# Human Activity Recognition via An Accelerometer-Enabled-Smartphone Using Kernel Discriminant Analysis

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***Abstract*—Nowadays many people use smartphones with built-in accelerometers which makes these smartphones capable of recognizing daily activities. However, mobile phones are carried along freely instead of a firm attachment to a body part. Since the output of any body-worn triaxial accelerometer varies for the same physical activity at different positions on a subject's body, the acceleration data thus could vary significantly for the same activity which could result in high within-class variance. Therefore, realization of activity-aware smartphones requires a recognition method that could function independent of phone's position along subjects' bodies. In this study, we present a method to address this problem. The proposed method is validated using five daily physical activities. Activity data is collected from five body positions using a smartphone with a built-in triaxial accelerometer. Features including autoregressive coefficients and signal magnitude area are calculated. Kernel Discriminant Analysis is then employed to extract the significant non-linear discriminating features which maximize the between-class variance and minimize the within-class variance. Final classification is performed by means of artificial neural nets. The average accuracy of about 96% illustrates the effectiveness of the proposed method.**

***Keywords*-Human activity recognition; Autoregressive Models; Kernel Discriminant Analysis; Accelerometer; Smartphone**

## I. Introduction

Physical activity recognition via wearable sensors can provide valuable information regarding an individual's degree of functional ability and life style. It is a vital technology with potential applications such as smart environments and lifecare. Quantification of daily physical activities requires an objective and reliable technique that can be used under conditions of daily living. Over the past decade, many activity recognition systems have been developed which incorporate triaxial accelerometers. Most of these systems investigated the use of multiple accelerometers attached at different sites on a subject's body [1]–[10]. This approach, though capable of providing higher recognition rate, is not feasible for long-term activity monitoring because of two or more sensor attachment sites and cable connections. Comparatively, a small number of studies have investigated the use of a single accelerometer mounted at waist or sternum [11]–[19].

A large number of classification methods have been investigated. Many studies incorporated the idea of simple heuristic classifiers [1], [4], [11]–[13]. While others employed more generic and automatic methods from the machine learning literature including decision trees, nearest neighbor and Bayesian Networks [3], [5], [6], [16], support vector machines [16], neural networks [2], [5], [9], [20], and Markov chains [7], [8], [15].It is still hard to say which one of these is most effective for human activity recognition since each provided different recognition rates under different settings.

Even for the same activity, the output of any body-worn TA depends on the position it is attached to. The TA signals for walking, for example, vary at three different positions as shown in Fig. 1. Thus placing an accelerometer loosely at different positions results in high within-class variance. Therefore, almost all previous works require accelerometers to be firmly attached to a specific body part such as arm, wrist, chest, thigh etc, making them impractical for long term activity recognition.

Moreover, nowadays there exist a variety of smartphones with advanced features like internet, touch screens, built-in-cameras, accelerometers for user interface control, and so on. Now the R&D labs at major cell phone/OS vendors plan to turn accelerometer-enabled future smartphones into really clever handsets capable of understanding what people are doing at any moment of time, anticipating what they would do next, and providing services automatically and accordingly [21]. However, owners of smartphones are more likely to carry their handsets freely in their pockets, hands or even bags rather than attaching them firmly to a specific body part. The acceleration data thus could vary significantly for the same activity, leading to poor recognition results.

Translating the idea of activity-aware smartphones into an actual product thus requires an activity recognition method that can function independent of phone's position along subject's body and is capable of providing high recognition results even in the absence of adequate amount of training data from different positions. For such a recognition system extracting discriminating features, which maximize the between-class variance and minimize the within-class variance, is crucial.

In this paper, we present a comprehensive approach to address the above problem. First, we modeled the 3D acceleration data from the smartphone, for five different activities from five different body positions, using Autoregressive (AR) Models [20]. The AR-coefficients were then augmented with Signal Magnitude Area (SMA) [11], [12], [20] to form an augmented feature vector. Second, we used Linear Discriminant Analysis (LDA) [22] and Kernel Discriminant Analysis (KDA) [23] to minimize the high within-class variance and compared their results. KDA employs the kernel technique to perform LDA in high-dimensional feature space to extract significant non-linear discriminating features. Finally, activity recognition was performed by means of Artificial Neural Nets (ANN). Results show that KDA outperformed LDA significantly in improving the class separation, providing an average recognition rate of up to 96%.

