IS-ACTIVE

Inertial Sensing System for Advanced Chronic Condition Monitoring and Risk Prevention

WP4 – Algorithms

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1. Overview

This document gives a short overview of the state of the art in activity recognition and briefly describes the developments undertaken in the IS-ACTIVE project regarding activity recognition. These developments articulate along three directions: (1) activity monitoring, (2) recognition of object handling and (3) recognition of walking activities. The results are available as prototypes, used for experimentation and evaluation.

2. A survey of activity recognition algorithms

This section gives a short survey of activity recognition algorithms using inertial sensors for medical, home monitoring and assisted living applications. More information can be found in Avci et al. [1].

The goal of activity recognition is to recognize the actions and goals of a person or a group of persons from the observations of the persons' actions. Traditionally, researchers used vision sensors for activity recognition [2][3]. However this type of activity recognition is intrusive and disruptive in some applications [4] and violates the privacy of the users in some cases [5]. With the advancements in microsensor technology, low-power wireless communication and wireless sensor networks (WSNs), inertial sensor systems [6] provide a low-cost, effective and privacy-aware alternative for activity recognition.

2.1. Medical applications

Traditional health care systems require patients to apply to the health care provider for a scheduled evaluation or in case of an emergency. Such clinical visits might either take a snapshot of patients' condition or be too late for any interventions [7]. In both cases, early indications of an illness might be missed. In addition to this lack in healthcare system, long term health care costs increase year-by-year [8][9]. Therefore, there is a rapid shift from a clinical setting to a patient or home centered setting with the help of wireless sensor network systems, which fill the gap in health care monitoring between clinical visits [10]. Continuous physical and physiological monitoring in any environment would shorten hospital stay for patients, improve both recovery and reliability of diagnosis [7] and improve patients' quality of life, as well.

Monitoring & Diagnosis Jiang et al. [11] present a remote health care service with movement and fall detection capabilities. Wu et al. [7] also propose a patient monitoring and medical diagnosis system in a similar manner. Wu et al. use physiological body-worn and contextual sensors located in the environment thus enable medical personnel to see the raw sensor data other than features extracted from sensors.

Rehabilitation Someren et al. [12] investigate the effect of medication on Parkinson patients and tremor duration after medication by using an actigraphy, which is a solid state recorder used for long-term continuous measurement of movement. Walker et al. [13] explore the activity and disability in patients with heumatoid arthritis(RA) and Bartalesi et al. [14] suggest a system using kinesthetic wearable sensors for upper limb gesture recognition in stroke patients.

Correlation Between Movement and Emotions Picard et al. [15] propose a framework for emotion recognition in order to understand the correlation between intelligence and emotion in people and to build machines appearing more intelligent. In a similar way, Myrtek et al. [16]

succeed in detecting the emotional activity by separating the metabolically induced heart rate from the emotionally induced heart rate.

Child & Elderly Care Children and elderly people constitute the most sensitive group in our society and they need continuous observation. Najafi et al. [17] propose a system for activity recognition and shows the results for classification of postural transitions in hospitalized elderly people and monitoring elderly people during their daily lives. Beside these, fall related hip fractures in elderly people are really dangerous and economic burden to the victim. Wu et al. [18] present a portable system which detects fall before the impact. In a similar manner, Busser et al. [19] propose an acceleromety-based ambulatory system for monitoring daily activities of children living under treatment or for diagnosis.

2.2. Home monitoring and assisted living

Assisted living systems are used to provide supervision or assistance to the residents to ensure their health, safety and well-being. In order to accomplish this, assisted living systems provide services such as tracking, fall-detection, and security [20]. Some of these home monitoring and assisted living systems can be categorized as follows:

Tracking, Monitoring & Emergency Help Hou et al. [20] present an assisted living system providing services such as time-based reminder, vital sign measurement, human and object tracking, and fall detection and emergency help services. Assistance for People with Cognitive Disorders Assisted living systems are also widely used for people with cognitive disorders. A person with cognitive disability is defined by DSM-IV [21] as someone who is "significantly limited in at least two of the following areas: self-care, communication, home living, social/interpersonal skills, self-direction, use of community resources, functional academic skills, work, leisure, health and safety". External assistive systems are used to remind people with cognitive disorders to accomplish daily activities and these systems range from paper-and-pencil methods [22] to specialized software applications [23]. Osmani et al. [24] present a scenario about activity recognition and reminding system composed of environmental and wearable sensors for a dementia patient. Dieter et al. [25] also propose an adaptive prompter system for Alzheimer patients which recognizes activities of the user by using various sensors and prompts appropriate messages verbally or visually.

Assistance for People with Chronic Conditions Besides physiological measurements, daily physical activity of chronic patients represents an important reflection of quality of their daily lives. Moreover, Berry et al. [8] investigate the economics of chronic heart failure and they emphasized the importance of reducing the rate of hospitalization. For this purpose, Davies et al. [26] present a lightweight sensor system in order to evaluate cumulative movement of limbs for patients with chronic heart failure. Marshall et al. [27] introduce a smart-phone application for self management of specific chronic diseases and they test the system for patients with chronic obstructive pulmonary disease (COPD). In a similar manner, Steele et al. [28] developed a system for monitoring daily activity and exercise in COPD patients.

3. **Activity monitoring**

It has been shown that health condition and quality of life are directly influenced by the amount and intensity of daily physical activity [30]. This is particularly relevant to persons suffering from COPD. They enter a vicious circle, in which being active causes discomfort, making them progressively more sedentary, and deteriorating their health. Monitoring the daily activity can stimulate people to perform exercises and to be more active in general by providing feedback and assistance to better manage the physical condition [29].

The activity level of a person is best assessed in terms of energy expenditure. This is therefore a relevant feature for the IS-ACTIVE use cases. The IMA algorithm presented in *D4.1 – Distributed feature extraction* is shown to produce a good estimate of the activity level / energy expenditure.

