Context Awareness for GPS-Enabled Phones

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BIOGRAPHY

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ABSTRACT

We study the problem of recognizing the motion mode of users using solely signals from phone embedded GPS receiver and 3-D accelerometers. Motion mode recognition is motivated both by its usage in low-cost inertial aiding systems and as a preprocessing step for other motion mode dependent algorithms. Drawbacks of traditional inertial navigation can be mitigated by context information, enabling automatic zero-velocity updates and pedestrian dead-reckoning mechanization. As an example of other applications, we present 3-D acceleration based road condition monitoring system. The algorithms developed for this study are tested with real data collected with mobile phones, resulting in a realistic identification of limitations and possibilities of context-aware positioning applications.

1 INTRODUCTION

Modern mobile phones include GPS receivers, enabling the development of location based services. However, the usage of GPS often suffers from poor signal quality. In urban canyons and inside tall buildings, the received signal is corrupted by multipath and is very weak. Thus, the accuracy of the position solution is degraded, and often cannot be provided at all. Inertial navigation systems (INSs) can provide position and velocity in the absence of external signals, and thus can be used to improve GPS availability and accuracy.

INS mechanization normally requires high-quality gyros and accelerometers as sensor noise is integrated many times in the process. Such sensors cannot be embedded into mobile handsets due to high cost, power consumption and size. On the other hand, low-cost inertial microelectromechanical sensors (MEMS) can be easily integrated to consumer devices. In order to avoid problematic integrations of INS mechanization, special constraints can be applied to the mechanization. One such constraint is to concentrate on pedestrian movement and count steps to obtain distance traveled. Such approach is commonly referred as to pedestrian dead reckoning (PDR). Another way to reduce inertial errors is to estimate sensor offsets when the unit is detected to be non-moving, a method commonly referred to as zero-velocity update (ZUPT).

Both PDR and ZUPT require knowledge of the motion mode, preferably obtained without GPS (or any GNSS) to keep the system errors independent. In this paper, the goal is to find out how well motion modes of interest can be distinguished from each other. As 3-D accelerometers are already included in mobile devices such as phones (Nokia N95, Apple iPhone), acceleration data was selected as the input for the algorithm. Our approach to motion mode recognition consists of the following steps:

- Collect a labeled training set including data from all motions of interest.
- Select features from the training data that can be used to discriminate one motion mode from another.
- Use the selected features to build a statistical model of the training data.
- Apply a discrimination procedure for the future observations, using maximum a posteriori as a decision rule.

Most known applications of pattern recognition are related to speech recognition and image processing, but there has been growing interest in these methods in the navigation field [8, 5, 4]. Closely related applications are activity monitoring using mobile phones [16], gesture recognition using accelerometer data [10], and accelerometer-based sports performance analysis [12]. In this study, we will restrict the classification problem to modes of transportation which are distinguishable by acceleration data (but GPS speed is used when available). As the resources (power, CPU time) are limited in mobile environment, we try to keep the algorithm complexity and data rates as small as possible.

An outline of the paper is as follows. In Section 2, we describe the basic mathematics needed to solve the recognition problem. In Section 3, the motion modes of interest are presented, along with features that can be used for discrimination. In Section 4, we link the motion mode recognition algorithm with accelerometer-based road anomaly detection. Finally, in Section 5 we introduce a framework to pass the recognition results via internet to other users, enabling co-operative use of context information.

2 PATTERN RECOGNITION

In of the simplest forms, pattern recognition is discrimination between p multivariate normal populations. The Bayes theorem is applied to obtain the probability of the originating population class (motion mode in our examples) given the observation vector.

First, a training data set with known states is collected to obtain

$$\mathbf{z}_j \sim \mathrm{N}(\mu_j, \Sigma_j), \tag{1}$$

the distribution of observed q-vector $\mathbf{z}$ given that the observation comes from population class j. The mean vector $\mu_j(q \times 1)$ and the covariance matrix $\Sigma_j(q \times q)$ are actually estimates and not perfectly known, but we will proceed with the assumption that there is no uncertainty in μ_j and Σ_j. This assumption holds well if the training data set is large. Furthermore, we assume that the training data cannot be used to specify the prior probability $P(C_j)$, the probability of event that the future observation comes from class j. $P(C_j) = \frac{1}{p}$ is a safe choice. For the departure from these assumptions [3] provides interesting insight.