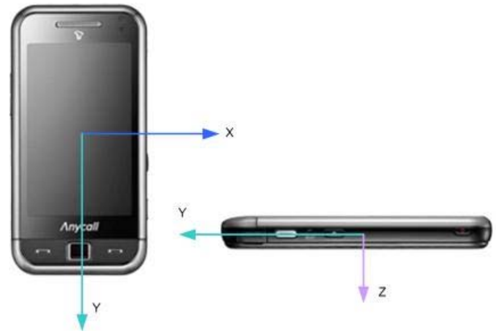


Fig. 2. TOmnia(SCH-M490), a smartphone from SamSung with a built-in triaxial accelerometer. The X axis is along the width of the device, and positive on the right direction. The Y axis is along the length of the device, and positive on the down direction. The Z axis is along the depth of the device, going into the screen

## II. METHODS

### A. Sensor Device and Data Collection

In this study, we used SCH-M490, a smartphone from Samsung, also called TOmnia. It supports a triaxial accelerometer which can measure acceleration in the range of $\pm 2g$. TOmnia accelerometer's resolution is 0.004g and its axis directions are shown in Fig. 2. We have used the Samsung Windows Mobile SDK and Windows Mobile 6 SDK to obtain the accelerometer's data and store it on phone's storage card. Activity data was collected by placing the phone on 6 healthy subjects on five different positions: shirt's top pocket, jeans' front-left pocket, jeans' front-right pocket, jeans' rear pocket, and coat's inner pocket. The five activities to be recognized were resting (sitting), walking, walk-upstairs, walk-downstairs, and running. For realistic recognition, brief movements such as stretching or changing posture were allowed during resting. For a natural setting, walking, walk-upstairs, walk-downstairs, and running were performed outdoor at various speeds.

### B. Noise Reduction

The real time data from an accelerometer contains some noise that needs to be filtered out before using it for activity recognition. A moving average filter of order 3 was incorporated to filter out the random noise.

### C. Feature Extraction

*1) Autoregressive Coefficients:* In our previous study on human activity recognition via triaxial accelerometer [20], we proposed the AR-modeling of triaxial acceleration signals for the first time and proved the feasibility of using the AR-coefficients for activity recognition. An AR-model can be represented as

$$y(t) = \sum_{i=1}^{p} \alpha(i) y(t-i) + \varepsilon(t) \tag{1}$$

where $\alpha(i)$ are the AR-coefficients, $y(t)$ the time series under investigation ,which in our case is the acceleration signal from the sensor unit, and $p$ the order of the filter, which is generally very much less than the length of the series. The noise term or the residue $\epsilon(t)$ is assumed to be the Gaussian white noise. In other words, the order of an AR-model refers to the number of past values of $y(t)$ used to estimate the current value of $y(t)$. The problem in the AR-analysis is to derive the "best" values for $\alpha(i)$ given a time series $y(t)$. We incorporated the use of the Burg's method [24] to estimate the AR-coefficients. Once the AR-coefficients have been estimated, they are combined with SMA to form an augmented feature vector.

*2) Signal Magnitude Area:* SMA has been found to be a suitable measure for distinguishing between static vs. dynamic activities using triaxial accelerometer signals. It is calculated according to

$$SMA = \sum_{i=1}^{N} (|x(i)|) + (|y(i)|) + (|z(i)|) \tag{2}$$

where $x(i)$, $y(i)$, and $z(i)$ indicate the acceleration signal along x-axis , y-axis, and z-axis respectively. The fact that different activities register different SMA makes it a suitable distinguishing feature.

### D. Linear Discriminant Analysis

LDA, a second order statistical approach, is a supervised classification approach that utilizes the class specific information maximizing the ratio of the within and between class scatter information. It looks for the vectors in the underlying space to create the best discrimination among different classes. In order to obtain the maximum discrimination, it projects data onto the lower dimensional space so that the ratio of the between and within class distance can be maximized. The within $S_w$ and between $S_b$ class comparison is done by following equations:

$$S_b = \sum_{i=1}^{c} J_i(\overline{m}_i - \overline{\overline{m}})(\overline{m}_i - \overline{\overline{m}})^T \tag{3}$$

