Smart-Walk: An Intelligent Physiological Monitoring System for Smart Families

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***Abstract*—A healthy lifestyle can be maintained by analyzing the physical activities of individuals. Understanding the lifestyle of a family can help in improving quality of life. Wearable devices for activity tracking have become a rapidly growing industrial sector. However, with multiple functionalities embedded in a small device, their accuracy and power consumption can be suboptimal. This paper proposes a piezo-electric based accelerometer sensor design which helps in tracking the physical activities of family and friends. The accuracy of the activity-sensing algorithm is analyzed by various parameters analyzed through the sensor output. The proposed framework was validated using the TI MSP432, Educational BoosterPack and MATLAB® and the learning parameters were modeled using WEKA. The feature based human activity monitoring algorithm gives 97.9% efficiency in the worst case scenario.**

Index Terms—Internet of Things (IoT), Smart Health, Wrist-worn device, pedometer, activity tracking, WEKA

I. INTRODUCTION

The Internet of Things (IoT) has revolutionized human lifestyle. It has been widely employed across many industrial sectors such as smart health care, agriculture, surveillance systems etc. [1] Smart health care is expected to be a significant element in peoples' lives in the future [2]. Continuous health monitoring systems that come in the form of smart watches or other wearable devices are gaining popularity due to their small form factor, accuracy, ease of use, efficiency and previously infeasible functionalities (e.g. continuous tracking of heart rate, breath or physical activity). Figure 1 shows how smart watches can bring the whole world on to the wrist and are at par with smart phones in their applications and efficiency.

In smart healthcare monitoring systems, there is scope for research in the aspects prior to the data acquisition phase and those after the data acquisition. In pre-data acquisition, the focus is on the design and integration of sensors based on the application and cost of the design. Required data may be collected by integrating commercially available sensors or those in smart phones [3]. Following data acquisition, the focus is typically on the design and development of efficient algorithms to make use of the signal values collected from the sensors. The type of data depends on the available sensors and the intended application. For example, if the system is designed to monitor an individual's thyroid function [4], then his/her data needs to be continuously logged into a smart phone application or a database, to help medical practitioners for a complete analysis. But if the doctor is interested in monitoring every patient's thyroid functioning in a hospital, then an altogether different framework to monitor and schedule the data is needed. In this paper, research is concentrated on the post-data acquisition phase. Algorithms are used for human step-detection and their learning parameters are analyzed through different classifiers. The data obtained are stored in a common platform, which permits authorized individuals access to this information.

Fig. 1. Smart watch and its features.

The rest of the paper is organized as follows: The novel contributions are described in Section II. A broader perspective of the smart-walk system in the IoT is presented in III. Existing research work for detection of vital signs is presented in Section IV. An overview of the design of the smart-walk system is presented in Section V. The implementation of the designed blocks along with simulation results are discussed in Section VI. Conclusions are presented in Section VII.

II. NOVEL CONTRIBUTIONS

Currently, many healthcare systems are focused on obtaining an individual's health information. This is either done by using smart sensors or wearables. In this research, a framework to monitor the physical health of family and friends is proposed. The proposed system helps in identifying the features unique to the particular user and accordingly the parameters are estimated. Whenever there is an abnormality in the parameters, the authorized users are notified immediately. With a dynamic calibration module, this wearable, when developed as a product, can help in obtaining higher accuracy as the features are unique to each individual. In order to analyze the physical health of the concerned person, a sensor design based on an accelerometer is proposed where a feature-based human step detection method is proposed. The algorithm is validated using a classifier which analyzes different learning parameters and dynamically calibrates the sensor system.

III. SMART-WALK SYSTEM IN THE IoT: A BROAD PERSPECTIVE

Figure 2 shows the framework of the Smart-Walk system though the IoT. In this framework, the vital signs to be monitored are obtained through the sensor system. This can constitute sensors available in the smart phone or smart watches or any form of wearables. The data obtained through the sensor system are processed through various algorithms, in order to convert the raw signals into some meaningful values.

