Biometric in Motion: Identification Using Acceleration Data

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Abstract

As cellphones and other smart devices are closer to our daily life than ever, we are curious to know how the data gathered by accelerometers on them impact our lives, particularly in terms of identifying users of devices via such data. In this project, we try to answer this question with machine learning techniques. We will first study how to implement such biometric techniques by retrieving useful identification information from raw accelerometer data and building classifiers. Then we will show how such techniques impact our lives.

1 Introduction

1.1 Motivation

Why is it important Ubiquitous computing had never been so close to us as our phones become smarter and more powerful today. Sensors equipped in our cellphones like GPS, gyroscope, accelerometer and even barometer collect data from the surrounding environment and ourselves. This information collected from our cellphones and other mobile devices can boost many more applications than just adjusting the brightness of the screen and rotating it automatically. Google uses the GPS data from our phones to provide real-time traffic conditions. Apps can track how well you sleep by just putting your phone beside you on bed. Indoor localization takes advantage of wireless fingerprint, sound from microphone, footsteps from accelerometer and even colors from the camera to tell you where you are when GPS signal is weak inside buildings. Fancier applications far beyond the original purposes of these sensors are on the way. How to retrieve more information from the raw sensor data is one of the hottest and promising topics today.

What is the problem Accelerometer is one of the most interesting sensors in our cellphone, which records the acceleration data in 3D. Posture of the phone, gestures and footsteps of the user, and even the user's sleeping condition can be measured by the accelerometer.

In this project, we tried to explore a novel usage of the accelerometer: biometric identification. In other words, can we identify the user by only looking into how he (she) moves? We believe that everyone has his (her) own unique pattern of movement. If this assumption is true, we can identify the person when we match the current data from the accelerometer with the historical data we have learned.

Brief outline of solution In this project, we chose the already available accelerometer dataset gathered by Kaggle. Due to the poor structure of the raw data set, we first did some preprocessing, mainly splitting and re-sampling. Then we extracted discriminative features from preprocessed dataset. The features we used included FFT coefficients, the distribution of timestamp intervals, and the set of possible acceleration readings. Finally, we applied several classifiers to the feature vectors. Now we

have got a score of almost 0.90 in terms of area under the ROC curve, which is satisfactory, although further improvement is still needed.

1.2 Related Work

A human being's walking gait can reflect the walker's physical characteristics and psychological state, and therefore the features of gait can be employed for individual recognition. The use of accelerometer data for biometric identification is relatively new but has been increasingly explored in recent years. Existing methods for gait recognition have shown good performance.

Gafurov et al. [1] attach multiple sensors to a subject at different body parts. Xu et al. [2] developed an Android App to collect gait acceleration data. With a reasonably sized dataset, by matching gait patterns across different paces, they show preliminary results indicating that not only can smart phones be used to identify a person based on their normal gait but also that there is potential to match gait patterns across different speeds.

Tao et al.[5] focus on the representation and pre-processing of appearance-based models for human gait sequences. Two major novel representation models are presented, namely, Gabor gait and tensor gait. Experiments show that the new algorithms achieve better recognition rates than previous algorithms.

Pan et al. [4] proposed algorithm based on signature points, instead of the whole gait signal. They consider acceleration-based gait recognition insensitive to changes of lighting conditions and viewpoint. Their algorithm firstly extracts signature points from gait acceleration signals, and then identifies the gait pattern using a signature point-based voting scheme. The experimental results shows the accelerometer-based gait biometrics is promising.

Kwapisz et al.[3] collect some data and also perform identification experiments . Based on the 600 raw accelerometer readings, they generated 43 features, which are variations of 6 basic features including average acceleration value, standard deviation, time between peaks and so on. They applied two classification techniques decision trees neural networks to classify and the identification performance turned out to be fairly good.

2 Information on the Kaggle competition

We got the dataset from the Kaggle competition "Accelerometer Biometric Competition". The dataset consisted of 3 parts: a training set, a testing set and a question set. Each single sample point in training and testing sets contained a time stamp in milliseconds, acceleration measurements in 3 dimensions, and an associated DeviceId (for the training set) or a SequenceId (for the testing set).

In the training set, there were 30 million samples, which were collected from 387 different devices as labeled. These samples were demarcated into 387 segments, each containing samples for a single device. In the testing data set, there were also about 30 million samples without label. These samples were demarcated into 90,024 sequences of 300 points, each with a SequenceId. In the question set, for each SequenceId, there was a proposed DeviceId.

The task on Kaggle was to tell whether each sequence's proposed DeviceId was the sequence's real DeviceId. For each sequence, we were required to give a belief, in real number, about the credibility of the proposed DeviceId. This competition was designed to investigate the feasibility of using accelerometer data as a biometric for identifying users of mobile devices. For more detail, please refer to the competition website as listed above.

