Activity and Environment Classification using Foot Mounted Navigation Sensors

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Abstract—**Foot mounted navigation systems can be deployed for tracking military personnel, first responders and offenders. Determining the activity and environment of individuals can provide valuable information to those monitoring these individuals. This paper provides activity and environment classification for a foot mounted device that uses an IMU and GPS receiver. Using information from the navigation filter (e.g. velocity), GPS signal tracking parameters, and IMU measurements this paper presents an algorithm that classifies the following activities: indoor, outdoor, stationary, crawling, walking, running, biking, moving in vehicle, level, up or down elevator and up or down stairs. Multiple probability density functions that map each feature (i.e. metric) to an activity are provided. Then a naive Bayesian probabilistic model is used to determine the probability of an activity. To improve reliability and accuracy of the classification several conditions are added. The algorithm shows excellent results for activity classification, however environment classification is less reliable due to variations in GPS tracking abilities as a function of the environment. Results are shown with images from the data collection.**

Keywords-Activity classification; Acvtivity recognition; Motion Analysis; Pedestrian Pattern Recognition; Offender Management; First Responder.

I. INTRODUCTION

Military personnel and first responders, such as fire fighters or police officers, can be equipped with foot mounted location devices in order to coordinate efforts or assist others in distress. Since GPS alone does not provide sufficient continuity and accuracy in all environments, navigation systems often include additional sensors (e.g. accelerometers, gyros, barometers and magnetometers) to improve performance. These sensors can be used in parallel to classify certain activities that can be of interest. Often, activity classification is performed using sensors mounted on the upper body without the use of GPS signals. This paper classifies activities using GPS and sensors mounted on the foot of the user.

A specific application of interest where activity and environment classification are of use is offender tracking. This growing application of navigation technology utilizes GNSS tracking of individuals who pose a risk to society. The classification of activity and environment helps officers monitor the behavior of individuals and can assist in determining if probation orders are breached. Other applications extend to people working alone in dangerous conditions or elderly people whose mobility is limited.

Another benefit of activity classification can be to turn off particular sensors or modify their particular power settings based on activity. For example, GPS receivers could operate in reduced power or be turned off completely when the user is stationary and reactivated when motion occurs. This particular logic can greatly reduce power consumption and improve battery life.

Activity classification has been an openly researched topic during the past few years (e.g. [1], [2]). Classification can provide information to modify the navigation algorithms and improve performance. Other applications are utilizing activity classification to reduce navigation errors (e.g. [3]). Some researcher have focused on the use of multiple fixed body sensors (e.g. [4]), while others have dealt with mobile phone classification (e.g. [5] and [6]). The majority of the studies use raw accelerometer data. Environment detection has also been of interest to assist in filter tuning or multipath classification (e.g. [7]).

The method of classification varies with each study. Most involve aspects of Bayesian logic but different methods are commonly used. A Bayesian network to classify the user's activities is used in [8] where the authors use 19 features computed from the raw IMU data mounted on the waist to determine six activities: sitting, standing, walking, running, jumping, falling and lying down.

This paper utilizes a combination of inertial sensors and GPS measurements for classification. When combined, the system can also provide more information or features that improve classification. The following activities and environments, some of which are subsets of others, classified herein are: walking, running, stationary, moving up stairs, moving down stairs, moving in a vehicle, moving on bike, crawling and moving indoor or outdoor as shown in Figure 1.

The algorithm uses a 10 s window where the probability of each activity is determined based on several metrics (i.e. features) measured by the ankle mounted system. Ten seconds was selected because it achieved a good balance of observing the activity, but not so long as to have multiple activities within the window. The probability of each activity is determined based on a combination of features. Features shown in Figure 2 include cadence, pitch, mean acceleration norms, variances of the gyro and accelerometer norms, average speed, GPS carrier

