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AUTOMATIC HUMAN DAILY ACTIVITY SEGMENTATION APPLYING SMART SENSING TECHNOLOGY

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Abstract- ***Human daily activity segmentation utilizing smartphone sensing technology is quite new challenge. In this paper, the segmentation method combining statistical model and time series analysis is designed and implemented. According to designed partition procedure, real measured accelerometer datasets of human daily activities are tested. The segmentation performance of sliding window autocorrelation and minimized contrast algorithms is analysed and compared. Experiments demonstrate the effectiveness of this proposed automatic human activity separation method focusing on the application of mobile sensor. As the properties of signal, mean, variance, frequency and amplitude are all useful features on the case of motion sensor-based human daily activity segmentation. In the end, the suggested work to improve the developed partition model is presented.***

Index terms*:* Smart sensing, activity segmentation, sensor signal processing, autocorrelation, statistical model.

I. INTRODUCTION

Based on standard integrated sensor, smart sensor increases intelligent capabilities by assistant hardware, software and operating system, i.e. the on-board microprocessor [1]. As smart phones are becoming very popular used and indispensable device in human beings' everyday lives and most of them have integrated inertial and optical sensors as Figure 1 including accelerometer, gyroscope, camera, and magnetometer with motion information provision [2], mobile phone with smart sensing technology is enabling new sensing applications across a wide variety of fields, for instance, mobile health, social networks, education, gaming, entertainment, and transportation.

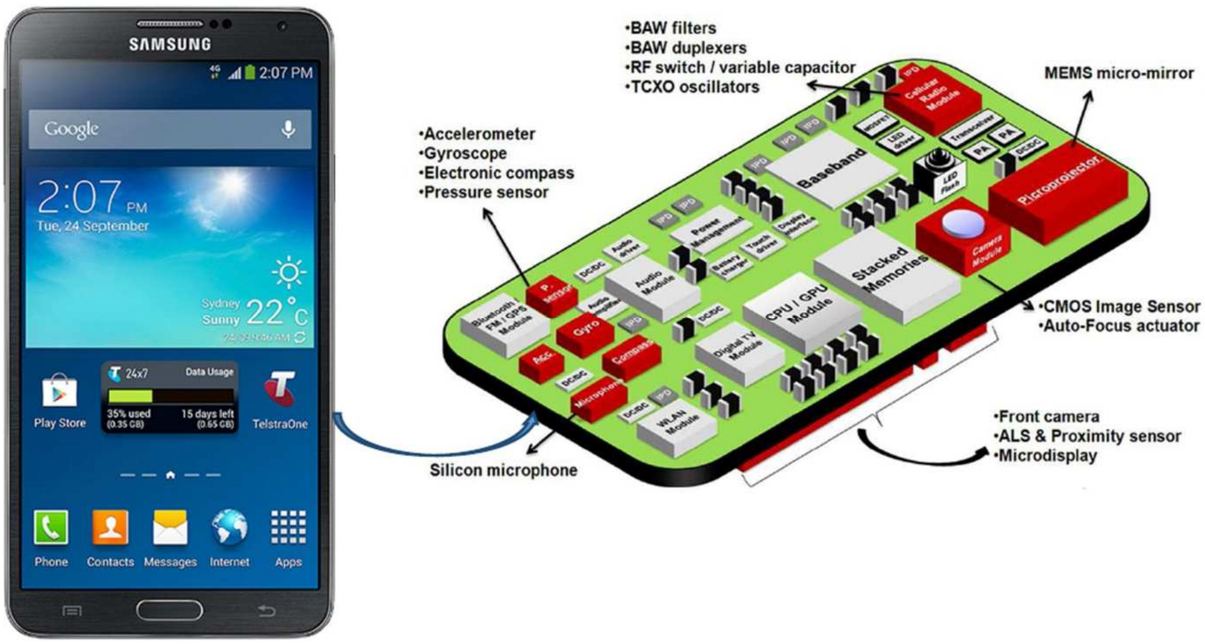


Figure 1. Smartphone with embedded sensors

Providing wearable sensors or mobile phone sensors, there have been relatively feasible scientific solutions and mature research contributions for human daily activity recognition. The recognition accuracy performance utilizing classification algorithms which map the data item into one of several predefined classes can surpass 92% [3-4]. Nevertheless, automatic human daily movement segmentation problem which is to separate human activity data into independent activity sections, still needs to deep analyse and solve. The achievement of daily activity partition could help to collect information or make inferences about people's behaviour and their life patterns for personal and community healthcare, smart transportation systems, and automatic information service.

