Child-activity recognition from multi-sensor data

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Child-Activity Recognition from Multi-Sensor Data

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ABSTRACT
The automatic recognition of child activity using multi-sensor data enables various applications such as child-development monitoring, energy-expenditure estimation, child-obesity prevention, child safety in and around the home, etc. We formulate the activity recognition task as a classification problem based on multiple sensors embedded in a wearable device. The approach we propose in this paper is to apply spectral analysis techniques of multiple sensor data for activity recognition. Quadratic Discriminant Analysis (QDA) classifier is then trained using manually annotated data and applied for activity recognition. The obtained experimental results for the recognition of 7 activities based on a limited data set are promising and show the potential of the proposed method.

Author Keywords
Activity recognition, feature extraction, activity classification.

ACM Classification Keywords
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INTRODUCTION
The automatic recognition of activities by using sensors such as tri-axial accelerometers can be used in a variety of applications. A first category entails context-aware applications. It consists in adapting, in real-time, the environment according to the recognized activity, such as changing the light condition according to the posture of the person (lying-down, sitting, etc). Other examples are giving an alarm if an elderly person falls, or when a child demonstrates potentially hazardous activities (such as climbing the stairs). The second category of applications is behavior monitoring. It consists in analyzing the activity on the longer term and the identification of trends or certain lifestyle properties. As an example, the amount of physical activity can be monitored to quantify a person's energy expenditure, possibly combined with coaching activities to monitor progress during physical training. Moreover, as a sedentary lifestyle is becoming a commodity in many developed countries, monitoring and stimulation of physical activity can be used to prevent obesity, both with adults as well as for children [1].

In this work we are interested in the automatic recognition of child activities. We distinguish two categories of targeted applications: *real-time* automatic recognition relevant for acute child safety (such as fall detection and stair-climbing), and *long-term* activity recognition and logging to track child development and to support preventing child obesity. The recognition and quantification of sedentary activities such as lying-down, sitting, watching television, etc are relevant to assess any required changes in lifestyle. This can be achieved by stimulating the children by mean of games or rewards. Additionally, activity recognition can help to improve energy-expenditure estimation (e.g., the activity *level*) since it has been shown that the energy expenditure is dependent on the type of activity [2].

The field of automatic activity recognition has been extensively researched. Accelerometers have been employed for many years in the analysis of body posture and activity especially in a clinical setting [3]. In [4] small biaxial accelerometers have been worn simultaneously on different parts of the body. Features such as mean, standard deviation, energy, correlation and frequency-domain entropy are used. The study in [5, 6] investigated the use of multiple sensors (bi-axial accelerometers, light and temperature sensors, microphones) placed at different body locations to recognize human locomotion.

ACTIVITY RECOGNITION
The automatic activity recognition of children is formulated as a classification problem where two stages are involved: a feature extraction stage and a classification stage.

Feature extraction
The multi-sensor device we used in this research provides tri-axial acceleration data, air pressure data, and tri-axial gyroscope data. The use of multimodal analysis is expected to enrich the data and enable the recognition of wider

number of activities. The feature extraction is obtained through two cascaded steps: first-order and second-order feature extraction. The first-order features are chosen to be robust to noise and sensor orientation. For the second-order feature extraction, we employ a spectral variance analysis as previously used for the classification of audio and music signals [7].

First-order features

In order to be robust against noise and invariant to a certain extend to the sensor orientation we considered the vector magnitude of acceleration (AccMag) and vector magnitude of gyroscope data (GyrMag). Additionally, the normalized z-component of the accelerometer (AccZ/AccMag) and the measured pressure (Pres) are used. Thus our first-order feature vector consisted of 4 components [AccMag, GyrMag, AccZ/AccMag, Elev].

Second-order features

To allow analysis of the dynamic behavior of first-order features, a second-order feature extraction stage was employed. Each of the 4 first-order features were processed as follows:

- **Moving average** by applying a first-order low-pass filter with a cut-off frequency of 0.1 Hz;
- **Moving variance** by first filtering the signal with a 2^{nd} order band-pass filter (0.15-20 Hz), subsequently computing the square of the individual samples, and averaging the result with a low-pass filter with a cut-off frequency of 0.5 Hz;
- **Moving RMS 0.1-2 Hz** by filtering the signal with a 2^{nd} order band-pass filter (0.1-2 Hz), computing the square of the individual samples, averaging the result with a low-pass filter (0.5 Hz cutoff frequency), and computing the square-root of the result;
- **Moving RMS 2-4 Hz** same procedure as the previous one except for the first band-pass filter having a pass-band of 2 to 4 Hz;
- **Moving average slope** by first applying a 4-th order low-pass filter (0.1 Hz), computing the difference of subsequent samples, and applying a smoothing filter (0.5 Hz cutoff frequency).

Thus we extracted 5 second-order features for each first-order feature, hence in total 4 x 5 = 20 features are obtained. This feature vector is then used as input for the classification stage.

