Hierarchical-distributed approach to movement classification using wrist-mounted wireless inertial and magnetic sensors

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Abstract—**Wireless Sensor Networks (WSN) can be used for patient monitoring, analysis of daily activities, and emergency or fall detection. Using a WSN of two wrist mounted 9-degree-of-freedom (9DOF) sensor boards, movement classification can be reliably done. The sensor boards or motes contain a tri-axial magnetometer, a tri-axial gyroscope, and a tri-axial accelerometer. If the classification is assigned to only one mote, which is using the data from both sensor boards, high energy consuming wireless data transfer is required. In this paper, a hierarchical-distributed algorithm is presented, where the motes are calculating their own movement classes, which can be combined on one mote, to determine the movement of the entire body and arms. The proposed method requires less and smaller classifiers, which can be easily implemented on low performance motes. Eleven movement classes were constructed, and data were collected with the help of nine subjects. By distributing the process, some movements can be merged and seven classes can be defined for each arm. Their combination determines the class of the entire body. Two classification hierarchies were tested and various Time-Domain Features (TDF) were calculated with different processing window widths. Altogether 48 training and validation data sets were constructed by different configurations of the sensors. The Minimum Distance (MD) with usage of the Linear Discriminant Analysis (LDA) dimension reduction method and the MultiLayer Perceptron (MLP) classifiers with and without LDA were tested.**

Index Terms—**movement recognition, wireless 9 degree-of-freedom sensor motes, time-domain features, linear discriminant analysis, minimum distance classifier, multilayer perceptron**

I. INTRODUCTION

Using Wireless Sensor Networks (WSN) for analysis of human behaviour is a widely studied field of health and medical applications. It can be used for fall and emergency detection [1-2], telerehabilitation [3], analysis of the daily activities, patient or health monitoring [4-5], and also for industrial applications. Because of their low cost and small energy consumption, miniature inertial and magnetic sensors are reliably used for these applications. Usually these sensors are built into a small, light-weight sensor board, capable of digital signal processing and wireless communication. These boards or motes can be wearable and therefore they can make real-time wireless monitoring widely available.

A potential application of the proposed system is an intelligent WSN, which can be used for emergency detection, or monitoring the movement of the patients in a hospital, or at home.

During the research of movement classification numerous combinations of the sensor types, position of the sensors, various defined movement classes and classification methods were found in the literature. In [6] a detection and classification system of a surveillance sensor network is presented, which classifies vehicles, persons, and persons carrying ferrous objects, and tracks them with the use of Passive Infrared Sensor (PIR), microphone, and magnetometer. Hierarchical classification architecture was used to distribute sensing and computation tasks at different levels of the system. Altogether the system achieved 90% accuracy with 200 sensor nodes. An application of biomedical wireless sensor network is presented in [7], which attempts to monitor patients for specific conditions. The proposed system uses a three-axis accelerometer to determine if the arm movement of a person is similar to a person suffering from a seizure. The results of the presented algorithms have been verified on test subjects and showed few occurrences of false positives. One waist-worn bi-axial accelerometer was used in [8] to monitor the movement of patients. A decision tree algorithm was used for classification, which classified the movements into six movement classes, with a success rate of 90%. In [9] a tri-axial waist mounted accelerometer was used for movement monitoring, in which the classification was done by a hierarchical binary decision tree algorithm into seven classes. The overall accuracy of the system was 97.7% over a data set of 1309 movements. In [10-12] a tri-axial magnetometer, a tri-axial gyroscope and a tri-axial accelerometer were used together as a sensor unit. In [10] five sensor units were used on the body. Multi-Template Multi-Match Dynamic Time Warping (MTMM-DTW) was used to classify the movement into 8 movement classes with 93.46% accuracy. Six sensor units were used in [11] for fall detection. Least-Squares Method (LSM), k-Nearest Neighbour (k-NN), Support Vector Machines (SVM), the Bayesian Decision Making (BDM), DTW and the Artificial Neural Network (ANN) classifiers were tested based on time and frequency domain features. The results showed that 99% accuracy is

achievable with k-NN and LSM. In [12] five sensor units were used on the body. The Bayesian Decision Making (BDM), the Rule-Based Algorithm (RBA), the Least-Squares Method (LSM), the k-Nearest Neighbour (k-NN), DTW, Support Vector Machines (SVM), and the Artificial Neural Networks (ANN) classifiers were compared to each other to classify into 19 movement classes. The results showed that the performance of the SVM and k-NN is good, but the BDM was the best.

In this paper an energy-efficient hierarchical-distributed classification algorithm is presented, which is tested with two different hierarchies, and is capable of classifying the movement of a human body based on the data of two wrist-mounted wireless 9DOF sensor boards. The constructed wearable wireless sensor system enables easy data collection and real-time monitoring.