In this section, we describe our experience with evaluating a physical activity monitoring and stimulation system using wireless sensor networks and motion sensors. We conduct experiments on multiple test subjects, performing multiple normal daily activities. The results from our experiments represent the motivation for and a first step towards robust complex physical activity monitoring with multiple sensors distributed over a person's body. The activity montioring algorithm is fully implemented and operational on the ProMove nodes. More information can be found in Bosch et al. [29].

3.1. Tests

To obtain a view on how well the IMA value maps to the energy expenditure of a particular person, we conduct tests with multiple subjects performing various activities of interest. The tests are performed in the course of several experiments.

Office The main and longest experiment is performed by nine members of our department. This includes the daily and home activities. The sensors are worn the whole day, except during sleep. The experiment lasts three days. As the nodes can only record 36 hours, the logs are collected each day during a collective meeting in the afternoon. The subjects keep a coarse log of what they have been doing all day. These logs are evaluated during the meeting and compared to the logged hourly activity levels. The recorded activities include the normal activities, home activities and transportation.

Ski Two sensor nodes are taken on a skiing holiday in the mountains. The two subjects keep a coarse log of their daily activities, including skiing, resting and driving the car.

Sports Four separate experiments are performed in which the subjects are engaged in sports: tennis, badminton, volleyball and cycling. Tennis is performed by two persons, volleyball is performed by four persons and cycling is performed by three persons at the same time. The badminton experiment is spread over multiple parallel matches involving four subjects. Each experiment lasts more than an hour to record only the activity of interest.

3.2. Results

Table 1 shows the average IMA value for various activities. Because the sensor nodes log the activity level on a per-hour basis, the presented values are the hourly averages of the same activity performed by multiple persons at multiple time instances. The table also shows how many hours of data are involved in computing the average and how many subjects were involved in a particular activity. Since activities do not necessarily change on the hour boundaries, the IMA averages are solely based on those hours during which only one activity was performed with certainty.

Activity	Recorded Hours	Persons Involved	IMA
Not Worn	129	9	373
Home Activities	33	6	1581
Office Activities	58	9	1144
Sitting	25	6	1120
Walking	4	2	7767
Cycling	3	3	6466
Tennis	2	2	11411
Badminton	6	4	10874
Volleyball	4	4	9464
Skiing	40	2	1496
Driving a Car	31	2	827
Presenting	1	1	2655

Table 1. Activity recording results.

The recorded activities are as follows:

- Not worn: the sensor node is not worn by anyone and just lies stationary somewhere.
- Home activities: the subject is engaged in the typical home activities, such as cooking, washing, childcare etc.
- Office activities: the subject is engaged in the typical office activities, which mainly consist of sitting, but also intermittent walks between offices and fetching coffee.
- Sitting, walking: the subject is continuously sitting or walking respectively.
- Tennis, Badminton, Volleyball, Cycling: the subject is playing tennis, playing badminton, playing volleyball or riding a bicycle respectively.
- Skiing: the subject is skiing downhill.
- Driving in a car: the subject is driving in a car.
- Presenting: the subject is giving a presentation during a meeting.

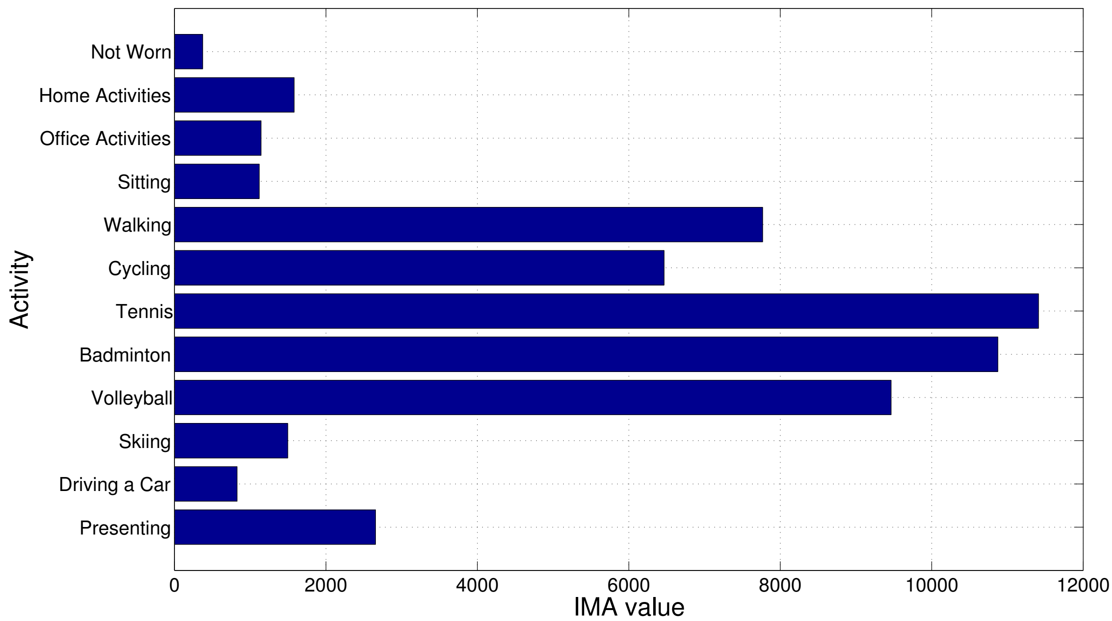


Figure 1 - IMA values for various activities

Figure 1 graphically illustrates the difference between the activities in terms of the measured IMA value. We notice that the results show that the IMA value always greater than zero, even when the sensor is not worn, due to the integration of accelerometer noise.