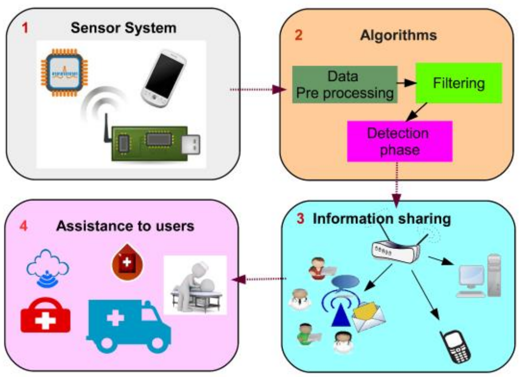

Fig. 2. Framework of the Smart-walk system.

Pedometers consist of 3-axis accelerometers which help in analyzing the amount of walking and gait [5]. The accelerometer provides three variations along its axes namely, roll, pitch, yaw which helps in accumulating walking and jogging motions [6]. Step-detection methods can be broadly classified into correlation-calculation methods, and the peak detection method. Step length modeling using Kalman filter and Gauss-Markov process has been proposed in [7] and [8].

IV. RELATED PRIOR RESEARCH

Activity tracking is generally centered on peak detection [9]. Peak detection algorithms in physiological monitoring have been proposed by many researchers. Peak detection method involves detecting the number of peaks based on the threshold [10,11]. Though this method is easier to implement, it might not be accurate as the threshold value to detect peaks differs from person to person [12]. An ambulatory monitoring system through the IoT has been proposed in [13] while a smart shoe design for acquiring gait information through the IoT has been proposed in [14]. A smart phone based solution has been proposed in [15]. A zero-velocity update method is used to detect a user's steps based on the idea that zero-velocity moment should occur for a single step [16,17]. An ambulatory system for estimation of spatio-temporal parameters using gait analysis has been proposed in [18].

V. SYSTEM LEVEL DESIGN OF SMART-WALK SYSTEM

The system level design can be divided in three sections: sensor design for data acquisition, feature extraction to calculate the learning parameters, and algorithm development to detect human activity (specifically detecting the number of steps and estimating the step length). Figure 3 shows the data path involved in the sensor design for the smart-walk system. The data acquisition is done using the 3-axis accelerometer. The input to the feature extraction module are the values of the 3 axes. By using these values, features such as maxima and minima, kurtosis and skew are extracted, which are used to compute step length, step detection and distance traveled. Periodically the sensor system is recalibrated and the features are again extracted with the values stored in a database. This

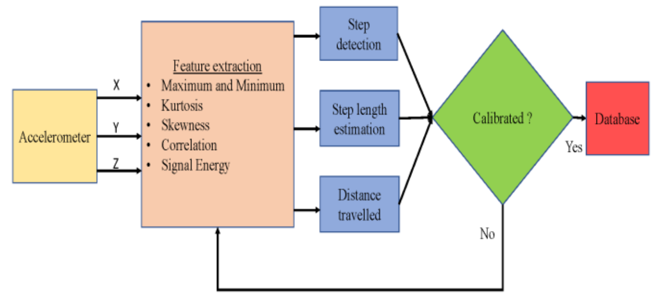

Fig. 3. Proposed method for efficient parameter estimation.

recalibration process takes place very quickly, almost real-time.

A. Feature extraction for data analysis

A 3-axis accelerometer provides data as x axis, y axis and z axis where the x axis indicates twisting or turning, the y axis indicates leaning backward or forward and the z axis indicates movement against gravity. It is important to give meaningful interpretation to these values such that the physical activity of the wearer can be interpreted based on these values. Features such as kurtosis, mean, standard deviation, maxima and minima and skewness, help in analyzing a pattern in human step detection and activity estimation [19].

