Use of Accelerometer Sensors for Monitoring the Health Status of Disabled People

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ABSTRACT: *Patients with disabilities and their health status detection is significant in the intelligent computing. When there is no health support people for the disabled people, a system using accelerometer sensors is able to monitor the conditions. While we use the KNN classifier after raw data pre-processing, we have identified six modes of activities. We are able to draw incredible data results which can bring useful data analysis of the observation and detection of the health status of the observed disabled people for a longer time.*

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1. Introduction

Human activity recognition based on data obtained by wearable sensors has been investigated for numerous years now [1]. It has various applications such as monitoring the performance of sportsman, medical observation of patients during active treatment and rehabilitation mainly during the presence of medical personnel, warfare activities evaluation and analysis and many others. In the recent years the use of low-cost sensors, primarily accelerometers embedded in smartphones, become popular for general use among wider groups of users [2]. With the increase of the amount of individuals suffering from different disabilities who don't need permanent support by nursing staff it becomes a need to have distant monitoring of their daily activity accomplishments. Thus, it is possible to evaluate the evolution of their condition for prolonged time and possibly take proper measures in the future for enhancing their way of life.

Multiclass hardware-friendly support vector machine (SVM) was used by Anguita et al. [3] for the classification of human activities. They incorporated inertial sensors from a smartphone inside the proposed system with the idea to reduce power consumption by using fixed-point arithmetic. The average precision with this modified multi-class SVM is 89.23%, very close to the 89.95% precision of the classical one got at the same experimental setup.

Another more accurate but instruction non-sparing multiclass SVM is tested in [4] by the same team where 96.67% precision is reported. There a new database is suggested to the public containing data from static and dynamic activities implemented for periods from 12 to 15 sec. Volunteers in a group of 30 people performed standing, sitting, laying down, walking, walking downstairs and upstairs. Totally, 2947 patterns were produced and used within the tested recognition engine.

Su et al. [5] presented an extensive classification of the particular components of the most common activity recognition systems using smartphone sensors. They presented 11 kinds of sensors forming 5 groups of 39 activities. The experimental setups met in literature are split to number of subjects (single and multi), sensor amount (single and multi), sensor location (7 types), and location of activity (2 types). The recognition features may be generated from values in time-domain and in frequency-domain. The classifiers are seen as base-level ones including decision tree, decision table, k-NN, HMM, SVM, etc. and meta-level classifiers – with voting, stacking, cascading, etc.

Lara and Labrador [6] looked through most of the productive methods for human activities recognition (H AR). All of them have been reported as successful in the following everyday use: ambulation, transportation, phone usage, fitness, and military. They generalized the overall structure of a HAR system starting from the input signal being location data, physiological signals, acceleration signals, and environmental signals. From all of them features are formed separated as structural and statistical. After learning and inference recognition models are created and then the actual recognition takes place. The complete HAR systems, e.g. Ermes, eWatch, Tapia, etc. assure accuracy from 71% to 98%. Single recognition engines are also classified in relation to their precision varying in the interval 77-99%.

Hierarchical Hidden Markov Models (H-HMM) is the foundation of a HAR system proposed by Lee and Cho in [7]. For additional enhancement of the recognition rate the authors divide into a cascade style the input data to activity and action. A set of actions processed by HMMs in probabilistic fashion and forming a weighted decision as an output leads to the final activity recognition. Most accurately is recognized the standing, close to 100%, followed by running with close to 95% and ascending – 85%, and then walking and descending – with less than 80%. Other activities have been also evaluated with the tendency of better performance for the HHHM over artificial neural networks (ANNs) only for the descending activities.

Bayat et al. [8] also developed their own HAR system. Subjects from 29 to 33 years of age performed running, slow walk, fast-walk, aerobic dancing, walking stairs-up, and stairsdown. With 79573 data samples gathered the researchers tried the following classifiers which produced accuracy of: Multilayer Perceptron – 89.5%, SVM – 88.8% Random Forest – 87.6%, LMT – 85.9%, Simple Logistic – 85.4%, Logit Boost – 82.5% when the smartphone is held in hand.

