Self-Monitoring system for diabetic individuals based on 3-axis accelerometer

Hanh Ngoc Dang

***Abstract*— In this study, we aim to develop a miniaturized stand-alone system that can detect a wide range of daily activities based on a single integrated consumer 3-axis accelerometer. A novel k-means based classification algorithm was constructed to interpret and translate signals from accelerometer into a recognizable cluster of pre-defined activities. The developed system has given encouraging results with a 100% success rate of classification of the three basic classes of activities based on resting, walking and running, and an 84% success rate for the lower level of different pace of walking and running. The potential extension towards self-monitoring systems for people suffering from diabetes mellitus has been considered by converting the activities into metabolic equivalents that will help predict the associated energy expenditure.**

***Index Terms*— Classification algorithms, 3-axis accelerometer, feature extraction, activity recognition.**

1 INTRODUCTION

Lifestyle related chronical diseases have in part been related to the lack of physical activity combined with unhealthy diets. Combating lifestyle related diseases have been based on both diet and exercise, in which the latter have focused on accelerometer based wearable devices as a tool of self-monitoring.

The target user group of this study is the growing number of people suffering from diabetes mellitus in which physical activity is paramount of maintaining a healthy glycemic control that reduce long term detrimental effects, as well as preventing the onset of the disease in people diagnosed with prediabetes and impaired glucose tolerance. Diabetes is a metabolic disorder that results in abnormally elevated or sup-pressed blood glucose (BG) values due to the inability or reduced ability of the body to metabolize glucose [1]. Although diet plays an important role in maintaining stable levels of BG, physical activity has the added benefit of preventing an unwanted rise in BG by burning off excess glucose available in the blood stream [2-5]. Sophisticated motion detectors that are able to distinguish between different classes of activities in real time would provide a much more comprehensive picture of the activity which can be related to a given energy consumption.

The first and popular tools of self-monitoring are pedometers that were originally designed on 1-axis motion sensors named step counters [4-6] or pedometers. These are on-body sensing devices that typically measure the number of "steps" an individual takes in a continuous manner, can only record a limited set of activities (i.e. distinguishing walking from resting) and estimate the distance walked based on steps.

Micro - ElectroMechanical systems - MEMS and BioMEMS have a prerogative for miniaturization and automation to such an extent that it can be integrated in wearable devices based on watches and ultimately miniaturized implantable sensor systems. Modern MEMS accelerometers are an electromechanical device designed to measure acceleration caused by gravity or relative body movement, not only count the steps taken, but also sense the force that is applied to the respective motion [5-20]. Free-living physical activities can be recorded using a tri-axial accelerometer (or the combination of two dual-axis accelerometers) that are able to measure three degrees of freedom alone. This makes the device less dependent on the orientation of the

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device with respect to the user. Some studies have investigated the use of acceleration signals to analyze and classify different subsets of the same physical activity (e.g. walking along a corridor, as well as up and down stairs) [8-9]. Others have employed them for recognizing a wide set of daily physical activities such as lying, sitting, standing, walking, and running [10] as well as cycling [11]

Multiple accelerometers can be used in parallel on different locations on a person's body (e.g., wrist, ankle, thigh, knee, elbow and hip) [12] in order to extend the range of physical activities that is monitored. While this approach is known to generate a high degree of accuracy such an 88.1% rate of recognizing the 13 activity types which is 12.3% higher than using a hip accelerometer alone, it is not feasible in everyday use because of two or more sensor-attachment sites and the associated cable connections that would interfere with normal activities.

The acquired motion signals from the accelerometer are then extracted to get the features of signal-magnitude area (SMA) and tilt angle (TA) [10] or parameters such as averages, energy, entropy, standard deviation, or correlations [13, 14]; and frequency spectrum [15]. These features are then used in a pattern recognition protocol that should decide which movement is being performed. Some studies have incorporated the idea of using simple heuristic classifiers [16], whereas others have employed more generic and automatic methods such as advanced computational techniques from the machine learning literature including decision trees [11], k-means and Bayesian networks [17], support vector machines (SVM) [12], artificial neural networks (ANN) [10-11] etc.