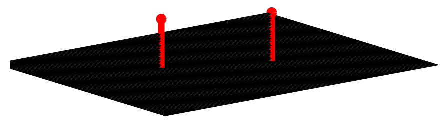

Figure 1: Uninformative prior probabilities.

To proceed with recognition, we define a discrete type random variable

$$\mathbf{x} : \Omega \to \mathbb{R}^q,$$

mapping events such that

$$\mathbf{x}(C_j) = \mu_j. \tag{2}$$

Using this definition, $\mathbf{z}$ can be thought of as an observation of true state corrupted by zero mean noise with covariance Σ_j. Now we have the prior probability mass function (Fig. 1)

$$p_{\mathbf{x}}(x) = \begin{cases} \frac{1}{p} & \text{if } x = \mu_{j \in \{1,\ldots,p\}} \\ 0 & \text{otherwise.} \end{cases}, \tag{3}$$

and $\mathbf{z}$ given $\mathbf{x} = \mu_j$ has multivariate normal distribution

$$\mathbf{z}|\mathbf{x} = \mu_j \sim \mathrm{N}(\mu_j, \Sigma_j). \tag{4}$$

The unconditional distribution of the observation is (Fig. 2)

$$p_{\mathbf{z}} = \sum_{j=1}^{p} p_{\mathbf{z}|\mathbf{x}=\mu_j} p_{\mathbf{x}}(\mu_j). \tag{5}$$

Defining $p_{\mathbf{z}|\mathbf{x}} = 0$ if $p_{\mathbf{x}} = 0$, we can apply Bayes' theorem,

$$p_{\mathbf{x}|\mathbf{z}} = \frac{p_{\mathbf{z}|\mathbf{x}} p_{\mathbf{x}}}{p_{\mathbf{z}}}, \tag{6}$$

resulting the desired probability mass function (Fig. 3). The actual recognition is then made by selecting class j that has the highest probability. This selection rule forms a decision boundary to $\mathbb{R}^q$, which can be used to compute probabilities of misclassification (as described in Figure 4). Applying Eq. 2 we can now state the pattern recognition problem with very similar terms as (a Bayesian interpretation of) a Kalman filter, with observation equation

$$\mathbf{z} = \mathbf{x} + \mathbf{n}_j, \tag{7}$$

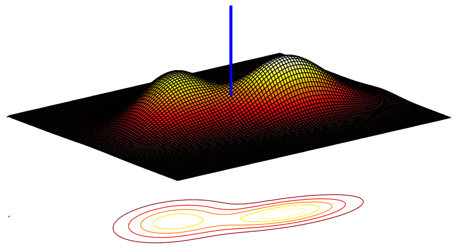

Figure 2: Distribution of the observation, $p(\mathbf{z})$.

where $\mathbf{n}_j \sim \mathrm{N}(0, \Sigma_j)$ is the noise vector with covariance being dependent on the true state C_j. For the 'prediction' equation we need to define probability matrix (transition matrix) that describes how $\mathbf{x}$ evolves over time. We will describe $\mathbf{x}_t$ as Markov chain, defining

$$\pi = [p_{\mathbf{x}}(\mu_1)\ p_{\mathbf{x}}(\mu_2)\ \ldots p_{\mathbf{x}}(\mu_p)]^T . \tag{8}$$

Probability matrix Φ tells us how distribution of $\mathbf{x}$ changes over time step,

$$\Phi = \begin{bmatrix} P(\mathbf{x}_t = \mu_1 | \mathbf{x}_{t-1} = \mu_1) & P(\mathbf{x}_t = \mu_1 | \mathbf{x}_{t-1} = \mu_2) & \cdots \\ P(\mathbf{x}_t = \mu_2 | \mathbf{x}_{t-1} = \mu_1) & P(\mathbf{x}_t = \mu_1 | \mathbf{x}_{t-1} = \mu_2) & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix}, \tag{9}$$

where sum of the elements in any column must be one. Prediction step is then obtained by

$$\pi_t = \Phi \pi_{t-1}, \tag{10}$$

and distribution of $\mathbf{x}$ (Eq. 3) can be updated accordingly. As in Kalman filtering, the successive predictions without observations tend to make the distribution more flat (assuming there are no absorbing states). For regular Markov system $\lim_{k\to\infty} \Phi^k$ times any π_0 yields the steady state probability vector π_∞, and $\pi_\infty = \Phi\pi_\infty$. Furthermore, if $\Phi^T = \Phi$, in the limiting distribution π_∞ all states are equally probable [2]. That is a reasonable requirement, as

