Situational Awareness for Tactical Applications

Ruotsalainen L., Guinness R., Gröhn S., Chen L., Kirkko-Jaakkola M., Kuusniemi H.,
Department of Navigation and Positioning, Finnish Geospatial Research Institute, Finland

BIOGRAPHIES

Dr. Laura Ruotsalainen is a Research Manager and Deputy Director of the Department of Navigation and Positioning at the Finnish Geospatial Research Institute (FGI), Finland, where she leads the research group on Sensors and indoor navigation. She received her doctoral degree in 2013 from the Department of Pervasive Computing, Tampere University of Technology (TUT), Finland. Her doctoral studies were partly conducted at the Department of Geomatics Engineering at the University of Calgary, Canada. Her doctoral research was focused on vision-aided seamless indoor/outdoor pedestrian navigation. Her current research interests cover adaptive integration of sensors and radio positioning means for robust navigation, situational awareness and Global Navigation Satellite systems (GNSS) interference mitigation.

Robert Guinness is a Research Manager at the Finnish Geospatial Research Institute, where he leads the research group on Intelligent Mobility and Geospatial Computing. He received his M.Sc. in 2006 from the International Space University, and he is currently a doctoral candidate at Tampere University of Technology, Finland. His research interests include context awareness for navigation applications, machine learning, and privacy-preserving location technologies.

Simo Gröhn is a research scientist and a PhD student at the Department of Navigation and Positioning at FGI since 2015. The topic of his thesis is the integration of vision based positioning and sensor data for indoor positioning. His research focus consists of vision-aiding in positioning, sensor error modelling and integration algorithms. Mr. Gröhn holds a Master of Science (tech) degree and before joining FGI has worked in research and development projects related to optical sensors in industry.

Dr. Martti Kirkko-Jaakkola is a Senior Research Scientist at the Finnish Geospatial Research Institute. He received his M.Sc. and D.Sc. (Tech.) degrees from Tampere University of Technology, Finland, in 2008 and 2013, respectively. His research interests include various precise GNSS positioning and inertial navigation applications using low-cost equipment.

Dr. Liang Chen received the M.Sc. degree in control theory and control engineering from Jiangsu University, China, in 2004, and the Ph.D. degree in signal and information processing from Southeast University, China, in 2009. He was a Post-Doctoral Research Scientist with the Department of Mathematics, Tampere University of Technology, Finland, from 2009 to 2011. He is a Senior Research Scientist with the Department of Navigation and Positioning, Finnish Geospatial Research Institute, Finland. His research interests include statistical signal processing for positioning, wireless positioning using signals of opportunity, and sensor fusion algorithms for indoor positioning.

Prof. Heidi Kuusniemi is the Director at the Department of Navigation and Positioning at FGI. She is also an Adjunct Professor at TUT, Finland, and Aalto University, Finland, where she also is a lecturer on GNSS technologies. She is the President of the Nordic Institute of Navigation. She received her M.Sc. and Doctor of Technology degrees from TUT in 2002 and 2005, respectively. Her doctoral studies on reliability monitoring in personal satellite navigation were partly conducted at the Department of Geomatics Engineering at the University of Calgary, Canada. Kuusniemi's research interests cover various aspects of GNSS and sensor fusion.

ABSTRACT

This paper presents the results of detecting various motion states, essential for infrastructure-free tactical situational awareness, using Machine Learning (ML) for motion classification. We investigated if the use of multiple IMUs will bring additional information and improve the sensing of motion contexts. Namely, we used three different Inertial Measurement Units (IMUs) with the first attached to the user's torso, the second to the foot, and the third to the helmet. We also studied the best combination of sensors, measurements, and features used for detecting the contexts and for obtaining an accurate position solution. The full set of sensors studied included the three IMUs, a camera, a barometer, and an ultrasonic sensor. The method was tested with data collected in two experiments encompassing various motion patterns. Results showed that all sensors bring added value to the motion detection and that the motions having multiple instances in the data, even the ones considered as difficult to be identified like crawling, could be accurately classified. Also, the selection of features used for the classification process is discussed and evaluated as well as few different ML algorithms for classification. This research is a significant step towards infrastructure-free situational awareness for tactical applications.

