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How Many Calories People Burn? Physical Activity Recognition Using Acceleration Data with Mobile Phones

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In this paper, we used ACSM Metabolic equations and physical activities recognition technology to estimate phsical activities amount and calorie consumption based on what kind of physical activity people do. Also we describe and evaluate a system that uses phone-based accelerometer and gyroscope to perform activity recognition. The physical activities we tried to detect were walking,running,bicycling,stationary,going upstairs,going downstairs while they carry their mobile phone in the front trousers pocket .These activities are the most common for the people living in cities everyday. We explore orientation-independent features extracted from several components in acceleration. Our approach achieves over 95% accuracy in 5 cross validation for six physical activity. For going upstairs and going downstairs,which is the hardest to be recognize,the accuracy is over 85%.

1. Introduction

Nowadays,many works [BKGP92] [SD90] indicated that daily phsical activities can reduce the risk of decease. In addition,people are conscious about how much exercise and calories burn they do everyday more than ever, especially those people work in a city. Moreover,many survey,like TIME Mobility Poll *1 , ABI Research *2, Ovum *3, showed smartphone was very popular in the world.

1.1 Mobile Sensor-Based Method

In Miluzzo and Nicholas D.'s works[MLF+08],they presented the design, implementation, evaluation, and user experiences of the CenceMe application.which represents combines the inference of the presence of individuals using smart phones with sharing of this information through social networking applications such as Facebook and MySpace.Part of it showed the activity recognition for several activity which was sitting, standing,walking,running. Using the mean, standard deviation, and number of peaks of the accelerometer readings from the three axes of the accelerometer as features which is less computational than those features such as FFT.They collected training data from ten people that randomly placed the mobile phone inside the front and back pockets of their pants for several days.Finally,using a J48 decision tree to be classifier.

In Jennifer R. Kwapisz's [KWM11],they wanted to recognize walking,running,going upstairs, going downstairs, sitting and standing.The data is from 29 subjects accelerometer data of mobile phone with the specfic orientation in users pocket.Using average,standard Deviation,average bbsolute difference,average resultant acceleration,time between peaks,binned distribution as the feature.They used different algorithm,such as J48,Logistic regression,Multilayer Perceptron,straw man.The result showed that going upstairs and going downstairs are the hardest two to be recognized and the patterns in acceleration data between walking,going upstiars and going downstairs are similar features.The best performance for going upstiars and going downstairs are 50% to 61.5%.

In Brezmes, T.'s work[BC09],using accelerometer data to recognize walking,going upstairs, going downstairs,sitting,standing,falling.Using K-nearest neighbors for training a model of each user.Each user can train the modelconsidering his usual way to hold the mobile phone.such as a chest pocket,front trousers pocket,a rear trousers pocket,an inner jacket pocket,etc.The author used the feature of time domain and frequency domain to assess his goals separately.However,in this case,the model is not universal for every people.

In Lin Sun's work[SZL+10],they intended to recognize stationary,walking, running, bicycling, going downstairs, sitting,standing,driving in the natural setting where the mobile phones position and orientation are varying.The accelerometer data were from 6 pocket positions which were left front pocket of trousers,right front pocket of trousers,left rear pocket of trousers,right rear pocket of trousers,left front pocket of coat,right front pocket of coat.He combined the magnitude of axes x,y,z data with the orignal accelerometer reading to be new vector to relieve the influences of the phone orientations.By using mean, variance, correlation, FFT Energy and Frequency-Domain Entropy of it as feature and used 4 second half overlapping windows with 1 second frame windows.The best performance was 93% by using SVM and grid search.

In Jun Yang's work[Yan09],he intented to recognize sitting, standing, walking, running, driving and bicycling in order to record physical activity everyday.The accelerometer data were from front pocket of trousers.He estimated gravity accelerotion by averages of all the measurements on those respective axes x,y,z for the sampling interval.He computed the magnitude of the horizontal components and the

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*1 http://www.qualcomm.com/media/documents/files/time-mobility-poll-in-cooperation-with-qualcomm.pdf

*2 http://www.abiresearch.com/press/45-million-windows-phone-and-20-million-blackberry

*3 http://ovum.com/press_releases/ovum-expects-smartphone-shipments-to-reach-1-7-billion-in-2017-and-android-to-dominate-as-os/

amplitude of the vertical components by using [Miz03] approach to be a way to avoid orientation problem of mobile phone.And extracted feature by mean, standard deviation, zero crossing rate, 75% percentile, interquartile range of these two component and cross-correlation between these component. For calories consumption estimation, there are many way achieve.Heart rate sensor is the direct way to know calories burn of people.But the sensor is not popular now a day.For example,Garmin*4 developed a lot of products for different sport to record information and estimate calories during excerise.But heart rate sensor is extra for those products. In the other way, people use a pedometer to check how many step they walk.Then It estimate the calories burn by those information like fitbit *5. It is too simple to estimate burn of special case. For example, people walk and run for same distances with same step number. We may get the the same calories burn by pedometer.Also the estimation can be wrong if people is riding a bicycle.

Mobile phone is very popular in people. According to TIME Mobility Poll*6 in 2012 which showed that 88% people from 5000 sample in wideworld couldn't go out without mobile phone in 1 day and 72% of those people checked their phone in every thirty minutes.

In addition, the global installed base of smartphones will total 1.4 billion by the end of 2013, according to the latest forecasts from ABI Research. *7 Also smartphone shipments are expected to increase at a compound annual growth rate of 24.9 percent over the next five years, according to research firm Ovum. *8 . Due to the capability of computation of smartphones, we can build model directly and not need the help of internet. There are serveral works using Metabolic Equations to estimate calories burn.