Current methods used to evaluate the energy expenditure (EE) includes the employment of direct and indirect calorimeters that estimates the energy production by measuring the oxygen uptake and/or heart rate. However, these methods require large supporting instrumentation that is stationary and performed in a hospital or lab setting, and are therefore not feasible for home monitoring. By detecting the acceleration of each stride, estimation has been shown to correlate well with true energy expenditure [18]. One way of using the metabolic equivalent of a task [19], will be applied in our study to estimate the total EE.

In this study, we aim to develop a miniaturized stand-alone system a system that can detect a wide range of daily activities based on a single integrated consumer 3-axis accelerometer. It also offers a wireless protocol making it more unobtrusive in nature. Considering the basic daily activity, and based on the selected set of particular features, the k- means gives a promising approach for our system.

The remainder of the paper is presented as follows. The materials and methodology are discussed in Section 2. Section 3 presents the experimental protocol that followed with results in section 4. Section 5 concludes with implications.

2 MATERIALS AND METHODOLOGY

2.1 Development Platform

This project will focus on using a single triaxial accelerometer to develop a system that is capable of recognizing a broad set of daily physical activities. The motion detection system was based on the TI eZ430-Chronos (Texas Instruments, US), development platform which is a highly integrated, wearable wireless system contained in a sports watch package that measures 48x33x16 mm^3 and weights 100g [20]. This development tool features the CMA3000 accelerometer, the CC430F6137 microcontroller and the CC1101 sub-1-GHz RF transceiver used in this project (eZ430-Chronos Development Tool User's Guide, 2009). It is supplied with a USB-based CC1111 wireless receiver that is connected to the PC. The accelerometer data was sampled at 50 Hz, before transmission to the receiver.

2.2 Motion classifier

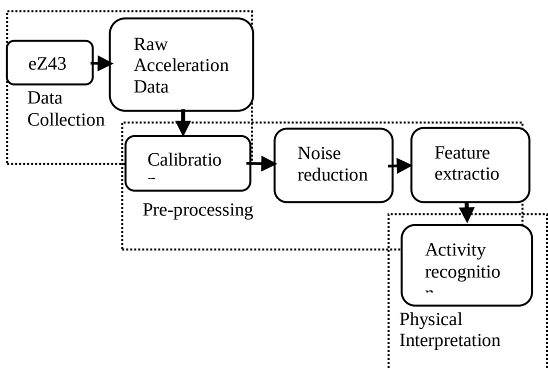


Fig 1. Block diagram for our proposed recognition technique.

The system will be used for unsupervised monitoring of daily activities defined into 3 basic motion classes of activities of resting, walking and running. Resting includes the specific sub-classes of sleeping, sitting, standing. Walking includes the sub-classes of slow, normal and brisk walk, whereas running are selected into the sub-classes of slow, normal and fast run at full speed. The illustration of the system architecture for monitoring basic daily movements can be seen in Fig 1.

First, raw acceleration signals from eZ430-Chronos are wirelessly collected and streamed it into a binary file from the COM port of PC using the "ez430 Acquire and Store" Labview application. Three directions of acceleration of human body were measured simultaneously with X-axis for back forth direction, Y-axis for up and down direction, and Z-axis for right and left direction of the acceleration signals (see Fig 2.). Next, at the terminal, Matlab is the language used to analyze the signals. The inference method is briefly divided into two steps of pre-processing and classification. Some pre-processing steps need to be applied to the measured acceleration signals in order to improve the accuracy and efficiency of the classification model, including the process of removing or reducing noisy data, and signal pre-conditioning where relevant feature values are extracted from the acceleration signals to form a set of features of each activity, that is efficiency for classification. The classification method of using k-means clustering algorithm is then implemented to identify the activities during time doing those activities.

2.3 Classification Algorithm

Cluster analysis is dividing groups of data based on their similarity to patterns in a training set [21]. K-means is a partitioned clustering approach that divides data into non-overlapping subsets. K-means is also known as center-based clustering algorithm, means that each cluster is associated with a centroid (or center point - the average of all the points in the cluster) and each point is assigned to the cluster with the minimum distance from it to the centroid of that cluster. When computing the distance from an unlabeled pattern to training patterns, different distance metrics can be used such as Euclidean distance, cosine similarity, correlation, etc. The Euclidean distance is most commonly used as in equation (1) below.