The results show that home activities produce higher activity values than office activities. The reason is that in the office people barely leave their desk for hours. At home, activities such as doing laundry, cleaning etc. contribute to a higher activity level. It is interesting to see that what people describe as sitting matches well with the office activities. The activity value for cycling is the average of the IMA value from three persons making a bicycle trip. For this test the activity results vary wildly, with values ranging from 5635 to 7542. These differences are probably caused by differences in the bicycles, the exact path taken on the road and the way the subjects ride their bicycle.

The results for tennis and badminton are very similar, since these two sports and the movements involved therein are very similar as well. Volleyball produces lower activity values. This is due to two main reasons: more people are involved in the ball game, spreading the activity over more persons, and the game is interrupted for longer periods of time.

The most interesting data results from the skiing activity. Although skiing is certainly not an activity with a low energy expenditure, the sensors show a low activity value. This value is lower than walking, even though skiing is much more exhausting. The reason is that during skiing the amount of variation in the acceleration of the person is relatively limited in comparison to walking. The regular motion of the gait of walking is not present when sliding down a hill on skis. The energy expenditure from skiing is more the result of the act of leaning in the bends and keeping ones legs steady.

According to the results displayed in Figure 4, walking is more active than riding a bicycle, but the spread in the activity values is relatively large. This is unexpected, since the walking experiments were conducted with a normal walking pace, whereas the cycling experiments were performed at speed. Therefore, we would expect to see a higher activity result for the cycling experiments. We attribute this discrepancy to the same effect as for the skiing experiments.

The ski experiment also shows that the orientation and the way sensor is mounted influences the result. After in the middle of the experiment, the pouches in which the sensors are worn were exchanged between the subjects. The persons kept their own sensor. During the week, the recorded activity values were similar, with the trend that one was reported to be more active than the other most of the time. After the exchange of the pouches, this trend inverted. The main observable difference between these pouches is the fact that one is worn vertically and the other horizontally.

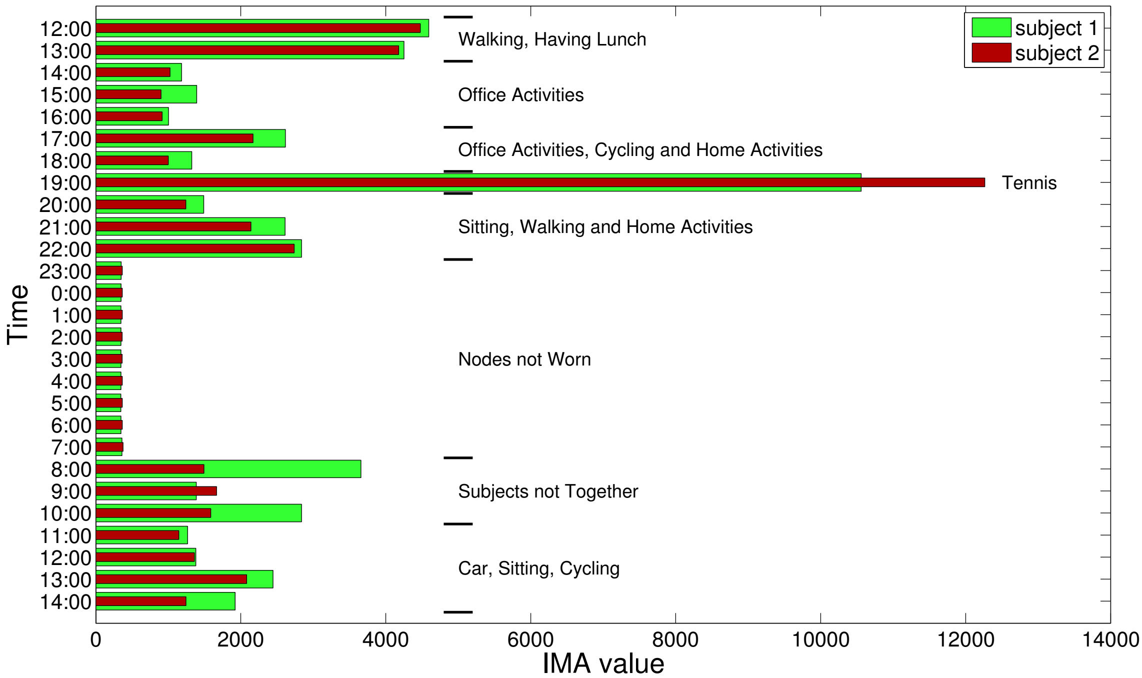


Figure 2 - Example activity values recorded during 27 hours from two subjects

Figure 2 shows an example of an activity log for two subjects. For most of the day, these subjects were together and engaged in the same activities. The graph shows a clear correlation between the two subjects. At 19:00 they played a tennis match for one hour, which is much more active than anything else recorded during the experiment. Between 23:00 and 7:00 the sensors were not worn. As shown, the IMA values are constant in stationary conditions.

4. Recognition of object handling

An essential component of an ambient assisted living system is the ability of detecting which objects are being used at any moment, in a non-intrusive manner. A number of solutions have already been proposed in the literature: RFID [31][32], contact switches [33][34] and power consumption monitoring of electrical appliances in the home [35]. Each of these has its own limitations. RFID systems may erroneously mark an object as being held by the user just because it is in close proximity or, conversely, the user's interaction may be missed when the object is grabbed at a great distance from the RFID tag. The techniques using contact switches and monitoring the power consumption of appliances in the home provide no information on the user's identity and therefore those only provide a suitable solution when the identity of the user either is known implicitly or not important. Furthermore, the use of contact switches requires that there is an actual contact involved in the user action, for example when the object has a knob. Monitoring an appliance's power consumption gives solely an indirect estimate of the usage and is restricted to electrical appliances.

Inertial and magnetic motion sensors is an alternative technology that we consider in the IS-ACTIVE project. If worn by the user and attached to objects, such sensors can detect that an object is being used by a particular user by correlating their movements. This approach has two important advantages over the previous alternatives: (i) it gives a direct measure based on the actual object use (and not based on proximity to the object, for example) and (ii) it provides much more and finer grained sensor information, thus making possible to also detect how the user is interacting with the objects (which can lead, for example, to inferring the user's activities). The main limitation of this approach is that it assumes some dynamics involved in the interaction, i.e. the user is supposed to actually handle and move the objects.

