A Preliminary Study of Sensing Appliance Usage for Human Activity Recognition Using Mobile Magnetometer

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ABSTRACT

Human activity recognition and human behavior understanding play a central role in the field of ubiquitous computing. In this paper, we propose a novel method using magnetometer embedded in the mobile phone to recognize activities by detecting household appliance usage. The key idea of our approach is that when the mobile phone user performs a certain activity at home, the embedded magnetometer is capable of capturing the changes of the magnetic field strength around the mobile phone caused by the household appliance in operation. Our mobile application uses these changes as magnetic signatures for each of these appliance such that the daily household acitivities associated with these appliance such as cooking can be recognized.

Author Keywords

Human activity recognition, mobile devices, magnetometer, magnetic field sensing.

ACM Classification Keywords

H.5.2 User Interfaces; I.5.4 Pattern Recognition: Applications

General Terms

Design, Experimentation, Measurement, Performance.

INTRODUCTION

The recognition of various types of human activity and understanding human behaviors acts as one of the most basic problems in the field of ubiquitous computing. This problem is important because it is the basis for a wide range of applications that would provide significant benefits to our daily lives. The most commonly used sensing device to track people's activity is the commodity camera. Although rich visual information can be captured, camera may not be the best sensing device for ubiquitous applications for individuals since people may feel uncomfortable if they are tracked by cameras all the time.

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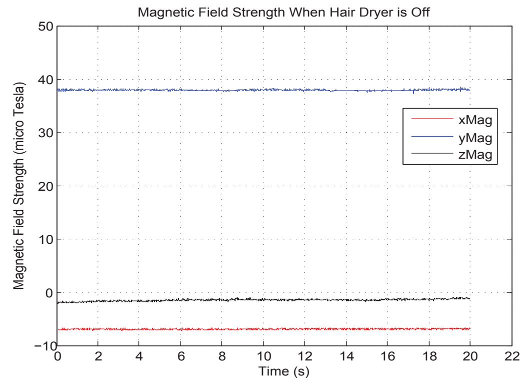
Over the past decades, with the advances and proliferation of the MEMS technology, many different types of sensing technologies have been explored with the goal of making activity recognition at both high and low levels more useful and applicable for individual usage. For example, in [5], researchers built high-level activity models based on the wearable GPS sensor measurements to infer people's mode of transportation (e.g., driving to office from home). In [1], researchers studies the impact of physical activity on peoples' health conditions by attaching wearable accelerometers onto the human bodies to infer low-level activities such as walking, cycling, and jogging, and estimate the energy expenditure based on the inference results. As an even further step, researchers in [6] used RFID technology to detect the interaction between people and the everyday objects and provided a fine-grained activity analysis to better understand human behaviors at home.

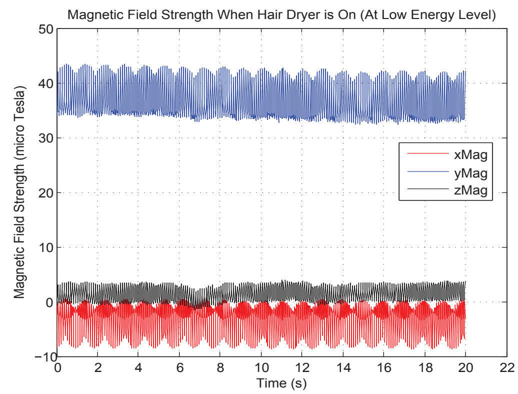
It is interesting to note that some of the sensing devices just mentioned (GPS, and accelerometer) now become an integral part of the mobile devices (e.g iPhone, Android phone). Besides these sensors, many recent mobile devices also have integrated three-axis magnetometers. The magnetometer measures the strength and the direction of the earth's magnetic field and is mainly used for outdoor orientation detection navigation purposes. The research work conducted in [3] extended this idea and developed technique for indoor navigation by utilizing the ambient magnetic field inside buildings. Recently, some researchers used magnetometer to develop technologies for human-computer interaction. For example, the authors in [4] used a properly shaped permanent magnet to interact with the magnetometer inside the mobile phone. The movement of the magnet affects the earth's magnetic field sensed by the magnetometer, and this movement pattern is recorded and used for gesture recognition. In this work, we are exploring the possibility of using the magnetometer to build mobile applications for recognizing household human activities and understanding daily human behaviors. Instead of sensing the strength of the ambient magnetic field in the home, we use the magnetometer to sense the strength of the magnetic field generated from the electronic devices and household appliance used by people in their daily lives. The magnetic fields of different electronic devices and appliance exhibit different patterns when they are in operation. Our mobile application is capable of capturing these pattern differences and infer what activity is being performed by detecting appliance usage.