3 Methods

In this section, we describe the methods we have used for preprocessing, feature extraction, and classification. This is not necessarily the final version of our approach.
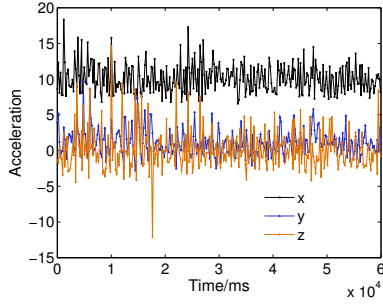
Figure 1: A good sequence from raw data. Samples points were close in time. We regarded these points as representing a single activity.
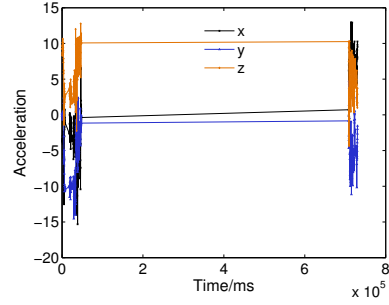

Figure 2: A bad sequence from raw data. This piece essentially contains information about 2 separate activities that were far apart in time. The line segments in the middle of the figure was due to the large time intervals between adjacent sample points.

3.1 Preprocessing

There were two problems with the raw dataset for further processing: 1) accelerometer data for each device was not properly segmented; 2) accelerometer readings were not uniformly sampled. For the first problem, we performed segmentation on 387 training sequences and 90024 testing sequences. For the second problem, we performed re-sampling based on cubic spline interpolation.

3.1.1 Segmentation

First, the raw data was not properly segmented. For each sequence, the time intervals between two adjacent sample points were less than 500 ms most of the time. However, some intervals could be as huge as 100,000 ms. This problem was illustrated in Figures 1 and 2. They contain two test sequences of 300 points. In the first sequence (Figure 1), all the points were close in time, and we could regard these points as representing a single activity. In the second sequence (Figure 2), there were two points that were far apart in time (so all the other points were pushed to two sides of the figure), and we can consider this sequence containing information about two separate activities.

Clearly, we couldn't consider the second sequence as representing information for a single activities, since so much information was unknown between the two far apart sample points. Such huge time interval was not uncommon in the dataset. This could be attributed to two reasons: 1) in preparing this dataset, sequences of samples during periods of rest exceeding 10 seconds were removed by Kaggle; 2) the device could be off or the app could be closed during the whole data collection process.

To overcome this problem, we performed segmentation on the raw data to split each sequence into subsequences. Our segmentation had two phases. In the first phase, we split the sequence at points where the time interval was larger than 10 seconds (this value was based on how Kaggle prepared the data set). After this, for each original sequence, we got several shorter sequences that had sample points close in time. In the second phase, we continually split the longest subsequence among all the subsequences until 1) we got $k_{\#\text{seq}}$ subsequences from the original sequence, or 2) the longest subsequence was shorter than l_{maxL}. Also, sequences shorter than T_{short} were thrown.

We did the second-phase segmentation because after the first-phase segmentation, some resultant sequences were too short (less than 1000 ms) so that not much reliable features could be extracted, and some were too long (longer than 100 seconds) so that it might contain information about multiple activities of the user.

In this manner, on the one hand, we make more sequences from one device, hopefully keeping more information about the device's diverse patterns. On the other hand, we keep the sequences long enough, so that they contain reliable information about patterns of the device.

3

3.1.2 Re-sampling

After segmentation, for each device, we got several subsequences. However, these sequences were not uniformly sampled, due to various reasons. To make feature extraction simpler, we interpolated each segment using cubic spline and uniformly re-sampled each sequence with τ_{resample} being the re-sampling time interval.

3.1.3 The result of preprocessing

After segmentation and re-sampling, for each raw sequence (from training set or testing set), we got several shorter re-sampled subsequences.

3.2 Feature extraction

Feature selection as well as extraction is the most important part of the entire classification process. A great feature should pinpoint reveal the underlying differences between the users (also known as DeviceId in this project). In this section, we describe how to extract features from the data.

3.2.1 Frequency domain features

The only assumption we made so far in this research project is that a human being moves in his/her own characteristic pattern. This pattern could be a sequence of outstanding events, or it could be some repeated, characteristic events as well. Noticing that accelerometer records data with unpredictable length and quality, we cannot assume that the complete sequence of events could be well recorded. Thus, our hope rests on the latter one.

It is customary to use frequency analysis for repeated events. In our approach so far, simple Fast Fourier Transformation is adopted. The basic idea is just making FFT on the refined data sequence we talked about in previous section.

A better idea is to make windowed FFT on them. The reason is, as each of the sequence has different length, if we make full FFT on each sequence, the frequency components produced by FFT have different meanings on different lengths of FFT. For example, we make full FFT on two sequence with length 17 and 29 respectively, the resultant points are not matched in the frequency domain. The results will be hard to be interpreted and compared. To this end, we make the transformation in a given window size, w_{fft}. Thus, multiple transformations are performed in a sliding window manner. We can average each corresponding points from different transformations, as they are matched in the frequency domain.

However, another concern arises. If we make one windowed FFT on a pretty long sequence, some information is erased by the sliding window averaging. This is true if we believe that a longer sequence could contain more information than a shorter one.