Unsupervised learning is used in the work of Know et al. [9] for recognizing human activities when their number is previously undetermined. It turned out that Gaussian mixture method copes with the problem when this number is firstly known while hierarchical clustering (DBSCAN) is more than 90% accurate without that prior knowledge using Calinski– Harabasz index. They processed walking, running, sitting, standing, and lying down. The normal mutual information (NMI) is 0.8670 for the k-means clustering, 1.000 for the GMM and 0.9092 for the HIER approach. The proposed approach is expected to produce efficient results also for greater number of activities.

Relatively different approach was undertaken by Duong et al. [9] where they argue about the efficient duration and hierarchical modeling when recognizing human activities that inherent hierarchical structures are also beneficial to the process. Coxian distribution is found useful when building Coxian Hidden semi-Markov Model (CxHSMM) for the complex temporal dependencies. It possesses several advantages among others the multinomial or exponential family distributions, proper density in nonnegative distributions, easier parameterization, and thus faster computational execution with the opportunity for closed-form estimation solutions. Hierarchical and duration extensions of the HMM are then combined into Switching Hidden Semi-Markov Model (SHSMM). Classification accuracy achieved in one of the experimental setups was 88.24% for HMM and 94.12% – for CxHSMM while the number of activities was $k = 4$. The Early Detection Rate (EDR) in same time was 9.12 against 8.35 respectively.

Weiss and Lockhart [10] suggest the use of personal and impersonal (universal) models for human activity recognition. While the personal ones are adapted to each user independently the universal is considered applicable to every new user's behavior processed by the system. Both models were applied over a dataset consisting of the following actions: walk, jog, stair, sit, stand, and lie with 9291records from 59 users. The following classifiers were used during testing: decision trees, Random Forest, instance-based learning, neural networks (Multilayer Perceptron), rule induction, Naïve Bayes, Voting Feature Intervals, and Logistic Regression. The highest accuracy was achieved for the multilayer perceptron with 98.7% for the personal method and only 75.9% for the impersonal. For the separate activities jogging was found most frequently with 99.8% and 95.2% respectively. Within the confusion matrices the walk has highest rank with a level of 2480 for impersonal and 3359 for the personal approach. The results clearly show that the personal method is much more accurate even with shorter input records rather than seeking a generalized model from the users.

In Section 2 description is given for the most common types of accelerometers used in practice and the compared classification algorithms with the applied technique employing reduction of dimensionality for faster execution during our study, in Section 3 – quantitative representation and analysis of some experimental results, and then in Section 4 a conclusion is made.

2. Description of Sensors and Proposed Algorithm

2.1. Types of Accelerometers

The most common types of accelerometers applicable in various devices include:

• **Piezoelectric Accelerometer with Charge Output –** It is based on the piezo-effect most often working with a quartz crystal which forms a connection with an object weighting preliminary known mass; the last is pushed by the outer acceleration and leads to charge flowing through the crystal which later is measured and gives indication of the inertial processes;

• **Piezoelectric Accelerometer with Voltage Output –** Its working principle is analogous to the above described kind but additional electronic circuit transforms the generated charge to a voltage;

• **Resistive Accelerometers –** A metal plate changes its electrical resistance in function of its deformation under the influence of the measured acceleration from the outside environment. Typically 4 plates are connected in a Vin's bridge for more accurate measurements;

• **Piezo-resistive accelerometer –** Analogous in working principle to the resistive one but the deformable material is made of semiconductor material which assures higher sensitivity during measurement;

• **Capacitive Accelerometer –** A flat capacitor changes its capacitance when an inner plane under the outer influence moves between its plates and shows the acceleration;

• **Optical Accelerometer –** Optic fiber changes its properties under deformation and in particular its optical conductivity and when connected in a system of interference filters where a narrow spectral band is selected the ratio between the inducted and reflected light exhibits the acceleration;

• **Thermo Accelerometer –** More rarely used, consisting of a heater and a thermo couple in a sealed environment; when stationary the sensor is in thermo steady state but when moving at variable speed the inside air moves making the inner ambience thermo unstable and the thermo couple registers the change by producing particular voltage which then is converted in acceleration units.

