Classification Algorithm Improvement for Physical Activity Recognition in Maritime Environments

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Abstract

Human activity recognition using wearable sensors and classification methods provides valuable information for the assessment of user's physical activity levels and for the development of more precise energy expenditure models, which can be used to proactively prevent cardiovascular diseases and obesity. The aim of this study was to evaluate how maritime environment and sea waves affect the performance of modern physical activity recognition methods, which has not yet been investigated. Two similar test suits were conducted on land and on a small yacht where subjects performed various activities, which were grouped into five different activity types of static, transitions, walking, running and jumping. Average activity type classification sensitivity with a decision tree classifier trained using land-based signals from one tri-axial accelerometer placed on lower back and leave-one-subject-out cross-validation scheme was 0.95 ± 0.01 while classifying the activities performed on land, but decreased to 0.81 ± 0.17 while classifying the activities on sea. An additional component produced by sea waves with a frequency of 0.3–0.8 Hz and a peak-to-peak amplitude of 2 m/s^2 was noted in sea-based signals. Additional filtration methods were developed with the aim to remove the effect of sea waves using the least amount of computational power in order to create a suitable solution for real-time activity classification. The results of this study can be used to develop more precise physical activity classification methods in maritime areas or other locations where background affects the accelerometer signals.

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1 Introduction

Physical activity classification is used for human activity recognition, which provides information about user's movement and activity levels and can be used to develop more precise energy expenditure models [1]. Physical activity classification is usually based on acceleration signals, for which acceleration could be measured in various locations on the human body [2]. For this purpose it is possible to use the accelerometers inside smart phones [3] and smart watches [4] or integrate them into necklaces [5] and garments [6].

In activity recognition studies the accelerometer signal is often separated into static and dynamic components. The static component (Acc_S) is affected by gravity and gives information about body posture, the dynamic component (Acc_D) is based on motion and captures the body movement information. Different filtration methods have been used to separate these components, such as applying low-pass filter to separate Acc_S and subtracting Acc_S from acceleration signals to find Acc_D [7, 8] or using two different filters [5, 9]. While acceleration signals measured on land are mostly only affected by gravity and body movement, accelerometers on sea also capture the fluctuation caused by sea waves, which could be decreased by applying appropriate filters.

The aim of this study was to evaluate how physical activity classifiers perform in maritime environment where sea waves affect the accelerometer signals and to develop a filter to remove acceleration induced by waves.

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2 Methods

2.1 Instrumentation

Tri-axial acceleration signals were measured using Shimmer3 sensor platform accelerometer. Sensor was placed on the back of the lower trunk. This location was chosen because it is suitable for integrating the accelerometers inside garments and previous studies have had good results with accelerometers attached near the center of the body mass [10]. Signals were recorded using Wide Range accelerometer setting with dynamic range of ±16 g and sampling rate of 512 Hz.

2.2 Test Overview

Two different test suits were carried out to evaluate the differences between signals measured on land and signals measured in maritime environments. The land-based signal measurements were done in a sports facility with ample space for movement. Accelerometer signals were measured during standing, sitting, lying, picking up objects, transitions between standing, sitting and lying, hopping on one leg and on both legs, walking and running. During walking and running subjects were asked to alternate their pace. For activity recognition and classification these signals were divided into different activity types of static, transitional, walking, running and hopping. The collected signals and their length are shown in Table 1.

The sea-based test suit was carried out in the cabin of a sailing yacht on an open gulf. During the experiments there was constant moderate wind of 10–11 m/s and the height of the waves was between 0.5 and 1 m. This test suit was very similar with the land-based test suit, with minor differences in time schedule. The size of the test area was about 6 m^2 and the height of the cabin was about 2 m. The measured signals are shown in Table 1.

Table 1 Classified activity types and length of conducted activities

Activity type	Activities carried out in land test suit (in minutes)	Activities carried out in sea test suit (in minutes)
Static	Standing (1), sitting (1), lying (1)	Standing (2), sitting (2), lying (2)
Transitional	Picking up objects (1), sit-stand transitions (1), lie-sit transitions (1), lie-stand transitions (1)	Picking up objects (1), sit-stand transitions (1), lie-sit transitions (1), lie-stand transitions (1)
Walking	Walking (3)	Walking (3)
Running	Running (3)	Running (3)
Hopping	Hopping on one leg (1), hopping on both legs (0.5)	Hopping on one leg (1), hopping on both legs (0.5)

2.3 Study Group

The study group for the land test suit consisted of 12 subjects, of which 10 were male and 2 female. The study group for the sea test suit consisted of 4 males. The subjects' anthropometric parameters are shown in Table 2.

2.4 Signal Resampling and Filtration

Tri-axial accelerometer signals measured with sampling frequency of 512 Hz were resampled to 100 Hz using MATLAB function *resample* without changing the signal spectrum.

Two different filtration methods (filtration method 2 and 3) were used in this study to test their ability to filter out acceleration caused by sea waves from the accelerometer signals and their effect on classification performance compared to a filter unable to filter out sea waves (filtration method 1). Butterworth type IIR filter was chosen, since IIR filters require less computational power than comparable FIR filters and are thus more suitable for real-time wearable systems. The filtration methods are shown in Table 3.