Nanami Ryu's work [RKA08],they intented to recognize sitting, standing, walking,running by mobile phone. Then Metabolic Equations corresponding these activities.Lee's work [LKK11],they intended to create a system to recording a personal life log of daily activities is an emerging technology for u-lifecare and e-health services on mobile phone.They used two layer classfier to classfly static activites and dynamic activities.After that,Metabolic Equations are adapted to estimate calories burn. Both of them motivate us to apply this method.

2. Data Collection

We needed to collect the data from mobile phones which is user acceleration, gravity and distances. User acceleration and gravity can be got by accelerometer and groscope.Also we used GPS location to estimate the distance. However, GPS signal are different in indoor and outdoor which is a big affect to the distance estimation. We estimated the distance according to the users' stride size and step times and estimated the distance during bicycling by GPS location. We chose the sample rate 10Hz to collect data [Hal05].

Table 1: The number of extracted sample with 8 seconds window for building model

ID	Walk	Runn	Stationary	Bicycle	Up	Down	Total
1	43	31	30	44	19	20	187
2	30	21	29	26	17	15	138
3	52	18	39	39	19	16	183
4	35	24	35	32	18	16	160
5	16	11	59	39	14	12	151
6	24	32	32	35	18	17	158
7	69	29	47	46	22	20	233
8	37	17	40	14	20	21	149
9	101	25	16	46	18	19	225
10	69	36	39	31	18	16	209
11	76	0	28	26	20	15	165
12	22	14	90	44	17	14	201
13	24	12	25	32	18	16	127
14	14	11	36	27	16	14	118
15	24	18	32	26	16	12	128
16	40	14	32	22	14	13	135
17	26	24	20	14	16	15	115
18	83	18	34	13	22	18	188
19	42	12	26	34	17	16	147
20	57	11	25	19	19	15	146
21	43	7	30	29	18	15	142
Sum	927	385	744	638	376	335	3405
%	27	11	22	19	11	10	100

Table 2: The number of extracted sample with 8 seconds window for calories consumption estimation

ID	Walk	Runn	Stationary	Bicycle	Up	Down	Total hours
1	658	28	1876	131	54	63	6.24
2	350	43	2456	392	35	32	7.35
3	361	66	2296	174	90	42	6.73
4	526	46	3135	306	66	38	9.15
5	637	94	3167	846	168	72	11.08
Sum hours	5.63	0.62	28.73	4.11	0.92	0.55	40.55
%	14	2	71	10	2	1	100

3. Data Description

For building model, 21 people data of six activities, which are walking,running,stationary, bicycling, going upstairs and going downstairs,were recorded. The process of recording is that the users clicked the record button of the application on smart phone with each activity name first. Then, they put the phone in their front trousers pocket. Afterward, they do the activity they just click. For calories consumption estimation experiment, 5 days data from 3 person were collected. These people were asked to record their whole day activity as complete as they can. We labelled it in the same way as the data for building model.Table 1, 2.

4. Data Observation

Similar Data

As we mentioned before in Kwapisz's work **??**. The acceleration data of walking, going upstairs and going downstairs are very similar. And a experiment in the experiment part later in Table 3 4 also show the same case in our data.

*4 http://www.garmin.com.tw/
*5 www.fitbit.com/
*6 http://www.qualcomm.com/media/documents/files/time-mobility-poll-in-cooperation-with-qualcomm.pdf
*7 http://www.abiresearch.com/press/45-million-windows-phone-and-20-million-blackberry
*8 http://ovum.com/press_releases/ovum-expects-smartphone-shipments-to-reach-1-7-billion-in-2017-and-android-to-dominate-as-os/

here we show the magtitude of accelerator reading. figure 1 and 2

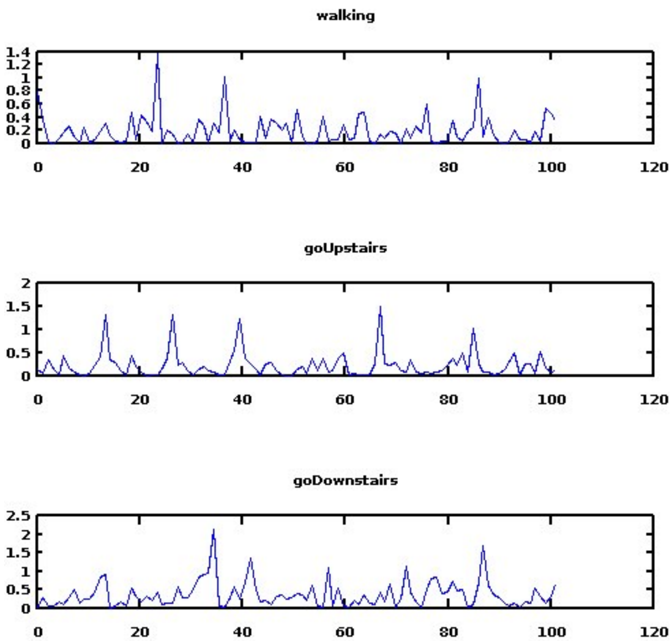

Figure 1: The magtitude of accelerator reading for walking, going upstairs and going downstairs

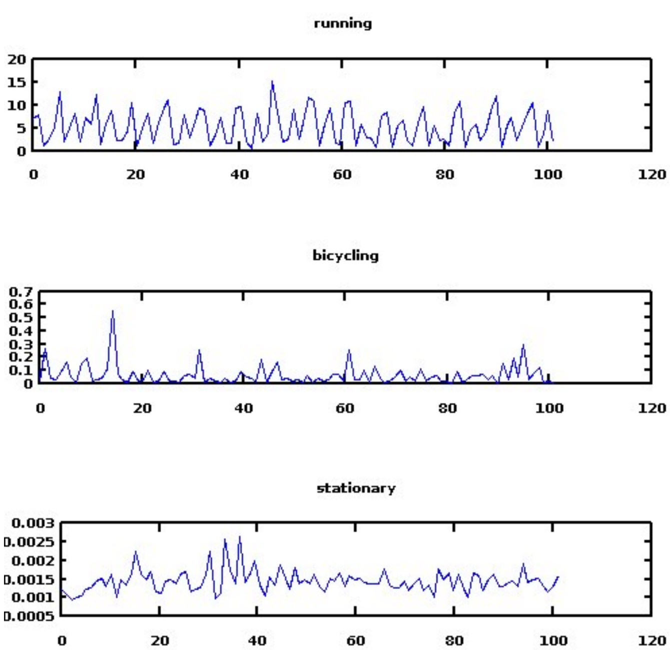

Figure 2: The magtitude of accelerator reading for running, bicycling and stationary

Ambiguous Activity

In some case,the activity can be label to mutliple type of activity. For instance, there is a small turn between two stairway in the most of stairway in campus. It is supposed to be part of going downstairs, but actually it is walking if we ignore the context.