To this end, we prefer to perform partitioning on long sequences before doing windowed FFT. There are two thresholds in the partitioning process. One is the lower bound of number of generated sub-sequences, $k_{\#\text{seq}}$, the other is the upper bound of the maximum length among all the generated sub-sequences, l_{maxL}. The procedure of partitioning goes as follows. The input sequence is halved into two sub-sequences until either of the following conditions satisfied: a) the number of sub-sequences is greater than $k_{\#\text{seq}}$; b) all the sub-sequences are shorter than l_{maxL}. In this manner, on the one hand, we make more sequences from one device, hopefully keeping more information about the device's diverse patterns. On the other hand, we use the second threshold to make the sequences not too short, so that they contain reliable information about patterns of the device.

So far, the results of FFT is the extracted features as we shown above. As there are three dimensions, and the independent values of FFT with window size w_{fft} is $1/2w_{fft}$, we build a feature space with $3/2w_{fft}$ dimensions.

3.2.2 Time domain features

As the mobile devices people use are increasingly diverse, the characteristics of different devices offer us a set of very distinguishing features for recognizing users. One of these characteristics is the sampling frequencies of devices.

As we observed from the timestamps of training data of each device, the sampling frequencies of devices has a range of approximately 10-250ms. Thus, we used the histogram of differences of timestamps in each sample as the time domain features.

3.2.3 Accelerometer reading features

Apart from the sampling times of devices, we found another set of features with potential ability of distinguishing devices, which is the accelerometer readings.

During observation of data, we found that each kind of device can only provide certain discrete values, this may be due to the accuracy limitation of accelerometers. Thus, the set of accelerometer readings a device can provide is also treated as a set of features.

3.3 Classification

This is the ongoing part of out work. The basic idea is to leverage various kinds of classifiers and optimize their parameter for more accurate results.

We start from some naive classifiers. The performance of K-Nearest-Neighbor depends on the number of K and the definition of distance function. This classifier leads us to a baseline result. Then we move on to popular classifier such as support vector machine. Optimizing SVM via kernel and parameter selection will be discussed in next section.

4 Implementation and Evaluation

In this section we show how our approach performs. We will also manipulate and justify the selection of parameters of both reprocessing and classifiers.

4.1 Parameter selection

In this subsection we discuss how to determine the parameters and thresholds we defined in the previous sections.

T_{splite} is set to be 10 second in consistent with the preprocessing setting done by Kaggle. It is pointless to set the threshold above 10 seconds as those sequence shorter than 10 seconds have already been eliminated. We keep this threshold as large as possible to generate longer continues sequences. T_{short} is set as 4.8 seconds for training set and 3.2 seconds for test set based on empirical study.

We let $\tau_{resample}$ be 200 millisecond. This value is chosen based our statistic result of the distribution of the original data. Any value near 200 ms is a reasonable choice because most of the intervals lie in this range. Choosing a value deviating from 200 ms could misinterpret the data. (put a figure here for CDF of interval?)

The window size of FFT, w_{fft}, is 64 sample points, which means a window with length 12.8 seconds. We chose this value to balance the details of data and dimensions of feature space.

$k_{\#seq}$ and l_{maxL} are more flexible as the result is less sensitive on these values.

4.2 Optimizing classifier

This is the To Be Done part.

4.3 Results

According to the rules of this compitition, classification results were judged on area under the ROC curve. The three kinds of classifiers we used were k-nearest neighbors, SVM with Gaussian kernel (using LIBSVM) and L_2-regularized logistic regression (using LIBLINEAR). The results along with the compitition baseline provided by Kaggle (kNN, with the mean of all accelerometer readings as the feature vector for each device in the training set, and the the mean of all readings as the

feature vector for each sequence in the testing test), is shown in Table 1. For k-nearest neighbors (k-NN-FFT in the table), only the frequency domain features were used, with $k =$. For SVM with Gaussian kernel (SVM-RBF-FFT in the table), $C = 5, \gamma = 10$ was used in LIBSVM, and only the frequency domain features were used. For logistic regression (LR-3 in the table), $C = 2$ was used in LIBLINEAR, and all three kinds of features were used.

Table 1: Testing results of four methods

Methods	k-NN-Mean (baseline)	k-NN-FFT	SVM-RBF-FFT	LR-3
AUC	0.50277	0.58590	0.80077	**0.89729**

Appendix

Our plan for future goes here.

If possible, we will evaluate our technique not by testing it on the Kaggle dataset, we will also develop apps for our smart phones to collect real time data for learning and evaluation. We hope this approach will give us the clue of how to protect our id privacy.

We will learn a few things from this project besides a better understanding of machine learning itself if our machine learning algorithms finally identify users. First, the assumption about pattern of movement could be true. Second, applications such as anti-theft, health monitoring and emergency detection that adopt this novel identification technique will be available in the near future. Third, we will be able to know how much data from the accelerometer is sufficient to cause the leak of one's identity, which can trigger a serious privacy issue.

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