MAGNETIC FIELD SENSING

The most common application for magnetic field sensing using magnetometer is to sense the earth's magnetic field for navigation. In this scenario, magnetometer is often referred to as compass. The earth itself acts as a gigantic magnet. The magnetometer measures the strength and the direction of the earth's magnetic field in three-dimensional space. Besides navigation, magnetometer can also be used for detecting magnets and ferromagnetic materials. This is because the ferromagnetic material can change the magnetic field in the space around the magnetometer and the values of its strength near ferromagnetic material differ significantly from the strength of earth's natural magnetic field. Since almost all electronic devices and appliance used in people's daily lives contain iron or steel components (they both are ferromagnetic materials), they can be easily detected by magnetometer. Furthermore, when these devices are in operation, the magnetic field around them presents a different pattern compared to the scenarios when these devices are turned off. As an example, Figure 1 shows the magnetic field strength along three axis in physical space of a hair dryer when it is turned off (see Figure 1(a)) and when it is in operation (see Figure 1(b)). As illustrated, the magnetic field strength in each axis remains quite static when the hair dryer is turned off. In comparison, when the hair dryer is in operation (operating at low energy level in this case), there is a significant oscillation of the magnetic field along each axis. This is because the hair dryer has a motor inside that generates magnetic field synchronous to the frequency of the household AC electric power [2]. As will be shown later, this feature will play a significant role in differentiating different electronic devices and household appliance.



(a) Magnetic Field Strength When Hair Dryer is Off



(b) Magnetic Field Strength When Hair Dryer is On (At Low Energy Level)

Figure 1. Comparison of Magnetic Field Strength of Hair Dryer between Off and On (At Low Energy Level)

HOUSEHOLD HUMAN ACTIVITY RECOGNITION BASED ON MAGNETIC FIELD SENSING

The key idea of using magnetometer to recognize household human activities is that when the mobile phone user performs a certain activity (e.g. using microwave oven to cook his meal), the magnetometer embedded in the mobile phone captures the changes of the magnetic field strength around the mobile phone caused by the electronic device or household appliance in operation. These changes exhibit different patterns for different devices and act as the signatures of the devices. We use machine learning techniques to learn these patterns and build model for each electronic device in the training stage. After training, we can recognize which device is in operation by matching the detected magnetic field patterns to the learned models.

Learning the Magnetic Signature

We use a sliding-window-based approach to segment the magnetic signals. In this work, the segmented window is 6 second long with 50% overlap. This is long enough to capture the magnetic signature for each electronic device. As shown in Figure 1, the magnetometer senses the strength of the magnetic field along three orthogonal axis in physical space. Analyzing this 3-channel signal directly is problematic because the sensed strength of the magnetic field in each axis is dependent on the orientation of the magnetometer. In other words, we will get different values for each magnetometer axis if we hold the mobile device differently. To solve this issue, we first accumulate the information from these 3 channels into a single channel signal by calculating the overall magnetic field strength via:

$$M(t) = \sqrt{mag_x(t)^2 + mag_y(t)^2 + mag_z(t)^2} \qquad (1)$$

Then, we extract a number of features from this single channel signal within the 6 second segmented window. As explained, the features to be used should be less dependent on the orientation of the mobile device. Therefore, we use frequency domain features to capture the magnetic signatures. In addition, based on the observations in Figure 1, signal oscillation act as another significant characteristic to capture. Therefore, we also include standard deviation, mean derivatives, and mean crossing rate into our feature set. The full feature set is listed in Table 1. After extracting these features, we stack them into a feature vector and import it into a linear-kernel Support Vector Machine (SVM) to learn the model (magnetic signature) for each electronic device.