INTRODUCTION

Situational awareness requires accurate and reliable positioning, formation of a map from a possibly unknown area, information about the environment, and information about the user's motion.

The long-term goal of our research is to develop a method for infrastructure-free situational awareness for tactical and rescue applications. Infrastructure-free situational awareness is a particular case of situational awareness, where the methods for detecting the situation do not rely on some particular infrastructure or prior knowledge specific to the environment. For example, methods that rely on pre-deployed wireless radios or even an existing floorplan would not constitute infrastructure-free situational awareness.

Due to this infrastructure-free requirement, observations used for positioning, mapping, and sensing the environments and the user motion have to be made using sensors carried by the user. This in turn places constraints on the equipment; it has to be small and must perform well in diverse, unknown environments, including indoors. Additionally, the equipment needs to be inexpensive, since the system should be deployed among many personnel.

Accurate and reliable positioning is a key technology for situational awareness. Positioning is challenging in indoor environments where signals from Global Navigation Satellite Systems (GNSS) are denied. Self-contained sensors, such as inertial sensors, provide infrastructure-free relative position measurements of the user, i.e. measurements that may be transformed into attitude and translation used to propagate the user's position when the initial position and heading are known (Collin 2006). Low-cost micro-electromechanical (MEMS) sensors fulfill all the requirements discussed above; however, they suffer from errors that deteriorate the position solution quickly. Careful integration of measurements from multiple sensors with complementary error characteristics may provide a position solution that has sufficient accuracy for the applications. In our previous research we have integrated a foot-mounted inertial measurement unit, a camera, a barometer, and an ultrasonic sensor using particle filtering (Ruotsalainen et al. 2016b). With careful modeling of the measurement errors introduced from the sensors, the system is feasible for positioning indoors for a limited time. However, the accuracy of the solution will be improved if the motion context of the user is observed and incorporated into the position computation. Previous research (Groves et al. 2013) has shown that context-adaptiveness of a navigation system enables it to adapt to different environments and strengthens its performance, namely accuracy and reliability, under challenging situations. In addition to improved positioning solution, user motion classification will aid in assessing the user's status for communicating the information to e.g. the command center.

In this paper, we present a method for automated detection of user motion context. The motion patterns are detected using classifiers built with supervised machine learning algorithms (Marsland 2009). In this research, we compare the performance of several machine learning algorithms.

The process of building the classifiers includes two phases both of which utilize labeled data: the training phase and the testing phase. In the training phase, a function is learned from the training data using one of many available machine learning algorithms. The learned function is called a classifier because it maps each input vector to a target class. In the testing phase, the classifier is used to infer the most likely classes for training samples, and the performance of the classifiers are measured by comparing the obtained output with the actual class. The correct classes have been labeled manually from the known truth beforehand. After building these classifiers using training data, they may be imported into the real-time system for observing the user context without going through the training and testing phases anymore.

Previously we have modelled simple user motion contexts with promising results using data collected with an Xsens MTi-G-700 Inertial Navigation System (INS) attached to the user body (Ruotsalainen et al., 2016a). By processing the obtained IMU, barometer, and magnetometer data we obtained the acceleration and heading of the user as well as the air pressure of the environment and the orientation of the INS. Using these measurements we were able to classify with 98.5% success rate the motion-related activities of the user, namely the user standing, walking very slowly, slowly and with normal pace, running, ascending and descending the stairs, turning around, crouching and getting up from crouching. However, only a limited training data set was collected and some application-specific motion contexts, e.g. crawling, were not investigated.

In the research described in this paper we study the three main aspects affecting the formation of user independent classifiers for motion recognition. Namely, we will investigate the best set of sensors used for collecting the measurements, the best set of features representing the data and used for motion classification, and the best machine learning algorithm for performing the classification.