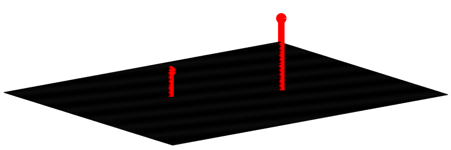

Figure 3: Posterior (mass) distribution, given the observation marked with blue line in Figure 2.

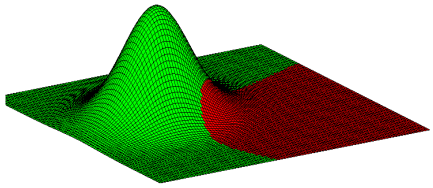

Figure 4: Distribution of $(Z|\mathbf{x} = \mu_2)$ and the decision boundary. Integral of this distribution over the red area gives the probability of error given the true state is 2.

we started with equiprobable states in Eq. (3). Then, as time passes and no observations are available, we will return to the probabilities we used at the very beginning. The motivation for using state transition probabilities in motion mode recognition is the fact that the motion mode does not change very often. If person is walking, it is very likely that he/she will be walking after five seconds. This can be modeled by having elements close to one in the diagonal of Φ.

To summarize, we have prediction step (Eq. 10) and observation update step (Eq. 6) as in Kalman filtering. The major difference is that the process to be estimated is a discrete process. If one wants to exploit additional information of future observations (as in Kalman smoothing), a Token Passing algorithm can be implemented in this framework [17, 5]. Essentially, we formulated a hidden Markov model (HMM) in a way that is more familiar to the navigation community. Reference [11] gives a thorough discussion of similarities between HMMs and Kalman filtering.

3 MOTION MODE RECOGNITION

For the motion mode recognition, we use features that are extracted from the accelerometer signal. Modern smartphones, such as Nokia N95, include a 3-D MEMS accelerometer, and the data interface is relatively easy to use. We use N95 accelerometer data in this study, with input range $\pm 2g$ and 8-bit resolution [16].

The 3-D MEMS accelerometer contains a small seismic mass, and the forces acting upon it are measured to deduce acceleration with respect to inertial space [14]. More precisely, the measurement of the accelerometer is acceleration in inertial space minus the local gravity vector (gravitational forces are locally unmeasurable). Output is thus

$$a_B = C_L^B[\ddot{r} - g], \tag{11}$$

where r is position vector in chosen reference coordinate frame L, $\ddot{r}$ denotes second time derivative of r, and g is local gravity vector. For simplicity, reference frame L is assumed to be a non-rotating, non-accelerating frame. A direction cosine matrix C_L^B transforms vectors from local reference frame L to the body frame B (defined by sensor sensitivy axes). In inertial navigation this matrix is updated using gyroscopes, and in the present application this matrix remains unknown. In addition, orientation information via C_L^B would not be informative for motion state recognition in personal positioning, as orientation can be arbitrary with respect to the moving platform. To remove the effects of orientation, the Euclidian norm of the accelerometer output is used:

$$\|a\| = \sqrt{a^T a}, \tag{12}$$

where $\|a\|$ is the input to the recognition algorithm, and a is the measured specific force vector. A direction cosine matrix is orthogonal, and invariancy to changes in orientation follow directly from this property:

$$\begin{aligned} \|a_B\|^2 &= a_B^T a_B \\ &= [C_A^B a_A]^T C_A^B a_A \\ &= a_A^T [C_A^B]^T C_A^B a_A \\ &= a_A^T a_A \\ &= \|a_A\|^2 \end{aligned}$$

Combining Eqs. (11) and (12) yields

$$\begin{aligned} \|a\| &= ([\ddot{r} - g]^T [\ddot{r} - g])^{\frac{1}{2}} \\ &= ((\ddot{r}_x - g_x)^2 + (\ddot{r}_y - g_y)^2 + (\ddot{r}_z - g_z)^2)^{\frac{1}{2}} \end{aligned}$$
$$. \tag{13}$$