Kurtosis is very similar to skewness and helps in learning the feature value distribution. Kurtosis helps in analyzing the amount of peakedness and flatness in the signal, which can be very useful for estimating the step length. Zero crossings are generally taken into account when only time series data are considered, where the mean is 0. Zero crossing represents the number of times the signal crosses the median. Signal energy is the area between the signal curve and time axis which can be calculated by adding the squared values. Skewness helps in understanding whether the dataset is symmetric, i.e. if the skewness value is greater, then the dataset is asymmetric and is above the mean value.

B. Human Activity Monitoring Algorithm

The human activity monitoring algorithm can be divided in two main phases: step detection and step length estimation. Human step detection or activity detection cannot be monitored just by the direction values obtained from the accelerometer. The difference between the walking and standing phases are generally considered to count the number of steps taken by the user. In order to remove the noise from the signal, the three axis values are squared and summed together. The sensor data are further converted into scalar values and based on the number of crossing events across the thresholds, the number of steps are counted.

Step length is measured from heel to heel, i.e. it is the approximate distance from the initial point of contact of one heel and the initial point of the next heel. Human step length estimation varies linearly in accordance to the walking frequency and accelerometer variance as follows:

$$\text{StepLength} = \alpha f + \beta v + \gamma \quad (1)$$

where f denotes the walking frequency, v denotes the variance of the accelerometer and α, β and γ are pre-learned parameters which influence step length. Analyzing the right parameters for α, β and γ, influence the accuracy of the algorithm.

VI. IMPLEMENTATION AND VALIDATION OF SMART-WALK SYSTEM

To evaluate the efficiency of the proposed human activity detection method, a public database consisting of 10,291 instances of smartphone based human activity data were considered from Kaggle. These data were grouped into six categories of activity: sitting, standing, walking, climbing downstairs, climbing upstairs, and laying.

Choosing appropriate features from the data is a crucial step. For example, calculating minima and maxima of a given sensor's values can help in characterizing the range of movements whereas calculating zero crossings can only be used for differentiating between running and walking. So in order to analyze the features suitable for differentiating between the activities, the kurtosis value was taken into consideration. The smart phone based data were divided into training and test datasets which were converted into Attribute-Relation File Format (ARFF) files to be given as input to WEKA.

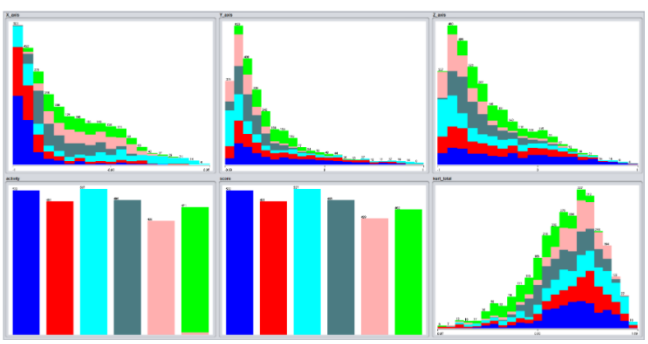

Fig. 4. Kurtosis Analysis in WEKA.

Figure 4 shows the data analysis in WEKA. The top 3 subcolumns represent the x, y, and z axes, respectively. The 3 subcolumns in the second row indicate the data grouped based on activity, score and kurtosis values. Kurtosis values are higher for walking upstairs and downstairs whereas they remain low for sitting, standing and laying. After analyzing this feature, different classifiers were tested in order to build a better model. The classifiers along with their correlation coefficient and error values are tabulated in Table I. An M5 rules based classifier has a better correlation coefficient and lowest values of relative absolute error and root relative squared error. M5 rules use a separate and conquer approach. The next best efficient classifier for kurtosis is the multilayer perceptron which maps input data to corresponding output data. It is to be noted that the traditional or most commonly used classifiers such as SMO, linear regression and Gaussian process yielded a very high error rate, proving them to be inefficient to be used in this analysis.

