World Academy of Science, Engineering and Technology
International Journal of Electrical and Computer Engineering
Vol:10, No:9, 2016

Investigating Activity Recognition Using 9-Axis Sensors and Filters in Wearable Devices

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***Abstract*—**In this paper, we analyze major components of activity recognition (AR) in wearable device with 9-axis sensors and sensor fusion filters. 9-axis sensors commonly include 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer. We chose sensor fusion filters as Kalman filter and Direction Cosine Matrix (DCM) filter. We also construct sensor fusion data from each activity sensor data and perform classification by accuracy of AR using Naïve Bayes and SVM. According to the classification results, we observed that the DCM filter and the specific combination of the sensing axes are more effective for AR in wearable devices while classifying walking, running, ascending and descending.

***Keywords*—**Accelerometer, activity recognition, directional cosine matrix filter, gyroscope, Kalman filter, magnetometer.

I. Introduction

As IT technologies advance, many people utilize high performance smart devices in a daily life. These devices are commonly used to identify user behaviors based on individual sensors. Especially, GPS, accelerometer, gyroscope and many sensors embedded in smart devices require various AR researches. [6]-[8] Human AR is to analyze sensor data from user movement and classify what kind of behavior like running, walking sitting, etc. Typical application areas cover healthcare, localization, context-awareness, game etc.

An accelerometer is vulnerable to external environments and has more energy consumption than other sensors. Many AR researches have employed it as one of the primary sensor components. Previous studies [1], [2] found several features of AR by attaching the smart phone or hanging wearable device to the parts of the body. Another research [14] designed the AR algorithm with a lower sampling frequency data from 3-axis accelerometer in smart phone. Recent wearable devices come into the market with high performance and reasonable price. After developing MEMS (Micro-Electro-Mechanical Systems) technology, smart watch technology employs the variety of sensors and easily estimates user movement. AR is also applied to the portable device for healthcare service [3]. However, these aggregated sensor technologies usually require more battery capacity and complex designs. This paper identifies major components of AR using sensors and the relevant filter designs. These components will be able to increase effectiveness of AR and solve the cost and power-related optimization problems.

In this paper, we obtained AR data from walking, running, ascending stairs, and descending stairs using 9-axis sensor (3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer) and made sensor fusion values using the data. Classification by accuracy uses the sensor data and filter data. We analyze the results and major components of AR.

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In Section II, we briefly introduce background review of AR and sensor fusion filters. Section III explains procedures for finding major components of AR. We present and analyze experiment results in Section IV. Finally, the conclusion appears in Section V.

II. Background

A. AR

Various research areas such as context-awareness and healthcare use AR technology [5]. Typical application of AR is to gather sensor data from activities using smartphone attached to the parts of body or sensor device holding in hands, pockets and bags. The study found data features relevant to the activity which consists of sitting, standing, walking, running, ascending and descending using an accelerometer embedded in smartphone.

Another work [6] conducts AR using two different sensors that are accelerometer and magnetometer integrated in smartphone. The magnetometer implements digital compass in this case. It has lower power dissipation than the accelerometer and provides absolute direction information using magnetic north point. It can be complementary to the accelerometer which provides relative direction information in AR.

Gyroscope can also be used to AR in conjunction with the accelerometer [7]. The gyro-sensor measures angular velocity of an object and reacts faster than the accelerometer. It also provides accurate direction information in short time.

In [8], Accelerometer, gyroscope, temperature, heartbeat and light sensors is used in AR. The research classifies 13 kinds of behavior of the elderly. This study provides information and intelligent services to elderly people for health care and found that accelerometers are the most important sensors and heart rate data can be used to boost classification of activities with diverse heart rates.

B. Kalman Filter

R. E. Kalman [9] presented Kalman filter (KF) that was a new approach to linear filtering and prediction problems in 1960. This filter incorporates mathematical statistics and control systems. We can estimate future states of the given system, based on the past and present states. It provides a general filter and estimation template for various observation data. KF is less sensitive to its initial value. Its iterative structure achieves reliable convergent results by quickly decreasing influence of initial values. It also requires a small number of previous states as well as a short time for training.

KF is a dynamic model which varies in time. Based on the recursive structure, it combines the previous output with the current observation and predict new state estimation.

$$x_t = F_t x_{t-1} + w_t \tag{1}$$

$$y_t = H_t x_t + v_t \tag{2}$$

State equation (1) is an estimated state variable of the KF model and the output equation (2) corresponds to the estimation value. The two equations have error w_t and v_t which are normal distribution models having zero mean values. The errors are independent from each other. The subscripts t and $\mathrm{t}-1$ denote the present and the previous time. F_t is the transition matrix that changes state vector x_{t-1} to x_t. H_t is an input vector which maps the state equation to the output equation.