This paper is organized as follows. The fundamental problem and the proposed solution are described in Section II. The used hardware and software for the measurements is presented in Section III. Section IV presents the classes, the classification algorithm and the used techniques for the classification. In Section V the generation of the input data and the usage of the extracted features are presented. Section VI presents the experimental results, while Section VII concludes the paper.

II. PROBLEM DESCRIPTION

A. Previous Research

As described in [13], above 90% recognition efficiency can be achieved using proper processing window widths if the TDFs computed using the measurement data from both sensor motes are used together in the classification algorithm. Multiple classifiers were compared with and without the use of the LDA-based dimension reduction, and their comparison showed that the Multi-Layer Perceptron networks (MLP) are the most effective, but the performance of the Minimum Distance (MD) classifier is also acceptable, moreover, the implementation and training of this classifier is faster and easier. The LDA-based dimension reduction of the input data before the classifiers can improve the recognition efficiency, and decrease the training time.

B. The Problem

Since the proposed algorithm in [13] uses the measurement data from both sensor motes, its implementation requires high energy consuming radio communication for data transfer between the motes, or the two motes and a processing unit. It was reasonable to split the classification algorithm into a hierarchical approach to get a distributed network, so the motes can calculate their own movement classes. Using the proposed hierarchical-distributed technique, only the movement class is needed to be transferred periodically based on the value of the window shift. The determined classes are combined to get the movement of the entire body and arms. Besides that using the proposed algorithm less data transfer is required via wireless communication, the classifiers have less

input features and output classes. Therefore it is more energy-efficient and easier to implement the algorithm on motes.

C. The System

The proposed system is shown in Fig. 1. Both motes compute their own movement class, based on the measured acceleration, angular velocity and magnetization. After the classification, the movement class of the slave mote is sent to the master, which combines the received class with its own class. In the last step, the final result is computed, which can be sent to another wireless device, and can be used for monitoring purposes. Another approach can be to send the computed classes from both motes to a processing unit, which combines the classes and use the final result. In this case a more energy-efficient operation is available, because it is not necessary to keep the reading channel operating on the motes. Only the processing unit has to read the data from the sensor boards.

Previously a distributed approach was proposed in [14], where the seven classes of the two arms were organized into one hierarchical level. Two training setups were tested where the training data were constructed in two different ways in case of the merged classes. The results showed no major difference between the two setups. The MLP and MD classifiers were tested with LDA-based dimension reduction, and the two methods provided similar results. The classifiers were trained for the arms separately, and the results showed only slight differences in the recognition efficiencies for the two arms. The algorithm would be improved if the same classifier could be used for the two arms.

III. MEASUREMENT

Analyzing the movement of the human body with a wearable sensor system can be very tiring for the subjects. Therefore it is necessary for a wearable movement classification system to be small, comfortable and also wireless. For this reason a 9-degree-of-freedom (9DOF) sensor board, the IRIS wireless mote was chosen.
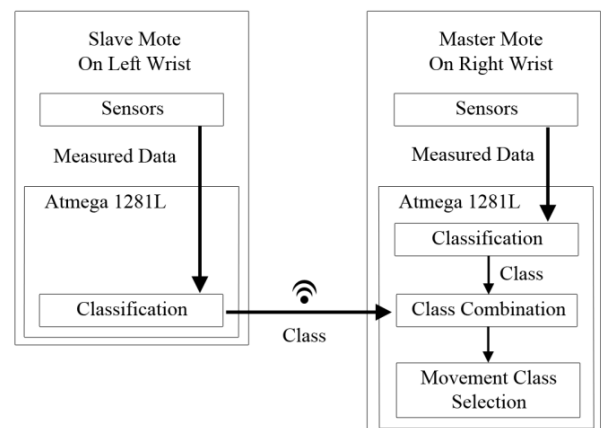
The IRIS mote contains an Atmel ATmega 1281L 8-bit
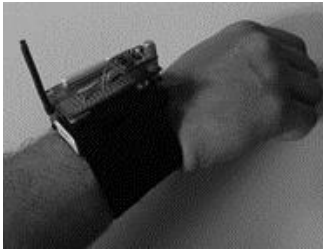

Fig.1. The architecture of the used system

Fig. 2. Wireless sensor mote mounted on the wrist

Fig. 3. The first movement hierarchy

microcontroller, a 512 Kbyte Flash with SPI communication, and an RF231 radio transceiver. The radio transceiver can provide a maximal data throughput of 250 kbps, and its outdoor range is 300 m. The transceiver requires 16 mA current draw for receiving, and 17 mA for transferring data. The IRIS mote has a 51-pin expansion interface, which can be used to connect different sensor boards to the mote. An MDA100 prototype board was used for connecting the 9DOF sensor board to the IRIS mote.