Especially, we will study if the use of multiple IMUs will bring additional information and improve the sensing of motion contexts. Namely, we test the use of three different IMUs with the first attached to the user torso, the second to the foot, and the third to the helmet. The full set of sensors studied includes the three IMUs, a camera, a barometer, and an ultrasonic sensor. In addition, in this paper we discuss the use of the developed classifiers for real-time sensing of motion context. Also, incorporation of the obtained motion context information into the integration algorithm for improved positioning will be discussed.

This paper is organized as follows. First, we will introduce the motion states to be recognized and the sensors selected for the system providing infrastructure-free situational awareness. Then, the features used for motion pattern recognition are discussed as well as the machine learning algorithms used for forming the situational awareness. Finally, results from applying the machine learning algorithms to test data as well as conclusions drawn from the study are discussed.

MOTION STATES AND SENSORS

As described above, our research aims at providing soldiers and rescue personnel accurate localization and mapping information in unknown environments using only sensors carried by the user. In addition to the measurement errors that grow over time, the application area addresses challenges for the formation of situational awareness. Both soldiers and rescue personnel operate in harsh environments experiencing sudden and unexpected changes. Therefore, also the motion of the users is unpredictable; motion modes change rapidly and the motion is often untypical for navigation applications (e.g. crawling). We have identified 14 motion modes typical for tactical applications:

- Standing
- Walking
- Running
- Moving forward in crouching pose
- Crawling
- Turning
- Ascending stairs
- Descending stairs
- Getting down to crouching
- Staying static at crouching pose
- Rising from crouching to standing
- Getting down from standing to crawling pose
- Rising from crawling to standing
- Jumping

Tactical and rescue applications set strict requirements for the system setup. The set of sensors and their locations have to be justified and a balance between the system performance and the disadvantage from having multiple sensors has to be carefully detected. However, the different body parts of an unmounted person experience very different motions and therefore it is anticipated to achieve important information for the motion state detection from attaching e.g. the inertial sensors to three different body parts. As stated above, the sensors used in this research includes three IMUs, an ultrasonic sensor, a barometer, and a monocular camera. Below, measurements obtained using the selected sensors are described.

IMUs

The outputs of a conventional strapdown IMU are a specific force measurement $\mathbf{f}^b$, which may be used for computing the acceleration by knowing the orientation of the IMU and the local gravitational acceleration, and an angular rate measurement ω^b, both corresponding to the IMU's body coordinate frame *b*. The measurements may be used to provide a full six-degrees-of-freedom strapdown inertial navigation solution by solving the system of differential equations (Titterton and Weston 2004). However, the measurements from especially a light-weight, small and cost-effective Micro-Electro-Mechanical (MEMS) sensors suffer from large errors and therefore distort the solution quickly.

Previous research (Skog et al. 2010) has shown that when foot-mounted, IMUs provide transcendent positioning accuracy compared to body-mounted sensor units due to the ability of remove the errors to some extent using so-called zero-velocity updates (ZUPT) to the error-state filter whenever the IMU is detected to be at rest. However, it was anticipated that especially the more uncommon motion patterns, such as crawling, may not be identified using a foot-mounted sensor unit alone. This research studies the added value the two additional IMUs, namely one attached to the body of the user and the other to the head, bring for the motion recognition.

Camera

A camera can be considered as an additional self-contained sensor when integrated to a navigation system via specific mechanization (Ruotsalainen 2013). When the camera is attached to the body, motion of features in consecutive images may be transformed into heading information in a straight forward manner under favorable conditions. Observation of the absolute translation information is more challenging when using a monocular camera and therefore a method using a specific configuration of the camera has been developed. The developed methods are called visual gyroscope and visual odometer and have been discussed thoroughly in our previous research (e.g. Ruotsalainen et al. 2016b)

Barometer

A barometer observes the ambient pressure which depends on the altitude, pressure and temperature according to the International Standard Atmosphere model (e.g. Parviainen et al. 2008). Therefore, the measurements will further be used in the infrastructure-free SLAM-algorithm for observing the altitude of the user. However, for the motion state detection we have used the raw pressure measurements to the unbiased information without any predictions about the temperature and pressure changes.