In other case, some of the them may keep stationary for a while during bicycling for a few seconds. It can be labelled to sationary if we ignore the context also, but actually it is also a part of bicycling actually.

We illustrate these case in the below figure. 3

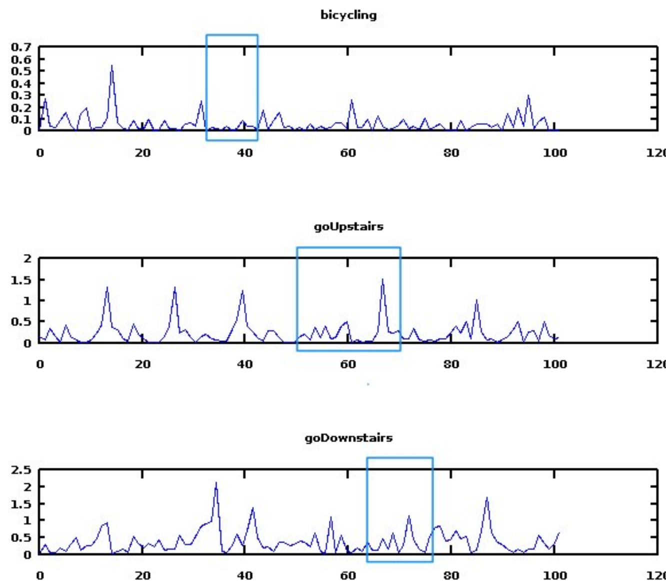

Figure 3: The picture of ambiguous label case
The blue square in bicycling is stationary, the ones in going stairs is walki

5. Data Processing

Filtering:

Filtering can drop out the noise, smoothing data and gain the useful data from orginal. Here we tried filter moving average filter,which is a simple low pass filter, and not use any filter. We think we don't need to use low pass filter because the sample rate for collection is 10hz [Hal05]. The reuslt also determine our idea. Figure 4

6. Physical Activity Classification Method

6.1 Orientation Problem

Most perious works on physical activity recognition used varied sensor attached to the body in known position and orientation.They assumed the sensors like accelerometer sensor were fixed on the body. Also,most perious works on physical activity recognition by mobile phone had the same assumption too. Under realistic conditions, mobile phone should be in any orientation related to the body so the assumption is no longer valid.

Berchtold, M. et al [BBG^{+}ct] also mentioned the orientation problem in their work. They said the way in which the device was carried greatly affects the ability of conventional classifiers to recognize activities under realistic conditions.

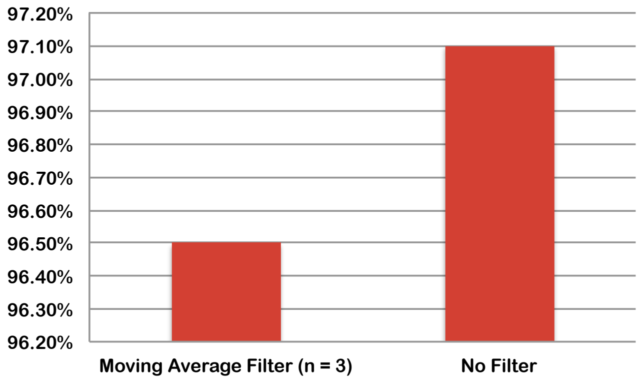

Figure 4: Compared the average accuarcy in moving average filter and no filter using proposed method

Table 3: The confusion matrix of magnitude method

		Predicted Class					
		Walk	Run	Stat.	Bicycle	Up	Down
Actual Class	Walk	841	0	0	5	36	45
	Run	6	361	3	6	1	1
	Stat.	0	0	731	12	1	0
	Bicycle	10	0	3	601	21	3
	Up	130	3	0	38	171	34
	Down	168	0	0	6	55	106

First, the direct solution to avoid orientation problem is using the magnitude of each (x,y,z).We extracted features from the magtitude of each (x,y,z) instead of the orignal (x,y,z) signal. However,the operation will lose 3 dimensional directional information of the mobile phone.

Second, in [Miz03], Mizell et al had shown how they decomposed 3 dimensional vecter (x,y,z) to horizontal component and vertical component and extracted the features from the amplitude of the vertical components (scalar projection) and the magnitude of horizontal components to bulid the model. They used 10 seconds or so to estimate the gravity which was also used in [Yan09]. But here we used that groscope reading and accelerometer reading to estiamte the gravity instead.

Here we compare these two method for activity recognition those six activities. We extracted feature as same as Yang's works [Yan09] in magtitude method. Figure **??** When we read confusion matrix of these two method. Table 3 4. We noticed that walking, going upstiaris, going downstairs are easy te confuse each other. as [KWM11] mentioned before.