The sensor board contains a tri-axial ADXL345 accelerometer, a tri-axial ITG3200 gyroscope, and a tri-axial HMC5883L magnetometer. The accelerometer`s maximal sampling rate is 3.2 kHz, and it can measure up to ±16g. The gyroscope has a ±2000 deg/s measurement range, and 8 kHz sampling rate. The magnetometer is capable of an output resolution of ±8Ga and it can sample on 160 Hz.

With the help of the TinyOS operation system a sensor driver was implemented on the IRIS mote to configure the sensors and read the measured data. The driver and the sensors communicate via I2C communication protocol. A TinyOS application was developed for data collection, which can read the measurement values with 8 ms (125 Hz) period, and the measured data are sent to a BaseStation mote. The data from the BaseStation mote are forwarded to the PC via serial communication, and are then stored on the PC.

The measurements were performed using two wrist-mounted IRIS motes, as seen in Fig. 2. Eleven movement classes were defined for the movement classification and the data were collected for all classes with the help of 9 subjects. Data were collected in 20 s long sessions for each class. With the sampling rate of 125 Hz this means 2500 measures per mote.

IV. CLASSIFICATION ALGORITHM

A. Measurement System

Movement classes were constructed in order to recognize specific arm movements in stationary positions and also during the movement of the body. The used movement classes were the following:

1. "standing without movement of the arms";
2. "sitting with the arms resting on a table";
3. "walking";
4. "turning around in one place";
5. "jogging";
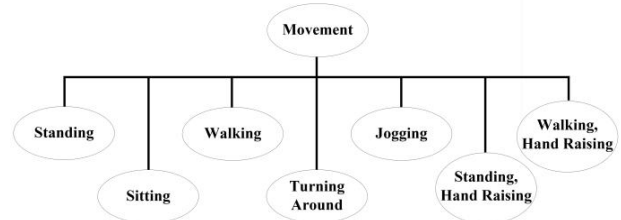6. "raising and lowering the left arm during standing";

7. "raising and lowering the right arm during standing";
8. "raising and lowering both arms during standing";
9. "raising and lowering the left arm during walking";
10. "raising and lowering the right arm during walking";
11. "raising and lowering both arms during walking".

In order to develop a distributed algorithm in which the two motes can determine their own movement type, some classes were merged by the role of the arm in the given movement. For example classes 1 and 6 can be merged in the case of the right arm, because in both cases the right arm is not moving during standing. This way the reduction of the classes can be done in four cases, so the total number of classes can be reduced to seven for both arms. Merging for the left arm can be done for the classes: 1 and 7; 3 and 10; 6 and 8; 9 and 11. For the right arm these cases are: 1 and 6; 3 and 9; 7 and 8; 10 and 11. Two different approaches were tested for the classification hierarchy. In the first approach the movements are equally distributed, all of them are on the same level. The first hierarchy can be seen in Fig. 3. The second hierarchy has been distributed into five parts based on specific selections of the main movement classes. The classification algorithm uses these distributions to decide which element of the hierarchy matches the actual movement. The second hierarchical approach can be seen in Fig. 4, and the corresponding distributions (D) are:

- $D1$: *1* or *2*
- $D2$: *a* or *b*
- $D3$: *c* or *d* or *e*
- $D4$: *I* or *II*
- $D5$: *III* or *IV*

For example the first distribution D1 decides that the actual movement is stationary or not. Through these distributions a hierarchical classification can be provided.

B. Movement Classes

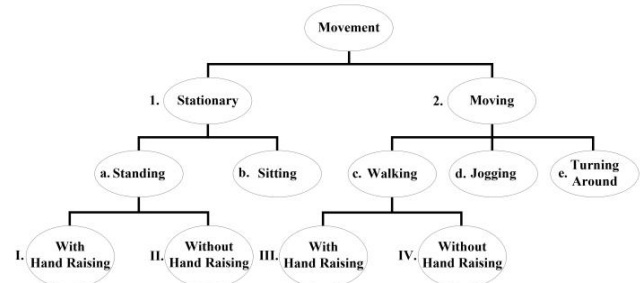In Fig. 5 the main parts of the classification algorithm are

Fig. 4. The second movement hierarchy approach

Hierarchical-distributed approach to movement classification
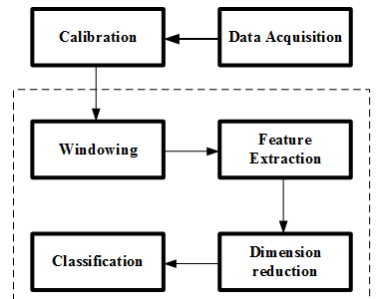using wrist-mounted wireless inertial and magnetic sensors