Inferring Human Activity

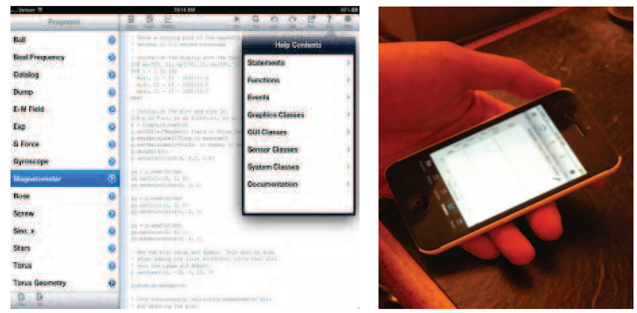
Once the magnetic signature for each electronic device is successfully registered, we use the learned signature to infer human activity by matching the magnetic field signals gen-

(a) Laptop (b) Microwave Oven (c) Television (d) Hair Dryer (e) Mobile Phone

Figure 2. Electronic devices and appliance used in this study

Feature	Description
Standard Deviation	Measure of the spreadness of the signal over the window
Mean Derivatives	The mean value of the first order derivatives of the signal over the window
Mean Crossing Rate	The total number of times the signal changes from below average to above average or vice versa normalized by the window length
Dominant Frequency	The frequency corresponding to the maximum of the squared discrete FFT component magnitudes
Dominant Frequency Magnitude	The magnitude of the dominant frequency
Energy	The sum of the squared discrete FFT component magnitudes
Spectral Entropy	Measure of the distribution of frequency components

Table 1. Features used in this work



(a) techBASIC programming interface (b) techBASIC visualization interface

Figure 3. techBASIC user interface

erated by the electronic device in operation. Similar to the training stage, the sensed magnetic signals are segmented into the 6 second windows. Features in Table 1 are computed and the corresponding feature vector is used to match with the registered magnetic signature by SVM.

EVALUATION

Sensing Hardware and Software

In this work, we use the 3-axis magnetometer embedded in the iPhone 4GS for magnetic field sensing. The magnetometer measures the strength of the magnetic field in unit of microtesla (μT). Due to the limitation of the embedded magnetometer, we set the sampling rate of the magnetometer to 15 Hz. For software, we use the techBASIC[1] mobile application which can be downloaded from Apple App Store. techBASIC is a programming environment for iPhone-based mobile applications. Here we use techBASIC to collect the magnetometer data and visualize the magnetic field signals in real time (see Figure 3). Further data analysis is performed in the MATLAB computing environment on a desktop machine.

Household Activities

We consider five daily household activities each of which is associated with one electronic device or household appliance. These five activities are: (1) web surfing using a laptop; (2) cooking a meal using a microwave oven; (3) watching television; (4) drying the hair after shower using a hair dryer; and (5) talking to a person using a mobile phone (see Figure 2). We recruited three participants to perform each activity 5 times per person. Each activity lasts from 2 minutes (cooking a meal using a microwave oven) to 15 minutes (web surfing using a laptop). We partition the whole dataset such that half is used for training and the other half is used for evaluating the performance.

Preliminary Results

As an illustration of the evaluation result, Figure 4 and Figure 5 show two scatter plots in 2D feature space. Specifically, Figure 4 illustrates the 2D feature space based on dominant frequency magnitude and energy. As shown, different household appliances do not have clear boundaries between each other, which indicates frequency domain features extracted from our restricted low frequency band (0 to 7.5 Hz) do not help much for the recognition task. Figure 5 illustrates the 2D feature space based on standard deviation and mean crossing rate. Compared to frequency domain features, these features performs better. Specifically, The activities associated with hair dryer and microwave oven exhibit higher standard deviation values compared to other three activities. This is because microwave and hair dryer need more power when they are in operation such that the magnetic fields around them are significantly affected. For the activities associated with laptop, television, and mobile phone, although they have similar standard deviation values, they have different mean crossing rates which are used as their magnetic signatures to identify each of them respectively.