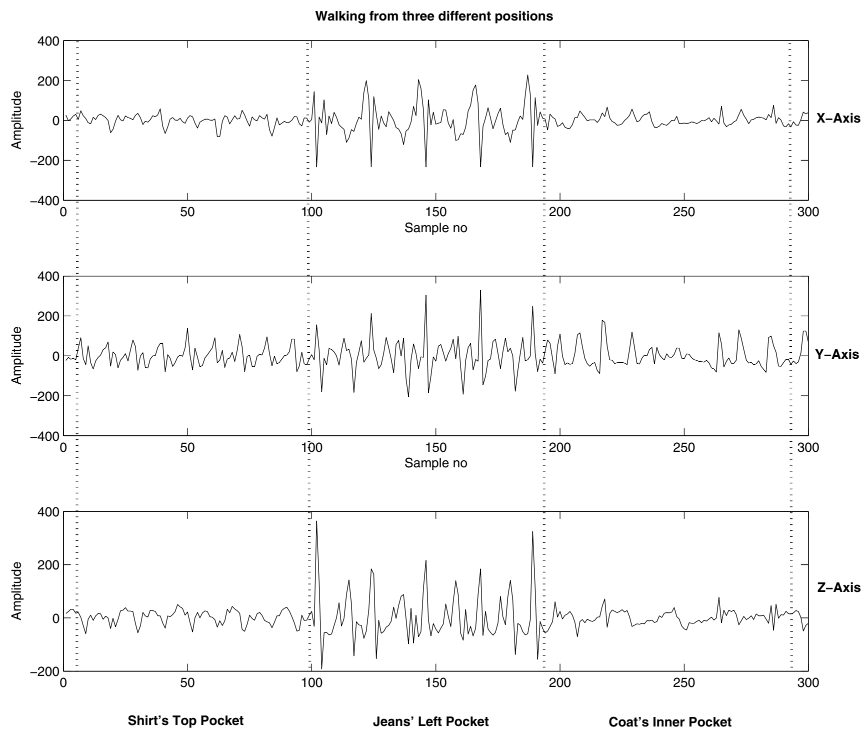


Fig. 1. Sample acceleration signals for walking from three different positions recorded using a triaxial accelerometer

$$S_w = \sum_{i=1}^{c} \sum_{m_k \in C_i} (m_k - \overline{m}_i)(m_k - \overline{m}_i)^T \tag{4}$$

where $J_i$ is the number of vectors in $i-th$ class $C_i$. $c$ is the number of classes and in our case it represents the number of activities. $\overline{\overline{m}}$ represents the mean of all vectors, $\overline{m}$ the mean of the class $C_i$ and $m_k$ the vector of a specific class. The optimal discrimination projection matrix $D_{opt}$ is chosen from the maximization of ratio of the determinant of the between and within class scatter matrix as

$$D_{opt} = \arg\max_{D} \frac{\left|D^T S_b D\right|}{\left|D^T S_w D\right|} = [d_1, d_2, ..., d_t]^T \tag{5}$$

where $D_{opt}$ is the set of discriminant vectors of $S_w$ and $S_b$ corresponding to the $c-1$ largest generalized eigenvalues $\lambda$ and can be obtained via solving (6). The size of $D_{opt}$ is $t \times r$ where $t \leq r$ and $r$ is the number of elements in a vector.

$$S_b d_i = \lambda_i S_w d_i \;\; i = 1, 2, ..., c-1 \tag{6}$$

where the rank of $S_b$ is $c-1$ or less and hence the upper bound value of $t$ is $c-1$.

### E. Kernel Discriminant Analysis

KDA is a non-linear discriminating approach based on kernel techniques to find non-linear discriminating features. Suppose we have a set of $m$ augmented feature vectors $\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_m \in \mathrm{R}^{3p+1}$ belonging to $C$ activity classes where $p$ is the AR-model order. Let

$$\mathbf{x}_i = [a_{x1}, a_{x2}, \cdots, a_{xp}, a_{y1}, a_{y2}, \cdots, a_{yp}, a_{z1}, a_{z2}, \cdots, a_{zp}, s]^T$$

where $a_{xi}$, $a_{yi}$, and $a_{zi}$ are the AR coefficients for three axes and $s$ is the SMA. We considered the problem in a feature space $F$ induced by some nonlinear mapping $\varphi : \mathrm{R}^{3p+1} \rightarrow F$. Our choice of $\varphi$ was the radial basis function. For a properly chosen $\varphi$ an inner product $\langle , \rangle$ can be defined in $F$ which makes for so called reproducing the kernel Hilbert space. More specifically, $\langle \varphi(\mathbf{x}_i), \varphi(\mathbf{x}_j) \rangle = \mathrm{K}(\mathbf{x}_i, \mathbf{x}_j)$ holds where $K(.,.)$ is a positive semi-definite kernel function. To find the linear discriminant in $F$, we needed to maximize

$$J(\omega) = \frac{\omega^T S_b^{\varphi} \omega}{\omega^T S_w^{\varphi} \omega} \tag{7}$$

where

$$S_b^{\varphi} = \sum_{k=1}^{C} m_k (\mu_{\varphi}^k - \mu_{\varphi})(\mu_{\varphi}^k - \mu_{\varphi})^T \tag{8}$$

$$S_w^{\varphi} = \sum_{k=1}^{C} \left( \sum_{i=1}^{m_k} \left(\varphi\left(x_i^k\right) - \mu_{\varphi}^k\right) \left(\varphi\left(x_i^k\right) - \mu_{\varphi}^k\right)^T \right) \tag{9}$$

are the between-class and within-class scatter matrices respectively in $F$ and $\omega$ is the KDA basis vector. $\mu_{\varphi}^k$ and $\mu_{\varphi}$ are the mean of the $k$-th class and the global mean respectively.