Table 4: The confusion matrix of Mizell's method

		Predicted Class					
		Walk	Run	Stat.	Bicycle	Up	Down
Actual Class	Walk	823	1	0	3	41	59
	Run	2	363	3	5	3	1
	Stat.	0	0	740	3	1	0
	Bicycle	6	0	2	619	10	1
	Up	85	4	0	9	252	26
	Down	113	0	0	2	28	192

Table 5:

	A	B	C	D	E
Walk	90.70%	88.80%	88.70%	94.50%	92.60%
Run	95.50%	96.30%	96.00%	96.60%	96.60%
Stat.	98.30%	99.50%	98.40%	98.50%	98.30%
Bicycle	94.20%	97.00%	93.10%	90.00%	94.20%
Up	45.50%	67.00%	54.80%	34.80%	52.10%
Down	31.60%	57.30%	38.50%	2.40%	14.00%

Table 6: Features extracted from each window segment of the data

Features	Descriptions
mean	the mean of each component segment
standard deviation	the standard deviation of each component segment
mean crossing rate	the mean crossing rate of each component segment
75% percentile	the 75% percentile of each component segment
interquartile range	the interquartile range of each component segment
cross-correlation	the different of the maximum and minimum of the cross-correlation of each two component

The other way to avoid the problem is to extract feature by the variation of magtitude of each (x,y,z) reading which was used in Yu-Chen Chang et al work [Cha10]. They tried to detect transportation mode by measuring the vibration of phones on legs. We used the best performance equation of the work in the follow experiment. The result in Table 5. A is Magtitude Method, B is Mizell's Method, C is Chang's idea which extracted the feature from the variation of magtitude. D is Chang's method with human definition which extracted feature from histogram clustering with special number of center we gave. E is Chang's method with bayesian information criterion which extracted feature from histogram clustering with the number of center bayesian information criterion detemine. The features we extracted in A,B,C method as same as the Yang's work [Yan09] (Table 6) and so we extracted in D,E is occurance probability in a windows. We would talk more detail in Component Type Clustering part.

6.2 Component Definition

Now we have gravity vecter $\{g_i = (gx_i, gy_i, gz_i), i = 1, 2, ...N\}$,user acceleration vecter $\{a_i = (ax_i, ay_i, az_i), i = 1, 2, ...N\}$,$N$ is the length of sample point. The vertical components and horizontal component is the same as [Yan09].The vertical variation component and horizontal variation component is by best performance equation in [Cha10].We also used θ, which is angle between gravity vecter and user acceleration vecter, to be one of our components.

Vertical Components:

$$\alpha = \mid a_i \mid \cos\theta_i = \frac{a_i \cdot g_i}{\mid g_i \mid} \tag{1}$$

$$v_i = \alpha \frac{g_i}{\mid g_i \mid} \tag{2}$$

Horizontal Component:

$$h_i = a_i - v_i \tag{3}$$

Angle Component:

$$\theta = \arccos(\frac{a \cdot g}{\mid g \mid}) \tag{4}$$

Vertical Variation Component:

$$vVibration_i = \mid vx_i - vx_{i-1} \mid + \mid vy_i - vy_{i-1} \mid + \mid vz_i - vz_{i-1} \mid \quad (5)$$

$$v_i = (vx_i, vy_i, vz_i), i = 1, 2, ...N \quad (6)$$

Horizontal Variation Component:

$$hVibration_i = \mid hx_i - hx_{i-1} \mid + \mid hy_i - hy_{i-1} \mid + \mid hz_i - hz_{i-1} \mid \quad (7)$$

$$h_i = (hx_i, hy_i, hz_i), i = 1, 2, ...N \quad (8)$$

6.3 Component Type Clustering

As we mentioned in 6.1, we can't get very good result from feature extraction in magtitude method,Mizell's way and Chang's way directly.

However,we thought chang's idea was a good motivation for us. We used similar skills to apply our components. 6.2

First, we transformed the data to histogram.Then, using unsupervised learning algorithm to cluster those histograms.

With histogram series, we converted each histogram for different clusters without any label. We used Kmeans++ being proposed in 2007 by David Arthur and Sergei Vassilvitskii[AV07] beacuse it can avoid the sometimes poor clusterings found by the standard k-means algorithm.

Moreover we used MDPA (minimum distance of pair assignment) [CS02] as the similarity function of two points. MDPA approach computed a distance between sets of measurement values as a measure of dissimilarity of two histograms.It had the advantage over the traditional distance measures regarding the overlap between two distributions;

However,we used two method to decide how many center the component data have. The first one was human definition which we defined the data by ourself. For these,we used Multidimensional Scaling Analysis to plot the component data by using the similarity matrix as distance matrix, then observe it to make a decision. The second one was bayesian information criterion,which is one of statistics method, to detemine it. Bayesian information criterion was used in X-means algorithm [PM00] before.

6.4 Physical Activity Classification

First we will show the result using the middle process flow (figure 5).We extracted the feature from component type clustering motivated by Chang's work [Cha10].

Second we will show the result by extracting feature from component directly.

Third we will combine the first one and the second one feature to run a test.

Feature Extraction from Component Clustering Type: We used component type occurance probability in specfic window as feature. We show the result from human definition one and bayesian information criterion one. Give more datil here about the feature,for example,if there are 6 center number for each component, we have 30 feature each turple because we have 5 defined component.Assume we output the histogram for each second,the window we choose is 8 seconds and the sensor rate is 1 sample each second. After we already cluster those histogram, if we look at the first component clustering data of 8 seconds window,we may get the vector like this {1,1,2,2,1,1,1,3}. Each number stand for which cluster the histogram belong to. So the feature turple for first component is {5/8,1/41/8,0,0,0},5/8 is the occurance probability of cluster 1 in the window.So as to others.Here we ran serveral algorithm.

Here we choose the 1 second window for histogram output and 8 window sizes for feature extraction . Using human definition and bayesian information criterion to detemine the number of center in components data. The accuracy of result are shown as Table 7, 8.