C. DCM Filter

The DCM [10] has used in aerospace applications and plays an important role in the design of inertial navigation systems. It is the most commonly employed method for generating the coordinate transformation matrix is based on the computation of DCM between each axis of one frame and every axis of another frame. This is calculated by the vector dot products between the axes.

The angle between two vectors r_1 and r_2 is represented by θ. The cosine of θ can be determined from the projection of r_1 or r_2 divided by the magnitude of r_2. The projection of r_2 on r_1 is given by

$$\frac{r_2^T r_1}{|r_1|} = \frac{r_2^T \mathbf{r1}}{(r_1^T r_1)^{1/2}} \tag{3}$$

The angle between the two vectors is defined as

$$\theta = \cos^{-1}\left[\frac{r_2^T r_1}{(r_1^T r_1)^{1/2}(r_2^T r_2)^{1/2}}\right]. \tag{4}$$

Any point in space can be located by the position vector $\mathrm{r} = [x\,y\,z]^T$ while its magnitude $|r|$ is given by

$$|r| = (r^T r)^{1/2} = [x\,y\,z]\begin{pmatrix} x \\ y \\ z \end{pmatrix}^{1/2} = (x^2 + y^2 + z^2)^{1/2} \tag{5}$$

The n-dimensional vector x can be expressed as

$$\|\mathrm{x}\| = (x^T x)^{1/2} = (x_1^2 + x_2^2 + x_3^2 \ldots . x_n^2)^{1/2} \tag{6}$$

Transformation matrices between two frames a and b resulting in an array of nine direction cosines as:

$$\begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix} \tag{7}$$

Therefore, the DCM C_a^b transforms (or rotates) a vector in R^3 from one frame into another.

Mathematically two coordinate systems are related by:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = C_a^b \begin{bmatrix} x \\ y \\ z \end{bmatrix}^b \tag{8}$$

III. Process of Investigating of AR

To implement AR efficiently in a power constrained system, we need to identify and focus primary components of each activity. Assume that wearable device collects sensor data among four user-activities. In this paper, we consider sensor fusion filters as Kalman and DCM filters. Fig. 1 shows a procedure for analyzing AR in this work.

A. Data Collection

We first start from the collected data by Pomares et al. [11]. The dataset comprises body motion recordings for ten volunteers of diverse profile while performing 4 physical activities. Wearable devices have three different sensors including accelerometer, gyroscope and magnetometer. The devices were respectively placed on the subject's right and left wrists. The recording data for sensors were sampled at 50 Hz. The sampling rate shows enough speed satisfying Nyquist-Shannon theory whereas body movements are limited in 20 Hz [12]. Online AR also meets this data rate [13].

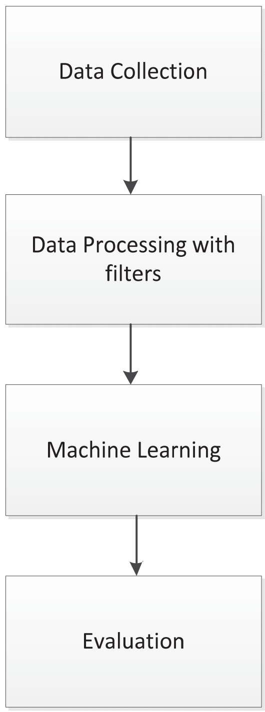

Fig. 1 Experiment procedure

B. Data Processing with Filters

IMU (Inertial Measurement Unit) which comprises accelerometer and gyroscope has accumulation of error in the time. The problem can be solved by fusion of IMU and magnetometer. Sensor fusion filters which are KF and DCM filter are used to the fusion which makes removing noise and estimating correct position. Unlike KF which works on linear system, DCM filter can be used on nonlinear system.

Collected sensor data contain uncertain and noise components. The sensor fusion filters calibrate and combine the data derived from disparate sources so that the resulting information has less uncertainty than the case when these sources are utilized individually.

C. Machine Learning and Evaluation

A classification model by accuracy requires the sensor data and the filter data. WEKA (Waikato Environment for Knowledge Analysis) [17] conducts the process using Naïve Bayes, SVM. We applied 5-fold cross validation [18]. The model uses 15 features which are obtained by 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer, 3-axis KF and 3-axis DCM filter outputs. We evaluate the results by accuracy of confusion matrix. In the field of machine learning, more specifically in the problem of statistical classification, a confusion matrix, also known as an error matrix [4], is a specific table layout that allows visualization of the performance of an algorithm. Each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class [16].