$m_k$ is the number of samples in the $k$-th class. The solution to equation (3) is a linear combination of $\varphi(\mathbf{x}_i)$ [4] with coefficients $\alpha_i$ such that

$$\omega = \sum_{i=1}^{m} \alpha_i \varphi(\mathbf{x}_i) \tag{10}$$

Let $\alpha = [\alpha_1, \cdots, \alpha_m]^T$ it can be proved [4] that equation (3) is equivalent to

$$J(\alpha) = \frac{\alpha^T \mathbf{KWK}\alpha}{\alpha^T \mathbf{KK}\alpha} \tag{11}$$

and the optimal $\alpha$s are given by the eigen vectors with respect to the maximum eigen values of

$$\mathbf{KWK}\alpha = \lambda \mathbf{KK}\alpha \tag{12}$$

where $\mathbf{K}$ is the kernel matrix ($\mathbf{K}_{ij} = \mathrm{K}(\mathbf{x}_i, \mathbf{x}_j)$) and $\mathbf{W}$ is defined as

$$\mathbf{W}_{ij} = \begin{cases} 1/m_k, & \text{if } \mathbf{x}_i \text{ and } \mathbf{x}_j \text{ belong to } k\text{−th class} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

For a new pattern $\mathbf{x}$ its projection onto a KDA basis vector $\omega$ in $F$ is calculated as

$$(\omega, \varphi(\mathbf{x})) = \alpha^T \mathrm{K}(:, \mathbf{x}) \tag{14}$$

where

$$\mathrm{K}(:, \mathbf{x}) = [\mathrm{K}(\mathbf{x}_1, \mathbf{x}), \cdots, \mathrm{K}(\mathbf{x}_m, \mathbf{x})]^T \tag{15}$$

More details are available in [23].

### *F. Classifier*

As validated by us in [20], we used ANNs based on the feed-forward backpropagation algorithm. Perceptron NNs with a different number of layers and neurons were tested in order to optimize the performance. The maximal value of the weights in the neuron connections was normalized to the modulus of 1. Different steps of the increment for the weights were also investigated.

After several trials, we chose one hidden layer assigned with ten neurons and one output layer with five neurons corresponding to the five classification outputs: resting (sitting), walking, walk-upstairs, walk-downstairs, and running. The training of the ANN was then repeated several times by changing the input order in a random fashion. For an unknown sequence of acceleration data, the correct activity was classified according to the output of the ANN. The training and the testing datasets were composed of mixture of activity data collected from five body positions.

## III. Results

In order to get meaningful coefficients, AR-modeling of any time-series generally requires the length of the series to be significantly larger than the model order. We used a sampling frequency of 45 Hz which consumed less power. However, it resulted in the failure of seizing meaningful AR-coefficients on second-by-second basis i.e., a window size of 45 samples. After several trials we concluded that the window size of 90 (2 seconds), with no overlapping between consecutive windows, is the most appropriate in our case. First, this time interval was not too long to result in a delayed response. Second, it provided enough raw data for extracting meaningful AR-coefficients. Thus for classification, acceleration data was fed every 2 seconds to the recognition system and the output was compared to the true activity. The performance of the proposed recognition system is then validated in the following three studies:

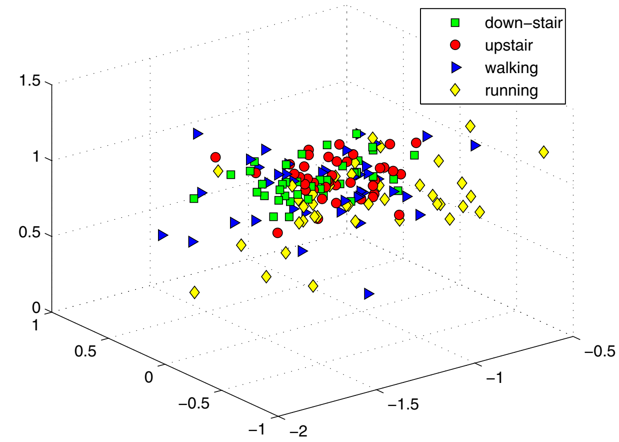


Fig. 3. Feature plot for four activities before LDA and KDA showing high with-in and low between-class variances.