Equation (13) shows that $\|a\|$ is zero only if the sensor unit is in free-fall motion. In addition, $\{\ddot{r} \mid \|a\| = \|g\|\}$ is a sphere centered at g. Thus, there are two types of motions, where $\|a\|$ equals the norm of local gravity: $\ddot{r} = [0\ 0\ 0]^T$ and certain downward accelerations that occur infrequently. Thus, if $\|a\|$ equals the norm of local gravity, it is very likely that the unit is not accelerating. Exact agreement cannot be expected due to sensor noise. In practice all vehicles vibrate when moving, and accelerometers measure that vibration. Thus, an immobile unit can be detected by analyzing the mean and variance of the accelerometer signal. Equation (13) is the basis for our further analysis.

3.1 Modes of Interest

The motion modes of interest for navigation applications are static, walking motion, and driving. Bicycling is also a mode that need to be studied, as accelerometer signals are quite similar when walking and bicycling.

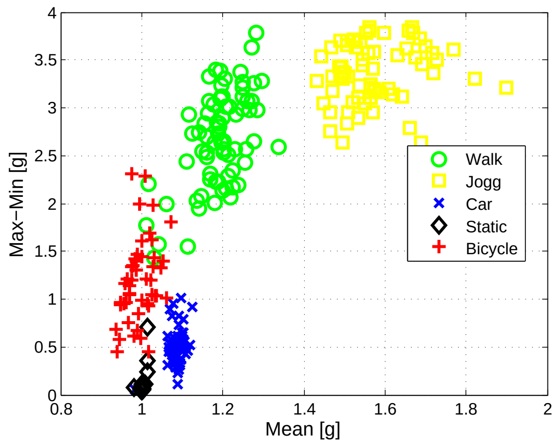

Figure 5: Training data, mean and max-min of each 5 second sample.

Static Successful detection of static unit (e.g., non-rotating, zero velocity in the Earth-fixed frame) would be very useful for many navigation algorithms. Doppler positioning algorithms can be applied [7]. All range observations from radionavigation system can be projected to same measurement epoch, and thus accuracy of position estimate will be improved. Observed delta-ranges can be considered as noise, which makes accuracy estimation easier. And, as the unit is not moving, the power consuming radionavigation hardware can be switched off until the user starts to move again [13]. Furthermore, gyro biases become observable as the input angular-rate is known (zero or the Earth rate, depending on the required precision). Features that are useful in detecting a stationary unit are sample mean and variance-related statistics, such as maximum value minus minimum value (Fig. 5). Noise of the sensor causes feature variations even when the unit is not moving. Sample variance statistic from normal population has χ^2 distribution [6], so normality assumption does not hold for this feature.

Driving When the unit is attached to a passenger car, the measured accelerations will include vibration due to the engine, and more importantly accelerations due to road imperfections such as road bumps. This fact makes it possible to perform simple road condition analysis with an accelerometer and GPS receiver. Figure 6 shows max-min (range) feature along with GPS speed.

Walking Demands for sensor accuracy in PDR are significantly lower than for the traditional inertial navigation. The double integration of accelerations is avoided by recognizing step occurrences and propagating the position step by step. The main sources of error are step length error and heading error, which grow in time slower than with the INS mechanization. Distinct

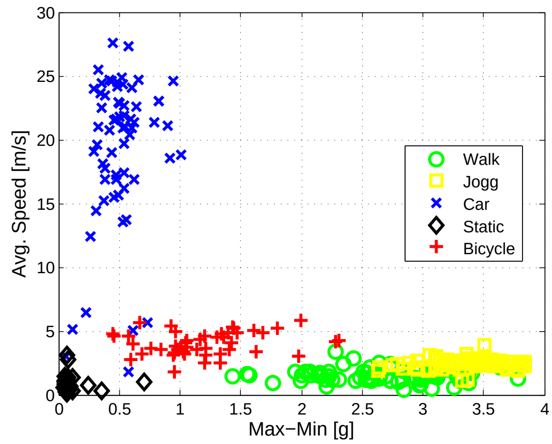

Figure 6: Training data, max-min and average speed of each 5 second sample.