Fig. 5. The parts of the classification algorithm

shown. Before the data could be preprocessed, the raw measurement data have to be calibrated. A previously proposed offline evolutionary algorithm-based method was used for the calculation of the calibration parameters, which is presented in [15]. For the necessity of the easy implementation requirements only TDFs were used, because the ATmega 1281L is a low performance microcontroller. Fixed length processing windows were used for the feature extraction, which were shifted by predefined values. The used window width and shift pairs were: 80ms width and 40ms shift, 200ms width and 40ms shift, 400ms width and 80ms shift, 800ms width and 80ms shift. Similarly as in [16], the used TDFs were:

1) Mean Absolute Value (MAV): The mean of the summed absolute values inside a processing window.

2) Willison AMPlitude (WAMP): Records the number of times, when the amplitude change of the incoming signals within a processing window are higher than a given threshold level

3) Number of Zero Crossings (NZC): The number of the algebraic sign changes of the signal, with a predefined threshold value.

4) Number of Slope Sign Changes (NSSC): The number of direction changes in the signal, where from three consecutive values the change of the first or the last are larger than a predefined threshold.

5) Waveform Length (WL): The length of the waveform in a window, which is calculated by the sum of absolute changes between two measurement values.

C. Dimension Reduction

The previous researches proved that the LDA dimension reduction method can improve the speed of the training process, and its implementation is easy, since it needs only multiplications and addition.

As described in [17-18], the purpose of the LDA method is to seek a set of optimal vectors, denoted by $\mathbf{W} = [w_1, w_2, \ldots , w_l]$, such when the Fisher criterion is maximized, which is given in (1).

$$J(\mathbf{W}) = tr\left(\mathbf{W}^T \mathbf{S_B} \mathbf{W} / \mathbf{W}^T \mathbf{S_W} \mathbf{W}\right), \qquad (1)$$

where $\mathbf{S_w}$ is the within-class scatter matrix, and $\mathbf{S_b}$ is the between-class scatter matrix. Equation (2) defines the within-class scatter matrix:

$$\mathbf{S_W} = \sum_{j=1}^{c} \sum_{i=1}^{N_J} \left(\mathbf{x}_i^j - \boldsymbol{\mu}_j\right)\left(\mathbf{x}_i^j - \boldsymbol{\mu}_j\right)^T, \qquad (2)$$

where $\mathbf{x}_i^j$ represents the ith sample of class j, $\boldsymbol{\mu}_j$ is the mean of class j, C is the number of classes, and N_j is the number of samples in class j. The between-class scatter matrix is defined in (3):

$$\mathbf{S_b} = \sum_{j=1}^{c} \left(\boldsymbol{\mu}_j - \boldsymbol{\mu}\right)\left(\boldsymbol{\mu}_j - \boldsymbol{\mu}\right)^T, \qquad (3)$$

where $\boldsymbol{\mu}$ is the mean of all classes.

The goal of the LDA method is to maximize the between-class variance while the within-class variance should be minimized. The solution of this problem is obtained by an eigenvalue decomposition of $\mathbf{S_W^{-1}S_B}$, and take the eigenvectors corresponding to the highest eigenvalues. There are *C-1* generalized eigenvectors.

D. Classifiers

Two classification techniques were used, which based on previous researches proved to be the best. The classifiers were the following:

1) Minimum Distance classifier: Calculates the Euclidean distance from the mean values in each class for each feature. The output is the class, which has the smallest sum.

2) MultiLayer Perceptron networks: As described in [19-20], the MLP is a feed forward the Artificial Neural Network (ANN), where neurons are organized into three or more layers. The first layer is the input and the last is the output layer, between them are one or more hidden layers, and each layer are fully connected to the next one using weighted connections. The base elements are the neurons, which have an activation function that maps the sum of their weighted inputs to their output. The most common method for training is the backpropagation algorithm, which uses the gradient descent technique that attempts to minimize the squared error between target values and the network output values.

V. INPUT DATA GENERATION

Altogether 48 different data sets were constructed depending on the TDF calculation methods, the four window width and shift pairs, and the four used sensor combinations. Data from five subjects were used for the training and the remaining four for the validation of the system. The accelerometer, the gyroscope, and the magnetometer were tested separately as well as together.