### *A. Recognition using Original Features*

In this study, the augmented feature vectors i.e., AR-coefficients and SMA, were calculated from the acceleration data and used to train the ANN. During testing, each test activity was modeled in a similar fashion and the resulting augmented feature vector was used by the ANN for final recognition. Freely placing the sensor at four different positions resulted in high within-class and low between-class variances in the input feature space as shown in Fig. 3. Only four activities are shown for the sake of visualization. The average recognition rate was only 46%. Results are summarized in Table I.

### *B. Recognition using LDA Features*

The purpose of this study was to evaluate the effectiveness of LDA in minimizing the within-class and maximizing the between-class variances. By taking LDA on the original features, one can improve the feature set as shown in Fig. 3. However, being a linear technique in nature, it was not effective enough and the average recognition rate was 60%. Results are summarized in Table I.

### *C. Recognition using KDA Features*

In this study, we applied KDA to the same feature set used in the previous study. The distribution of KDA patterns for four classes is shown in Fig. 4. Compare to that of LDA patterns, the improvement on class separability is significant.

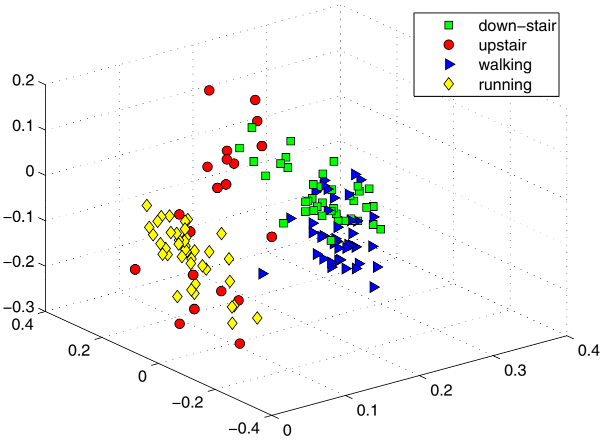


Fig. 4. Feature plot for four activities after LDA.

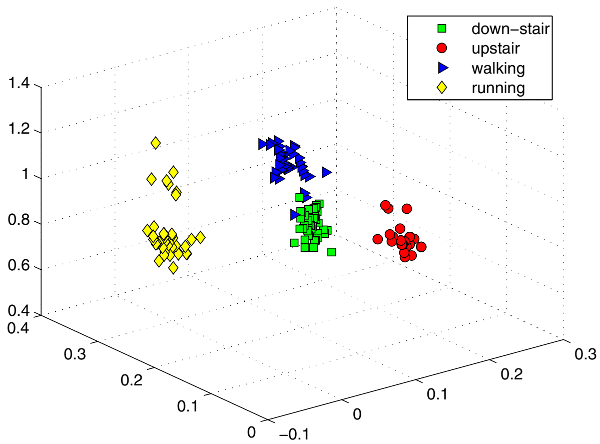


Fig. 5. Feature plot for four activities after KDA.

The average recognition rate for five activity classes was 96%, in this case. Results are summarized in Table I.

## IV. Conclusion

Nowadays triaxial accelerometers are commonly incorporated into daily-used electronic devices such as smartphones. Thus it would be desirable to recognize human activities through such devices. However these devices are carried along freely in pockets, hands or even bags. Thus the acceleration data could vary significantly for the same activity resulting in high within-class variance. In this work, we presented the architecture and implementation of a smartphone's position independent activity recognition system. Our system employs KDA to derive non-linear discriminating features, which maximize the between-class variance and minimize the within-class variance. The technique is validated using the activity data collected from five body positions using a smartphone. Our proposed system increases the applicability of activity classification systems. By using an accelerometer enabled smartphone, which could be placed in any pocket without firm attachment to a specific body part, activities could be monitored throughout a longer period of time.

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TABLE I
AVERAGE RECOGNITION RESULTS(%) FOR THREE STUDIES

| Activity | Original Features | LDA Features | KDA Features |
|---|---|---|---|
| Resting | 61 | 74 | 99 |
| Walking | 41 | 52 | 95 |
| Walk upstairs | 41 | 56 | 95 |
| Walk down-stairs | 37 | 49 | 92 |
| Running | 50 | 69 | 99 |
| Total | 46 | 60 | 96 |

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