This section gives an overview of our solution for automatic detection of object use based on wireless sensor nodes outfitted with three-dimensional accelerometer and compass sensors. We equip the objects of interest and the user's arm with sensor nodes that correlate their relevant motion features. The feature extraction, communication and correlation are performed on-line and cooperatively by the sensor nodes, which guarantees a fast response time to the user. The feature extraction methods are explained in *D4.1 – Distributed feature extraction*. The whole recognition algorithm is implemented and operational on the ProMove nodes. More detailed information about the proposed solution can be found in Bosch et al. [36].

4.1. Solution overview

Our solution is based on smart objects (also called sentient artifacts or cooperative artifacts [37]), which envelop sensing, processing and communication capabilities. Each object is equipped with a wireless sensor node with three-dimensional accelerometer and compass sensors. For a pair of sensor nodes under consideration, movement measurements are correlated in the time domain using the Pearson product-moment correlation coefficient. The accelerometer is used to measure linear motion, whereas the compass sensor is used to measure rotary motion. A node performs the correlation calculation using its local measurements and those communicated wirelessly from the peer node. To reduce communication and processing efforts and to improve the correlation performance, the raw sensor signals are first processed into concise feature values before being communicated and used in the correlation. Unlike actual activity recognition, temporal segmentation of the sensor data is not necessary to perform the correlation. For this application we are not so much interested in the composition of the movement, but rather in the correlation between the movements of the sensors.

4.2. Correlation algorithm

The correlation of the two motion features in the feature vector between two nodes is done in the time domain using the Pearson product-moment correlation coefficient:

$$\rho(X,Y) = \frac{\mathrm{cov}(X,Y)}{\rho(X)\rho(Y)} \qquad (1)$$

The correlation is calculated over the last H (correlation history length) features produced at both nodes. The result $\rho(X,Y)$ lies in the range [−1; 1], for which a value of 1 means that the signals are fully correlated and values ≤ 0 (in our case) mean that the signals are not correlated.

Using Equation 1, separate correlation values are calculated for the two feature values. These results have to be combined into a single value that indicates how well the motion of the two nodes correlates. The reliability of the accelerometer correlation is sensitive to rotational motion. Therefore, we involve the current compass rotation (f_{cra}) features from both sensors to produce a weighted average of the accelerometer correlation ρ_a and the compass correlation ρ_c. This done using the following heuristic formula:

$$\alpha = \frac{1}{4} + \frac{1}{8}(f_{cra,1} + f_{cra,2})$$
$$\rho = \alpha\rho_a + (1-\alpha)\rho_c \qquad (2)$$

The combined correlation result ρ is the average of both correlations when there is no instantaneous rotation ($f_{cra,1}$, $f_{cra,2} = 1$) and it is the compass correlation alone when both f_{cra} features are at their extreme value ($f_{cra,1}$, $f_{cra,2} = -1$). The correlation value produced by our algorithm lies in the range [−1; 1]. To obtain a discrete decision on whether an object is being held and used by the user, we need to define the thresholds for when the detector status changes from not used to used and vice-versa. These thresholds are not necessarily equal in both directions, yielding hysteresis between the two states. More details about the algorithm parameters, trade-offs and simulation results can be found in Bosch et al. [36].

4.3. Implementation details

We use the ProMove wireless inertial sensor nodes for this work. The ProMove board features a 3-D accelerometer and a 3-D digital compass. The main CPU of the sensor node is a low-power MSP430 microcontroller running at 8 MHz. The nodes can communicate wirelessly using a CC2430 SoC, which combines an IEEE 802.15.4-compatible radio with an 8051 CPU. The CC2430 CPU autonomously handles the wireless networking. The ProMove architecture thus allows implementing an application in a two-tiered manner: performing data processing on the MSP430 and wireless networking on the CC2430.

Figure 3 shows an overview of the software components involved in our implementation for a pair of nodes. Both nodes process the raw signals from their accelerometer and compass sensors into window intervals and calculate features from these intervals. This reduces the data rate and dimensionality, yielding a feature vector with only two values. Subsequently, the movement correlation between the two nodes is determined. The feature vector of one node is communicated wirelessly to the other node, which performs the correlation calculation. The accelerometer and compass features are correlated separately, yielding two distinct correlation values. The final stage in the process, the decision logic, combines the two correlation values into a discrete interaction assessment.

The nodes exchange the necessary correlation messages wirelessly using the IEEE 802.15.4 protocol. One node acts as the coordinator and broadcasts its feature vector to slave nodes, which check whether they are moving together with the coordinator. The sampling and feature extraction tasks running on the slave nodes need to be synchronized to the coordinator for proper correlation performance. For this, the nodes first synchronize sampling and then align the feature extraction. This achieves coarse synchronization within one sample.