2.2. Proposed Algorithm

In order to have smaller execution time for the recognition of a particular activity here a splitting of the raw input data is suggested by direction – x, y, and z for the cumulative acceleration returned by the sensor.

The Algorithm follows the Next General Steps:

1. Loading of files with the full database with all labels' set, training data and labels for them.
2. Separate vectors are obtained for the x, y and z axes.
3. All vectors are normalized in the range [-1, 1].
4. In the input of the classifier, in this case k-NN, a matrix is submitted containing the vectors for all three axes.
5. After classification the true positives, true negatives, false positives and false negatives are found.
6. Step 4 and 5 are repeated for separately passed x, y and z vectors.

The prototype of the function of the classifier contains its initializing parameters:

class = knnclassify(*sample, train, group, nv,' cosine','random'*)

where class is the parameter which presents the group where the respective sample belongs, sample – matrix with rows that need to be classified into groups and contains the same number of columns as train, train – matrix used for training of the algorithm with the same number of columns as *sample*, *group* – label (index) of the training vectors, *nv* – number of vectors used for training, '*cosine*' – parameter which defines the type of distance used for measuring in feature space, '*random*' – defines the rule on which the selection of how a particular sample is being classified.

The k-NN Classifier Relies on the Next Three Main Steps

1. Initializing of the list according to the training set of vectors.

2. Testing vectors for classification are assigned by minimal distance of cosine type:

$$d_{st} = \left(1 - \frac{x_s y_t'}{\sqrt{(x_s x_s')(y_t y_t')}}\right), \tag{1}$$

where x_s and y_t are the vectors between which the distance is calculated, x'_s and y'_t are their transposed form respectively.

3. Applying the rule on which the behavior of the classifier is determined – a value of *'random'* is selected which is a main type with random break point.

Additional features that may be employed in the process are [1]:

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i , \tag{2}$$

which is the arithmetic mean found by the *n* components y_i of the input vector over one dimension;

$$RMS(Y) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} y_i^2} , \tag{3}$$

and the *root mean square* (*RMS*) for the same set;

$$\sigma_y = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (y_i - \bar{y})^2} , \tag{4}$$

where σ_y is the *standard deviation* which could also be used in its quadratic form , that is the *variance*:

$$\sigma_y^2 = \frac{1}{n-1}\sum_{i=1}^{n} (y_i - \bar{y})^2 . \tag{5}$$

The *mean absolute deviation* (*MAD*) is another measure that can be included in the process:

$$MAD(Y) = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} |y_i - \bar{y}|} \tag{6}$$

or the *energy* derived from the Fourier Transform coefficients F_i(i – the number of the current component) of *Y*:

$$Energy(Y) = \frac{\sum_{i=1}^{n} F_i^2}{n} . \tag{7}$$

3. Experimental Results

In the presented experimentation the public database WISDM is used [12]. It consists of 29 subjects performing 6 types of activities carrying a smartphone in their trousers with the sensor. Sampling period is 50 ms (sampling frequency - 20 Hz). The total number of samples are 1098204, where 38.6% of them represent walking, running – 31.2%, walking upstairs – 11.2%, walking down-stairs – 9.1%, sitting – 5.5%, standing – 4.4%. The data format for storage is [user], [activity], [timestamp], [x-acceleration], [y-acceleration], [zacceleration].

All the testing is done on IBM®PC® compatible computer with Intel i7-2670QM CPU running at 2.8 GHz and 6 GB of RAM on MS® Windows® 7 Ultimate OS within Matlab® 2013a platform.

The results are presented in Table 1.

