Children activity recognition from accelerometer data

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Introduction. A growing number of physically inactive children who do not move enough, spend a lot of time sitting at a computer and playing computer games, leads to health disorders in childhood. Regularly monitoring parameters of physical activity we can determine the motions, evaluate total time of inactivity and control the child's physical activity. The classical pedometers are inaccurate, does not identify a person, a child can attach a pedometer on his friend or on an animal. We developed a method for recording accelerometer data from moving human as he performs daily activities such as walking, sitting, jogging, jumping and for identification of type, duration and intensity of movements. The developed method can be used for online activity recognition on low power microcontrollers. This device is working as USB key communicating with user's computer and, according to the human physical activity, controlling the time of computer usage.

Materials and methods. The proposed method for children activity recognition based on 3-axis accelerometer comprises the following 5 steps:

1) Collection of 3-axial accelerometer data of most popular activities;
2) Extraction of features;
3) Creating the feature matrix including feature sample vectors of different activities;
4) Collection of data during the experimental protocol;
5) Recognition of activities in experimental data set.

The mobile phone with built-in accelerometer was used to collect data for everyday activities such as low speed walking, high speed walking, sitting, running, squatting and jumping. This device was used only in development stage of presented method. The activities were performed by three persons, five times each by changing clothes, shoes. A special data collection software running on iPhone, *Inertial Logger*, was used to collect 10 seconds of accelerometer data (sampling frequency was set to 32 Hz) for each activity.

For feature extraction only data recorded during a stationary state of each activity has been selected. The linear 3-axial accelerometer data has been used to calculate features for each axis: the average ($\bar{a}_x$, $\bar{a}_y$, $\bar{a}_z$), the standard deviation (σ_x, σ_y, σ_z), maximum (max_x, max_y, max_z), minimum (min_x, min_y, min_z), frequency domain entropy (E_x, E_y, E_z), dominant frequency (F_x, F_y, F_z) and average resultant acceleration *ARA* [1].

The power spectral density *P* has been calculated for the definition of the harmonic content of the accelerometers signal. The frequency domain features of power spectral density are the dominant frequency F and frequency domain entropy E [2], defined as

$$E = \sum_{i=1}^{N/2} \left[P(i) \cdot \lg(P(i)) \right]. \tag{1}$$

The dominant frequency F is the frequency at which power spectral density function has the maximal value. The frequency domain entropy and dominant frequency has been calculated for each axis separately.

In this way a 19-dimensional feature vector has been constructed for each activity and the feature matrix size is 19 by 7. Each row of feature matrix contains features from one activity. Columns represent feature value changes for different activities, as shown in Table 1. Each feature values have been calculated as average from five estimations of the same activity performed using different clothes, shoes and at different time of the day. Feature matrix was stored in memory. The seventh row of matrix represents features of activity, which is unlike any of the existing activities (we used features of dog's movements).

Table 1. The feature matrix of one subject. Last row represents feature vector of dog movements.

Activity	$\bar{a}_x$	$\bar{a}_y$	$\bar{a}_z$	σ_x	σ_y	σ_z	$\max_x$	$\max_y$	$\max_z$	$\min_x$	$\min_y$	$\min_z$	E_x	E_y	E_z	F_x	F_y	F_z	*ARA*
Running	-0,29	-0,74	-0,09	0,5	0,81	0,28	1,03	0,63	0,74	-1,54	-2,22	-0,81	29,12	37,9	12,1	3,21	3,21	3,25	1,11
Fast walking	-0,33	-0,94	-0,05	0,22	0,34	0,19	0,28	-0,31	0,24	-0,76	-1,5	-0,53	8,42	4,02	3,62	1,78	1,84	1,87	1,03
Slow walking	-0,32	-0,93	0,04	0,07	0,06	0,09	-0,13	-0,79	0,22	-0,48	-1,17	-0,16	1,14	0,53	1,24	0,62	3,4	0,62	0,99
Sitting	0,02	0,01	-1,08	0,01	0,01	0,01	0,03	0,01	-1,08	0,02	0,01	-1,08	0,01	0,01	0,01	0,62	4,59	2,43	1,08
Jumping	-0,02	-0,46	-0,66	0,17	0,64	0,98	0,32	0,44	0,97	-0,58	-1,97	-2,23	6,36	53,5	47,9	1,68	1,65	1,65	1,08
Squatting	0,01	-0,88	-0,39	0,2	0,27	0,37	0,37	-0,29	0,07	-0,47	-1,42	-1,09	3,51	8,88	8,66	0,62	1,09	0,62	1,01
Dog	0,05	0,59	-0,84	0,47	0,65	0,59	1,15	1,48	0,3	-0,77	-0,1	-1,91	9,87	9,36	18,3	5,46	2,75	5,46	1,19

During the experimental protocol the subjects performed five most popular activities in random sequence. 3-axial accelerometer data has been collected by using mobile phone. Additionally, all subjects motions has been captured by using Merlin F-146C camera from Allied Vision Technologies GmbH. Accelerometer data collection and video capturing was started synchronously by using camera external trigger signal from small tactile sensor installed in touch screen pen for iPhone. Camera is working in Trigger Mode 15, combining one external trigger event with continuous internal trigger. In this case, by touching the Start button on touch screen of the phone the camera starts capturing predefined amount of images. A collected accelerometer data has been separated into a number of fixed size partially overlapping frames. The size of each frame is 160 samples (5 s time interval). The following features were extracted from each frame: the average, the standard deviation, maximum, minimum, frequency domain entropy and dominant frequency.