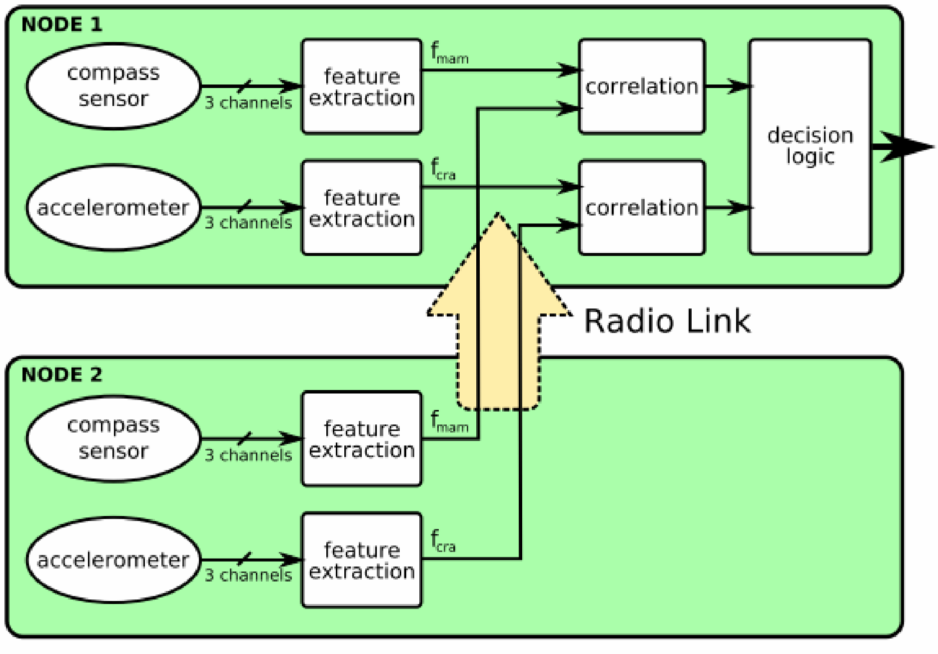


Figure 3 - Implementation overview

4.4. Tests and results

To evaluate our implementation, we perform a series of experiments with handling objects equipped with our sensors. In each experiment, the user wears one sensor node on a bracelet on his arm and two other sensor nodes are placed onto or inside objects, as shown in Figure 4. The arm node acts as the protocol coordinator and the usage detection is performed in the object nodes. The exchanged feature vectors and the resulting assessments are logged by a PC with a gateway node for later evaluation. In these experiments the nodes are less synchronized compared to the offline evaluation (within one sample instead of microsecond range) and there is no compensation for the potential packet loss.

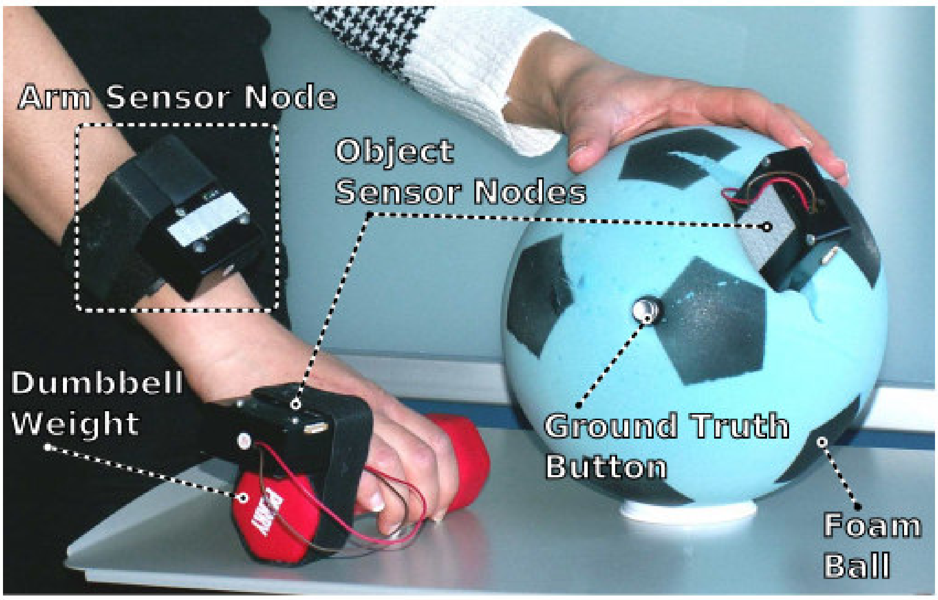


Figure 4 - Some of the hardware involved in the implementation experiments

We assess the response time and accuracy of the algorithm when correlating generic movement of an object held by the user. We let our test subjects perform random motion with the objects, i.e. any motion they see fit. We use two foam balls (one of which is depicted in Figure 8) that can be handled in any orientation. The user can handle one of the balls with the arm on which he wears the sensor. A second person moves the balls that are not currently held by the user, thus trying to generate false correlations. The user is not necessarily always moving one of the two balls, in which case the second person may move them both. Balls can be placed still on the table during the experiment for the other person to pick them up, but also handed over directly. We experiment with ten different users, which perform five individual tests. Each of these 50 individual tests lasts two minutes.

The push-buttons on the balls are used for automated annotation of the ground truth. While grabbing and holding one of the foam balls, the user with the bracelet keeps the ground truth button on that ball pressed continuously. The second person does not touch the buttons at all.

Figure 5 shows an example experiment, comparing the true object association as indicated by the button (solid black lines) and the output of our detection algorithm (dashed red lines). The produced correlation values are shown as well. The two plots show the object use association results for the two foam balls. Approximately at 4 s, both balls are picked up from the table and start moving. Ball 2 is held and moved by the user with the bracelet, while Ball 1 is moved by the second person. At 27.5 s, the user hands over Ball 2 to the second person, who at that point moves both balls at the same time. As shown in the graph, no ball is associated with the user at that time. A little later, at 47 s, Ball 2 is handed back to the user. At 65 s the balls are swapped between the user and the second person, which is the first time that Ball 1 is held by the user. At 88 s, the balls are swapped back. Just before the experiment finishes, both balls are placed back on the table.