Three different TDF calculation types were used. In the first type, the features for the x, y and z sensor axes were calculated separately (SEP), so one TDF type contains three different values. In the second type, the sum of the separately calculated TDF values was computed (SUM), thus possible misplacement of the motes on the wrists, or differences in movements of two persons can have smaller impact. In the third type, the TDFs were calculated using the magnitude (VL), which means that the features were calculated based on the changes in the Euclidean norms of the vectors. Some TDFs

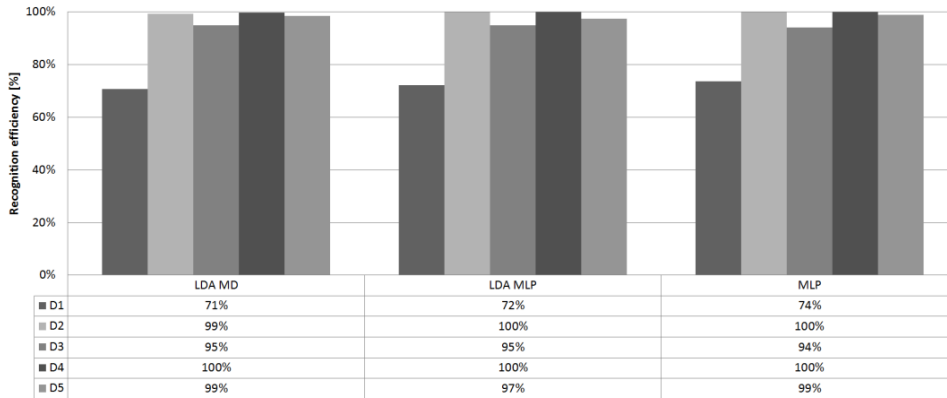|	LDA MD	LDA MLP	MLP
■ D1	71%	72%	74%
■ D2	99%	100%	100%
■ D3	95%	95%	94%
■ D4	100%	100%	100%
■ D5	99%	97%	99%

Fig. 6. Comparison of the classifiers in the case of the second hierarchy with validation efficiencies before combination, with 800 ms window length and separated TDFs of the sensors used together

were not computed, because they have no sense. The NZC cannot be calculated using the magnitudes, since they are always positive. The measurements of the magnetometer cannot be used for the MAV feature, because in ideal circumstances the magnitude of the magnetic field is constant.

For the generation of the datasets for both tested hierarchies the data from the merged classes were used in equal quantities, and the datasets for the two arms were used together for the training of the classifiers.

VI. EXPERIMENTAL RESULTS

All 48 data sets for the two training setups were tested with the classifiers described in III.C. The inputs of the MLP were used with and without the LDA dimension reduction method, while the inputs of the MD classifier were tested only with LDA. In [13] the LDA proved to improve the training process, but since in the second tested hierarchy type the classifiers have to classify into two or three classes, which means drastic dimension reduction, it was reasonable to test the MLP without dimension reduction too.

In the second tree-based hierarchy the first distribution is the significant, because the training and the validation efficiencies of the other distributions can reach 100% in the case of separated TDF values when the sensors were used together, or the accelerometer alone. Therefore, when speaking about the efficiency of the second hierarchy, the values are meant to be the values of the first distribution, because in a decision tree a wrong decision on the first level will cause a wrong final outcome. In Fig.6 the comparison of the distributions are seen in the case separately calculated TDF values with 800 ms window width, when all sensors were used together.

A. Minimum Distance Classifier

Analyzing the classification results achieved with the MD classifier on validation data before the combination on the master mote, it can be seen that in the separate cases the performance of the first hierarchy is higher, than the performance of the second hierarchy. The difference is about 5%. Despite this, in the sum and vector length cases the second hierarchy is proved to be better, the maximum

difference can be 20%. With the magnetic sensor with the first hierarchy the classification accuracy is around 30% with the smallest, and 35% with the biggest window width, but with the second hierarchy the accuracy with the smallest window is around 60%, and with the biggest it is 70%. In the first and second hierarchy, using the separately calculated TDF values 2-5% higher recognition rate can be observed with the magnetometer only. Comparing the efficiency of the gyroscope and the accelerometer, the accelerometer provides better results for all window widths in the first, but the gyroscope proved to be better in the second hierarchy only with 1-2%, if the TDFs are calculated for the axes separately. In the case of the summed and magnitude-based TDFs, the gyroscope provides the better recognition rates in both hierarchies. With the largest window width the highest efficiency with the accelerometer or the gyroscope is up to 65% in the case of the first hierarchy, and 71% in the second. Of course, the best classification rates can be reached when all the three sensors were used together. In this case, around 10% higher accuracy can be reached compared to the results of the accelerometer or the gyroscope using the same TDF types with the first, and 5% with the second hierarchy. But in some cases using only the gyroscope or the accelerometer are proved to be better. The highest efficiency with the first hierarchy was 77% and it can be reached with the separately calculated TDF values. With the second hierarchy the highest accuracy was 74%, and it can be reached with the magnitude-based TDF values.