Motion segmentation characterized by homogeneous behaviour on animal has been explored. Bayesian partitioning of sequence and contrast algorithm based on statistics model are implemented and tested for animal trajectory segmentation practice [5]. Additionally, human action segmentation in video streams has been analyzed via optimized Hough transform with skeleton based features [6], semi-Markov model [7], and unsupervised learning based on the isometric feature mapping (Isomap) algorithm which is for nonlinear dimensionality reduction (NLDR) [8]. However, human activity partition in smart sensor data has not been discussed anywhere.

Motion sensor data might be understood as nonstationary time series which is a sequence of data points with the measurement at successive points in time spaced at uniform time intervals [9-10], and whose statistical characteristics vary over time [11]. Therefore, automatic nonstationary time series segmentation methodologies could be utilized in human activity segmentation analysis. Piecewise Linear Approximation (PLA) that makes piecewise linear function closely matching each split segment and Piecewise Polynomial Approximation (PPA) which could approximate the time series with polynomial functions have been widely used as time series data segmentation methods for plasma etch endpoint detection, space shuttle telemetry, Electrocardiogram (ECG), and stock [12-15]. However, in the research problem of human daily activity segmentation, the different movement data is expected to isolate. Therefore, the research object is not to obtain detailed segmentation, but to divide a given number of observations into some subseries with statistical properties which are similar within each subseries and different between two subseries as the segmented effect in Figure 2.

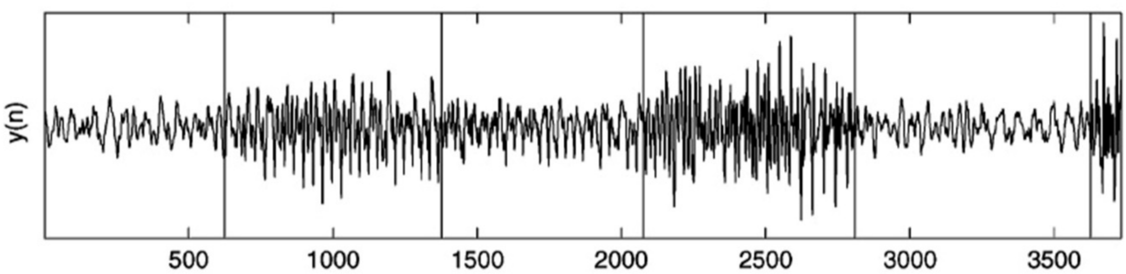


Figure 2. Segmented time series signal

In this paper, human daily activity segmentation solution using the data of accelerometer embedded in the smartphone is discussed. In contrast to the above mentioned methodologies, we select statistical and time series analysis in order to cover more possible signal segmentation characteristics. The statistical analysis exploiting the Gaussian model is applied and the algorithm of minimized contrast which chooses mean and variance as main observed partition properties is developed. At the same time, the algorithm of sliding window autocorrelation with change points locating based on the variation of frequency and amplitude in signal is implemented in this designed segmentation model.

This paper is organized as follows. Section II describes the sensor based human activity recognition research work and the existing segmentation methods on nonstationary signal. Section III explains human activity analysis system with the role and goal of automatic activity segmentation. The proposed daily activity segmentation model with minimized contrast and sliding window autocorrelation algorithms is presented in Section IV. Section V analyzes the experimental results with activity accelerometer datasets. Finally, Section VI provides concluding remarks and suggestions on future works.