Sonar

Ultrasonic sensors, i.e. sonars, produce high, centimeter level accuracy and millimeter level resolution range measurements. Sensors provide ranging measurements from the time-of-flight of transmitted and again received sound signals reflecting from structures traversing at the speed of sound (Ijaz et al. 2013).

SLAM

Simultaneous Localization and Mapping (SLAM) is a key technology for providing an accurate and reliable infrastructure-free solution for indoor situational awareness. SLAM is a procedure where a map of the unknown environment is produced simultaneously while positioning the user in this newfound map. In the research discussed here, our approach is to integrate the sensor measurements discussed above to obtain a solution for SLAM based on the 1-point RANSANC SLAM-algorithm described in (Civera et al. 2010) and (Ruotsalainen et al. 2015).

FEATURE SELECTION

Selection of a set of features, derived from various sensor measurements that capture information about the various motion contexts is one of the most crucial steps for forming situational awareness. The used features have to be justified to suit the challenging application area because their usage consumes resources, such as power and memory, and the large amount and obtrusive locations of sensors may disturb the tactical operations. The motions relevant for the applications presented above involve varying physical phenomena, e.g. large horizontal accelerations (crawling), large vertical accelerations (jumping), and large heading changes (turning). However, when the goal is a real-time application, a balance between the number of different features used and computational cost has to be found. In some cases, features may be useful for classification but computationally expensive to generate. Frank et al. (2010) discussed reduction and selection of features for detecting motions.

Features are mainly computed from sensor raw outputs (specific force, angular velocity, ranges and pressure), but in the case of camera images we use the heading change and translation computed using the visual gyroscope and odometer processing described above. Based on previous research (Pei, Frank et al (2010) we have selected a set of 17 features for feature analysis. Table 1 presents the different features used, the sensors providing measurements for feature composition, and the number of instances (due to the number of sensors providing the measurements) for the corresponding feature.

According to (Frank et al. 2010), mean values of the measurements are used for recognizing repetitive activities, and variance for distinguishing between static and dynamic activities. The two main frequency components of the three-dimensional acceleration, their amplitudes and difference between the two main frequency components are used for distinguishing walking, running, falling and jumping from each other. The main frequency component is calculated using Fast Fourier Transformation (FFT) and finds the frequency carrying the maximum energy among the frequencies found in the spectrum (Telgarsky 2013). For the IMU measurements, the mean values and variations are computed for both horizontal acceleration and vertical acceleration, derived from the specific force measurements. The horizontal mean acceleration value distinguishes the static activities and variation dynamic activities, such as jumping, getting down to or up from crouching or crawling pose, from each other. Vertical acceleration on its behalf detects the different static poses from each other. However, in our experiments discussed below, we found that removing any of the individual features didn’t have significant effect on classification accuracy.

MACHINE LEARNING ALGORITHMS

Machine learning, also known as pattern recognition, is the tool we have chosen for obtaining situational awareness by classifying the different motion states using classifiers learned from training data. In previous research (Guinness 2015), we have studied the performance of different supervised learning techniques for similar classification tasks, including decision trees (DT), support vector machines (SVM), naïve Bayes classifiers (NB), Bayesian networks (BN), logistic regression (LR), artificial neural networks (ANN) and instance based classifiers (KStar, LWL and IBk). The performance was evaluated based on the classification accuracy and the computational burden of the classifier.

The classification accuracy obtained in the previous research was best when the decision-tree based RandomForest algorithm was used. However, the computational cost was ranked from lowest to highest as follows: SVM, ANN, LR, BN, DT, NB, IBk, LWL and KStar.