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \qquad (1)$$

where x_i is the unlabeled point in an n-dimensional feature space and y_i is the centroid point.

The k-means algorithm requires one parameter, k in the k-nearest neighbor, which is the number of clusters taken into account when dividing data points into clusters.

The basic k-means algorithm is very simple. Begin with specifying the number of clusters k, and then initial centroids are often chosen randomly. Then each data point then finds out which cluster it is closest to. Thus each cluster "owns" a set of data points now. Each cluster finds the new centroid of the points it owns. Therefore, clusters produced vary from one run to another. The k-means will converge for common similarity measures (no move of all centroids). Most of the convergence happens in the first few iterations. And all points falling into the same cell are assigned the same class label.

The high accuracy of the k-means classifier is proven when training data are representative and large enough. In the training phase of the basic k-means algorithm, all training patterns are just stored for comparison in the classification phase and all computation is done during the classification phase. The original k-means algorithm has huge computation and the accuracy of the resulting clusters heavily depends on the selection of random initial centroids. One method to improve the accuracy and efficiency of the k-means algorithm is combining a systematic method for finding initial centroids and an efficient way for assigning data points to clusters [22]. In this project, initial centroids can be assigned by trained features sets from training step. In the training stage, multidimensional feature vectors were established in time-frequency domain corresponds to a particular activity. For each movement, some training cycles are performed using different data of same activity. The mean values of these ones are used as the signature of that activity. In the classification stage, activity signal points are divided into clusters using the k-means algorithm. The majority of data points in clusters which correspond to a given class decide the label of that cluster (resting, walking or running). The majority is the highest percentage of data points have the minimum distance to the features set represented for that activity.

3 EXPERIMENTAL PROTOCOL

3.1 Data Collection

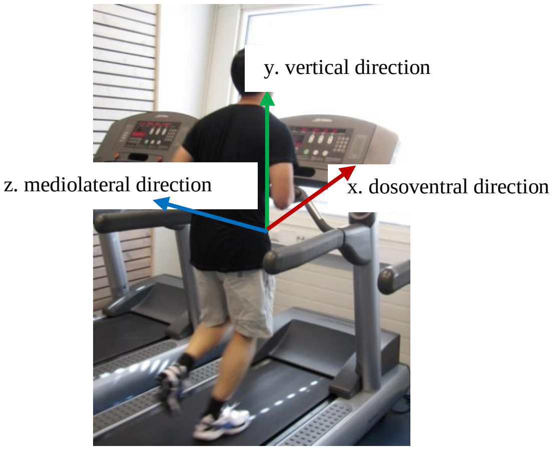


Fig 2. Measurement setup: Test person with the activity sensor around the waist and the recorded directions.

For the generation of data, measurements are collected in the sport center using our device. The device recorded the raw acceleration signals in three directions with a sampling frequency of 50 Hz. The measurement setup can be shown in Fig 2. The characteristics of the five people are chosen with large diversity in age, weight and height which gave the generality in evaluating our system.

Each person was equipped with our sensor fastened around the waist, was asked to perform a short list of walk and run on a treadmill. Different twelve activities are recorded includes resting (sitting down on an office chair, standing up, lying down on a bed), walking and running at different paces. The total duration of experiment of approximately a half-hour gave total 20 collected data of each activity with a length of 1 minute per each data. Separate data of each activity were segmented out into separate files so that each file would contain the complete duration of one particular movement or posture occurrence only. Activities were also continuously recorded for 20 minutes in a supervised setting for testing the performance of system in long time monitoring.

3.2 Classification Process

In general, data classification is a two-phase process as follows.

Phase 1 - Training phase. A model that describes a predetermined set of classes was built by analyzing a set of training data (half of data library). They were first segmented into 10s and each segment were features calculated. All features of all dataset were then analyzed some were chosen for representing each classes of activities. These mean values of features of each class are the trained features vectors for recognition stage.