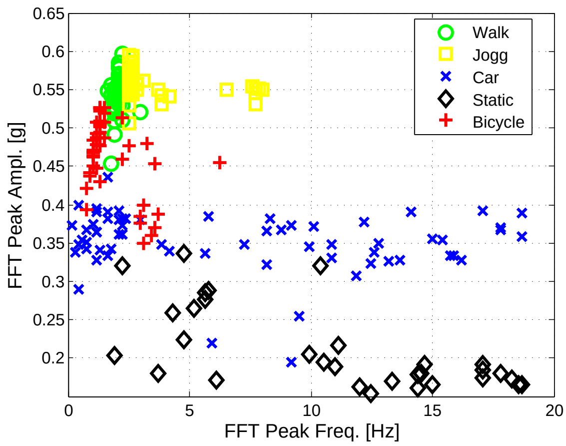

Figure 7: Training data, FFT peak frequency and amplitude of each 5 second sample.

features for walking are in frequency domain (peak frequency and amplitude, Fig. 7) and variance. We also included Jogging-mode, which might be of use in PDR step length algorithms and sport applications.

Bicycling Bicycling is not necessarily a motion mode of interest, but it is good to compare data from walking mode and bicycling. Misclassification of walking when person is actually bicycling can be disastrous for the PDR algorithm. To avoid this, features such as the zero-crossing rate and mean value seem to be useful, as shown in Figure 8.

The training data shown in the figures is a relatively small set of data, with less than hundred samples per class. In addition, the set was collected by single person and single mobile phone. Another training set, as described in [5], had much more data and was collected by various people and various sensors. GPS speed was not used in that study. We

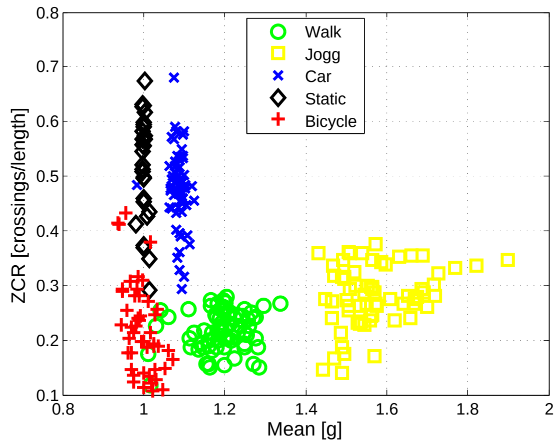

Figure 8: Training data, mean and zero-crossing rate of each 5 second sample.

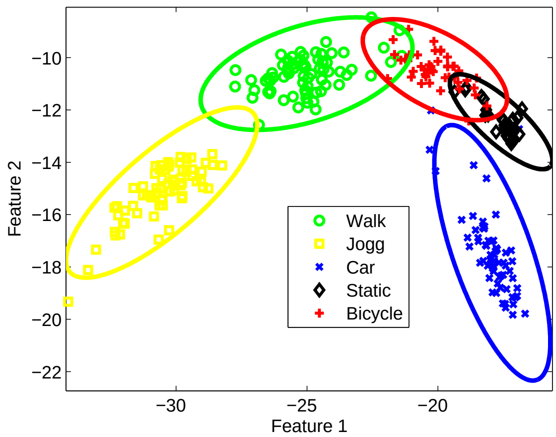

Figure 9: Training data projected onto best two linear discriminant directions. GPS speed information is used.

can compare visually these two distinct sets by applying principal component analysis and dimension reduction as described in [15]. By comparing Figures 9 and 10, it is clear that individually collected training data yields better separability. In particular, the Driving-mode spreads over other modes if there are many vehicles (with different vibration profiles) involved. The figures include contours enclosing 99 % of the probability mass, computed using a Gaussian fit. GPS speed also helps to move the Driving-mode distribution away from other distributions. The downside of individual training is the effort needed for labeling the training set - individuals may not adapt easily to systems that require this sort of work.