Following filtration signals were fragmented into fragments of 3 s with no inter-window gaps and without overlap, which has also been found suitable for classification in a previous work [11]. Afterwards each fragment was labelled with the corresponding activity type.

2.5 Feature Extraction

Machine learning based physical activity classification uses features which are extracted from signal fragments. These features are used as an input for training and evaluating the classifier and need to capture the specifics of human body movement and posture to increase the classification performance.

The feature set of 19 features used in this study was achieved after using feature selection methods on various sets adopted from previous studies [11]. Only time-domain features were used in order to keep the required computational power minimal.

2.6 Classifier Training and Evaluation

A machine learning based decision tree classifier was chosen, since it has been found to have a good performance

Table 2 Subjects' anthropometric parameters

Test suit	Number of subjects	Age (years) mean ± SD; range	Height (cm) mean ± SD; range	Weight (kg) mean ± SD; range
Land	12	30.3 ± 10.1; 15–46	176.8 ± 7.5; 167–189	71.1 ± 19.0; 45–115
Sea	4	36.3 ± 8.4; 26–57	181.8 ± 8.3; 171-190	87.0 ± 22.0; 65–115

Table 3 Filtration methods and filter parameters

Filtration method no.	Acceleration component	Filter type	Filter parameters (filter order, passband, stopband, passband ripple, stopband ripple)
1	Acc_S	Low-pass	3, 0.15 Hz, 2 Hz, 1 dB, 20 dB
	Acc_D	Found by subtracting Acc_S component from accelerometer signals	
2	Acc_S	Low-pass	4, 0.1 Hz, 0.3 Hz, 1 dB, 20 dB
	Acc_D	Found by subtracting Acc_S component from accelerometer signals	
3	Acc_S	Low-pass	6, 0.1 Hz, 0.2 Hz, 1 dB, 20 dB
	Acc_D	High-pass	6, 1.2 Hz, 0.8 Hz, 1 dB, 20 dB

with small classification time [10] and is thus also suitable for wearable systems. Classifier was trained using MATLAB's function *fitctree*, which returns a fitted binary decision tree.

To reduce overfitting errors, land signals were classified using a leave-one-subject-out cross-validation scheme, where each test subject's signals were classified using a classifier trained based on the signals of the other subjects. When classifying sea signals the classifier was trained based on all the land signals to determine how classifiers developed based on land signals perform on sea.

The results were evaluated using statistical measure sensitivity, which shows the ratio of true positives in relation to real positives [12].

3 Results

Figure 1 shows the *Z*-axis accelerometer values (axis perpendicular to the Earth) during lying of one test subject after applying the filtration methods shown in Table 3. Lying should be the most static position and so is chosen to illustrate the effect of the sea waves in the acceleration signals. The sea waves induced an additional component with a frequency of 0.3–0.8 Hz and a peak-to-peak amplitude of 4 m/s^2 in the sea-based Acc_D component signals and 2 m/s^2 in Acc_S component signals.

The average classification sensitivities using different filtration classifying land and sea signals are shown in Table 4. With all filtration methods the average classification sensitivity for land signals was higher than for sea signals.

4 Discussion

The average activity classification sensitivity of land signals was about 0.95 in this study, which is comparable to the results achieved by other researchers [2, 10]. No large difference could be noted in classification performance with different filtration methods. Figure 1 shows that while the Acc_D and Acc_S acceleration signals were more affected by sea waves with the first filtration method than with other filtration methods, the results of classifying sea signals were not considerably lower compared to other filtration methods based on the classification sensitivities in Table 4. Filtration method 2 was able to filter out sea wave induced acceleration from Acc_S, while filtration method 3 decreased it in both Acc_D and Acc_S. Also, with every filtration method sea signals were classified with lower performance than land signals.

There are several possibilities why filtering out the acceleration produced by the sea would not increase the classification sensitivities of sea signals to the same level as land signals. Some of the chosen features, such as mean of the signal, are only slightly affected by sea waves, which would not have an effect on the classification performance. The difference between sensitivities classifying land and sea signals could have been caused by using different testing areas—the size of the cabin of the sailing yacht might have restricted the subjects' movement, which could have caused the larger difference seen in classifying running and hopping activities compared to other activity types. Additionally, the study groups used in this study could have been too small, in which case additional measurements might be needed for definitive results.