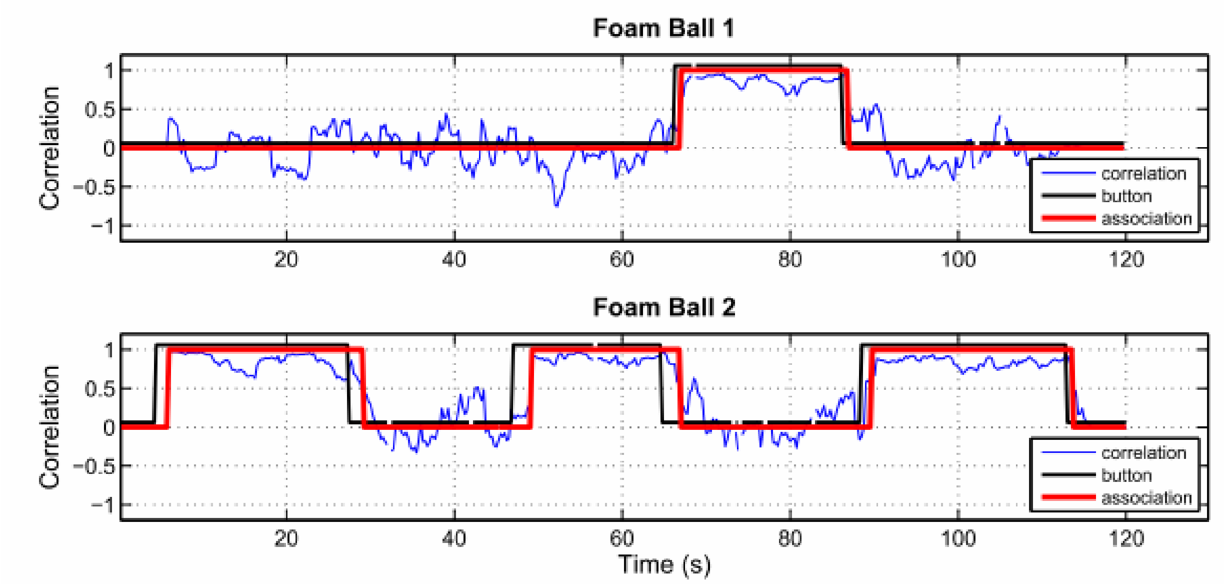


Figure 5 - Example of an experiment with the implemented system

The table below shows the overall performance of our implementation for all 50 tests. The response times are typically within the 2 s limit and the accuracy of the algorithm is adequate, with false correlation at about 3 % of the time and false non-correlation at about 2 % of the time.

	Response Time (s)		Errors (%)	
	corr.	non-corr.	corr.	non-corr.
User 1	1.61	1.41	4.44	2.05
User 2	1.66	1.48	0.96	2.17
User 3	1.41	2.00	0.37	2.37
User 4	1.73	0.76	5.77	2.39
User 5	1.23	1.59	3.44	0.53
User 6	1.82	0.89	6.66	1.04
User 7	1.21	1.21	5.45	3.87
User 8	1.05	1.86	2.81	1.80
User 9	1.20	2.28	0.68	2.48
User 10	1.23	1.95	0.40	1.14
Mean Performance	1.41	1.55	3.10	1.98
Standard Deviation	0.27	0.49	2.41	0.94

5. Recognition of walking activities

Activity monitoring systems can remind, stimulate and motivate people to be more active, especially when used within groups with a competitive nature. The recognition of critical daily activities and exercises draws a further step on the activity monitoring. In this way, a better approximation of the level of activity, a better assessment on the subject's current and future health conditions can be obtained.

In the current activity recognition solutions, the use of inertial sensing, mostly accelerometer-based, has been shown to offer substantial results. Among the activities studied, one of the most challenging activity set reported is related to walking. The walking activities include walking on flat surfaces, uphill and downhill, upstairs and downstairs. For these activities, recent studies acknowledge that the similarity among these activities and the nonstationary, nonlinear characteristics of the related signals make it difficult to accurately classify them using only time-domain features [39][40]. More complex frequency-time-frequency- or combined sets of time- and frequency-domain features are needed, as they better represent the instantaneous nature of these activities [41][42]. Another approach is to rely on gait analysis for the classification [43][44], which also achieves a high accuracy, but at the expense of even higher complexity.

We focus in this section on simple time-domain features of inertial and orientation sensors (accelerometer, gyroscope and compass), i.e. the features that can be extracted on-line by the sensor nodes. More information can be found in Yalçin et al. [38].

5.1. Experimental framework

We use the ProMove inertial sensor node, as described in Section 4.3. The sensor nodes are mounted on the waist and the right ankle of the subjects. Figure 6 shows the ProMove sensor node and its mount points.

In all experiments, the sampling frequency is set to 200 Hz. We collect one minute of accelerometer, gyroscope and compass data with all of the sensors on the mount points for each of five walking activities from five healthy people. We analyze the classification accuracy of all combinations of time-domain feature sets extracted from accelerometer, gyroscope and compass signals for both of the waist- and right ankle-mounted ProMove sensors. The accelerometer data is first filtered with a band-pass (0.25-18 Hz) elliptic filter to eliminate the gravitational acceleration component, noise and irrelevant frequencies [6,15]. As a common approach in the literature, a window size of 512 (equivalent of 2.56 sec) with half overlapping portions is selected to build the windows.

(a) ProMove (b) ProMove (hard case) (c) Mount points

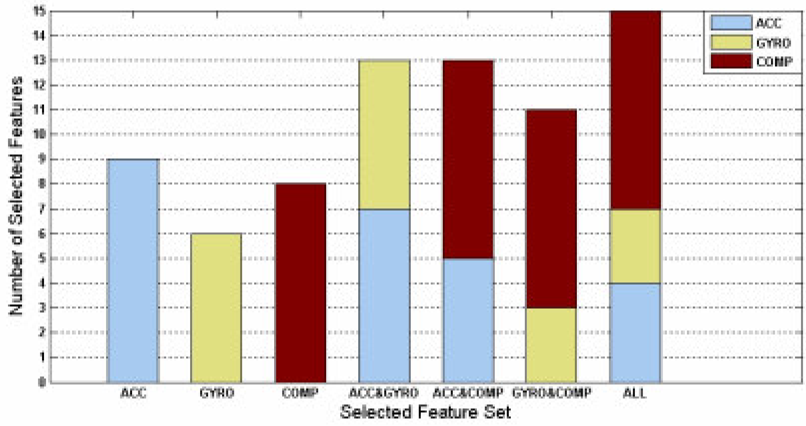
Figure 6 - ProMove inertial sensor node and its mounting points on the body