II. LITERATURE REVIEW

a. Human Activity Recognition Applying Sensors

The research about human activity recognition using wearable sensors for home and health applications has been discussed elsewhere. Evani et al. [16] implemented the patient activity monitoring system applying flex sensors worn on the knee. The experimental analysis demonstrated the recognition of human activities with an accuracy of 81% by classification. The hierarchical classification method for user activity recognition based on accelerometer for health monitoring is designed in [17]. The project shows the effectiveness of the proposed algorithm with about 85% recognition accuracy rate.

Supported by the Wireless Sensor Network, recognizing activities of daily living is implemented in [18], [19]. Electrical appliance monitoring sensor units are connected to appliances like Microwave Oven, Toaster, and Television etc. The usage of Bed, Couch, Toilet and Dining chair is monitored by attached force sensor units. Fabricated contact sensors are fixed to the Fridge and Grooming cabinet in order to recognize the usage of these appliances. Furthermore, activity labelling and chore identification are achieved by Sensor-ID status, time, day, also with the help of probabilistic learning method.

Regarding current activity recognition work using sensors, the start and end points of the activity could not be defined automatically. They are either provided by additional sensors or manually annotated during experiments [20]. In addition, the fixed size of sliding window in most classification algorithms reduces the ability to detect short-duration movements and occupies lots of resources with the consumption of battery power. Compared with their work, our designed and implemented activity segmentation model solves the automatic activity partition and the detection of change points with less consumption of classification computation and battery power.

b. Nonstationary Time Series Segmentation

There is some nonstationary signal segmentation research in the literature. Some artificial intelligence methodologies including neural networks, hidden Markov models, and supervised learning have been proposed to accomplish time series segmentation, whereas they do not focus on the variation of signal properties and the implicit methods influence the speed of learning [9], [21].

Anisheh et al. [22] developed the segmentation method based on wavelet transform and fractal dimension. Discrete stationary wavelet transform is used in pre-processing step and optimal parameters are chosen. Performance of the proposed method is analysed using both synthetic signal and real photon emission.

Additionally, the distribution of ordinal patterns is utilized in segmentation of time series in that the distribution of ordinal patterns has been found to reflect important qualitative features of the underlying system dynamics [23]. The algorithm employing kernel-based statistic, the Maximum Mean Discrepancy of ordinal pattern distributions, is discussed for the purpose of detecting and locating change points in the time series.

Financial data segmentation for identifying and storing important points in an Optimal Binary Search Tree is proposed in [24]. The degree of importance for turning points is calculated on the basis of its contribution to the preservation of the trends and shape of signal. The major advantage is that it is able to preserve more monotonous trends due to the identification of trend changes in data.

Considering the observation of more important signal properties and the amount of calculation in segmentation algorithm for online segmentation by Android smartphone, we design and accomplish statistical model based sliding window autocorrelation segmentation applying statistical analysis and time series processing.

III. HUMAN ACTIVITY ANALYSIS SYSTEM

In human action understanding, activity recognition which is the fundamental task recognizes a sequence of continuous actions such as running, walking and sitting. Figure 3 shows the recognition example of various activities for datasets of accelerometer.