Phase 2 - Classification phase. The classification algorithm was implemented and evaluated the performance using another half of data library, known as test dataset. Each data of test dataset annotated with name and speed of activity is divided into intervals of every 10 seconds. Each interval then go through the classification algorithm separately. The results of classification process are respected to be type and level of each activity in a certain time. The classified result was compared to the annotation of recording, then the sum of correct classification time can be calculated. The correct rate of the system was evaluated as percentage of total annotated time of recording using formula (2).

$$Rate = \frac{correct\ time}{annotated\ time\ of\ recording} \times 100\,\% \qquad (2)$$

3.3 Energy expenditure

The metabolic equivalent of a task (MET) is expressed as the energy cost of physical activities related to the resting metabolic rate (RMR). This have by convention been set to 3.5 ml $O_2 \cdot kg^{-1} \cdot min^{-1}$ or the equivalent of 1 $kcal \cdot kg^{-1} \cdot h^{-1}$ or 4.184 $kJ \cdot kg^{-1} \cdot h^{-1}$ [19]. Thus, one MET is considered as the resting metabolic rate (RMR) obtained during quiet sitting, and the total amount of energy consumed by individuals depends on the level of activity and on their body weight. The more active and heavier a person is, the more energy he/she requires. The compendium of physical activities and their MET values was first published in 1993 and updated later in 2000 as can be seen on Table I.

By knowing the type of activity undertaken, the MET can be derived and combined with a person's weight to yield the total EE as the following formula.

$$\text{EE (calories/ minute)} = 0.0175 \text{ x MET x weight (in kilograms)} \qquad (3)$$

4 EXPERIMENTAL RESULTS

This section contains the experimental results obtained using the methodology and experimental protocol based on the motion detection device described in section 2 and 3 with the use of

TABLE 1
METABOLIC EQUIVALENT OF A TASK (MET) RELATED TO A SPECIFIC ACTIVITY [19].

Physical Activity	MET
Light Intensity Activities	**< 3**
sleeping	0.9
At rest (RMR)	1.0
walking, 1.7 mph (2.7 km/h), level ground, strolling, very slow	2.3
walking, 2.5 mph (4 km/h)	2.9
Moderate Intensity Activities	**3 to 6**
bicycling, stationary, 50 watts, very light effort	3.0
walking 3.0 mph (4.8 km/h)	3.3
calisthenics, home exercise, light or moderate effort, general	3.5
walking 3.4 mph (5.5 km/h)	3.6
bicycling, <10 mph (16 km/h), leisure, to work or for pleasure	4.0
bicycling, stationary, 100 watts, light effort	5.5
Vigorous Intensity Activities	**> 6**
jogging, general	7.0
calisthenics (e.g. pushups, sit-ups, pullups, jumping jacks), heavy, vigorous effort	8.0
running jogging, in place	8.0
rope jumping	10.0

Energy expenditure: **1.0 MET = 4.184×10^{-3} J kg^{-1} h^{-1}**

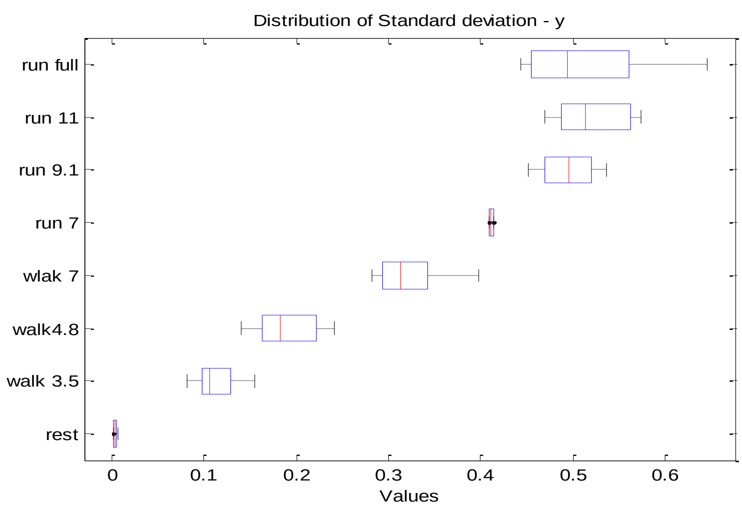
Matlab test bench. K-means are available in the Matlab bioinformatics and statistics toolboxes and Euclidean distance was chosen as the distance metric for classification processes.