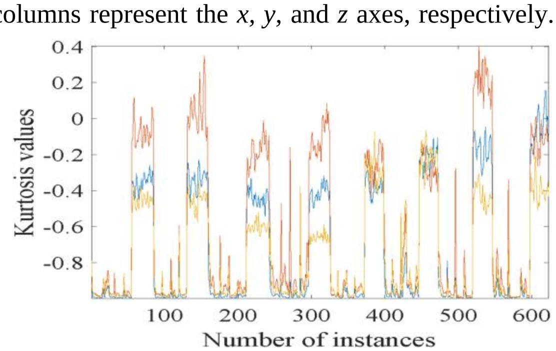

Fig. 5. Kurtosis values in different postures such as sitting, standing and walking obtained from 3 different subjects.

Table 1 CLASSIFIER EVALUATION FOR KURTOSIS VALUES USING WEKA.

Classifier	Correlation Coefficient	Mean absolute error	Root mean squared error	Relative absolute error	Root relative squared error
SMO Regression	0.7795	0.1029	0.1956	44.8049 %	67.68 %
Gaussian Process	0.7979	0.1146	0.1742	49.90 %	60.28 %
M5 Rules	0.9741	0.0409	0.0657	17.82 %	22.72 %
Decision Table	0.9263	0.0619	0.11	26.94 %	38.07 %
Linear Regression	0.7979	0.1142	0.1741	49.71 %	60.27 %
Multilayer Perceptron	0.9645	0.0597	0.0868	26.00 %	30.03 %
Additive Regression	0.9273	0.0856	0.111	37.26 %	38.41 %

Table 2 CLASSIFIER EVALUATION FOR MINIMUM AND MAXIMUM

Classifiers	Mean absolute error	RMS error
Input Mapped Classifier	0.0014	0.0018
SMO	0.222	0.3089
Decision Stump	0.2234	0.3342
Simple Logistic	0.0437	0.0587
Decision Table	0.0015	0.0002
Bayes Net	0.0009	0.3309
Multilayer Perceptron	0.0012	0.0016

Similarly, the maxima and minima values of the accelerometer were analyzed using different classifiers as shown in Table II. Based on analyzing the maxima and minima and kurtosis features, it can be seen that both decision table and multi-layer perceptron perform better on these features. To verify the framework, additional test data were acquired from a hand-held accelerometer mounted on a TIMSP432 integrated with the Educational Boosterpack MKII.

By analyzing the kurtosis values in Figure 5, it can be observed that the peaks can be significantly identified for walking activity whereas the output value is closer for sitting and standing. Hence to significantly analyze sitting and standing posture, the maxima and minima of the z-axis values need to be taken into account. It can also be observed that these features have significant changes amongst different subjects. Though the kurtosis values are taken using the same accelerometer, they significantly vary from person to person.

Table 3 PERFORMANCE COMPARISON WITH EXISTING RESULTS

Reference	Method	Features considered	Activities	Accuracy (%)
Shin et al [21]	Awareness algorithm of movement status	Step length and total walking distance	Walk and run	96
Chien et al [20]	Dynamic algorithm	Number of steps taken	Walking, jumping and jogging	95
This Work	Adaptive algorithm base on feature extraction	Step detection and step length estimation	Walking, sitting, standing	97.9

The results of this paper are compared with the algorithm proposed in [20,21] and are tabulated in Table III. By comparing the worst case accuracy of the system, a dynamically calibrated algorithm provides 97.9 % efficiency in computing the step length.

VII. CONCLUSIONS

In this paper, a framework for human activity monitoring system to keep track of physiological health friends and family is proposed. The human activity monitoring algorithm proposed for this framework is feature based which can dynamically calibrate based on the learning parameters. This method helps in improving the overall calibration of the activity monitoring system and helps in grouping the values easily. In case of abnormality in these values, the system's calibration can be checked. The decision table classifier using the data acquired from the sensing module yields 97.9% efficiency in worst case.

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