For the real-time infrastructure-free tactical situational awareness both the accuracy of the obtained classification and the processing time are relevant. Therefore we decided to re-experiment the performance of some of the previously studied algorithms. This is well justified also by the fact that both the sensors used and the motion states classified are different from our previous research. We decided to evaluate the performance of the motion state recognition using the SVM Sequential Minimal

Optimization (SMO) algorithm, two Decision tree algorithms, namely RandomForest and NBTree, and one Instance-based classifier, KStar.

DATA ANALYSIS

In this section we describe how the features discussed above and algorithms were used in our study to recognize the desired motion states from the sensor data.

Data was collected during two test campaigns and by two different test persons. Test campaigns were carried out in an indoor office environments using the sensors described above. Figure 1 shows the setup for the first campaign with three IMUS, one attached to the helmet (Xsens MTi-G-700), one to the shoulder-strap of the back bag (Osmium MIMU22BT IMU) and one to the upper of the shoe (Osmium MIMU22BT IMU). The Xsens Inertial Navigation System (INS) contained also a barometer. The sonar (HRUSB-MaxSonar) was attached to the hip of the test person pointing down to the floor, i.e. measuring the range from the hip of the test person to the floor. The camera (GoPro Hero) was attached to the shoulder-strap of the back bag. The second campaign used the same set of sensors except that there was no head-mounted sensor unit and the Xsens INS was attached to the body of the user. Data was collected with varying rates: 400 HZ for Xsens, 120 Hz for the two other IMUs, 10 Hz for camera and 8.2 Hz for sonar. A video was recorded of both campaigns to provide a reference for the true motion states.

The durations of the test first and second campaigns were 275 seconds and 115 seconds, respectively. First, the time epochs of the different motion states were manually detected from the video. Then, the data was processed in Matlab to obtain the acceleration, heading change, distance, pressure and translation observations. The features described above were calculated for data periods of 1 second using the observations as described in Table 1. Finally, the computed features were integrated with the corresponding labels. Table 2 shows the appearance of each label, namely how many seconds of data was found in the data set for each motion pattern. Implementations of the machine learning algorithms described above were provided by Weka, an open-source software framework for ML and data-mining, which also provides performance analysis functionalities (Weka project, webpage accessed 2016).

Table 2 Appearance of different motions

Motion	Instances in data [s]
Walking	73
Standing	53
Turning	29
Ascending stairs	26
Descending stairs	21
Running	18
Crawling	16
Staying static at crouching pose	13
Moving forward in crouching pose	10
Rising from crouching to standing	6
Getting down to crouching	5
Rising from crawling to standing	3
Getting down from standing to crawling pose	1
Jumping	1

Table 1 Description of the selected features

Feature	Sensors	Count
Mean Horizontal Acceleration	3 IMUs	3
Mean Vertical Acceleration	3 IMUs	3
Variance of Horizontal Acceleration	3 IMUs	3
Variance of Vertical Acceleration	3 IMUs	3
Mean of Heading Change	3 IMUs, visual gyroscope	4
Variance of Heading Change	3 IMUs, visual gyroscope	4
Mean range	Sonar	1
Variance of range	Sonar	1
Mean translation	Visual odometer	1
Variance of translation	Visual odometer	1
Mean of pressure	Barometer	1
Variance of pressure	Barometer	1
1^{st} dominant frequency of acceleration	3 IMUs	3
Amplitude of 1^{st} dominant frequency	3 IMUs	3
2^{nd} dominant frequency of acceleration	3 IMUs	3
Amplitude of 2^{nd} dominant frequency	3 IMUs	3
Difference between two dominant frequencies	3 IMUs	3

Figure 1. System setup

Analysis

The performance of the motion state recognition was tested for different machine learning algorithms, for different features, sensor combinations, and for data collected from two test persons during two data campaigns of different duration. Below the data are analyzed with these different variations.