to noise ratio (C/N$_o$), satellite availability and position accuracy. The paper fuses each activity probability through a naïve Bayesian model. Included are several mutually exclusive rules to enhance accuracy in estimating the true activity.
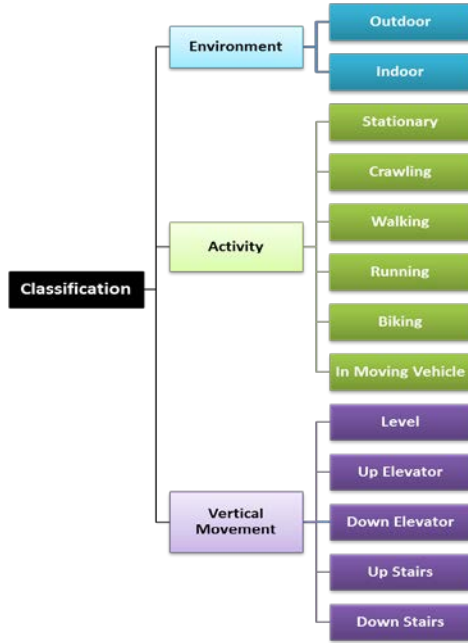

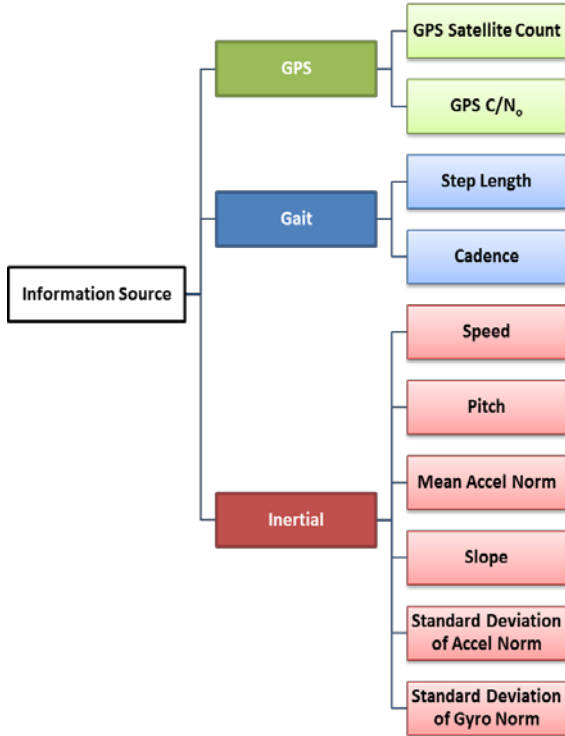Figure 1. Classification of Environment, Activity and Vertical Movement

Figure 2. Feature Sets (i.e. Metrics) used to Classify Activity, Environment and Vertical Movement

II. NAÏVE BAYESIAN PROBABILISTIC MODEL

The sample space (or potential outcomes) for the user's activity is denoted as S_A, the sample space for the environment is detonated as S_E and the sample space for the vertical movement is S_{VM}. The sample spaces (with their uppercase variable names in brackets) are given as

$$S_A \in \begin{cases} \text{Stationary(S), Crawling(C),} \\ \text{Walking(W), Running(R),} \\ \text{Biking(B), Moving In Vehicle(V)} \end{cases} \quad (1)$$

$$S_E \in \{\text{Outdoor(O), Indoor(I)}\} \quad (2)$$

$$S_{VM} \in \begin{cases} \text{Level(L), Up Elevator(UE),} \\ \text{Down Elevator(DE),} \\ \text{Up Stairs(US), Down Stairs(DS)} \end{cases} \quad (3)$$

The feature sets are shown below and are categorized based on three sources, namely GPS based features, gait based features and INS based features:

$$f_{GPS} = \begin{cases} \text{GPS Satellite Count } (n), \\ \text{MeanC/N}_o\ (p) \end{cases} \quad (4)$$

$$f_{Gait} = \begin{cases} \text{Mean Step Length } (l) \\ \text{Mean Cadence } (c) \end{cases} \quad (5)$$

$$f_{INS} = \begin{cases} \text{Mean Speed } (v) & \text{Slope } (m) \\ \text{Mean Pitch } (p) & \text{Std of Accel Norm}(\|\tilde{\alpha}\|) \\ \text{Mean Accel Norm } (\|\alpha\|) & \text{Std of Gyro Norm}(\|\tilde{\gamma}\|) \end{cases} \quad (6)$$

Each feature has a probability density function (PDF) that relates the features observed quantity to a probability of the activity. Since multiple features can relate to the same activity, the probabilities are combined to improve reliability. For example, detecting someone walking is based on speed (v), cadence (c), and step length (l).

