2018 15th IEEE Annual Consumer Communications & Networking Conference (CCNC)

What Can Data Analysis Recommend on Design of Wearable Sensors?

Igor Khokhlov, Leon Reznik, Suresh Babu Jothilingam, Rohit Bhaskar
B. Thomas Golisano College of Computing and Information Sciences
Rochester Institute of Technology
Rochester, USA
ixk8996@rit.edu, lr@cs.rit.edu, sj2322@rit.edu, bxb7772@g.rit.edu

***Abstract*—The paper aims at developing recommendations on the design and use of human activity recognition systems based on wearable sensors and their applications. Both the system structure and the application design challenges are addressed. Various design problems are investigated such as the selection of a number and types of sensors, amount of samples used for recognition, choice of machine learning techniques and the features set for a classifier design as well as the type of a training model employed. The design is implemented on the Android smartphone sensors platform and tested by conducting an empirical study in a real-life environment. The study results are provided and discussed. The recommendations on the sensor systems design are derived.**

***Keywords*-vulnerability; colluded applications; Android devices;**

I. Introduction

In the recent past, the scope of wearable sensor applications have expanded from the industrial sector, where they have a massive impact on healthcare systems, into the commercial sector [1]. The versatility of these sensors extends to their usage. For example, the sensors in smartphones, smartwatches and fitness trackers envelop a wide dynamic of useful applications from detection of falls in human beings [2], to remotely monitoring Parkinson's Disease in patients [3], to even mundane tasks such as monitoring high intensity sports activities or estimating workers' loads at warehouses [4] [5]. However, with the mass influx of these wearable sensors, manufactured by different vendors, being used across various software platforms for monitoring human activity, it becomes critical to evaluate the accuracy and quality of data coming out of them. Some parameters that may affect the data quality are mentioned below.

- Sensor type used to produce data, e.g. accelerometer, gyroscope, magnetic field sensor, orientation sensor, location sensor.
- Mounting positions of the sensor on the body, e.g. head, upper arm, sternum, wrist, waist, thigh, ankle.
- Activity type to be recognized, e.g. sitting, standing, sleeping, walking, running, walking up, walking down, cycling, nordic walking.
- Device type wherein a sensor is embedded, e.g. smartphone, smartwatch, fitness tracker.
- Machine learning classifier employed for a decision making, e.g. J48, Naive Bayes, Random forest, K-NN.

This paper aims at describing an empirical study employed to evaluate the quality of data obtained from wearable sensors, based on a subset of the aforementioned parameters. It further investigates the design issues that come with it.

II. Empirical Study Description

The empirical study for this research was conducted at the Rochester Institute of Technology. This section explains the modus operandi of our study.

A. Data Collection

Data was gathered from three types of sensors viz. accelerometer, gyroscope and pedometer. Six android smartphones exhibiting different versions of the Android operating system were used for the study, namely: HTC One, Google Nexus 4, Google Nexus 5, Samsung Galaxy S6, Samsung Galaxy Note, Google Nexus 6P. Three male subjects aged 24-28 participated in the data collection activities. The data was collected under a supervised environment, where the data collection process did not allow a subject's personal identification. The subjects were asked to perform a set of activities by the supervisor who also monitored and recorded the duration for which each activity was performed. The devices were either mounted tightly or loosely to the subject's body. The activities being monitored were sitting, standing and walking. The smartphones were controlled remotely by the supervisor on a computer running the Windows operating system. The raw values of the accelerometer and gyroscope measurements were extracted from each smartphone, with a measurement frequency of 100Hz, for a sampling window of 150 counts.

B. Data Processing

The initial data processing effort consisted of eliminating the null values - the missing values were replaced with the mean of the feature.

For further processing, the three dimensional accelerometer values were transformed into a scalar value that using the Euclidean distance.

978-1-5386-4790-5/18/$31.00 ©2018 IEEE

C. Classifier choice and design

The feature extraction process was critical for the classifier design paradigm. The four main features employed for the classifiers are mentioned below.

- Fundamental frequency - The average value of the three dominant frequencies of the magnitude signal obtained by applying the fast fourier transform to the sample window.
- Average Magnitude of Acceleration - Arithmetic average value of magnitude over sample window.
- Minimal Magnitude of Acceleration - Minimum value of magnitude over sample window.
- Maximal Magnitude of Acceleration - Maximum value of magnitude over sample window.