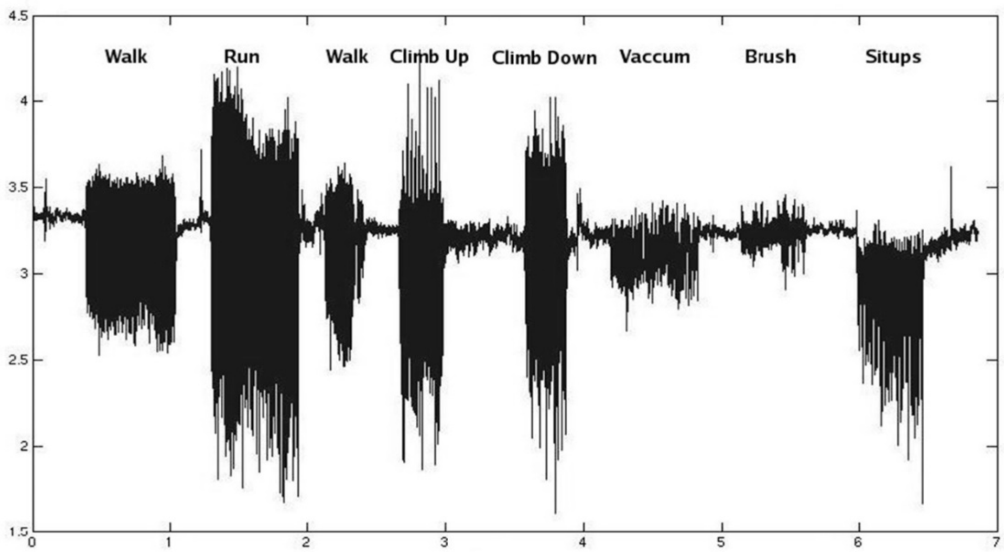


Figure 3. Human activity recognition example for datasets of accelerometer [25]

Typical activity recognition task using accelerometer could be fulfilled by the procedures described in Figure 4.

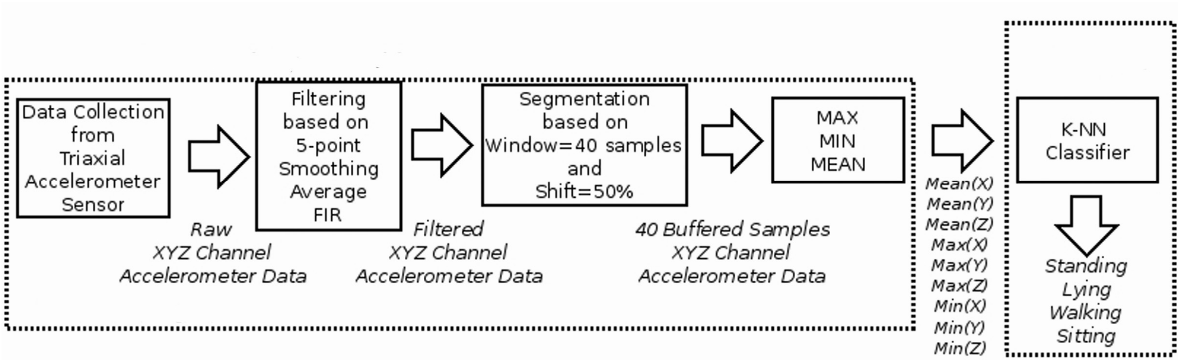


Figure 4. Activity recognition processing chain [26]

To correctly understand real measured human action data, it is necessary to intelligently segment a continuous series of movements into meaningful discrete action subsets. Therefore, automatic activity segmentation needs to determine the segment boundaries and make successful partition among different action-types. Figure 5 below illustrates the sequence of data processing and the data relationship for collection, pre-processing, segmentation, feature extraction and classification in activity analysis.

