Automatic Classification of Sport Exercises for Training Support

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Introduction

Common goals of an exercise training program in sports are among others an increase of muscle strength or size, an improvement of the sports performance and an improvement of the body composition (Hoffmann, 2002). A typical training program consists of several parameters that can be changed from workout to workout (Fleck et al., 1997), such as intensity of exercise, volume of exercise, frequency of training, choice of exercise and order of exercise.

A common possibility for the monitoring of these parameters is to setup written self-reports. The disadvantage is that self-reports are time consuming and the athlete is distracted in the training process. This distraction reduces and decelerates the success of the training program. Therefore, an objective measurement is desired for the parameter monitoring, which does not distract and influence the athlete in the training process.

This can be realized using small and lightweight physiological and motion sensors that are applied more and more widely in the field of sports in the recent years. In (James et al., 2004), for example, a performance analysis system for in situ elite athlete monitoring was introduced. This accelerometer based system was applied to classify different exercises in swimming. Further examples were multi-modal sensor systems consisting of several different sensor types like accelerometer, gyroscope, goniometer and temperature sensor for the monitoring of the athletes' rehabilitation (Glaros et al., 2003) and for swing feedback in golf (Ghasemzadeh et al., 2009).

A major need is a multi-modal sensor system for the classification of different exercises for the training support. Thus, the purpose of this paper is to apply inertial sensors consisting of an accelerometer and a gyroscope for the determination of different exercises in a training session. In detail, a training support system is developed which can automatically classify different sport exercises of a training session. With this system the athlete does not have to write a self-report with the ordering of the performed exercises and can concentrate on the exercise itself. This has the potential to improve the sports performance of athletes.

Materials and Methods

Hardware Four SHIMMER™ sensor nodes (McGrath et al., 2009) were used for the acquisition of inertial data. Each sensor node consisted of three accelerometer and three gyroscope axes. They were placed on the wrist, hip, chest and ankle. The sampling rate for all sensors was 204.8 Hz and the inertial data was stored on a SD-card. Fig. 1 shows the sensor node mounted on a shoe.

Fig.1: SHIMMER™ sensor node mounted on shoe (ankle position).

Data A study with 20 participants was performed. The subjects were asked to perform two exertion levels on a treadmill (5.6 km/h and 8.3 km/h) and two exertion levels on a bicycle ergometer (50 W and 100 W, 70 revolutions per minute for both levels). The duration for each exercise was 120 s. Fig. 2 shows the sensor placement indicated by the red circles during treadmill running and bicycling.

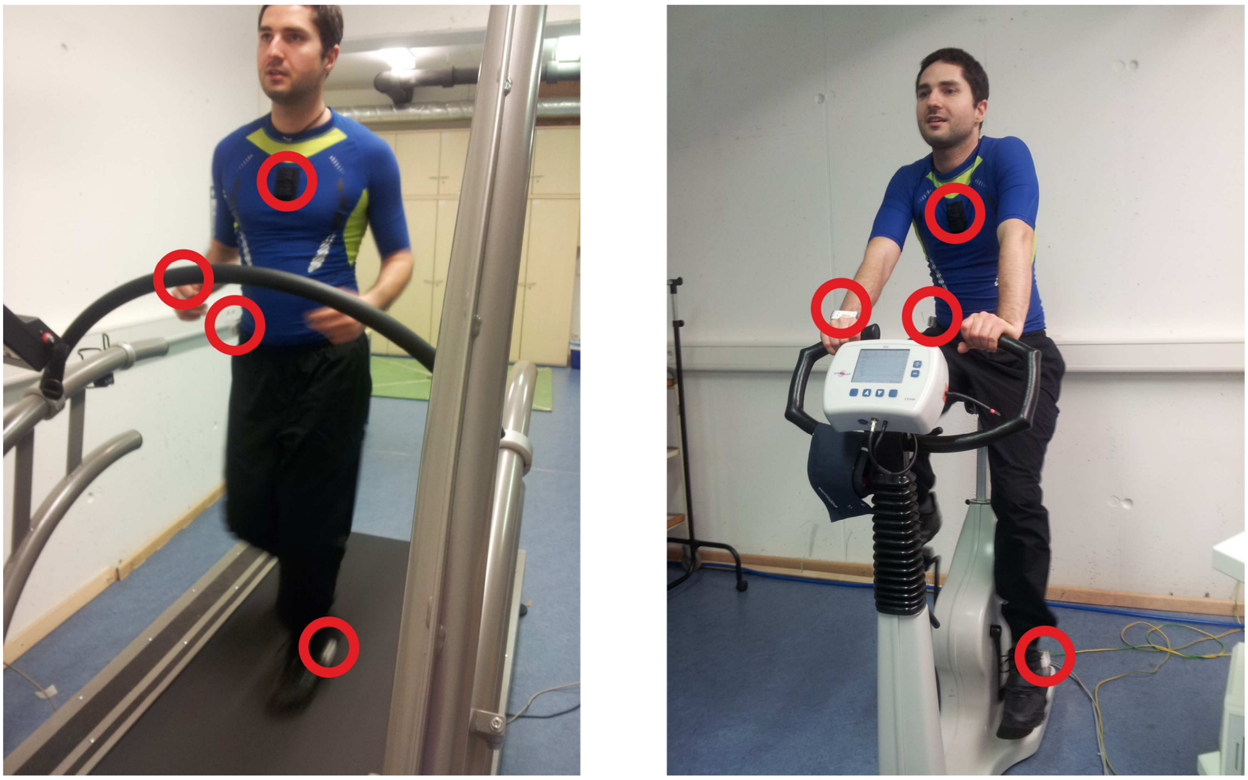

Fig.2: Treadmill running (left) and bicycling (right); sensors are marked by red circles.