The results of classifying the data, collected in the first test campaign, and processed with the RandomForest algorithm, using all features and all sensors, are shown in Table 3 in the form of a confusion matrix. In a confusion matrix, the true class labels and predicted labels comprise the rows and columns, respectively. The overall accuracy of the classification with this setup was 78.2 % (percentage of correctly classified instances). The main motions, even more unusual ones like crawling, are well detected from the data. However, motions like jumping and getting up from the crawling and crouching poses are often confused with other motions. The reason for this may be found from Table 2; the data available for training the classifiers to detect these motion patterns are too few. Also, there are some motions in the data that are not mutually exclusive, like turning that can happen while also walking or running. Classification for these motions resulted in confusion decreasing also the overall accuracy.

Feature and sensor analysis

Feature analysis was run both by looking at the percent of correctly classified time instances for each feature alone as well as for different sensor combinations. The results are shown in Table 4.

The head-mounted IMU seems to have a small positive impact on the classification process, the percentage of correctly classified instances grew from 76.7 to 78.2. The largest effect of the head-mounted IMU measurements was on the identification of crawling and descending the stairs, for which the accuracy increased 6% and 4%, respectively. When only one IMU, namely the foot-mounted IMU is used together with camera, barometer and sonar, the overall accuracy decreases to 75.6%, and especially the ability to identify crawling and descending stairs decreased significantly.

The results show that the use of barometer has a large effect on recognizing the motions having vertical movement. For example, the accuracy of classifying correctly motion “getting up from crawling pose” increased from 33% to 67%. The translation measurements provided by the visual odometer proved to have a significant impact on the classification accuracy. Evidence of this can be seen when the features “mean of translation” and “variance of translation” were removed from the data set, as the classification accuracy decreased from 77.7% to 73.9% and 74.9%, respectively.

The main conclusions from the feature and sensor analysis were that removing any of the sensors used in the data collection decreased the classification accuracy and that the only feature not contributing to the classification accuracy was the “Mean of heading change”. The results obtained using the second data set were in agreement with the results for the first data set, meaning that the classification using the selected features and sensors appears not to be strongly user-dependent. More test campaigns involving a greater number of users, however, are needed to confirm this finding.

Classification performance analysis

The data collected were classified multiple times using different ML algorithms, namely SMO, Random Forest, NBTree, and KStar, (using all features and all sensors) to compare the performance of the generated classifiers. The overall classification accuracy obtained using SMO was 60.8%, 77% for RandomForest, 68.9% for NBTree and 75.6% for KStar. The results show that the computationally light SMO algorithm has too poor performance for our purposes, and the computationally greedy KStar provided worse performance than the relatively fast RandomForest algorithm.

We note, however, that default parameters were used in the above analysis, and it is likely that different results would be obtained if the parameters were adequately tuned. Due to the limited amount of data available in this phase of our research, we have not yet proceeded to the phase of parameter tuning.

Future Work

The classifiers, obtained via the machine learning process, will be used in an integrated SLAM solution. A situational-adaptive SLAM system will detect the motion state of the user and use this information for tuning the integration algorithm behavior. The knowledge of the motion state is anticipated to give valuable information of the errors in the sensor measurements, for example, in the case the sensors output conflicting measurements. This knowledge may then be used in the integration, neglecting the erroneous measurements by tuning the statistical parameters of the respective measurements in the integration algorithm.

Also, recognition of the user motion states aids the formation of a map with additional information about the environment. When the user is e.g. detected to be ascending the stairs, the information about the existence of the stairs may be added to the map with higher trust. It is also self-evident that information about the user's motion state may be tied to information about the user's physical state, e.g. there might be something wrong with the user if he or she is static for a long time, or something threatening if the user is running rapidly.

CONCLUSIONS

This paper has discussed the detection of motion states for the development of infrastructure-free tactical situational awareness using ML for motion classification. We investigated the use of multiple IMUs for sensing the motion contexts. The results showed that having three IMUs, namely the first attached to the user body, the second to the foot, and the third to the helmet, will bring more information and therefore accuracy for the classification. We also studied the best combination of other sensors, measurements, and features used for detecting the contexts and found out that removing any of the sensors used in the data collection decreased the classification accuracy. The only feature not contributing to the classification accuracy was the "Mean of heading change".

