Classification of movement data and user's activity recognition via mobile phones

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### THE IDEA

## Motivation

MIT Technology Review

# 10 BREAKTHROUGH TECHNOLOGIES 2013

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### THE IDEA

### The challenge

- Collect user activity information with a smart-phone
  Position, speed, altitude and time information
- Analyze collected data using the smart-phone
  - Real-time classification of user's movement
- Visualize user trail
- Store user information in a data repository for future usage
  - Extract habits and make recommendations

GPSTracker

Android Application

http://galaxy.hua.gr/~it20934/

#### COMPARISON

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### **Related Applications**

#### **MyTracks**



#### **RunKeeper**





#### COMPARISON

### Features

Application	Motion Classification	Show on map	Biosignals
MyTracks	No	Yes	Yes
RunKeeper	No	Yes	Yes
GPSTracker	Yes	Yes	No

#### **APPLICATION ARCHITECTURE**

### **GPSTracker Architecture**



#### WIMS 2014 - Thessaloniki 20GPSTPacker

### Data Recording

- Android Service running in background
- Features
  - Longitude, Latitude, Average speed, Smoothed average speed, Near Metro Station, Altitude, Altitude change, Timestamp, Time zone, Day of the week, GPS Signal status
- An instance (*movement*) every 30 sec



### Movement Classification

- Recognize the type of each user movement
- Movement Types: Walking, Running, Biking, Driving, Metro, Bus, Motionless
- Collect training data for every type
- Build a *classification model*
- Store the model in the device
- Classify every new movement instance

### **Training Data Collection**







### Classification algorithm

- Weka API for Android https://github.com/rjmarsan/Weka-for-Android
- Tree-based classifiers
  - Fast predictions on mobile devices
  - Light model
  - Good performance
- RandomForests had the best performance

### Real-time Trail Visualization

Google Maps API for Android









### Visualization of stored trails





### Repository of user trails

- Upload user files to an online data repository
- Use Dropbox API so that data are stored in a private repository for each user



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### EXPERIMENTS

# Training Dataset

- 4518 training samples
- 10-fold cross validation on the training data
- Tree-based classifiers
- RandomForests had the best performance (92.81±0.99 at 99% confidence level)
- Confident model for movement predictions

Movement Type	Number of training samples			
Walking	770			
Running	177			
Biking	343			
Driving	650			
Metro	1256			
Bus	534			
Motionless	788			
Algorithn	n Accuracy (%	Accuracy (%)		
J48	90.73	90.73		
LMT	85.79	85.79		
RandomFore	ests <b>92.81</b>	92.81		
REPTree	87.61	87.61		
RandomTre	e 91.05	91.05		

#### **EXPERIMENTS**

### Learning Curves - Random Forests



2/6/2014

### CONCLUSIONS

### Future Work

- Extension of the set of features for motion classification
- Long term analysis of user information
- Post-processing of movement data from multiple users
  - using a shared data repository (and users' consent)
  - extract significant places and user habits
- Geospatial extension of SQLite RDBMS including public transportation stops and routes, parks, malls and shopping areas
- Personalized notification system

# Thank you for your attention?

## **Questions**?





### Accuracy on test data

Algorithm	Accuracy %	Accuracy % (no speed smoothing)
J48	89.12	88.43
LMT	80.47	84.33
RandomForests	92.14	92.00
REPTree	86.55	86.71



### Confusion matrix on test data

a	b	С	d	е	f	g	<-classified as
135	2	0	2	2	2	11	a = Walking
1	32	0	0	0	0	1	$\mathbf{b} = \mathbf{Running}$
1	0	70	0	0	0	0	c = Biking
1	0	0	127	1	0	1	d = Driving
4	0	0	0	243	2	1	e = Metro
12	0	0	0	1	93	1	f = Bus
12	1	0	1	4	1	139	g = Motionless