Activity classification

Generic classification approaches can be applied for activity recognition based on the extracted features. In this work we applied three classifiers namely Linear (LDA), Quadratic (QDA) and Adaboost classifiers [8]. LDA is computationally efficient but cannot deal with non-linearity that is usually present in data. Adaboost is a good classifier in term of generalization however it is known for its sensitivity to data size and noise. QDA provided a good trade-off between classification and computation efficiency. Manually annotated data were used to train and test the classifiers. The train and test set was obtained by recording sensor data while the sensor device was carried by a child. The considered activities are listed in Table 1 with the corresponding labels.

Label	Posture	Label	Posture
1	Walking	5	Falling
2	Lying-down	6	Standing-up
3	Running	7	Other
4	Climbing stairs		

Table 1. List of considered activities and corresponding labels.

EXPERIMENTAL PROCEDURE AND RESULTS

The experiment, which was approved by Philips Research ethics committee, was conducted during a normal activity of a 2-year old child in an indoor setting. As shown in Figure 1, the wireless sensor device was placed in the back pocket of the trouser. The sensor device is based on the Aquisgrain wireless sensor platform [9]. The sensor signals were sampled with a frequency of 50 Hz. Seven types of activities have been considered during the experiment. Approximately 30 minutes of sensor data has been recorded with a synchronized video material for ground-truth creation. The sensor device contains a tri-axial accelerometer with maximum acceleration of 2g, a tri-axial gyroscope for the determination of the sensor orientation and a pressure sensor for the determination of elevation. The data obtained from the pressure sensor needs to be normalized when both indoor and outdoor activity are analyzed. However, we limited the experiment to indoor activities. The elevation data obtained from the pressure sensor is useful to detect climbing and falling events.

From the acquired data, train and test sets were obtained by randomly splitting the data segments into training and test sets. A 3-fold validation was employed to obtain mean classification performance numbers including 95% confidence intervals.

The mean classification performance obtained using only first-order features amounted to 38.2%±1.5%. However the second-order features resulted in a good performance of 97.8%±0.2%. Second-order features computed from only accelerometer data i.e., [AccMag, AccZ/AccMag], provided 79.9%±1.5%. This result shows clearly the benefit of using a multi-sensor approach.

Figure 2 shows the normalized confusion matrix of the classification results obtained for the second-order features. The activities of *climbing stairs*(4), *falling*(5) and *standing-up*(6) have been recognized with more than 99% of accuracy. Such high accuracy is required for building safety applications based for instance on fall and stair-climbing detection. Most of the errors are obtained from the confusion between *walking*(1) and *running*(3). This can be explained by the fact that sometimes it is difficult to distinguish between walking quickly and running. To solve this issue, additional classes can be introduced to better describe the speed and the intensity of walking and running. Figure 3 shows an example of a sensor signal (AccMag) and the obtained classification result as a function of time. The output of the classification (in red) is according to the labels in Table 1.

Figure 1. A 2-year old child having the sensor device in the back-pocket of the trouser.

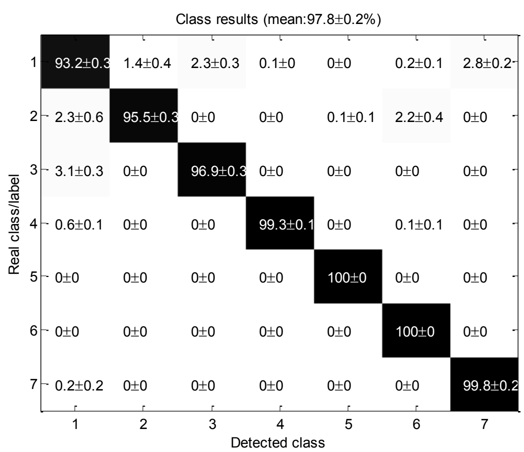

Figure 2. Normalized confusion matrix for 7 activities obtained with the proposed features.

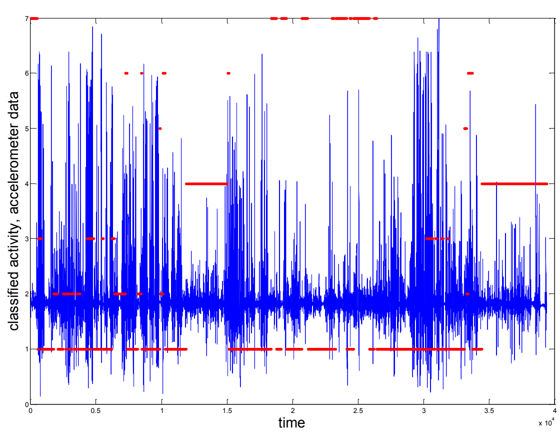

Figure 3. The magnitude of the acceleration is plotted together with obtained classification results. The magnitude was scaled to be able to plot both classification as well as sensor data.

CONCLUSIONS

Child-activity recognition is formulated as a classification problem where two stages are involved, namely feature extraction and classification. Second-order features by means of spectral analysis have been applied on a multi-sensor data where additional sensors beyond accelerometers have been used. The obtained results for a limited data set indicate the high potential for the proposed approach. As future work, both the extension towards more activities, as well as the validation of the results on a larger data set are required to better quantify the benefits of the proposed approach compared to state-of-the-art methods.

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