The probability of each classification is therefore denoted as

$$P\left(S_A \mid v, c, l, \|\tilde{\alpha}\|, \|\tilde{\gamma}\|\right) \quad (7)$$

$$P\left(S_E \mid n, p\right) \quad (8)$$

$$P\left(S_{VM} \mid m\right) \quad (9)$$

Each feature is considered independent of other features. This assumption, while perhaps simple, is based on the fact that

the features are computed using different methods, although most of the INS and gait parameters are derived from the same IMU data. Although the step length is the integration of the velocity over one step and cadence is the duration of that step, the feature is independent since it relates a different metric that vary for each person. With each feature being independent, a naïve Bayesian classifier is an excellent choice for combining the probabilities.

Combining n independent probabilities using a naïve Bayes assumption is computed as

$$P\left(a \mid x_1, x_2, \ldots\right) = \frac{\prod_{i=1}^{n} P\left(a \mid x_i\right)}{\prod_{i=1}^{n} P\left(a \mid x_i\right) + \prod_{i=1}^{n}\left(1 - P\left(a \mid x_i\right)\right)} \quad (10)$$

This equation is a form of the Bayes Theorem and is based on the measurement probabilities for independent events. Equation (10) does not use $P(a)$ which would indicate the probability of doing a particular activity without any measured data. The ability to predict how often one bikes, runs or rides in a vehicle is far too variable between individual styles and thus the naïve Bayesian classifier can equally weight the probability of activities. This classifier can also provide a confidence of the classification a critical aspect given the number of activities that are outside the sample space.

Consider an example of a user walking at 7 km/h, with a cadence of 1.4 steps/s and a step length of 1.8 m. The $P(W/v{=}7) = 0.658$, the $P(W/c{=}1.4) = 0.541$, $P(W/l{=}1.8){=}0.782$. Each feature does not completely identify the activity as walking, however the combination of all features indicates that the probability of walking is 89.4 %, $P(W/v{=}7,c{=}1.4,l{=}1.8){=}0.894$ and that of running is 6.5 %, $P(R/v{=}7,c{=}1.4,l{=}1.8){=}0.065$, leading to a much more confident classification.

An alternative to the naïve Bayesian classifier is the weighted z transform [9] method. The z transform combination is shown in the following equation. This method converts the probabilities of each feature to normally distributed z scores, combines them using a weighted averaging technique and then converts them back to a probability. Both algorithms provided similar results in the tests presented below, indicating that the combination of different features is the strength of the classification and that the assumption of normal distributions for each feature is acceptable.

$$z_a = \frac{\sum_{i=1}^{n} w_i z_i}{\sqrt{\sum_{i=1}^{n} w_i^2}}, \; z_* \sim N\left(0,1\right) \quad (11)$$

Although included herein as a potential alternative, the z transform is not used in this paper.

There are several general rules that can be used to improve accuracy given the probability of certain events. The following rules are based on the fact that some activities and environments are mutually exclusive (note Equations (1) - (6) provide the variable definitions):

$$P\left(\mathrm{B} \cap \mathrm{I}\right) = 0 \quad (12)$$

$$P\left(\mathrm{V} \cap \mathrm{I}\right) = 0 \quad (13)$$

$$P(\mathrm{US} \mid c = 0) = 0 \quad (14)$$

$$P(\mathrm{DS} \mid c = 0) = 0 \quad (15)$$

$$P(\mathrm{UE} \cap \mathrm{O}) = 0 \quad (16)$$

$$P(\mathrm{DE} \cap \mathrm{O}) = 0 \quad (17)$$

Equation (12) indicates that a pedestrian cannot be on a bicycle while indoors, Equation (13) indicates that one cannot be driving indoors. Equations (14) and (15) indicate that one must be taking steps (i.e. have a nonzero cadence) in order to be going up or down stairs. Admittedly, equation (13) fails when one is driving in an indoor parking lot. Equations (14) and (15) also fail if the subject is on an escalator, but these are considered to be special cases in addition to walking on moving vehicles (e.g. a train). Equations (16) and (17) indicate that one cannot be both outdoors and moving up or down in an elevator.

III. FEATURE MODELS

The average speed of a user over the testing interval is a key feature in classifying activity. This paper models each activity's speed as a distribution (normal, chi-squared or otherwise) which determines the likelihood of that activity given a speed. Table 1 provides the distributions of speed.