Activity and results	**Number of correctly classified vectors over the dimension(s) used for the feature**			
	[x,y,z]	**x**	**y**	**z**
Running	1102	1822	3418	3418
Walking	927	2407	0	0
Up-stairs	381	0	0	0
Downstairs	119	0	0	0
Sitting	133	0	0	0
Standing	0	0	0	0
Time, s	0,5963	0,2805	0.2667	0.2763
Accuracy, %	24,21	38,44	31,12	31,12

Table 1. Human Activity Recognition Accuracy by The K-NN Classifier for The full Data Set and Segmented Over Dimensions

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \quad (8)$$

which can be supplemented also by the following parameters:

$$\Pr ecision = \frac{TP}{TP + FP}, \quad (9)$$

$$\mathrm{Re}\, call = \frac{TP}{TP + FN}, \quad (10)$$

$$F - measure = 2.\frac{\Pr ecision.\mathrm{Re}\, call}{\Pr ecision + recall}, \quad (11)$$

where TP are the *True Postivies*, TN – *True Negatives*, *FPFalse Positives*, and FN – *False Negatives*.

Total number of the input samples is 10983. When working with all 3 dimensions for the feature vectors the amount of wrongly classified ones is 8437, for the *x*-dimension – 6754, for the *y* - 7565, and for *z* - 7565.

Graphically, the results among different activities are given in Figure 1.

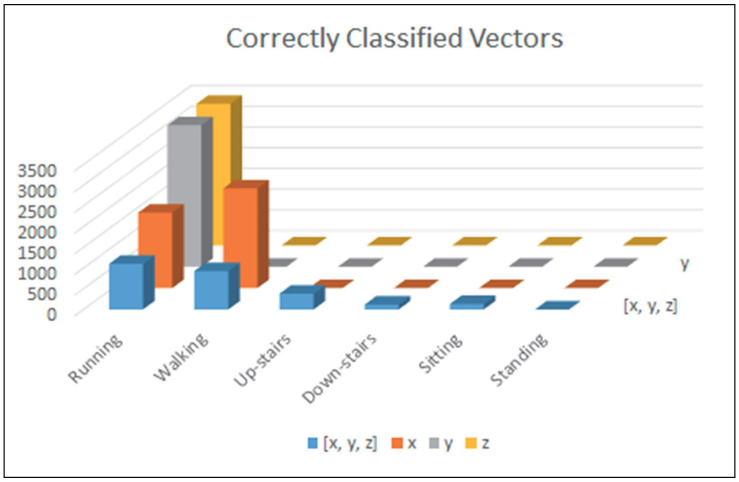

Figure 1. Recognition rate by type of activity

It appears that for the *walking* activity the *x* direction and for the *running* – the *y* or *z* (equally) are preferable to select for realization of initial stage of recognition (fast preliminary search) among all records from the database. This initial pass (round) may play a filtering role for considerable amount of feature vectors to be eliminated from furhter steps in a HAR system during further stages for refined search. Execution time reduction is 3.43 for each of these cases in comparison to the full feature set comprising of the three dimensions. This approach could be really effective in a parallel computation system where different dimensions are processed in a separate thread and even possibly each kind of activity is searched independently inside the records by independent processing unit. In such a multi-branch implementation some particular activites may be looked for simultaneously over more than one dimension, e.g. *running* – over *x* and *y*.

Further investigation should pose attention to the use of combinations of two directions, which additionally may reduce the number of undiscovered activities inside prolonged recordings at earlier stages, additionally speeding-up the whole recognition process.

4. Conclusion

In this paper was presented a study about the possibilities of application of low-cost inertial sensors built-in smartphones for medical condition assessment of patients with disabilities based on their daily activity. The experimental results show that separable representation of feature vectors over the principal dimensions of *x*, *y* and *z* could reduce the execution time of recognizing particular activities of the individual. Since each activity has predominant exhibition over certain direction which gives non-uniform distribution for the base coordinate axes one or two appropriate components may be employed. It allows faster searching among patient's database records on a prolonged time bases (daily, weekly, monthly, etc.) for establishing detailed statistic of his / her motor performance in comparison to the use of the full fetaures' values. In turn, this process provides shorter terms for prescribing proper measures by the medical personnel, possibly even in semi-autonomous mode. Further examination of more activities and combining 2 principal dimensions or one arbitrary direction for them during searching is to be accomplished.

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