The pre-processing includes calibration step creates a reference data file for further calibration the activity associated acceleration signals in three axis of accelerometer; and for the noise reduction, a 6-order Butterworth band-pass filter of 0.1 to 5 Hz have been developed and applied on acceleration signals. The DC values and high frequencies have been clear out of the acceleration signals.

4.1 Features Selection

From each interval of acceleration signals (a_x, a_y and a_z), some particular features need to be interpreted into a feature vector as the input for the classification system. The challenge in this stage is to find the features of the acceleration signals which describe and discriminate each activity the best. At first attempt, several features of 3 axes signals have been investigated. Using the training data set, the 23-dimensional considered features vectors of each activity have been calculated. These features are mean value, standard deviation, SMA, TA, fundamental frequency, Fast Fourier Transform (FFT) magnitude, spectral energy/entropy, cross-axis correlation, peak counts, and net acceleration of each direction.

Based on visual and statistical analysis using the distribution of each feature to show how it changes between different activities, the good features were selected. The more the distribution moves between activities and the less the distributions overlap, the better it is for discrimination of activities. If the distributions show considerable overlap with one another, means that it is not an easy task to construct a classifier to distinguish the activities.



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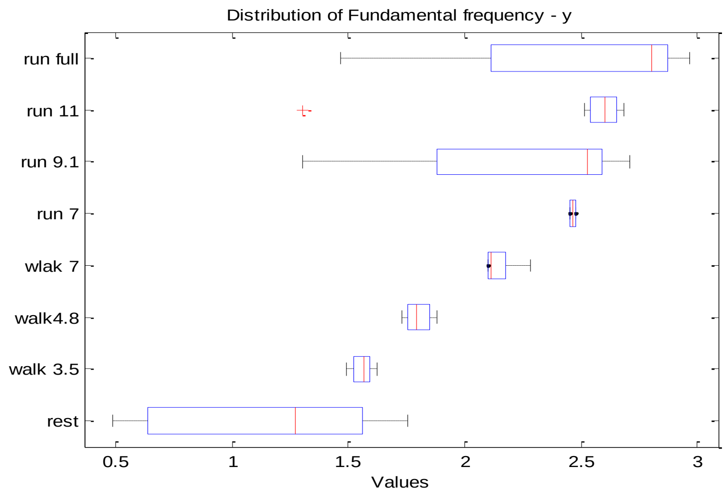

Fig 3. Distributions of the standard deviation (above) and the fundamental frequency (bottom) of back-forth acceleration for 3 classes of activity (at different paces).

The above plots of Fig 3. are the distribution of standard deviation; and the distribution of fundamental frequency. The plots have the red line at median value while the box has lines at lower and upper quartile; the whiskers show the extent of the rest of the data, and outliers for data beyond the ends of the whiskers. The distribution of standard deviation plotted in the Fig 3. shows that it can be used to determine whether the user is moving. Combining with other 4 features of fundamental frequency, spectral energy, entropy and the tilt angle, walking and running can be separated.

4.2 Classification of motion

4.2.1Trial system 1-classify three basic classes of activities

This system aims to classify three basic classes of activities using five features above.

Before going through the k-means algorithm, the acceleration signals need to be divided into the segment of t=10s and interpreted to get the five features. Three clusters of data points have been divided with the k- means algorithm (see Fig 4.). The decision of labelling the cluster as resting/walking or running was made based on the highest percentage of data points in that cluster belong to which class of activity when calculate the distance to trained features set of those classes.