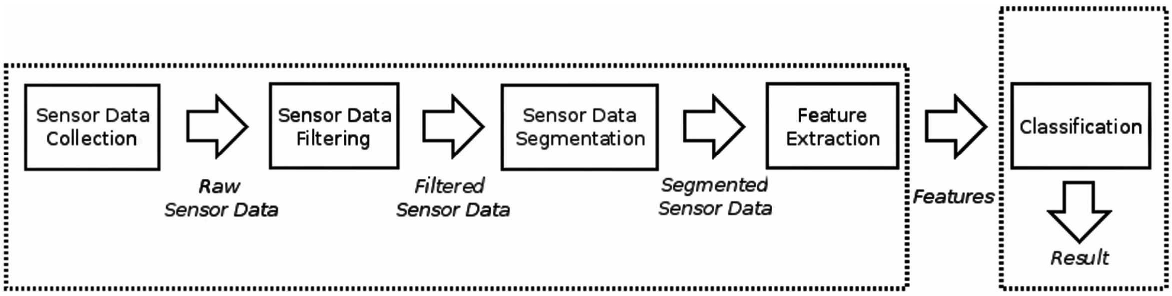


Figure 5. Human daily activity analysis system

IV. THE PROPOSED HUMAN DAILY ACTIVITY SEGMENTATION MODEL

In order to better detect change points in signal, more useful and effective signal properties are expected to cover in the segmentation algorithm. Statistics analysis based on Gaussian model is feasible method to observe the mean and variance. In addition, autocorrelation has been utilized in frequency estimation [27]. Therefore, statistical model and time series processing methods are chosen as main strategies in this research. Minimized contrast based sliding window autocorrelation algorithm is designed in the presented partition model. For the purpose of understanding daily activity segmentation in mathematical way, the definition of time series segmentation is interpreted by the contents below before the representation of designed segmentation model.

a. Nonstationary Time Series Segmentation Definition and Description

The observed data set is given in time series as variables $\{x_i\}$, where the index $i = 1, 2, ..., T,$ and corresponds to ordered periods of time with identical time intervals. The statistical properties of this nonstationary time series $\{x_i\}$ are not constant over time. The segmentation is to separate original data set into subsets with *m* change-points at the moments $k_1, k_2, \dots, k_M$, where $1 \leq k_1 \leq k_2 \leq \cdots \leq k_M \leq T$. The change points happen when statistical characteristics and signal properties vary abruptly.

b. Minimized Contrast Segmentation Algorithm

Basic segmentation algorithm which minimizes the difference between the observed series and the assumed Gaussian model with the influence component determined by the Bayesian information criterion (BIC) is achieved by

$$H(i) = J(i, x) + \beta M(i). \tag{1}$$

The observed data is supposed to produce by the Gaussian model as

$$X_i = \mu_i + \sigma_i \varepsilon_i, \tag{2}$$

where both the mean μ_i and the standard deviation σ_i change between segments, and ε_i is a sequence of zero mean random variables with unit variance. Then, the discrepancy function between the observed series and the model given above, which is based on a Gaussian log-likelihood, is defined by the following formulas,

$$J(i, x) = \frac{1}{T} \sum_{j=1}^{M} \mathrm{G}\left(X_{k_{j-1}+1}, \cdots, X_{k_j}\right), \tag{3}$$

$$\mathrm{G}\left(X_{k_{j-1}+1},\cdots,X_{k_j}\right)=\left(k_j-k_{j-1}\right)\log\left(\frac{1}{k_j-k_{j-1}}\sum_{i=k_{j-1}+1}^{k_j}\left(X_i-\overline{X}_{k_{j-1}+1:k_j}\right)^2\right), \quad (4)$$

where k_j is the change point for any $j(1 \leq j \leq M)$, and $\overline{X}_{k_{j-1}+1:k_j}$ is the empirical mean of $(X_{k_{j-1}+1},\cdots,X_{k_j})$ [28]. In (1), $\beta = 2\sigma^2/n$, σ is the empirical standard deviation of original series, and *M(i)* is the influence component which depends on the dimension $k(i)$ of index i and increases with $k(i)$.

c. Sliding Window Autocorrelation Segmentation Algorithm

As it is not sufficient to only focus on the obvious alterations of the mean and variance, sliding window based autocorrelation algorithm could help to detect the variations of other signal properties, including frequency and amplitude. The approach of two-models based sliding window helps to measure the differences between reference model which is hypothetical model before the change, and test model that is the model after the change [29]. The scheme of fixed reference window and sliding test window is designed. The window length should be long enough to reflect the slowest frequency and shorter than the smallest expected segment. Once the measured autocorrelation difference of signal between reference window and test window exceeds the specified threshold, the new segment is generated and next reference window immediately follows current segmentation boundary.

The signal autocorrelation within reference window and test window could be calculated with the formula below [30],

$$p(h)=\sum_{i=1}^{T-h}x_i x_{i+h}. \quad (5)$$

The amplitude difference (ADIFF) is gotten by the following calculation,

$$ADIFF=(\sqrt{p(0)_R}-\sqrt{p(0)_T})/\sqrt{p(0)_T} \quad (6)$$

where $p(0)_R$ is $p(0)$ for signal in reference window, and $p(0)_T$ is $p(0)$ for signal in test window. Signal autocorrelation in reference window and test window could be normalized as Figure 6.