Misclassification rates for mode j can be computed by integrating the conditional distributions (Eq. 4) over each decision area. The results are shown in confusion matrix form in Table 1, where each row has decision probabilities (DW=

Table 1: Confusion matrix computed using fitted Gaussian distributions

	DW	DJ	DD	DS	DB
TW	0.97	0.003	$5 \cdot 10^{-8}$	$4 \cdot 10^{-10}$	0.02
TJ	0.004	0.99	$1.8 \cdot 10^{-20}$	$6 \cdot 10^{-34}$	$4 \cdot 10^{-12}$
TD	$8 \cdot 10^{-8}$	$7 \cdot 10^{-37}$	0.999	$3 \cdot 10^{-4}$	$7 \cdot 10^{-4}$
TS	$1.4 \cdot 10^{-13}$	0	$1.1 \cdot 10^{-4}$	0.97	0.03
TB	0.009	$2 \cdot 10^{-35}$	$2.6 \cdot 10^{-4}$	0.04	0.95

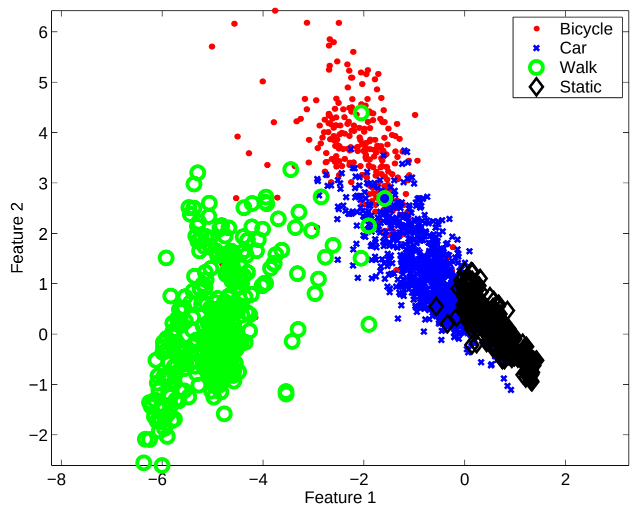

Figure 10: Training data from [5] projected onto best two linear discriminant directions.

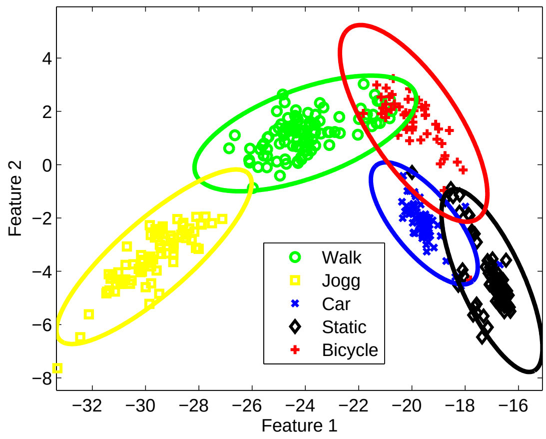

Figure 11: Training data projected onto best two linear discriminant directions. GPS speed information is not used.

decision *walk*, DJ= decision *jogging*, ...) given the true state (TW=Walk, TJ=Jogging, ...). These probabilities are a bit optimistic, because they rely on following assumptions:

1. Assumption of normally distributed feature statistics
2. Assumption that covariance and mean estimates are exact
3. Assumption of independent samples (feature statistics tend to be correlated)
4. Training data is personal
5. Assumption that there is always well-defined 'true' motion mode that is included in the list

To cope with the first two assumptions, leave-1-out classification results were computed and the results are shown in Table 2. This method gives larger misclassification rates, verifying the well-known fact that one should always test the recognition results with samples that do not belong to the training set. However, it should be noted that if the assumptions *do* hold, leave-1-out method introduces errors to the confusion matrix. The error would be largest for the TB/DB element, ± 0.06 (95% conf.). This value was obtained by Monte Carlo simulation, using the same sample sizes as in our training data, and comparing the exact confusion matrix to the one that leave-1-out method produces. Similarly, the error in Table 1 TB/DB element due to inaccuracies in mean and covariance would be ± 0.03 (95% conf.).

The value of having speed measurement from the GPS receivers can be seen by comparing Figures 9 and 11, the latter showing the results without GPS speed. The role of speed in the decision process is important, as it reduces the misclassification of Driving-mode to other modes when the speed is high.