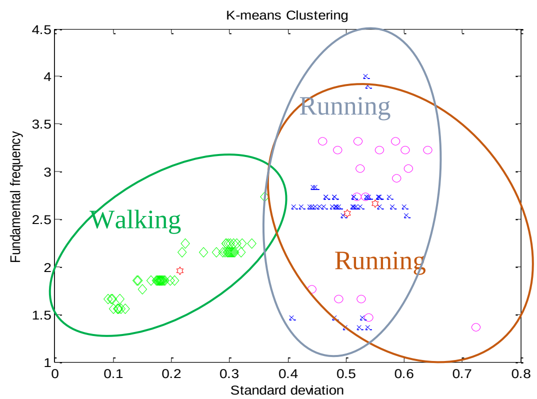

Fig 4. Plot of example three clusters after applying k-means on the 20 minutes acceleration signals of person 2. The same colored points were grouped in the same cluster. The red ones were the centroids of these clusters.

This trial system has been evaluated through the test dataset as well as 20 minutes signals of test people. The test results achieved the high accuracy at 100% of classifying 3 basic classes of activity.

4.2.2Trial system 2-classify different pace of walking and running

With the successful rate in identifying three basic classes of activity of trial system 1, this trial system takes a look deep inside the pace of walking/running. At first sight, the standard deviation, the dominant frequency, spectral energy and entropy are considerable to be used for determining the pace of running/walking. However, when we took a look at the distributions of some considerable features, we found that the distributions are overlapped between each pace of walking/running; especially in the running the features have large diversity. That means it was not an easy task to construct a classifier to distinguish them.

Following Fig 5. shows the distributions of features for determining pace of walking with standard deviation, peak frequency in vertical direction, its FFT magnitude, spectral energy and spectral entropy; while the distribution of features for determining pace of running is presented in Fig. 6 with standard deviation in vertical and dosoventral directions, frequency and spectral energy in vertical direction, counts of peak and net acceleration. The plots have the red line at median value, the box have lines at lower and upper quartile, while the whiskers show the extent of the rest of the data, and outliers for data beyond the ends of the whiskers.

Using considered features for determining the pace of walking and running, this system got the high success rate of 100% for classifying three pace of walking; whereas only 73% accurate rate obtained for determine the pace of running. The system gave a total rate of 84% for classifying the pace of walking and running. Details of result can be seen in Table 2.

TABLE 2
CLASSIFICATION RESULTS ACCORDING TO DIFERENT PACE OF WALKING AND RUNNING

Physical Activity Task	Classification Rate (%)
Level walking at 3.5 km/h	100%
Level walking at 4.8 km/h	100%
Level walking at 7 km/h	100%
Level running at 7 km/h	100%
Level running at 9.1 km/h	52%
Level running at 11 km/h	60%
Level running at 13-18 km/h	79%
Average rate	84%

4.3 Estimated Energy Consumption

The MET was estimated using the classified activity levels. The outputs of the classification system are the type and level of activities and also the total time during doing these activities. These outputs was used to estimate the energy expenditure using the MET conversion model (presented in section 3.3). Based on the result, one person can easily monitor their daily activities with the awareness of how much energy they spent during these activities.

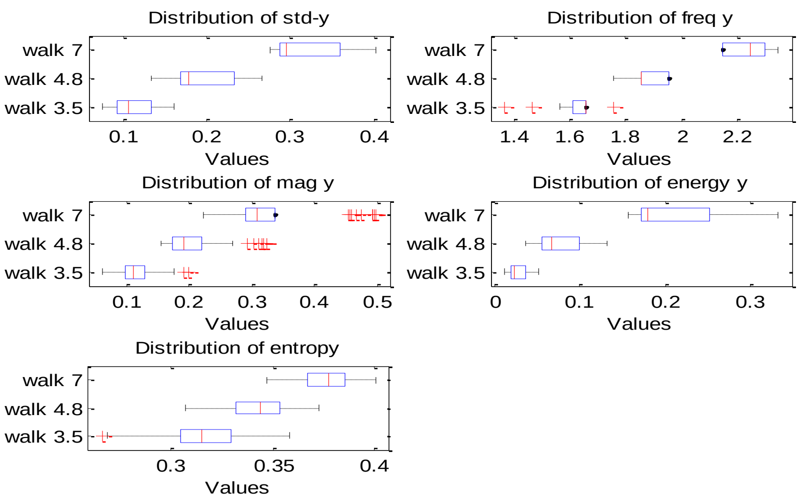

Fig 5. Distributions of features for determining pace of walking with standard deviation in vertical direction (top-left), peak frequency in vertical direction (top-right) and its FFT magnitude (centre-left), and spectral energy (centre-right) and spectral entropy (bottom-left).