All the PDFs in the sample space are normalized, providing the probability of each activity based on the speed. Summing all of the probabilities in the sample space equals one. Figure 3 shows the normalized probabilities based on speed.

Consider the example of a user traveling at 15 km/h. The models selected indicate that there is a 41 % probability of biking, a 30 % probability of running and a 29 % probability of moving in a vehicle. These probabilities are only based on the speed and are unrelated to the user's individual preference to use a vehicle, bike or to run. Additional information is required to improve the detection of the activity and since more sources of information are used, the model's accuracy is not required to be perfect.

TABLE I.   DISTRIBUTIONS OF FEATURES USED FOR ACTIVITY CLASSIFICATION

Source	Stationary	Crawling	Walking	Running	Biking	Moving In Vehicle
Speed (v) (km/h)	$N(0,0.5)$	$N(1,0.5)$	$N(6,1.5)$	χ^2_{12}	$N(15,5)$	$\int_0^\infty N(10,10)$
Cadence (c) (steps/s)	$N(0,0.02)$	$\frac{1}{8}N(0.3,0.1)$	$N(1.2,0.3)$	$N(1.5,0.3)$	$N(0,0.02)$	$N(0,0.02)$
Step Length (l) (m)	$N(0,0.02)$	$\frac{1}{10}N(0.5,0.15)$	$N(1.8,0.5)$	$N(2.2,0.5)$	$N(0,0.02)$	$N(0,0.02)$
Mean Accel Norm($\|\alpha\|$) (m/s²)	$N(9.8,0.3)$	$N(12,1)$	$N(17,3)$	$N(27,5)$	$N(13,1.5)$	$N(10,0.5)$
Std of Accel Norm($\|\tilde{\alpha}\|$) (m/s²)	$N(0,1)$	$N(7,1)$	$N(12,3)$	$N(22,3)$	$N(6,3)$	$N(1,1)$
Std of Gyro Norm($\|\tilde{\gamma}\|$) (°/s)	$N(0,0.4)$	$N(1,0.2)$	$N(2.1,0.6)$	$N(2.7,0.4)$	$N(1,0.2)$	$N(0.3,0.2)$
Pitch (p) (°)	$N(0,10)$	$N(-50,10)$	$N(-16,15)$	$N(-20,15)$	$N(0,15)$	$N(30,20)$
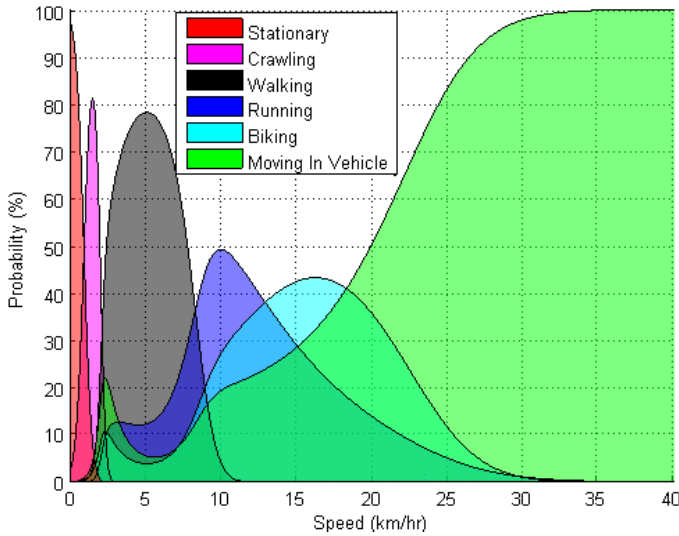
Figure 3.   Probabilities Assigned to Activity Based on the User's Speed

Figure 4.   Probabilities Assigned to Activities based on Cadence (Brown is a combination of red, blue, cyan and green).