The table below shows the features used for the accelerometer, gyroscope and compass. We apply the same features for the gyroscope and compass. We use the WEKA toolkit for feature selection and classification. Specifically, we apply correlation-based feature selection (CFS) algorithm on separate and combined sets of accelerometer, gyroscope and compass features. We employ Artificial Neural Networks (ANNs), specifically a multilayer perceptron, with backpropagation and Decision Tree (DT) implementations of the WEKA toolkit for the offline learning with the aforementioned feature sets, as these methods require lightweight implementations on the sensor nodes. We use a 10-fold cross validation procedure for both the feature selection and learning algorithms.

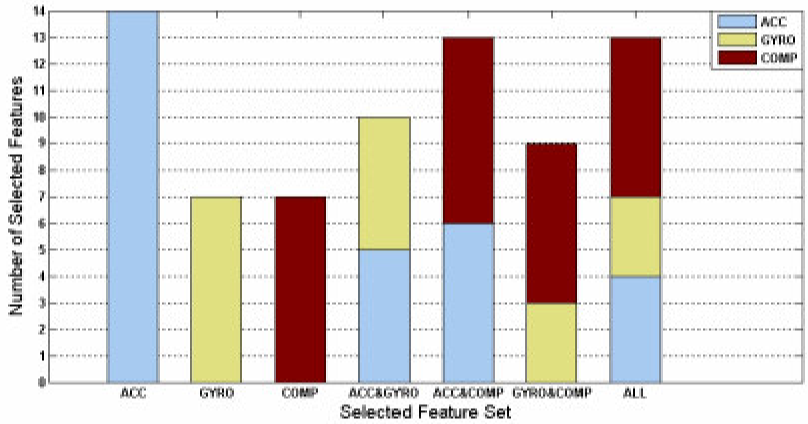
Accelerometer Features	Gyroscope Features	Compass Features
mean(a_x, a_y, a_z)	mean(g_x, g_y, g_z)	mean(c_x, c_y, c_z)
variance(a_x, a_y, a_z)	variance(g_x, g_y, g_z)	variance(c_x, c_y, c_z)
kurtosis(a_x, a_y, a_z)	kurtosis(g_x, g_y, g_z)	kurtosis(c_x, c_y, c_z)
interquartile range(a_x, a_y, a_z)		
mean acceleration magnitude		
mean absolute deviation(a_x, a_y, a_z)		
root mean square (a_x,a_y, a_z)		
zero crossing rate (a_x, a_y,a_z)		

5.2. Results

Based on the experimental setup explained in the previous section, Figure 7 shows the selection results for the features of accelerometer, gyroscope, compass and their combinations for the waist and right ankle positions, respectively.



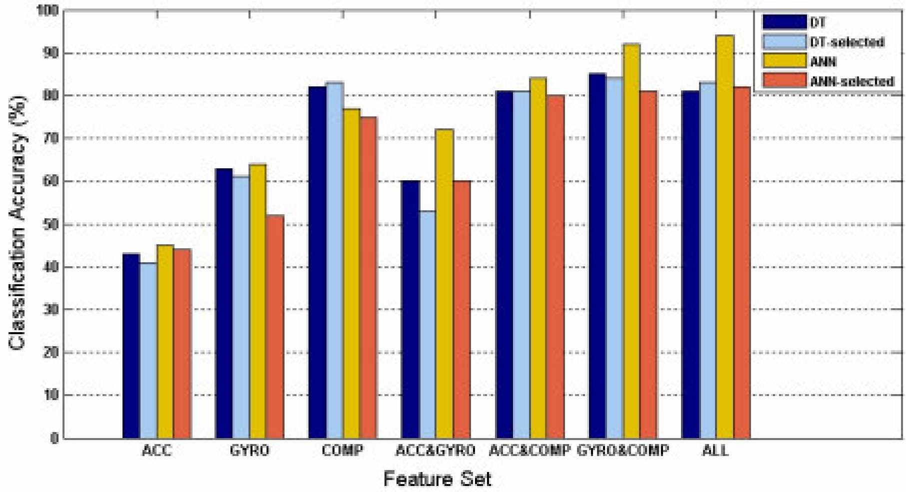
(a) Feature selection results for waist-mounted ProMove



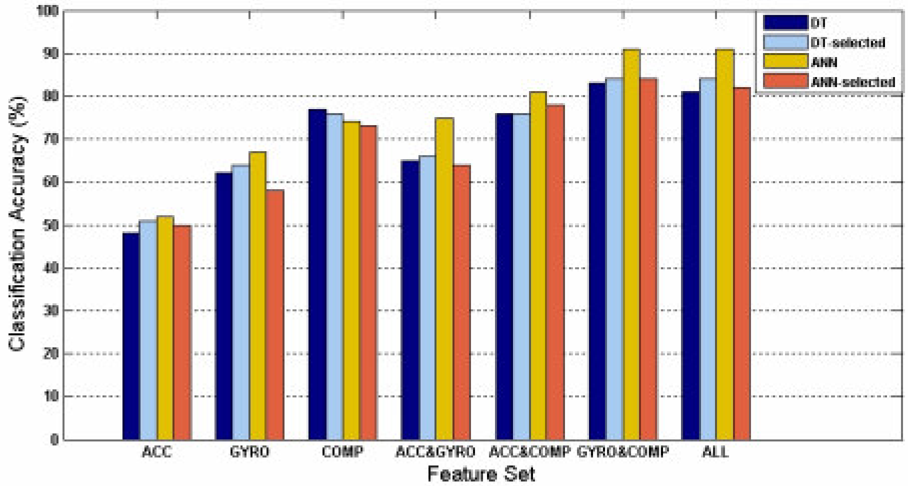
(b) Feature selection results for right ankle-mounted ProMove

Figure 7 - Feature sets vs. quantitative distribution of selected accelerometer, gyroscope and compass features

Figure 8 shows the overall classification results of all possible sensory combinations for each sensor node, respectively. Figure 9 shows the true positive rates for each walking activity for the compass-only, fused accelerometer and gyroscope, fused gyroscope and compass feature sets classified via ANN. The overall performance results suggest that although accelerometer features perform slightly better in the right ankle-mounted ProMove, in general there is not a significant difference in the recognition performance between the two selected body mount points. Besides, regardless of the mount point, the accelerometer's performance is the lowest among all sensors.