We realized it was still not enough high for walking, going upstairs and going downstairs.But we knew here SVM had the best performance. Then we test it in outputing histogram with different seconds. The result show that we got the best result in this case with 1 second window for

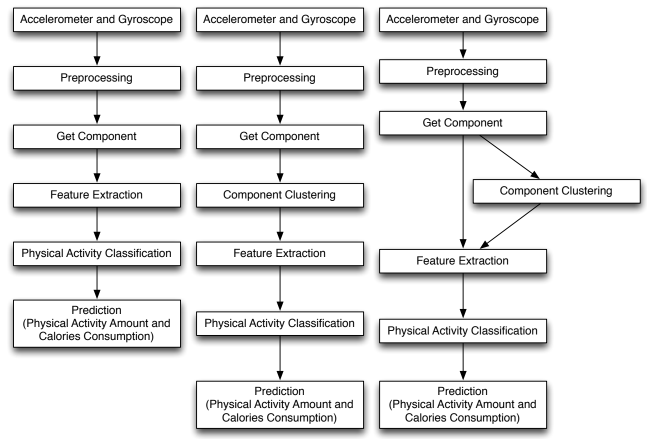

Figure 5: The process flow of physcial activity classification.

Table 7: The accuracy of the method which using component type occurance probability as Feautre with human definition

	J48	KNN	NB	Logistic	SVM
Walk	84.00%	86.20%	89.00%	87.30%	91.00%
Run	97.10%	97.60%	96.60%	97.10%	97.30%
Stat.	97.80%	98.70%	98.50%	98.50%	98.40%
Bicycle	93.90%	94.00%	95.10%	95.50%	95.30%
Up	69.70%	76.10%	64.60%	73.10%	78.50%
Down	55.20%	58.80%	56.70%	67.80%	71.90%

Table 8: The accuracy of the method which using component type occurance probability as Feautre with bayesian information criterion

	J48	KNN	NB	Logistic	SVM
Walk	83.60%	81.00%	87.80%	86.40%	93.40%
Run	94.20%	97.30%	97.30%	93.60%	97.90%
Stat.	99.10%	98.70%	97.60%	98.70%	98.90%
Bicycle	93.40%	97.30%	97.00%	96.40%	98.60%
Up	58.00%	63.30%	72.10%	78.70%	79.00%
Down	51.60%	62.40%	52.80%	75.80%	77.60%

Table 9: Features extracted from each window segment of the data

Features	Descriptions
mean	the mean of each component segment
standard deviation	the standard deviation of each component segment
mean crossing rate	the mean crossing rate of each component segment
75% percentile	the 75% percentile of each component segment
interquartile range	the interquartile range of each component segment
cross-correlation	the different of the maximum and minimum of the cross-correlation of each two component
Correlation coefficient	the correlation coefficient of each two component

Table 10: The accuracy of extracting feature from component with 8 seconds window

	J48	KNN	NB	Logistic	SVM
Walk	85.50%	95.10%	85.40%	95.60%	96.40%
Run	97.60%	97.60%	97.30%	96.60%	98.10%
Stat.	99.30%	98.70%	97.80%	98.70%	99.60%
Bicycle	96.40%	98.30%	96.10%	98.00%	98.90%
Up	75.00%	84.30%	75.30%	93.60%	94.90%
Down	68.70%	84.50%	70.40%	87.80%	90.10%

histgram output. The differentiation between the best and the worst result is in 3% to 5%.

Feature Extraction from Component:

Some features we extracted are the same to [Yan09], but we also extract extra feature, Correlation coefficient, for each two component. We can get best perferance after that. The feature table as follow. Table 9

We use different algorithm with 8 seconds window . Figure 10.

The result also show SVM are the best one. We extract the same features in different window sizes to bulid model to see if it is better or not.We noticed the weighted average accuacy don't raise up so fast since 6 seconds.

Combination Approach:

Then we combined feature from component and component type clustering above.Serveral algorithm will be also achieved here. We choose the 8 seconds window for feature extraction and 1 seconds with histogram output. We realized it was not so helpful which was only around 1 t 2% better although we used different window size for histogram output.

Best Approach

We choose the method which directly features from 5 components with SMV. The summary accuracy result as Figure 6

7. Calories Consumption Estimation

After We create a model for six activites,We used ACSM Metabolic Calculations [SGPD07] to estimate calories consumption.

First, we computed oxygen consumption of excerise according to equation corresponding differents activities.Then we computed the calories consumption according to 18 which indicate the relationship between oxygen consumption and calories.

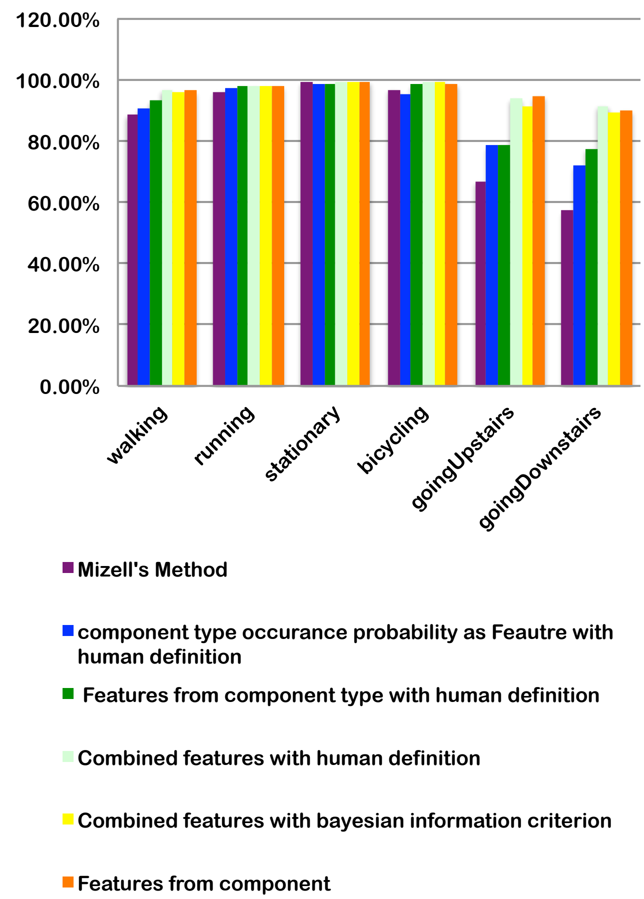

Figure 6: The accuracy of different method using SVM

7.1 Metabolic Equations for Net VO2

walking

$$VO2 = 0.1 \times Speed \quad (9)$$

running

$$VO2 = 0.2 \times Speed \quad (10)$$

stationary

$$VO2 = 1 \quad (11)$$

bicycling

$$VO2 = 1.8 \times WorkRate/BodyWeight \quad (12)$$

going upstairs

$$VO2 = (0.2 \times SteppingFrequency) + (1 \times 1.8 \times StepHeight \times SteppingFrequency) \quad (13)$$