The k-nearest neighbour (kNN) classification scheme was used for recognition of activities in experimental data set [3]. The k-nearest-neighbour classifier is commonly based on the Euclidean distance between a test sample and the specified training samples, but this metric can become very noisy for high dimensional problems where only a few of the features carry the classification data. To solve this problem the correlation distance has been used. This function looks at similarities in the shape of two traces rather than the exact values of the data, so it is acceptable for comparison of activity feature data. The definition of the correlation distance function [4] is given by

$$d_{st} = 1 - \left| \frac{(n-1)\sum_{i=1}^{n}(s_i - \bar{s}_n)\cdot(t_i - \bar{t}_n)}{\sum_{i=1}^{n}(s_i - \bar{s}_n)^2 \cdot (t_i - \bar{t}_n)^2} \right|, \quad (2)$$

where n – the size of feature vector, s_i – the values of sample vector, representing features of single activity, t_i – the values of test vector, representing features extracted from one frame of test data, $\overline{s_n}$ – average of all sample vector values, $\overline{t_n}$ – average of all test vector values.

During classification stage the values of test vector, representing features extracted from one frame of test data, are compared with the values in the feature matrix, created on third step. Because the number of nearest neighbours has been selected as *k=1,* then the frame is simply assigned to the class of single nearest neighbour, representing the corresponding activity. This frame is labelled as the activity for which the vote is the highest. The classification was repeated using next frames of test data and all frames were labelled. Finally, number of frames for each activity was calculated and total time of low physical activity evaluated.

Results. Presented method has been tested with three subjects: 2 females and 1 male. All subjects carried the mobile phone in the front pocket of their shirt during training phase and experimental test. Using training data the feature matrix for each of subjects has been formed. Later each subject performed the same activities in random order. The accelerometer data has been recorded using data collection software *Inertial Logger.* All subject’s motions has been captured by using camera. The same test scenario was repeated 5 times with different clothes of each subject. At the end of classification process the accelerometer signal of *z*-axis and labels of activities were displayed (Fig. 1). Activity recognition accuracy evaluated by viewing recoded video and creating vector with the true class labels for each observation frame and compared with classification results. The overall performance for presented method is 87.56% accuracy considering all activities. Only 2% of all accelerometer signal samples have not been classified.

Conclusions. The proposed an activity recognition method can be implemented using low power microcontroller, supporting training and classification while using only the accelerometer data. The method is simple, exhibited good performance and does not require big computational recourses. As a future work, more activities, such as biking, playing different sport games will be added to the classification states and more experimental tests will be done with more persons.

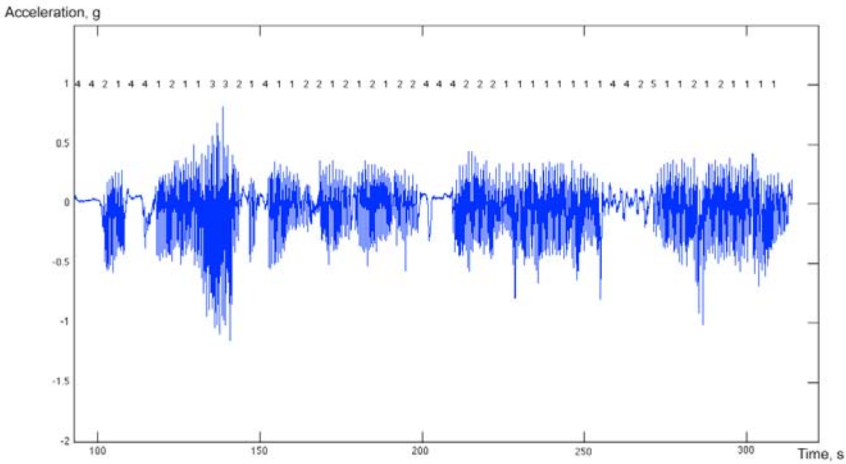

Fig. 1. Acceleration measured during the experimental protocol. Label highlight the signal measured during the tasks included in the test: 1) high speed walking; 2) low speed walking; 3) running; 4) sitting; 5) jumping.

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For online activity recognition of children the low power microcontrollers can be used. This device as computer USB-key can control the time of computer usage, because children are spending lot of time sitting at a computer and playing computer games. In this paper, method for physical motion recognition using k-nearest neighbour classifier is presented. The method is simple, exhibited good performance, don't requires big computational recourses. So, it can be implemented in portable devices.