(a) Results for waist-mounted ProMove



(b) Results for right ankle-mounted ProMove

Figure 8 - Overall classification accuracy of five walking patterns for distinct feature sets extracted from the waist and right mounted sensor node, respectively

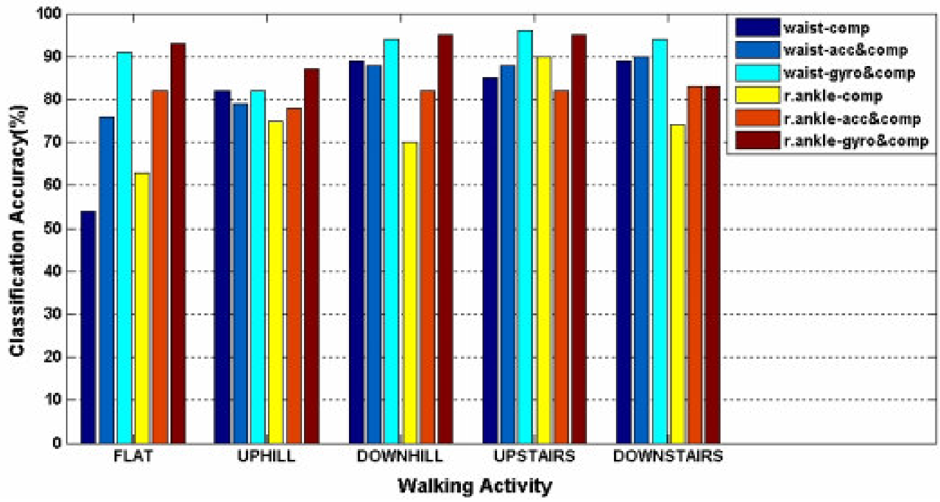


Figure 9 -Classification accuracy of each walking pattern for the compass-only, fused accelerometer and gyroscope, fused gyroscope and compass feature sets via ANN

The compass features are the most successful ones; they are performing even better than the combination of the accelerometer and gyroscope features. Considering the energy consumption and the performance, instead of employing all types of sensors together, the compass-only features or the fused gyroscope and compass features are preferable for both mounting positions. As the number of the fused gyroscope and compass features is the lowest among the high performing sets, we conclude that this is the best complexity-performance trade-off. Besides, favoring the complexity concern slightly more, the selected portion of the compass-only or of the fused gyroscope and compass features are again more preferable.

On the other hand, when we analyze the results at each activity level, we observe that flat walking is the least correctly classified walking activity together with huge performance variations at each mount point level. Furthermore, at both mount positions, the compass-only features are less preferable because of their significantly low performance in the recognition of the flat walking instances. To analyze this situation, we focus on the false negatives of the flat walking instances for both mount points. We observe that the false negatives show a uniform and a deviated distribution among the rest of the walking activities in the waist- and right ankle- mounted nodes, respectively. When we observe the most relevant features for the compass-only set, we conclude that in the classification of the walking activities, the characteristics of flat walking signals cannot be efficiently represented by the compass-only features that measure variation, i.e. variance, and peakedness, i.e. kurtosis. Considering the fact that the we do not experience the same situation in the gyroscope-only feature set, from the physical motion perspective, this result seems to be logical, as flat walking includes less amount vertical change in the position, although it does not in the angular motion, comparing to the other walking activities that includes a huge amount of vertical change in the position. Hence, the flat walking instances are probably outliers in the compass-only feature set space.

6. Conclusions

This document describes the activity recognition algorithms developed and tested in the IS-ACTIVE project, more specifically the activity monitoring algorithm and the algorithms for the recognition of object handling and the recognition of walking activities.

Regarding the experiments with our activity monitoring algorithm, multiple subjects were monitored during their daily activities (both at home and at the office) and additionally while performing sports such as badminton, tennis, volleyball, cycling and skiing. The results show that the recorded values correspond to the expected intensity for some of the performed activities, but certain activities, such as skiing and cycling, produce lower activity measurements than expected. Using multiple sensor nodes and sensor modalities per subject would improve the activity estimation performance, provided that the sensor nodes are small and inconspicuous.

The recognition of object handling algorithms provides information about the actual usage of objects instead of only the proximity of the user to the object. Our solution detects which objects the user is interacting with, while also offering the possibility to infer how the objects are used. More specifically, since we perform both feature extraction and feature correlation, the outputs of these building blocks could be used directly to implement distributed activity recognition. Furthermore, the method we propose is generic and can be applied to build associations of the type “moving together” for any entities equipped with sensors. It is therefore not restricted to a particular one-to-many or many-to-one interaction scenario. And finally, we prove that our solution can run on resource-constrained hardware, taking only a fraction of the CPU time and operating on an energy-efficient wireless communication protocol.

For the recognition of walking activities, we show that both the compass and gyroscope sensors outperform significantly the accelerometer sensor, which is typically used in previous related work. The best trade-off in performance vs. complexity is obtained by fusing the gyroscope and compass information, with an overall accuracy of 91%.

The prototypes of the activity recognition methods are available to the IS-ACTIVE consortium, most of them being implemented on the ProMove platform.

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