going downstairs

$$VO2 = (0.2 \times SteppingFrequency) + (0.33 \times 1.8 \times StepHeight \times SteppingFrequency) \quad (14)$$

VO2 is gross oxygen consumption in $mL{\cdot}kg^(-1).min^(-1)$
Speed is speed in $m \cdot min^(- 1)$
BodyWeight is body mass (kg)
WorkRate $(kg.m.min \cdot (-1))$
SteppingFrequency is the stepping frequency in minutes
StepHeight is step height in meters

7.2 Variable in the eqation.

We assume we know the user's sex, weight, height, bicycle weight and the coefficient of rolling resistance. And it is on asphalt road when bicycling.

Speed For Walking and Running

First,I detect the step count the user did according to [MM09]

Secord,the stride size computation according to the relationship between sex and stride size.

$$StrideSize = \begin{cases} Height \times 0.415 & if\ Sex = male \\ Height \times 0.413 & if\ Sex = female \end{cases}$$

(15)

Work rate and Resistance of Bicycling

$$WorkRate = Resistance \times Distance/ExceriseTime \quad (16)$$

$$Resistance = 9.8 \times (BodyWeight + BicycleWeight) * rollCoefficient \quad (17)$$

BodyWeight is body mass (kg)

BicycleWeight is body mass (kg)

RollCoefficient is the coefficient of rolling resistance, dimensionless (wooden track = 0.001, smooth concrete = 0.002, asphalt road = 0.004, rough paved road = 0.008) ref *9

7.3 Oxygen Consumption to Calories Equation

$$CaloriesConsumption = VO2 \times BodyWeight/200 \times ExceriseTime \quad (18)$$

Calories Consumption (kcal)

7.4 The standard of evaluation

After we estimate the calories burn,we will use the equation 19 to evaluate the result.

$$ErrorRate = \frac{CaloriesComsumptionEstimation - GroundTrue}{GroundTrue} \quad (19)$$

8. Active Learning

In a experiment of the calories comsumption estimation part Table9.2, we noticed the the accuracy of the physical activities was not the only factor to influence the result of calories comumption estimation. The confusing activities also affected the result. The more detail in the experiment part.

*9 http://www.flacyclist.com/content/perf/science.html

There are two ways to overcome this problem. One is cost-sensitve learning [LYA09] which we can give a cost martrix to change the problem to optimal problem. However, the cost is hard to get in our problem. Although we know the window size for each turple, we still can't know the varible required in the equation. Also the main goal in this work are phsical activities amount and calories consumption estimation. In this case, cost sensitve learning may decrease the accuarcy of activity recognition probably because it focus on the cost optimization. We used MetaCost and Cost sensitive classifier in weka to had a test which also show the same case. Another way is active learning because if the accuarcy of activity recognition increase,it will also raise the accuracy of calories consumption estimation up. We can satisfied both of our goal in this way.

The mainly query strategies of active learning are Uncertainty Sampling, Query-By-Committee,Expected Model Change, Expected Error Reduction, Variance Reduction, Density-Weighted Methods.[Set09] We found the SVM has the best performance in our problem. Also, we intended to implement in mobile phone so we chose the less computational one to do experiment which is uncertainly sampling. There are also three sampling method Least confident, margin sampling, entropy.

$$x^*_{LC} = \underset{x}{\operatorname{argmax}}\ 1 - P_\theta(\hat{y} \mid x) \quad (20)$$

where $\hat{y} = \underset{y}{\operatorname{argmax}}\ P_\theta(y \mid x)$, or the class label with the highest posterior probability under the model.

$$x^*_M = \underset{x}{\operatorname{argmax}}\ P_\theta(\hat{y_1} \mid x) - P_\theta(\hat{y_2} \mid x) \quad (21)$$

where $\hat{y_1}$ and $\hat{y_2}$ are the first and second most probable class labels under the model

$$x^*_H = \underset{y}{\operatorname{argmax}}\ -\sum_i P_\theta(y_i \mid x) \log P_\theta(y_i \mid x) \quad (22)$$

where y_i ranges over all possible labelings.

9. Evaluation of Experiment

In this section,the physical activity amount and calories consumption estimation are persented here. We used Weka with LIBSVM,a machine learning library for classifing the physical activity. Then we used the model we just built to recognize activities in those 5 days data. Finally we estimate calories consumption based on Metabolic Equations.

9.1 Physical Activity Model

The weka [HFH+09] with LIBSVM [CL11] are used in our experiments.

5 cross-validation

We showed the result of proposed method using SVM, Logistic, Decision tree, Naive Bayes,K-nearest neighbors which we mentioned before Figure 6

Leave-Out-User-Out Validation.

We use Leave-out-user-out validation,using the same machine learning algorithm as former.