Finally, Table 2 lists the recognition accuracy for each activity. Activity associated with microwave oven achieves an

[1] http://www.byteworks.us/Byte_Works/techBASIC.html

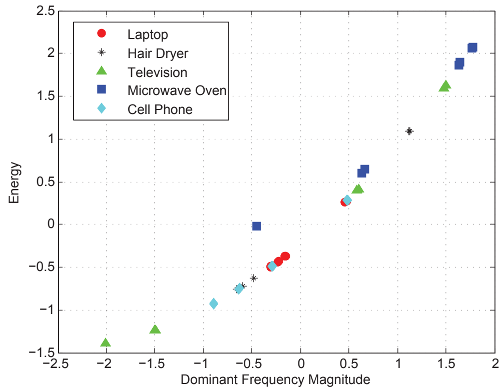


Figure 4. Scatterplot based on dominant frequency magnitude and energy

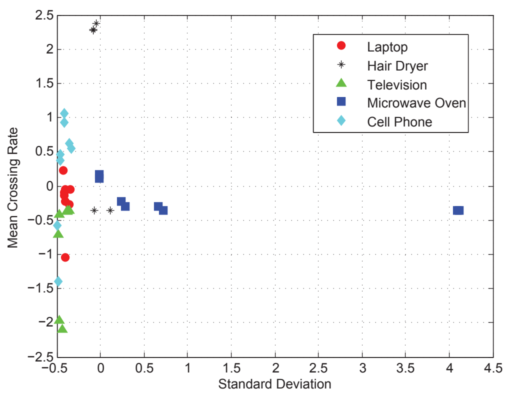


Figure 5. Scatterplot based on standard deviation and mean crossing rate

100% recognition accuracy. Activity associated with hair dryer achieves an 92.7% recognition accuracy and ranks second while activities associated with laptop, television, and mobile phone have similar accuracy rates all above 80%.

Activity	Laptop	Microwave Oven	Television	Hair Dryer	Mobile Phone
Accuracy (%)	84.3	100	81.6	92.7	83.4

Table 2. Recognition accuracy for each activity

Discussion and Limitation

As shown in the above preliminary experimental results, we have achieved a very interesting and promising result by using a single 3-axis magnetometer embedded inside the iPhone 4GS which is originally designed for use as a digital compass for orientation detection and navigation. Our result is interesting in the sense that we could find unique magnetic field signal patterns and correlate these patterns to five commonly used electronic devices and household appliances in operation. However, it should be noted that compared to other commercially available magnetometer (e.g. Honeywell HMC series magnetometer[2]), the one in the iPhone 4GS has a relatively low sampling rate (a maximum 15 Hz based on our experiments). In such case, the high frequency components in the magnetic field signal that may contain important information are not captured. As another limitation, in order to sense the appliance usage, our mobile phone-based solution requires users to take the phones with them whenever they use the appliance. This may not be practical in real world applications. Therefore, we envision that it would be more practical if we could combine the mobile magnetometer with other sensors such as light sensor, temperature sensor, and motion sensors which are pre-installed in the ambient home environment to sense household human activities.

[2]http://www.magneticsensors.com/

CONCLUSION AND FUTURE WORK

In this paper, we present a mobile application that uses a single 3-axis magnetometer embedded in the iPhone 4GS for sensing and recognizing five common household human activities associated with appliance usage. The experimental results validate the effectiveness of our approach. However, due to the hardware limitation, high frequency information in the magnetic field signal is not captured. As future work, we plan to integrate an external high performance magnetometer as a plug-in sensing module to the mobile phone and explore the benefits of high frequency information for sensing human activities associated with appliance usage. We will also explore the benefits of integrating other ambient sensing modalities with the mobile magnetometer.

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