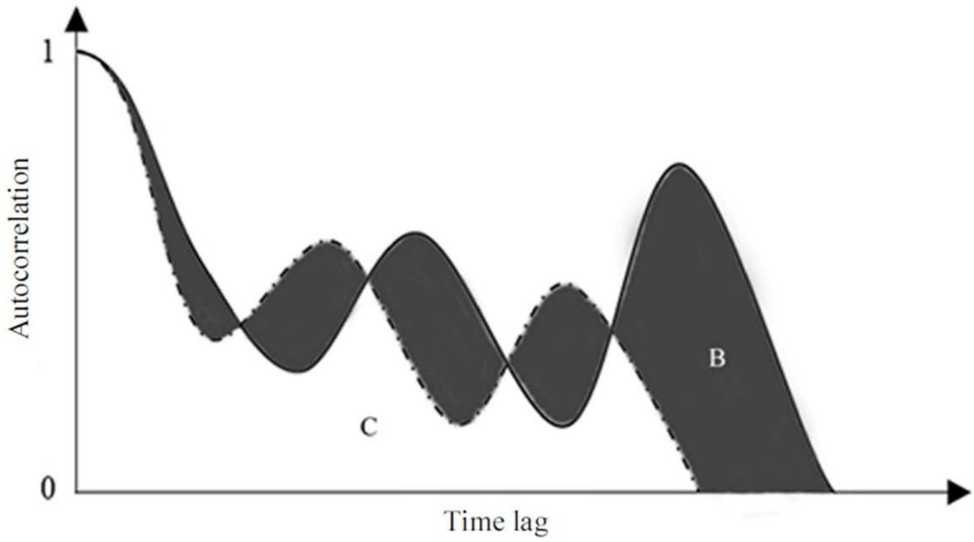


Figure 6. Normalized signal autocorrelation in reference window and test window

The frequency difference (FDIFF) is acquired via the following formula,

$$FDIFF = B/C. \tag{7}$$

Here, B and C are the difference and the common part of two normalized autocorrelation curves respectively before the first zero-crossing in the first quadrant. The autocorrelation difference (DIFF) is defined as follows,

$$DIFF = \frac{ADIFF}{ATHR} + \frac{FDIFF}{FTHR} \tag{8}$$

where $ATHR$ and $FTHR$ are thresholds for amplitude and frequency respectively.

d. Change Points Locating

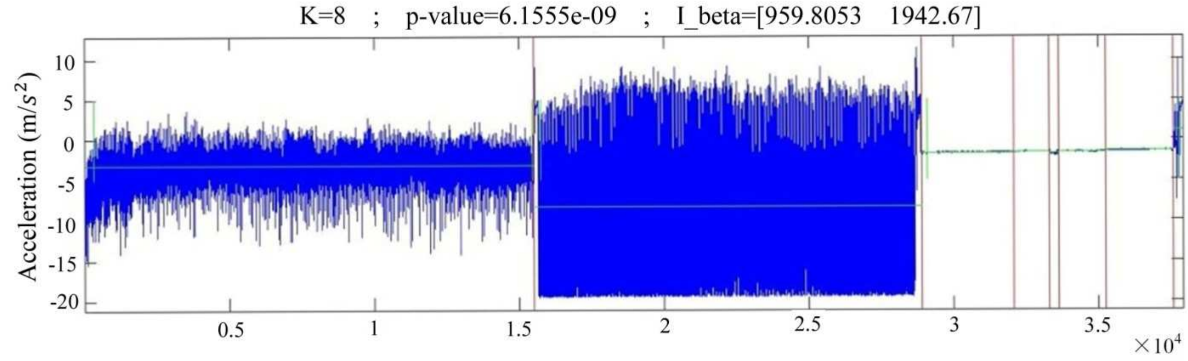
Normally, the boundary point of the test window is not an ideal estimate of the change point when segmentation happens. Nevertheless, the boundary point can be used to initialize the procedure of localizing change points. To search a more accurate change point within the test window from $i = p$ *to* $i = q$, it is divided into two portions by the split point r, and $r = p+1, \ldots, q-1$. The boundary position is estimated by the maximum DIFF between the two portions described above. The autocorrelation length is at least one-fourth of the longest cycle length, otherwise the changes of slow wave are underestimated.