Viewing the recognition on the training data with the first hierarchy, it can be seen that they were classified 10-15% more correctly than the validation data. The recognition of the training data with the second hierarchy proved to be 20-30% better than the validation data. For example when the recognition rate on the validation samples was 77%, the same was 92% on the training.

After the classes were combined, 80% on training and 60% on validation efficiency were reached with the first, and also 80% on training, but 55% on validation accuracies were reached with the second hierarchysamples.

B. MultiLayer Perceptron

It is obvious that with few hidden neurons only low recognition rates can be achieved, but by increasing the number of hidden neurons a converging tendency can be observed in the recognition efficiencies to a maximal value. Based on previous research it can be concluded, that this maximal value can be reached at most with 15 hidden neurons. Therefore increasing further the number of hidden neurons is not necessary, but it is required to know, that which hidden neuron number provides the best recognition rate. Consequently, the training of the MLPs for all data sets was tested with 1-15 hidden layer neurons, and the setups with the best recognition rates on validation data were used for comparison.

Before the combination of the final class selections, with the use of the LDA dimension reduction and the MLP networks on validation data in the case of the first hierarchy, the accuracy of the magnetometer is around 40%, the accelerometer and the gyroscope have very similar results, and they can provide around 70% efficiency with 800 ms window width. In the case of the second hierarchy the efficiency of the magnetometer is around 65%, the accelerometer and the gyroscope have also very similar around 70% accuracy with the window width of 800 ms. Using all three sensor types almost 80% accuracy can be achieved with both hierarchies. For the first hierarchy with all sensor configurations the results are significantly better when the TDFs are calculated separately for the sensor axes. For the second hierarchy only the magnetometer provides better results with separately calculated TDF values, the other sensors provide better results with the magnitude-based calculation. The maximum efficiency of the two hierarchies are very similar, the difference is about 1.5%. The recognition rates in the case of the training data are very similar between the MLP and MD

classifiers in the case of the second hierarchy. In the first hierarchy there are 5-10% differences between the results.

The MLP without LDA dimension reduction proved to be better both on and validation with 2-3% efficiency.

After the master mote combined the classes from the motes the highest validation efficiency was 66% with the first hierarchy, and 63% with the second in the case of the separated calculations of the TDFs with the use of all sensors together. On training data, the maximal accuracy in the case of the first hierarchy was around 82% and about 74% with the second.

The best training results can be seen in Fig. 7. and the best validation efficiencies in Fig. 8, on the figures the best accuracies of the MLP of [13] and the MLP of the proposed system with the required feature numbers shown, were compared, where V1 means the first and V2 means the second hierarchy type. The system of [13] used the data of the arms together, and classified them on the master mote. For the comparison after the combination of the classes, the MLP was used without LDA, because the simple MLP is better in the case of few classes. On validation data the best efficiency of [13] is 87%, while the proposed system provides 66% with the first, and 63% with the second hierarchy in the case of 800 ms window length, separately calculated TDF values using all sensors together. In the same circumstances on the training data the best accuracy of [13] is 100%, while it is 82% with the first, and 74% with the second hierarchy. The results of [13] are significantly better, and it is proved, that using the data from the arms together is a good approach, but energy consumption reduction has a decreasing impact on the efficiencies. On the other side, energy efficiency and lowering energy consumption in our growing civilization are very important, so the further development of the proposed system could be necessary, maintaining the reduced energy

