shows the mean class dependent classification rates and the overall mean classification rate after the decision level fusion of all four sensor nodes. The overall mean classification rate was 93.9 %.
Table 6 shows the confusion matrix of the proposed classification system. The rows and columns coincide with the true and predicted activities, respectively. In the table, each entry represents the number of class-dependent decisions. One decision corresponds to one five second sliding window.
Table 7 shows the overall mean classification rates regarding the number of sensors used in the decision level fusion.

4. DISCUSSION

The discrimination of complex daily life activities requires the usage of a multi-sensor based system, which can handle defect sensors and should be flexible when new sensors are added to the system. In this paper, a classification system was developed which performed decision level fusion using four sensor positions.

In the following section, the overall mean classification rates of the four sensor nodes are discussed (Table 3). Random

Forest was the best classifier for the sensor nodes on the wrist, hip and ankle and the second best for the sensor node on the chest. The reason might be that Random Forests are ensemble systems, which reduce the variance and increase the confidence of the classifier decision.
The best classification rate was obtained by the hip sensor which shows why this sensor placement is preferred in literature [10]. With a sensor closely attached to the body's center of gravity several different kinds of activities can be distinguished. The worst classification rate was achieved by the wrist sensor. Thus, with a sensor placed on the upper extremities only a subset of the activities like vacuuming might be classified.
All in all, an overall mean classification rate of more than 80.7 % was obtained for each of the four sensor nodes. Thus, the usage of one single sensor consisting of a triaxial accelerometer and a triaxial gyroscope is suitable for the classification of daily life activities.

In the following section, the mean class dependent classification rates of the best classifier regarding all four sensor nodes are discussed (Table 4). The wrist sensor had problems to classify ascending and descending stairs. It is assumed that the high similarity of both signal patterns from the wrist sensor resulted in classification rates lower than 73.1 %. Thus, the wrist sensor is not suitable for the distinction between ascending stairs and descending stairs.
The chest sensor had problems to classify sitting (Table 4). The reason might be that sitting was often misclassified as standing because of the comparable orientation of the chest sensor during these two activities. Nevertheless, the chest sensor obtained the best classification rate for lying. The reason might be that the movement of the chest was lower compared to hip, ankle and wrist, since the participant sometimes moved the arm or leg during the data acquisition.
The hip sensor had problems to classify ascending stairs and descending stairs (Table 4). It is assumed that the features based on the signal patterns of these activities did not differ substantially. In Fig. 2e and 2f, the minimum, maximum and mean of the amplitudes seemed to be in a comparable range. In order to further improve the performance of the proposed classification system, additional features in the frequency domain might increase the classification rates. Nevertheless, the hip sensor obtained the best classification rates for sitting and standing. The reason might be that the orientation of the hip sensor differed between sitting and standing, since the participant leaned back during sitting.
The ankle sensor had problems to classify sitting and standing (Table 4). It is assumed that the comparable orientations of the ankle sensor during sitting and standing resulted in classification rates lower than 83.5 %. Nevertheless, the ankle sensor reached the best classification rates for walking, ascending stairs and descending stairs, since these activities mostly involved lower extremity movements.
All in all, every sensor was able to classify a subset of the activities with a rather high classification rate, but also had some limitations regarding several activities.

In the following section, the decision level fusion is discussed. As can be seen in Table 3 and Table 5, the fusion of the information of different sensors improved the classification rates from 80.7 %, 89.6 %, 91.1 % and 91.3 % , using only one sensor node, to 93.9 %, using all four sensor nodes. All of the mean class dependent classification rates were above 93 % (Table 5), except for ascending stairs and descending stairs. It is assumed that most of the correct decisions of the ankle sensor were outvoted by the wrist, chest and hip sensors.

In the following section, the confusion matrix of the proposed classification system is discussed (Table 6). Several instances of ascending stairs and descending stairs were misclassified as walking (Table 6). This coincides with the observations in [15], in which inertial sensors (accelerometer and gyroscope) were placed on the foot and waist.

In the following section, the sensitivity of the proposed classification system regarding defect sensors is discussed (Table 7). The overall mean classification rate increased by 0.7 % using three of the four sensor nodes compared to using the whole set of sensor nodes. The reason of an increasing classification rate might be the majority vote approach in the decision level fusion. Majority voting suffers from higher degradation in noisy environment because all the sensors are weighted identically for all the classes, without previous statistic. For this case, an alternative decision level fusion approach like the Bayes fusion algorithm should be explored. An example was given in [14]. The fusion was done in the conditional probability of a certain sequence of classifier decisions given a certain class. The class was chosen which achieved the maximum conditional probability.
The overall mean classification rate decreased by 9.2 % using two sensor nodes compared to using three sensor nodes. Although the classification rate decreased, using only two sensor nodes also allowed acceptable results.
The overall mean classification rate increased by 2.8 % using one sensor node compared to using two sensor nodes. The reason might be again that all the sensor nodes are weighted identically for all the classes in the majority vote approach.

In sum, the overall mean classification rate of 93.9 % (Table 5) showed the general applicability of the proposed classification system in the field of activity recognition. It was shown that defect sensors only slightly decreased the classification rate and that new sensor nodes can easily be integrated into the majority voting scheme.
This offers a successful way to monitor the health status and to provide feedback about the individual quality of life.

5. CONCLUSION

The fusion of inertial sensor data is heavily used for the classification of daily life activities. In this paper, a classification system was developed, which performed decision level fusion. Four inertial sensors consisting of a triaxial accelerometer and a triaxial gyroscope were placed on the wrist, chest, hip and ankle. For each sensor node, six time features were computed for each axis. The features were classified, the decisions of the sensor nodes were fused and the final decision was obtained by majority voting. The proposed system reached an overall mean classification rate of 93.9 % by using Random Forests for the wrist, hip and ankle sensor and the SVM for the chest sensor.

In the future, it is planned to add new sensors to the system. Electrocardiogram (ECG) or electromyography (EMG) sensors will give more information about the physiological state of a person.
The proposed classification system can be used to monitor the health status and to provide feedback about the individual quality of life. The feedback can motivate physically inactive people to be more active. This leads to lower rates of various chronic diseases, which should be one major goal for the future.

6. ACKNOWLEDGMENTS

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