V. EXPERIMENTAL RESULTS AND DISCUSSION

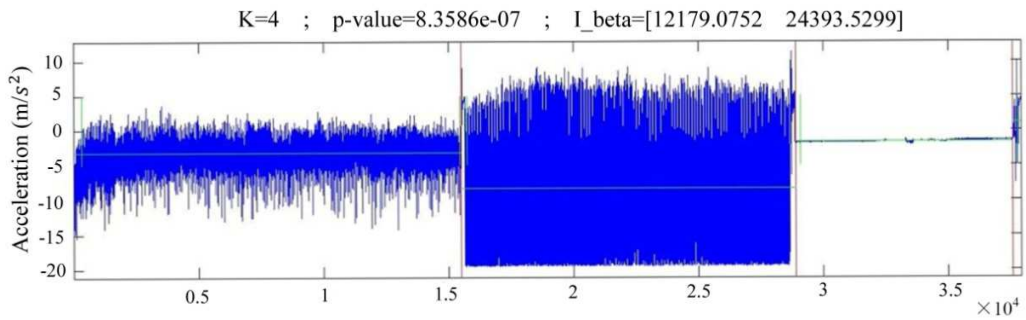
The inertial accelerometer embedded in mobile phone is measured to collect human daily activity datasets involving walking, running, sitting, and standing. The accelerometer data is gathered by our developed sensor data collection software in Android smartphone. Smartphone Samsung Galaxy Note 3 is put on the pocket of trousers by tester and the sample frequency of the accelerometer embedded in this Android smartphone is 100 Hz. The accelerometer signal filtering is implemented based on 5-point smoothing average finite impulse response (FIR) before segmenting data. Minimized contrast based sliding window autocorrelation segmentation model is developed with the assistance of change points locating. The overall procedure of the implemented segmentation can be summarized as follows:

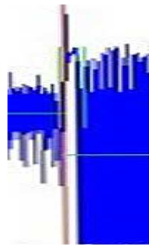
1. Generate minimized contrast function $H(i)$.
2. Calculate optimal segmentation number M.
3. Make segments applying minimized contrast segmentation algorithm.
4. Execute sliding window autocorrelation algorithm with change points locating.
5. Determine the segmentation with reasonable recommendation priority.

The test result of activity datasets including walking, running, and sitting is revealed in Figure 7(a)–(c) below.



(a)





(b) (c)

Figure 7. (a) The first suggested segmentation of activity datasets involving walking, running, and sitting by minimized contrast algorithm. (b) The segmentation by designed activity partition model. (c) Switch phase between walking and running.

The measured signal is the accelerometer data in the direction of the gravitational force, following movement sequence of walking, running, and sitting. The horizontal axis is data sample point number and the sample frequency is set as 100 Hz. The long red vertical lines which run through the whole vertical display range, separate data series applying segmentation algorithm of minimized contrast with influence component. In Figure 7(a)–(b), *K* is the calculated segmentation number, *p-value* is the confidence level with confidence interval consisted of the contrast *J(K-1)* and the polynomial of *K*, and *I_beta* is calculated interval for the influence parameter β in (1). The minimized contrast segmentation results are ranked in order of *p-value*.

Figure 7(a) shows the first suggested segmentation choice. Some separations simultaneously happen in sitting activity for both cases of the first priority option and the second presented outcome with 5 groups. The short green vertical lines from -5 to 5 divide the measured signal employing the sliding window autocorrelation algorithm with the change points locating. Combining the segmentation information described above, the most reasonable partition is the third proposed option in minimized contrast segmentation in Figure 7(b). The switch phase between walking and running recognized by autocorrelation segmentation algorithm in Figure 7(c), is merged into running activity data via minimized contrast algorithm. Walking, running, and sitting are separated successfully. Additionally, the drift at the beginning stage of measured movement signal and the noise at the end of sensor data are isolated correctly.