Comparison of the MLP Training Efficiencies After Combination

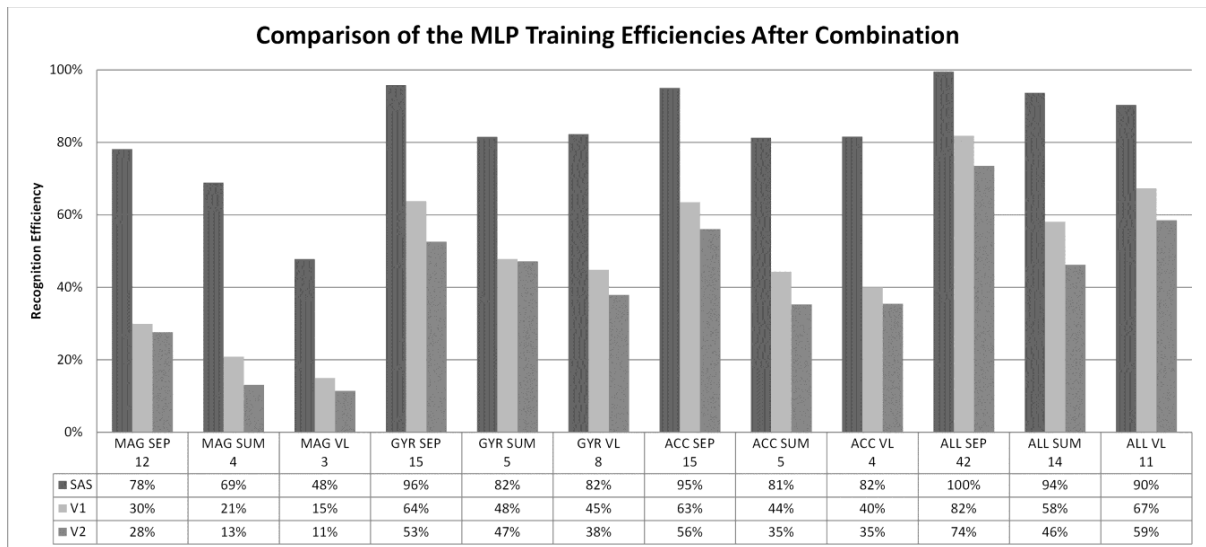|	MAG SEP 12	MAG SUM 4	MAG VL 3	GYR SEP 15	GYR SUM 5	GYR VL 8	ACC SEP 15	ACC SUM 5	ACC VL 4	ALL SEP 42	ALL SUM 14	ALL VL 11
■ SAS	78%	69%	48%	96%	82%	82%	95%	81%	82%	100%	94%	90%
■ V1	30%	21%	15%	64%	48%	45%	63%	44%	40%	82%	58%	67%
■ V2	28%	13%	11%	53%	47%	38%	56%	35%	35%	74%	46%	59%

Fig. 7. Comparison of the MLP training efficiencies after combination, 800 ms windows length, with the required feature numbers shown,
Abbreviations: MAG – Magnetometer, GYR – Gyroscope, ACC – Accelerometer, ALL – The TDFs of the three sensors together, SAS – Results from [13],
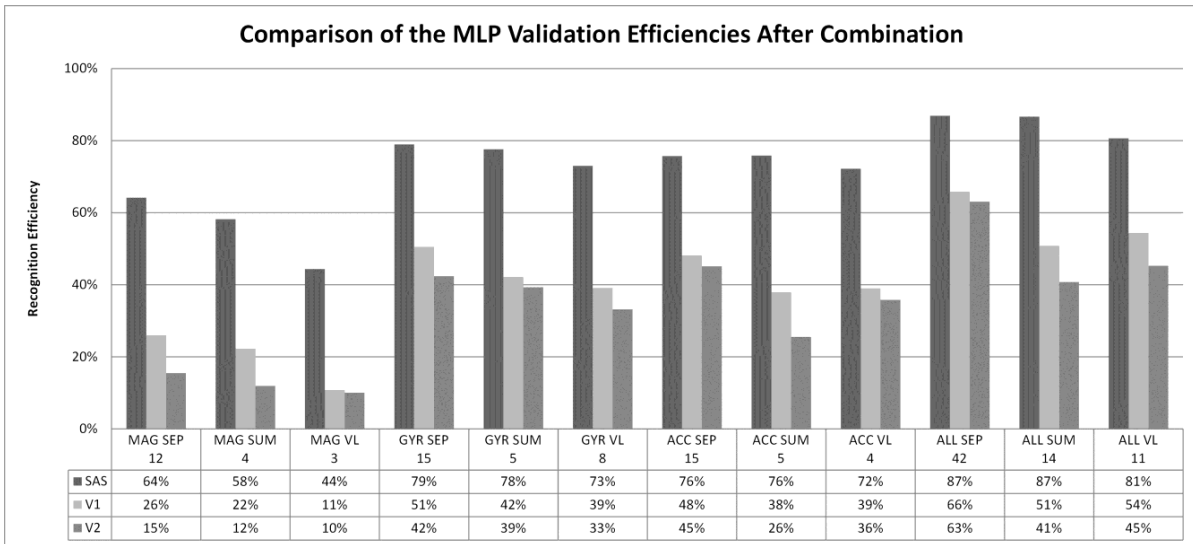V1 – First Hierarchy, V2 – Second Hierarchy

Fig. 8. Comparison of the MLP validation efficiencies after combination, 800 ms windows length, with the required feature numbers shown,
Abbreviations: MAG – Magnetometer, GYR – Gyroscope, ACC – Accelerometer, ALL – The TDFs of the three sensors together, SAS – Results from [13],
V1 – First Hierarchy, V2 – Second Hierarchy

consumption, but increasing the recognition rates.

Table 1 describes the needed RF communication and CPU computation tasks for each mote in the different algorithm types. The proposed algorithm in [13] can be realized in two different ways. In the first realization the slave mote has to send the measurement values (18 bytes/sampling cycle) to the master mote and the master mote makes the computation of the TDFs for both motes. In the second approach the slave computes the TDFs and only these values are sent to the master mote. The number of TDF values depends on the used configuration (10-50 bytes), and they should be sent after

every window shift. In the proposed hierarchical- distributed approach the computation is equally done by the two units, and only the movement class of the slave mote (1 byte) should be transferred to the master mote after every window shift.