Table 11: The Leave-Out-User-Out Validation result of SVM, Logistic, Decision tree, Naive Bayes,K-nearest neighbors with 8 seconds window for physical activity recognition

Accuracy					
	SVM	logistic	DR	KNN	NB
walking	88.87%	91.61%	78.21%	79.55%	80.58%
running	97.58%	91.84%	90.85%	91.99%	91.98%
stationary	97.41%	96.98%	96.96%	95.48%	96.96%
bicycling	97.16%	96.12%	93.89%	96.88%	94.88%
goingUpstairs	90.82%	89.35%	68.62%	70.07%	71.30%
goingDownstairs	84.97%	85.78%	70.83%	73.18%	60.81%

9.2 Calories Consumption Estimation

Lastly, we used the SVM model to do the calories consumption experiment. First we showed the accuacy of physical activity recognition detection for each day data. Secrond, we showed the final conlories consuption for each day data and how good it was .

The acccurcy of physical activity recognition We will compare our proposed method and Mizell's method.

Table 12: The acccurcy of proposed method

Accuracy						
	1	2	3	4	5	Average
walking	90.10%	82.60%	92.50%	77.40%	88.20%	86.16%
running	96.40%	100.00%	95.50%	100.00%	83.00%	94.98%
stationary	97.40%	99.60%	98.60%	95.70%	99.30%	98.12%
bicycling	96.90%	98.50%	98.30%	97.70%	97.40%	97.76%
goingUpstairs	96.30%	80.00%	85.60%	87.90%	72.60%	84.48%
goingDownstairs	77.80%	81.30%	83.30%	84.20%	79.20%	81.16%
Weighted Avg.	95.20%	97.30%	97.20%	93.30%	96.10%	95.82%

Table 13: The acccurcy of Mizell's method

Accuracy						
	1	2	3	4	5	Average
walking	78.90%	83.40%	91.10%	67.90%	86.50%	81.56%
running	89.30%	86.00%	95.50%	95.70%	83.00%	89.90%
stationary	97.10%	99.90%	100.00%	99.90%	99.80%	99.34%
bicycling	96.20%	98.00%	98.30%	97.70%	98.90%	97.82%
goingUpstairs	48.10%	31.40%	44.40%	42.40%	14.30%	36.12%
goingDownstairs	34.90%	25.00%	38.10%	34.20%	36.10%	33.66%
Weighted Avg.	90.40%	96.30%	96.20%	94.10%	93.90%	94.18%

The acccurcy of calories comsumption estimation

We showed calories comsumption estimation here for each day data. We compared two method, our proposed method and Mizell's method. The unit of calories compumption is Kcal. Also,we use the error rate defined in 19 to evaluate how good the methods are. MM is the estimation using Mizell's Method. PM is the the estimation using Proposed Method. GT is the Ground Truth which assume the variable values we got are correct. errorMM is the error rate of estimation in Mizell's Method. errorPM is the error rate of estimation in proposed method. Table 9.2, 9.2, 9.2, 9.2, 9.2

We noticed that the accuracy of the walking of Day 2 in Mizell's Method was slightly better than in Proposed method in activity recogntion part. But it is a huge better in calories consumption estimation because when we make the calaries estimation for walking, the walking data were classfied to going upstairs and going downstairs by mistake in our method and they are classified to stationary and going upstiairs in Mizell's method. The calories burn of going downstairs are absolutely more than those of stationary.

Day 1					
	MM	PM	GT	errorMM	errorPM
walking	592.1	448.3	352.3	68.06% 2	7.25%
running	31.5	32.4	32.9	-4.21%	-1.34%
stationary	320.8	314.7	284.5	12.75%	10.60%
bicycling	126.8	129.9	130.8	-3.07%	-0.68%
goingUpstairs	86.2	135.0	139.4	-38.14%	-3.16%
goingDownstairs	66.3	103.1	116.9	-43.23%	-11.79%
Total	1223.7	1163.4	1056.7	15.80%	10.09%

Day 2					
	MM	PM	GT	errorMM	errorPM
walking	266.1	275.2	186.7	42.53%	47.46%
running	58.6	49.2	49.2	19.10%	0.00%
stationary	373.6	377.4	372.5	0.31%	1.31%
bicycling	232.0	233.3	233.0	-0.42%	0.14%
goingUpstairs	46.0	73.5	86.9	-47.02%	-15.39%
goingDownstairs	29.5	56.1	60.6	-51.26%	-7.38%
Total	1165.0	1220.3	1148.3	1.45%	6.27%

Day 3					
	MM	PM	GT	errorMM	errorPM
walking	261.4	246.3	199.1	31.29%	23.73%
running	71.0	70.0	71.0	0.04%	-1.46%
stationary	348.2	370.5	348.2	0.00%	6.39%
bicycling	232.0	233.3	233.0	-0.42%	0.14%
goingUpstairs	147.6	208.1	235.8	-37.37%	-11.72%
goingDownstairs	44.9	70.6	79.4	-43.49%	-11.07%
Total	1105.2	1198.8	1166.5	-5.25%	2.77%

Day 4					
	MM	PM	GT	errorMM	errorPM
walking	434.1	406.7	263.8	64.58%	54.20%
running	51.9	52.8	52.8	-1.66%	0.00%
stationary	476.4	567.2	475.5	0.20%	19.29%
bicycling	348.9	353.7	356.07	-1.99%	-0.66%
goingUpstairs	92.8	145.6	162.8	-42.95%	-10.52%
goingDownstairs	39.4	63.8	68.7	-42.66%	-7.19%
Total	1443.6	1589.7	1379.5	4.65%	15.24%

Day 5					
	MM	PM	GT	errorMM	errorPM
walking	492.6	468.9	338.4	45.58%	38.56%
running	94.2	96.5	100.4	-6.18%	-3.90%
stationary	483.5	496.0	480.3	0.66%	3.27%
bicycling	981.0	972.0	987.4	-0.65%	-1.56%
goingUpstairs	160.7	353.9	448.1	-64.14%	-21.04%
goingDownstairs	76.1	114.7	132.6	-42.58%	-13.47%
Total	2288.2	2502.0	2487.3	-8.01%	0.59%

9.3 Active learning

We showed the result of active learning using the data of Day 2 for least confident, margin sampling, entropy in Uncertainty Sampling strategies. We would not want users need to keep labelling under reality so we focus on the number of points seen less than 30. We found out entropy method reach the best performance Figure 7, 8, 9. Then we showed the result of the error rate defined in Table 19 and physcial activity recognition using entropy method in 21, 60, 120 point that we know their class Table 14, 15.