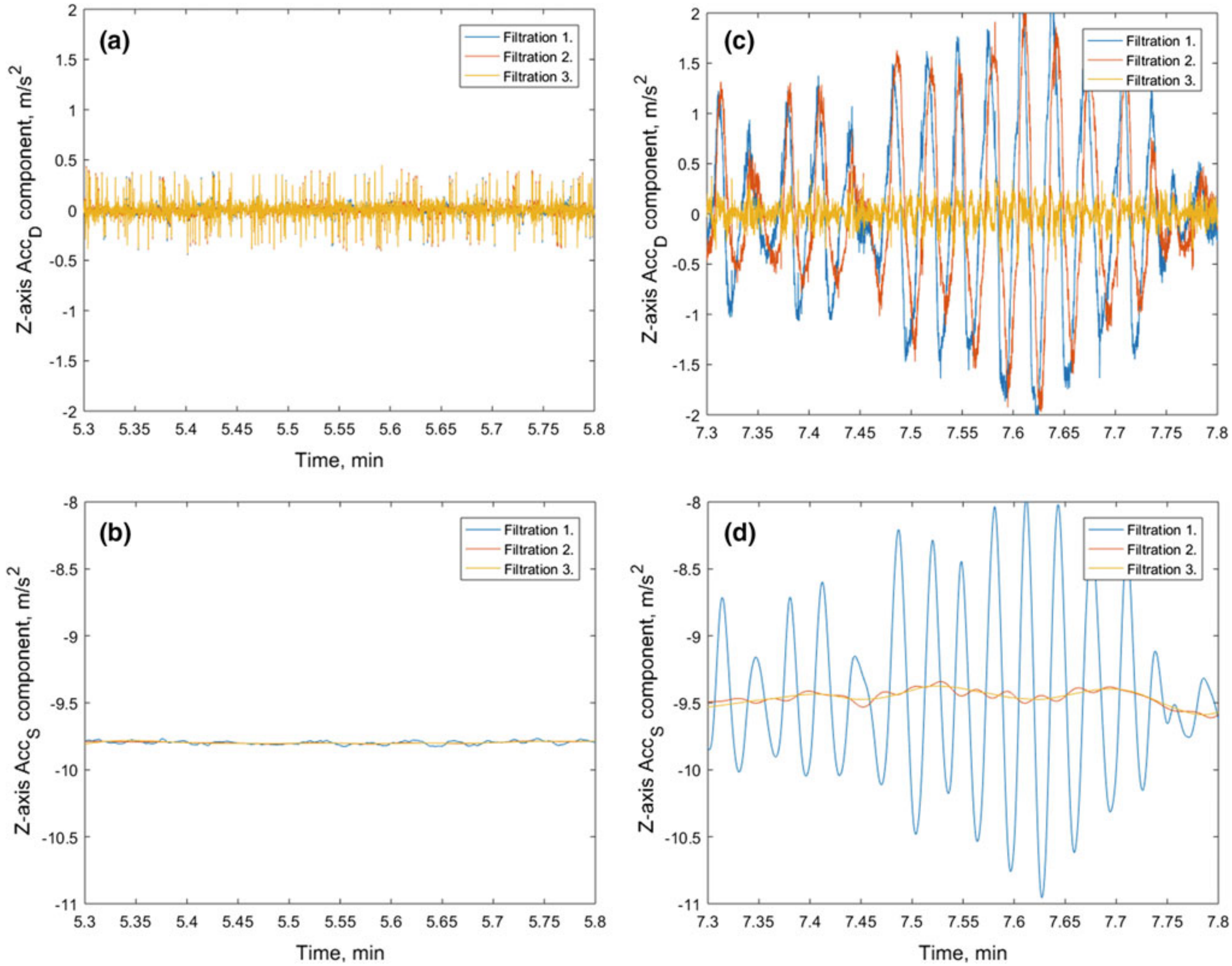

Fig. 1 *Z*-axis accelerometer signal values during lying from one test subject after applying different filtration methods. **a** Land, Acc$_D$ component, **b** sea, Acc$_D$ component, **c** land, Acc$_S$ component, **d** sea, Acc$_S$ component

Table 4 Classification sensitivities of different activity types with different filtration methods

Filtration method no.	Classified signals	Static	Transitional	Walking	Running	Hopping	Average
1	Land	0.97	0.94	0.94	0.94	0.96	0.95 ± 0.01
	Sea	0.82	0.94	1.00	0.56	0.72	0.81 ± 0.17
2	Land	0.97	0.94	1.00	0.82	0.93	0.93 ± 0.03
	Sea	0.92	0.89	0.99	0.66	0.81	0.85 ± 0.12
3	Land	0.97	0.95	0.99	0.92	0.84	0.94 ± 0.06
	Sea	0.89	0.89	1.00	0.47	0.72	0.79 ± 0.21

It is also important to note that the 0.3–0.8 Hz frequency of sea waves could contain important information for human activity recognition. In this case filtering out the sea wave induced noise would also lower the physical activity classification results, but in this study no large difference was found between classifying land signals when using different filtration methods. Only simple filtration methods using IIR filters were tested in the study, which are suitable for using in real-time wearable systems. Better results could be achieved with more complex filtration methods, but they would also require more computational power.

5 Conclusion

In this study it was evaluated how sea waves in maritime environment affect the performance of modern physical activity recognition methods. Even though the three different filtration methods used in this study removed the accelerations caused by sea waves in various degrees, no large differences could be noted between classification results. With every filtration method the classification sensitivities classifying activities performed on sea were lower compared to activities performed on land. This study helps to understand how sea waves affect the human activity recognition and is a good basis for further research.

Compliance with Ethical Standards

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The authors declare that they have no conflict of interest. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

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