Since the IMU and GPS receiver are collocated on the ankle, the mean step frequency (cadence) and mean step length (heel strike to heel strike of one foot) provide valuable information as to the activity. A similar approach to determining the probability of each activity given the mean cadence is shown in Figure 4. Figure 5 shows the activities' probabilities given an average step length.
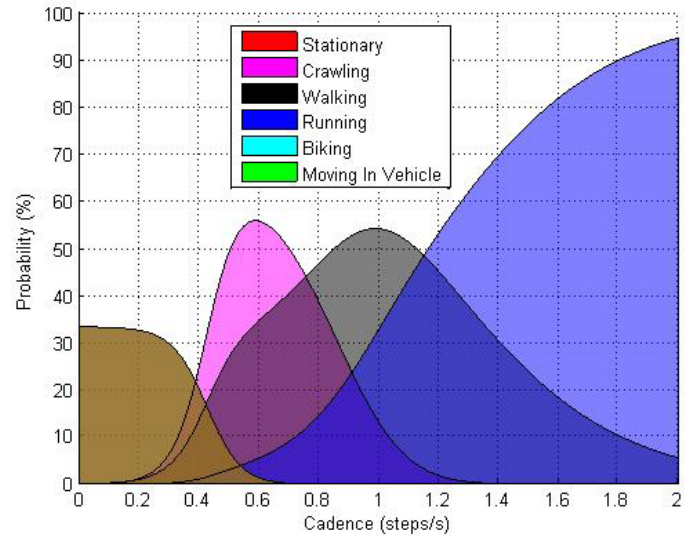
The distributions are generalized for the all people, accepting that shorter people tend to have shorter step lengths and a faster cadence. The distributions for step length and cadence are given in Table 1.
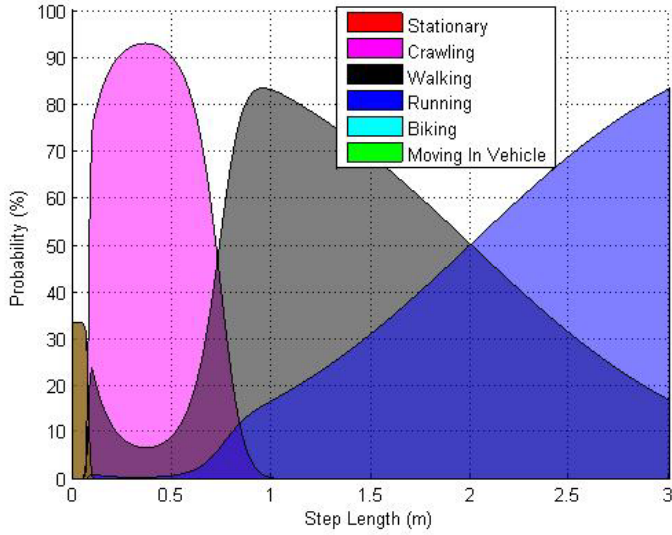
Figure 5.   Probabilities Assigned to Activities Based on the Step Length

The accelerometer's norm and the gyroscope's norm are given as follows:

$$\|\alpha\| = \sqrt{\alpha_x^2 + \alpha_y^2 + \alpha_z^2} \qquad (18)$$

$$\|\gamma\| = \sqrt{\gamma_x^2 + \gamma_y^2 + \gamma_z^2} \qquad (19)$$

The mean of the acceleration norm during the 10 s interval helps in distinguishing running from less vigorous activities such as driving a vehicle. However, it was observed experimentally that crawling and biking have very similar accelerations on the foot, hence other features will be relied upon in these cases. Figure 6 shows the PDFs based on the mean of the acceleration norm.
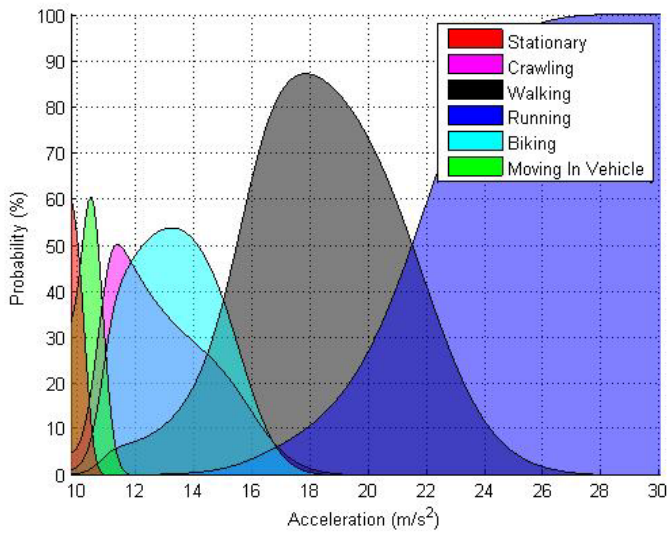