1) Naïve Bayes

Naïve Bayes [14] is a simple probabilistic classifier using Bayes' theorem. According to the theorem, the conditional probability that the event x belongs to k-th class c_k can be derived by the conditional probability of event x given event c_k.

$$\mathrm{P}(c_k|x) = P(c_k)\frac{P(x|c_k)}{P(x)} \tag{9}$$

Since (9) contains $\mathrm{P}(\mathrm{x}|c_k)$ meaning that class c_k includes event x, it can be used in pattern recognition problems. Assuming that all elements in x belongs to c_k are probabilistic independent, we can obtain (10):

$$\mathrm{P}(\mathrm{x}|c_k) = \prod_{i=1}^{n} P(x_i|c_k) \tag{10}$$

where x is a n-dimensional data vector.

2) Support Vector Machine

SVM [15] proposed by Vapnik is categorized into the probabilistic machine learning. It is based on clear mathematical theory and presents high quality performance of recognition in industrial areas. Two classes in vector area are divided by the optimal boundary which is calculated mathematically by SVM. Purpose of the machine learning is to minimize the error function and to find the optimized hyper plane for given object function from dataset and new input data.

IV. Results

The classification incorporates feature data which are obtained by 9-axis sensor, KF and DCM filter. We evaluated the AR accuracy and established the reference case. Major components of AR are identified by comparing cases to the reference.

A. Classification by Filters

Table I summarizes the average accuracies of AR between Naïve Bayes and SVM. According to the 5-fold cross validation, the results are the averaged one for five different accuracy results. The result of 9-axis sensor with DCM filter case is regarded as the reference case due to its highest accuracy number. 9-axis sensor with **KF** case is reported as having lower accuracy than the DCM filter case. The case with only 9-axis sensor is also more degraded than the case with the DCM filter only. From the results, DCM filter is most effective component in wearable AR.

TABLE I
AR Accuracy Rate for Sensor and Filter Data

	Accuracy (%)				
	9-axis	Kalman	DCM	9-axis with Kalman	9-axis with DCM
Naïve Bayes	85.27	85.29	93.88	90.85	95.03
SVM	75.03	72.49	82.69	81.52	84.43

TABLE II
Classification of AR Accuracy Rate

	Accuracy (%)						
	X	Y	Z	X with Y	X with Z	Y with Z	ALL
Walking	86.56	95.35	93.83	95.41	92.55	97.57	98.06
Running	90.58	92.36	91.05	92.79	92.01	94.31	95.21
Ascending	90.25	87.95	89.66	90.67	93.28	92.50	94.19
Descending	92.75	89.07	91.62	92.81	96.95	95.79	97.56

B. Classification by Sensors and Filters Axes

In this experiment, we separate X, Y, Z, combinations of X and Y, X and Z, Y and Z, and all axes case. We conducted classification in 9-axis with DCM filter. Table II shows averaged accuracy results of Naïve Bayes and SVM. The classification is also 5-cross validation. All axes case in all activities were set to the reference cases due to its highest accuracy. For walking and running, accuracy of Y axis with Z case is higher than the other combined two axis cases. The case of Y axis also has higher accuracy than the other single axis cases. For ascending and descending, accuracy of X with Z axis case is higher than the other two combined cases. Similarly, the accuracy of X axis case is also higher than the other single axis cases.

From the results, we conclude that Y axis with Z axis is more effective component for walking and running. Y axis can also be more major than the other single axes. For detecting ascending and descending behaviors, X with Z axis is more effective component and X axis is more major than the others.

V. Conclusion

The paper analyzes four user-AR in wearable device by using 9-axis sensors and the conventional sensor fusion filters. We obtained sensor fusion data from the individual sensor data and perform classification by accuracy using Naïve Bayes and SVM. On average, 9-axis sensor with DCM filter shows the highest accuracy. Accuracy of the sole DCM filter case is higher than the other single component cases. We conclude that the DCM filter is an effective component. In the same way, the combined axes data for Y and Z gives more accurate results for recognitions in walking and running. For ascending and descending, X with Z axis case can be a competitive combination. The choices of these components are able to increase the effectiveness of AR in a battery powered multi-sensor system.

ACKNOWLEDGMENT

This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2013R1A1A2060954).

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