In addition to these features, in the subsequent approaches, this base feature set was complemented by the average value of acceleration magnitude and the rate of rotation, about each individual axis, expanding the feature set by either three or six additional features. The data collected from the participants was split into a training set that compromised of 70 percent of the data and a testing set that compromised of 30 percent of the data. The classifiers investigated in this study were J48, Naive Bayes, Random Forest and K-NN.

TABLE I
RECOGNITION PERFORMANCE IN % (CORRECT/TOTAL)

Algorithm name	**4 features from accelerometer**	**7 features from accelerometer**	**10 features from accelerometer and gyroscope**
J48	94.8% (2891/3050)	96.5% (2908/3050)	96.6% (2947/3050)
Naive Bayes	76.2% (2323/3050)	96.4% (2942/3050)	96.5% (2944/3050)
Random Forest	95.0% (2899/3050)	97.5% (2974/3050)	97.6% (2978/3050)
K-NN	93.6% (2856/3050)	97.6% (2978/3050)	97.9% (2987/3050)

TABLE II
FLEXIBLE MOUNTING V STRONG MOUNTING USING 4 FEATURES OF ACCELEROMETER

Algorithm name	**Flexible Mounting**	**Strong Mounting**
J48	66.6%	99.4%
Naive Bayes	66.7%	98.4%
Random Forest	66.7%	99.6%
K-NN (k=1)	66.9%	99.8%

III. RESULTS

Given a generic implementation, it was observed that data from a single sensor, like the accelerometer in this case, provides ample classification accuracy viz. more than 70 % but upwards of 90% for most cases (see TABLE II). Increasing the number of features and incorporating data from another sensor, in this case, the gyroscope, didn't have a significant effect viz. 0.1-0.3% only on the classification accuracy. It was also observed that the K-NN classifier exhibited the highest classification accuracy viz. 97.8%.

The effect of mounting positions of the sensor can be profound in the case of activity recognition as exhibited in TABLE III.

It was observed that, by employing strong mounting techniques not allowing the sensor to move more than a few millimeters while being fastened to the human body, the classification accuracy was quite impeccable. However, allowing the sensor leeway to move 5mm to 5cm while fastened to the body in what we called a flexible mount, there was a drastic decline in the accuracy (up to 33%).

IV. CONCLUSIONS

Overall, our experiments provide us with adequate insights, when it comes to the question of designing better activity recognition systems for wearable systems. We can conclude that data from even a single sensor like the accelerometer might be sufficient to obtain desirable classification accuracy provided that the classifier is supplemented with enriched feature set. We can also conclude that complementing our feature set with data from other relevant sensors does not have a profound effect on the classification accuracy but does improve it nevertheless.In terms of classification techniques, the K-NN classifier gives the best accuracy. Finally, we can conclude that the type of mounting plays a critical role in classification accuracy with better results being achieved when the sensor is tightly mounted to the human body and poor performance when it is mounted rather loosely.

ACKNOWLEDGMENT

This material is partially based upon work supported by the National Science Foundation under Award # ACl-1547301 and National Security Agency under Award # H98230-I7-l-0200.

REFERENCES

[1] S. C. Mukhopadhyay, "Wearable sensors for human activity monitoring: A review," *IEEE Sensors Journal*, vol. 15, no. 3, pp. 1321–1330, March 2015.

[2] O. Aziz and S. N. Robinovitch, "An analysis of the accuracy of wearable sensors for classifying the causes of falls in humans," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 19, no. 6, pp. 670–676, Dec 2011.

[3] B. R. Chen, S. Patel, T. Buckley, R. Rednic, D. J. McClure, L. Shih, D. Tarsy, M. Welsh, and P. Bonato, "A web-based system for home monitoring of patients with parkinson's disease using wearable sensors," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 3, pp. 831–836, March 2011.

[4] M. Ermes, J. Prkk, J. Mntyjrvi, and I. Korhonen, "Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions," *IEEE Transactions on Information Technology in Biomedicine*, vol. 12, no. 1, pp. 20–26, Jan 2008.

[5] Q. Kong and T. Maekawa, "Sharing training data among different activity classes," in *Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication*, ser. UbiComp '13 Adjunct. New York, NY, USA: ACM, 2013, pp. 701–712. [Online]. Available: http://doi.acm.org/10.1145/2494091.2495991