In order to verify the segmentation effectiveness of more activities, the activity datasets of walking, sitting, running, and standing are tested using our developed segmentation model.

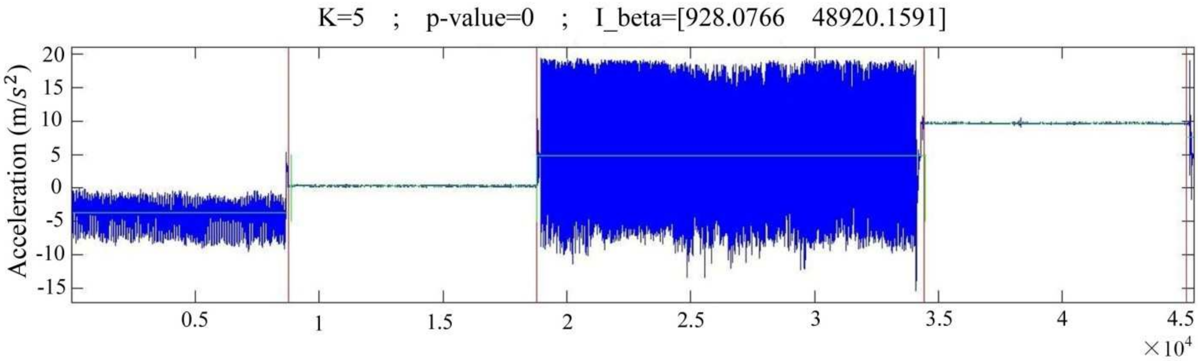


Figure 8. Segmentation of activity datasets involving walking, sitting, running, and standing via designed activity separation model.

Although both the sitting and standing are static activities, the direction of mobile phone put on the pocket of trousers, is different for specific activity. Therefore, the measurements of accelerometer in the direction of the gravitational force fluctuate on distinct level for different activities. The accelerometer data of sitting keeps around zero, while the measured acceleration of standing activity maintains on gravitational acceleration. The characteristic described above could be beneficial to human daily activity segmentation. With the correctness of sliding window autocorrelation segmentation, four daily activities are separated successfully. In addition, the noise at the end of sensor data is isolated in Figure 8.

These experiments reflect that sliding window autocorrelation could get relatively stable and reasonable segmentation results, however the segmentation information of minimized contrast algorithm is required to correct the separation solution especially on the cases of drift and switch phase. Conversely, sliding window autocorrelation effectively helps to modulate suggested priority on the segmentation output of minimized contrast algorithm.

VI. CONCLUSIONS

In this research, the automatic segmentation model with minimized contrast based sliding window autocorrelation algorithm, is designed and implemented in order to separate human movement data into different daily activities subsets. Human daily movement datasets are acquired by the measurement of accelerometer embedded in smartphone. The segmentation experiments provide interesting information about the effect and performance of minimized contrast and sliding window autocorrelation algorithms. The analysis of experiments presents that the properties of human daily movement signal including mean, variance, frequency, and amplitude, are all important signal features used for segmentation. The designed segmentation model successfully divides human movement data into distinct activity subsets via test and analysis. The effectiveness of the proposed partition model proves the contribution to human activity segmentation applying mobile sensor by integrating statistical model and time series analysis. Additionally, some information of segmentation supplies more explanations on real measured sensor signal, such as: drift, switch, and noise. Pushing these achieved techniques into the smartphone, we turn it into a cognitive phone. In the future, based on the given qualitative analysis on the choice of segmentation result, more formulas and equations will be designed and used for the purpose of making quantitative solution. Additionally, this human daily activity segmentation model will be ported to Android smartphone for online processing.

VII. ACKNOWLEDGEMENT

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