As shown in [13], the needed memory for the implementation of the three tested classification methods is very similar. The needed memory in case of different number of inputs for the two tested hierarchical-distributed approaches and the non-distributed approach in case of the MLP classifier can be seen in Fig 9. For the calculation of needed bytes ten hidden layer neurons were applied for the non-distributed approach, V1, and D1 of V2, while for D2-D5 in V2 only one neuron was used. The results show that for the implementation of V1 less memory is needed than in case of the non-distributed approach, since the movements need to be classified into fewer classes, which reduces the size of the artificial neural network. It can be also noticed that V2 is the most memory consuming of the three methods.

Table 2 summarizes the comparison of the efficiencies based on the separately calculated TDF values.

TABLE I
RF COMMUNICATION AND CPU TASKS FOR THE MOTES

Radio communication	Master mote	Slave mote
Master processing (transmission of measurement data)	Reception of measurement data	Transmission of measurement data
Master processing (transmission of TDF values)	Reception of TDF values	Transmission of TDF values
Distributed processing	Reception of the slave mote`s movement class	Transmission of the arm`s movement class

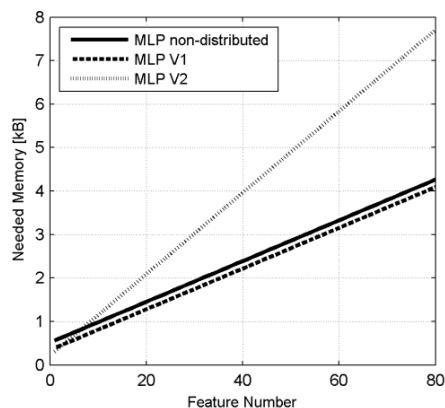| CPU computation tasks		
Master processing (transmission of measurement data)	Computation of the TDFs for both motes; computation of the movement class of the entire body and arms	None
Master processing (transmission of TDF values)	Computation of the TDFs; computation of the movement class of the entire body and arms	Computation of the TDFs
Distributed processing	Computation of the TDFs; computation of the arm`s movement class; class combination	Computation of the TDFS; computation of the arm`s movement class

Fig. 9. The memory consumption in case of the MLP classifiers

TABLE II
SUMMARY OF SEPARATELY CALCULATED TDF BASED EFFICIENCIES, IN CASE OF 800 MS WINDOW WIDTH

Hierarchy	First								Second							
Sensor	MAG		GYR		ACC		ALL		MAG		GYR		ACC		ALL	
Combination (Before/After)	B.	A.	B.	B.	B.	A.	B.	A.	B.	A.	B.	A.	B.	A.	B.	A.
LDA MD T. (%)	51	36	76	70	75	74	92	74	89	53	93	56	90	55	97	80
LDA MD V. (%)	35	25	65	59	66	60	77	60	68	49	71	51	70	50	71	55
LDA MLP T. (%)	55	25	79	58	83	62	96	80	90	27	95	53	90	47	99	64
LDA MLP V. (%)	41	22	66	52	67	54	78	61	65	20	70	45	70	40	72	58
MLP T. (%)	58	30	84	64	84	63	98	82	91	28	98	53	95	56	100	74
MLP V. (%)	46	26	68	51	69	48	79	66	67	15	71	42	73	45	74	63

VII. CONCLUSION

In this paper, a hierarchical-distributed movement classification algorithm was described and tested for an energy-efficient system built up from two wrist-mounted wireless 9DOF sensor boards.

Results showed that the MLP classifier for few classes is better without LDA dimension reduction. Also the results of the MD classifier with LDA are similar to the MLP with LDA. In the proposed system the MLP classifier provides the best training with 82% and validation with 66% efficiencies in the first hierarchy, and 74% on training, 63% on validation accuracies in the second hierarchy in the case of separately calculated TDF values using all sensors together with 800 ms window length. In the proposed system the best classifier is the MLP with the first hierarchy, because the LDA dimension reduction has small effect on few classes, so the numbers of dimensions are few too. The results of the proposed system have been compared to the results of a previous approach, which used the data from the arms together, but classified them on the master mote. The final result is that a system that classifies the data on the master sensor board is better in recognition rates, but requires more energy. Therefore keeping in mind the low energy consumption the proposed system could be acceptable with further development on the recognition rates.

The implementation of the proposed system is more optimal than the algorithm presented in [13], but further development is required to reach the recognition rates of [13].

Future work could be the development of a better algorithm, the testing of more feature extraction techniques, or energy consumption optimization.

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