We compared the performance of several different ML algorithms for learning the classifiers. Results showed that the decision-tree based algorithm RandomForest outperformed all other tested algorithms using default parameters.

Lastly, we discussed briefly the use of the developed classifiers for real-time sensing of motion context and incorporation of the obtained motion context information into our SLAM algorithm, which will be subject of our future research. We will also continue collecting more data and especially in more realistic environments and situations, e.g. in changing temperature and pressure conditions.

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Table 3 Confusion matrix for the RandomForest algorithm applied to the dataset

		Asc	Crawl	UpCra	UpCro	CroPose	Crouch	Desc	Run	Jump	Stand	DCraw	DCro	Turn	Walk
Actual Label	Asc	92.3	0	0	0	0	0	0	0	0	0	0	0	7.69	0
	Crawl	0	100	0	0	0	0	0	0	0	0	0	0	0	0
	UpCra	0	0	66.7	0	0	0	0	0	0	0	0	0	0	33.3
	UpCro	0	0	0	33.3	16.7	16.7	0	0	0	16.7	0	0	0	16.7
	CroPose	0	0	0	23.0	53.8	0	0	0	0	7.69	0	7.69	0	7.69
	Crouch	0	0	0	10.0	10.0	80.0	0	0	0	0	0	0	0	0
	Desc	0	0	0	0	0	0	90.5	0	0	0	0	0	9.5	0
	Run	0	0	0	0	0	0	0	88.9	0	11.1	0	0	0	0
	Jump	0	0	0	0	0	0	0	0	0	0	0	0	0	100
	Stand	0	0	0	0	0	0	0	0	0	88.7	0	0	0	11.3
	DCraw	0	0	0	0	0	0	0	0	0	0	0	0	0	100
	DCro	0	0	0	0	0	0	0	0	0	50	0	0	0	50
	Turn	17.2	0	0	0	0	0	24.0	0	0	6.9	0	0	37.9	17.2
	Walk	1.4	0	0	0	0	0	0	0	0	6.8	0	0	5.5	86.3

Table 4 Feature selection analysis using RandomForest algortihm

Feature set	**Overall classification accuracy [%]**	**Main effect on the accuracy of classifying**
Individual features, all sensors	**78.2**	
Mean Horizontal Acceleration	75.6	Crouching forward, Descending stairs, Descending stairs
Mean Vertical Acceleration	76.3	Crouching forward, Crawling
Variance of Horizontal Acceleration	76.7	Crouching forward, Descending stairs
Variance of Vertical Acceleration	77.4	Crouching forward, , Descending stairs
Mean of Heading Change	78	
Variance of Heading Change	74.9	Crawling, Crouching, Crouching forward
Mean range	75.2	
Variance of range	76.3	
Mean translation	73.9	Crawling, Crawling to stand, Turning, Running
Variance of translation	74.9	
1st dominant frequency of acceleration	75.6	Crawling, Crawling to stand
Amplitude of 1st dominant frequency	75.6	Crawling to stand, Descending stairs
2nd dominant frequency of acceleration	76	Descending stairs
Amplitude of 2nd dominant frequency	75.9	
Difference between two dominant frequencies	76	Descending stairs
All features, all sensors except		
Head-mounted IMU	76.7	
Foot-mounted IMU	75.6	Crouching, Crouching forward, Turning
Body-mounted IMU	77	Crouching, Running
sonar	75.3	Crawling to stand, Crouching to stand
camera	77.7	Crawling to stand
barometer	76.7	Descending stairs, Crawling to stand
Only following sensors with all possible features		
3 IMUs	74.6	Crawling to stand, Descending stairs, Crouching
Sonar, camera, barometer	76.3	Crouching
Foot-mounted IMU, sonar, camera, barometer	75.6	

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