The participants consecutively performed the four exercises under supervision. For each exercise the start and end time were saved for offline labeling. The start point of the exercise was set when the subject reached the desired level (km/h or W). The end point of the exercise was set after 120 s. The inertial data was labeled regarding the exercise grouping.

The labeled inertial data was divided into segments of 5 s for further processing. Fig. 3 shows the vertical acceleration measured by the ankle sensor for the two exertion levels of treadmill running and bicycling. In the following the labeled 5 s inertial data of the four SHIMMER nodes are denoted as instances.

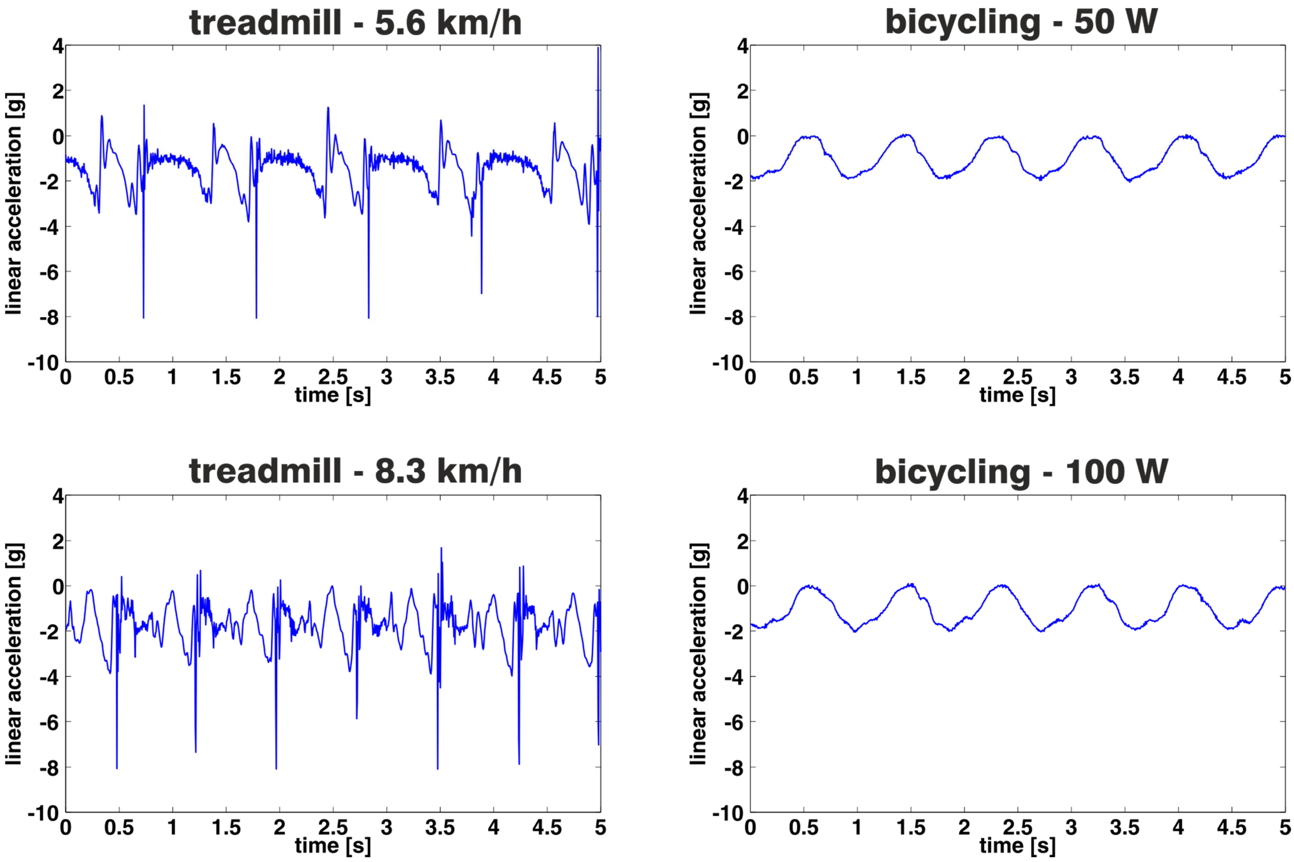

Fig.3: Linear acceleration in vertical direction of ankle sensor; treadmill running at 5.6 km/h (upper left), treadmill running at 8.3 km/h (lower left), bicycling at 50 W (upper right) and bicycling at 100 W (lower right).