9.4 Conclusion

In this paper, mainly we investigated phyiscal activity recognition using mobile phone with built-in accelerometer and gyrocope sensors. We used the technology to estimate

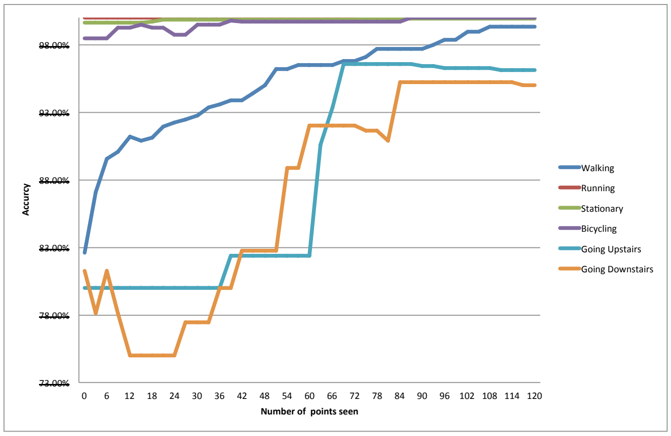

Figure 7: The result of using least confident

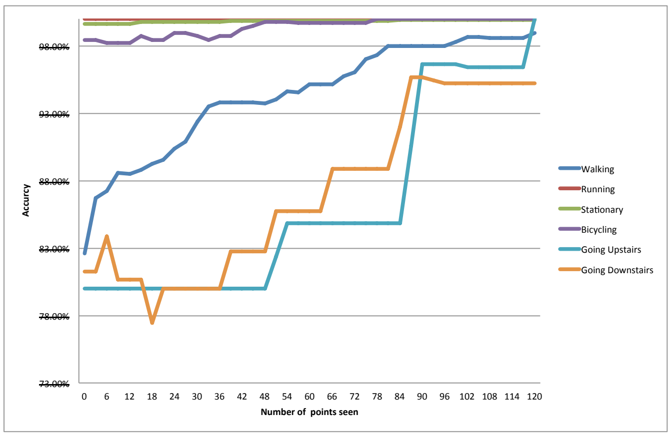

Figure 8: The result of using margin sampling

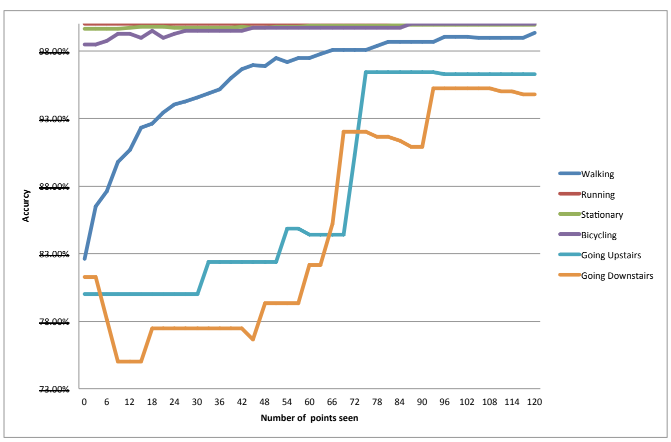

Figure 9: The result of using entropy

the physcial activity amount and calories consumption for users. The low pass filter was not helpful in our data because of the low sample rate. Since the phone's position in the font trousers front pocket is varying from everytime. We explored orientation indepentent features from serveral way for six most common activities. The feature extraction we tried is directly from magnitudes, vertical, horizonal components, vertical and horizonal variation component etc; And

Table 14: activity recognition result of Day 5 in different number of points required

	0	21	60	120
walking	82.60%	93.40%	97.50%	99.30%
running	100.00%	100.00%	100.00%	100.00%
stationary	99.60%	99.80%	99.80%	99.90%
bicycling	98.50%	99.00%	99.70%	100.00%
goingUpstairs	80.00%	80.00%	84.40%	96.30%
goingDownstairs	81.30%	77.40%	82.10%	94.70%

Table 15: the result of Day 5 in different number of points seen

	0	21	60	120
walking	47.43%	17.74%	8.71%	2.59%
running	0.00%	0.00%	0.00%	0.00%
stationary	1.31%	0.77%	0.40%	0.20%
bicycling	-0.91%	-0.73%	-0.26%	0.00%
goingUpstairs	-15.39%	-15.39%	-10.87%	-3.41%
goingDownstairs	-7.38%	-14.48%	-11.25%	-2.91%
total	6.27%	0.86%	0.08%	0.13%

indirectly from the components clustering. For walking, going upstairs and going upstairs, they are the hardest ones to be recognized. In our approach, we added the variation component and the angle component to recognize these similar activities because the variation in vertical and horizonal way is always different as well as their angle change during these activities. Eventally, we found out the SVM was the best in five algorithm with directly feature extraction from the components. In the calories comsumption estimation part, we noticed the the accuracy of the physical activities was not the only factor to influence the result of calories comumption estimation. The confusing activities also affected the result. We consided two possible way to solve the problem. Eventually we chose active learning because we wanted to achieve our two goals at the same time.

There are still a problems worth further consideration. sensor data calibration,We noticed it was different in different mobile phone when we estimated gravity by accelerator and gyroscope. Even for the same phone, one stationary orientation has distinct estimated gravity readings between facing up and facing down so the angle component in these two case are not the same. How to calibrate sensor readings and normalize them to the same scale across mobile phones is a problem.

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