Table 2: Confusion matrix computed using leave-one-out method

	DW	DJ	DD	DS	DB
TW	0.93	0	0	0	0.07
TJ	0	1	0	0	0
TD	0	0	0.97	0.015	0.015
TS	0	0	0	0.87	0.13
TB	0.02	0	0	0.06	0.92

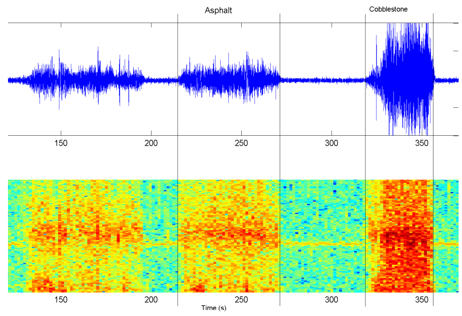

Figure 12: Acceleration measurement and spectrogram, asphalt and cobblestone road.

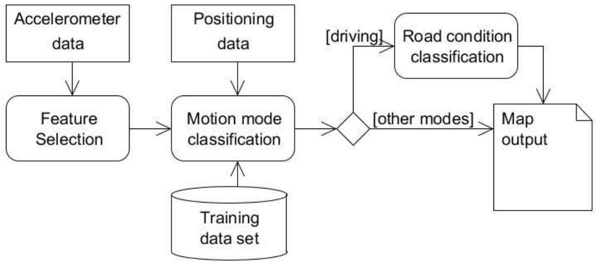

Figure 13: Data flow diagram

4 ROAD ANOMALY DETECTION

Road condition information can be useful for both road users as well as for the road network maintenance. The problem we consider is to find road anomalies that, when left unreported, could cause unnecessary wear of vehicles, lesser driving comfort and vehicle controllability, or an accident. Detection of road anomalies can be thought as a sub-class within the Driving-class described in above. Features such as max-min and signal variance are again important, as can be seen from Figure 12. The procedure for recognition is very similar to motion mode recognition, but the optimal length of samples might be different. This is because a road anomaly such as pothole would show up in the data only for a very short period. In addition, the accelerometer reading should be polled constantly so that all anomalies can be found. In motion mode recognition, the system can be in idle state for long periods, as motion mode transition occurs relatively rarely. The road anomaly detection algorithm will be described in detail in [9]. Optimal combination of motion mode recognition with other subclasses (such as running style, etc.) is one interesting direction for future research.

5 IMPLEMENTATION

The implemented software consists of the following elements:

- Reference data database (labeled training set).
- Feature selection and dimension compression routines.
- Classification by maximum a posteriori rule.
- Software components that send the data from a mobile phone to a web server that displays selected motion mode icon on usert's location.

Collected location-based data is sent in real-time from mobile phones via GPRS to a remote server in a public network, where it is processed to recognize the motion mode. The connection is not necessarily open all the time, so the frequency of updates is adjustable parameter in the software. When the mode is driving, the acceleration and GPS data are used to analyze road condition. At runtime this application uses the following data processing steps: feature extraction from acceleration and GPS signals, feature fusion, and classification. These components were implemented on top of an existing sensor network middleware. Fig. 13 shows the application data flow. As a platform we used Global Sensor Network, an open source sensor network middleware developed in EPFL [1]. It features a modular architecture, easy system configuration, and simple API. The resulting road condition categorization is made available on the middleware, for example for visualizing a publicly available map application in a web browser.

Since the remote server is situated in public network, it allows both road users and road operators to observe the real time situation. In winter, the road condition may change rapidly, making up-to-date information valuable. The system is extendable to new types of in-vehicle and roadside sensors. For example, On-Board Diagnosis (OBD) data and local road weather condition data could be fused with accelerometer data to improve the accuracy of road condition recognition.

6 CONCLUSIONS

The classification results show that accelerometer data can be used to separate the motion modes of interest, but the decision error rate is quite high for navigation filter purposes. For example, bicyclist and pedestrian acceleration waveforms are very similar when the phone is carried in a pocket. If the PDR algorithm is applied to a bicyclist, the results will be very unfavorable. Yet, there are many applications where infrequent false detections can be tolerated; road condition analysis is one such example. As positioning-enabled mobile phones with internet access are becoming more and more common, it will be easy to distribute time and location-dependent information to others. Benefits of context awareness in personal navigation devices are thus twofold – location estimation will be more efficient, and useful location-tagged information can be given for other road users.

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