Feature Extraction Each of the 5 s instances consisted of recordings from three accelerometer and three gyroscope axes of four sensors. For each axis, seven features in the time and frequency domain were computed. Thus, 168 features were extracted for each instance in total.

In detail, in the time domain, five linear predictive coding coefficients (Rabiner et al., 1993) were computed. In the frequency domain, the spectral centroid and the bandwidth (Agostini et al., 2003) were computed.

Feature Selection and Classification The classification of the two treadmill levels and the two bicycling levels was solved in a hierarchical manner. The discrimination of the four classes was divided into three classification experiments: treadmill vs. bicycling (level 1), 5.6 km/h vs. 8.3 km/h on treadmill (level 2a) and 50 W vs. 100 W on bicycle (level 2b). The treadmill and the bicycling class in level 1 included the two speed and resistance levels.

For performance assessment, the mean class dependent classification rate and the overall mean classification rate were computed with a leave-one-subject-out-procedure. In order to reduce the number of features, the sequential forward selection algorithm (Theodoridis et al., 2008) was used. The feature selection was cross-validated in every leave-one-subject-out trial with an inner leave-one-subject-out loop.

The Support Vector Machine (SVM) with linear kernel was used as classifier (Theodoridis et al., 2008). The cost parameter C of the linear SVM was set to 1.

Results

The mean class dependent classification rates and the overall mean classification rates of the three classification experiments can be seen in Tab. 1. The distribution of the features after the feature selection regarding the sensor type (accelerometer/gyroscope) and the sensor placement (wrist/chest/hip/ankle) can be seen in Tab. 2.

Table 1: Classification rates (in percent) of the three classification experiments.

	level 1			level 2a			level 2b		
	treadmill	bicycling	mean	5.6 km/h	8.3 km/h	mean	50 W	100 W	mean
class. rate	*97.3*	*99.0*	*98.2*	*99.6*	*98.3*	*99.0*	*60.5*	*61.6*	*61.1*

Table 2: Feature distribution (in percent) after feature selection

	sensor type		sensor placement			
	accel	gyro	wrist	chest	hip	ankle
level 1	68.4	31.6	31.6	36.8	26.3	5.3
level 2a	100	0	28.6	42.9	28.6	0
level 2b	57.1	42.9	28.6	27.1	18.6	25.7

Discussion

The high overall mean classification rate of level 1 (Tab. 1) indicates that the two sport exercises treadmill running and bicycling can be separated by the inertial data of the four SHIMMER sensor nodes and the corresponding feature set. Thus, the chosen sensor locations seem to be suitable for this classification experiment.

The high overall mean classification rate of level 2a in Tab. 1 indicates that the two treadmill speeds can be separated by the sensors and the corresponding feature set.

The rather low overall mean classification rate of level 2b in Tab. 1 indicates that the discrimination of the two resistance levels of bicycling is more difficult than the first two classification experiments. The reason is the high similarity of the two signals because the revolutions per minute were kept constant (see Fig. 3, right column). Additional features as well as choosing different kernels for the SVM might increase the classification rates.

Regarding the sensor type it can be seen in Tab. 2 that most of the selected features were measurements from an accelerometer signal. However, in the case of the level 2b experiment, the chosen features were almost equally distributed regarding the sensor type. Thus, it is speculated that accelerometers and gyroscopes are needed for exercises that are similar in the shape of the signal.

Regarding the sensor placement most of the features of the level 2a experiment were chosen from the chest sensor. It is assumed that the linear accelerations measured by the chest sensor increase with higher speed level. In the case of the level 2b experiment, most of the features were chosen from the wrist sensor. The reason might be that the participants do not regularly bicycle. Thus, the higher resistance level is more exhausting for the participants, which is reflected in a slightly different shape of the wrist sensor signals compared to the lower resistance level. It was shown that depending on the exercises different sensor locations are important. Especially in the level 2b experiment the distribution of the chosen features was almost equal regarding the sensor placement. Thus, for exercises that are similar in the shape of the signal, the contribution of all sensors seems to be important.

The rather low classification rates for the level 2b experiment show that the system cannot distinguish between all exercises. Nevertheless, the rather high classification rates of the level 2a and especially level 1 experiment indicate that such a system is suitable for automatic classification of different sport exercises of a training session. However, the accuracy of the system must still be optimized for certain exercises.

Conclusion

Self-reports are a common possibility of monitoring parameters in a training program. These self-reports rather distract the athlete during the exercise.

In this paper, a multi-modal sensor system was presented that has the potential to automatically distinguish between different exercises after a training session, which can replace the need for self-reports for the ordering of exercises. The athlete can concentrate on the exercise itself.

The system is a good starting point for further research and will be tested on more exercises. Besides the determination of the exercise type, the multi-modal sensor system can also be used to give the athlete feedback about the quality of exercise execution. This has the potential to improve the sports performance of athletes.

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