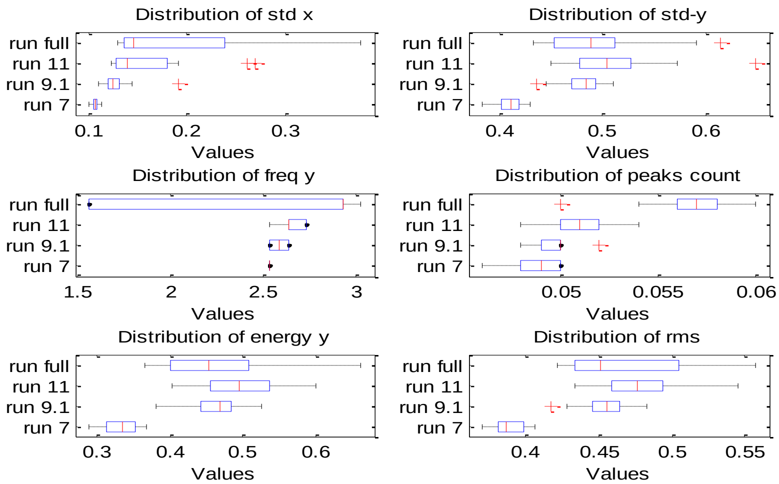

Fig 6. Distribution of features for determining pace of running with standard deviation in vertical and dosoventral directions (top), the frequency in vertical direction (center-left) and counts of peak (center-right), spectral energy in vertical direction (bottom-left) and net acceleration (bottom right).

To evaluate the method of using the MET model combined with classified activities to calculate the energy expenditure, the estimated MET values should be compared with the values measured directly along with the resting metabolic rate measurement. However, due to the lack of respiratory gas exchange system, the evaluation of estimated energy consumption is only based on the evaluation of the classification of motion. The higher the success rate in identifying the correct type and level of activity together with the related time, the more accurate the energy expenditure assessment will be.

5 CONCLUSION

In this paper, practical methods for the automatic recognition of physical activities using data from a single wearable activity sensor were studied. A signals interpretation and classification method was developed based on annotated data libraries collected under controlled laboratory conditions. The performance of this method was evaluated with the collected data and encouraging results were obtained.

The single 3-axis based system located at the waist was able to accurately distinguish between activity and rest. It could also distinguish between different postures of resting and detect a different pace of walking with a high degree of accuracy. The classification of different pace of running was not good and it will be a challenge for future studies to investigate this further.

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Hệ thống giám sát tự động cho người bệnh tiểu đường dựa trên máy đo gia tốc 3 trục

Đặng Ngọc Hạnh

***Tóm tắt*—** Trong nghiên cứu này, chúng tôi mong muốn phát triển một hệ thống thu nhỏ độc lập được thu nhỏ có thể phát hiện một loạt các hoạt động hàng ngày dựa trên máy đo gia tốc 3 trục dùng cho cá nhân. Một thuật toán phân loại mới dựa trên k-means mới được xây dựng để giải thích và chuyển đổi các tín hiệu từ máy gia tốc vào trong một máy nhận dạng của các hoạt động được định nghĩa trước. Hệ thống được phát triển đã mang lại kết quả đáng khích lệ với tỷ lệ thành công 100% về tỉ lệ phân loại ba lớp cơ bản của hoạt động cơ bản dựa trên gồm nghỉ ngơi, đi bộ và chạy bộ, và tỷ lệ thành công 84% đối với các mứctốc độ đi bộ và chạy khác nhau. Sự mở rộng tiềm năng đối với các hệ thống tự giám sát cho những người mắc bệnh đái tháo đường đã được xem xét bằng cách chuyển các hoạt động này thành các thông số tương đương trong quá trình trao đổi chất sẽ giúp dự đoán được lượng năng lượng tiêu hao.

***Từ khóa*—** Giải thuật phân loại, Gia tốc kế 3 trục, trích đặc trưng, nhận dạng hoạt động.