Figure 6.   Probabilities Assigned to Activities Based on the Mean
Acceleration Norm of the Foot Mounted IMU

Using the norm of the accelerometer and gyro measurements, the variance during the interval is computed as

$$\|\tilde{\alpha}\|^2 = \frac{\sum_{i=1}^{n}\left(\|\alpha\|_i - \|\bar{\alpha}\|\right)^2}{n-1} \qquad (20)$$

$$\|\tilde{\gamma}\|^2 = \frac{\sum_{i=1}^{n}\left(\|\gamma\|_i - \|\tilde{\gamma}\|\right)^2}{n-1}. \qquad (21)$$

The accelerometer's variance is a strong indicator of activity independent of speed. A low acceleration variance indicates motion on a vehicle, whereas a high acceleration variance indicates walking or running. This is due to the jerk of heel strike. The acceleration PDFs are shown in Figure 7.
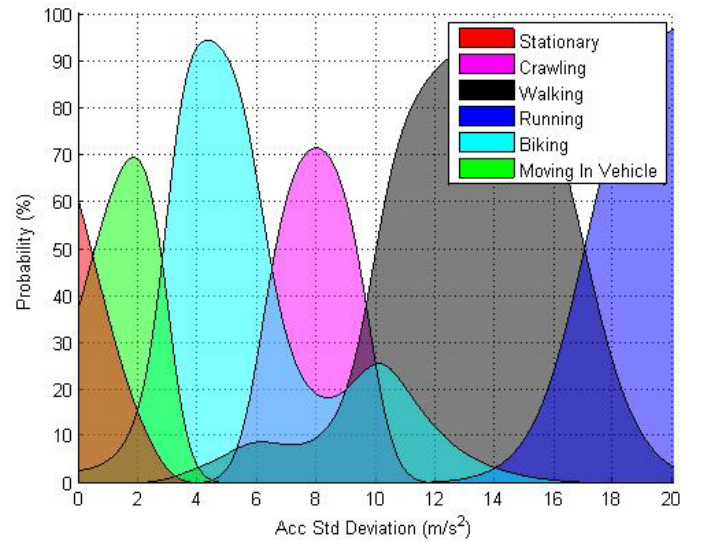

Figure 7.   Probabilities Assigned to Activities Based on the Acceleration
Variance Based on the Foot

Similar to the accelerometer variance, the gyroscope variance is a strong indicator of activity that is independent of speed. Activities such as running and walking have high variances compared to motion on a vehicle. Figure 8 provides the PDFs based on the gyroscope variance.
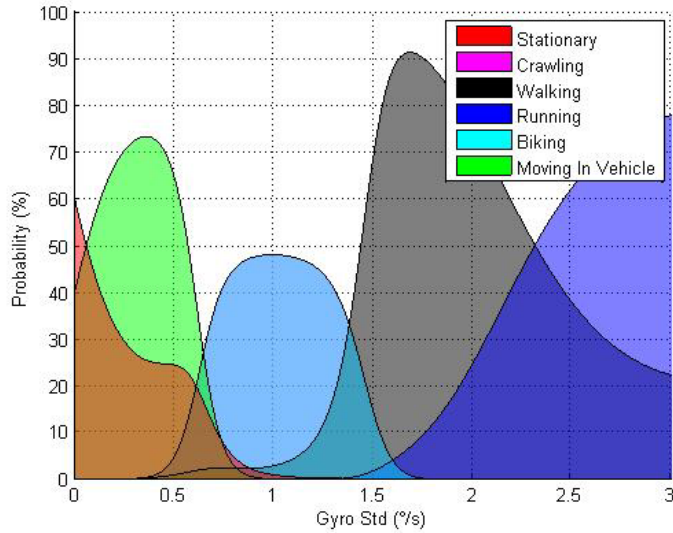
Figure 8. Probabilities Assigned to Activities Based on the Gyro Variance on the User's Foot

The mean pitch of the foot, relative to the local level plane, provides useful information when differentiating between walking and crawling. While crawling, one's foot is typically angled downward. A driver's foot would likely be angled upward in order to use the pedals; using this feature helps in distinguishing driving from biking, which typically does not have the higher pitch angles. Figure 9 shows the PDF of activities based on the mean pitch of the user. Note that positive pitch is upward.
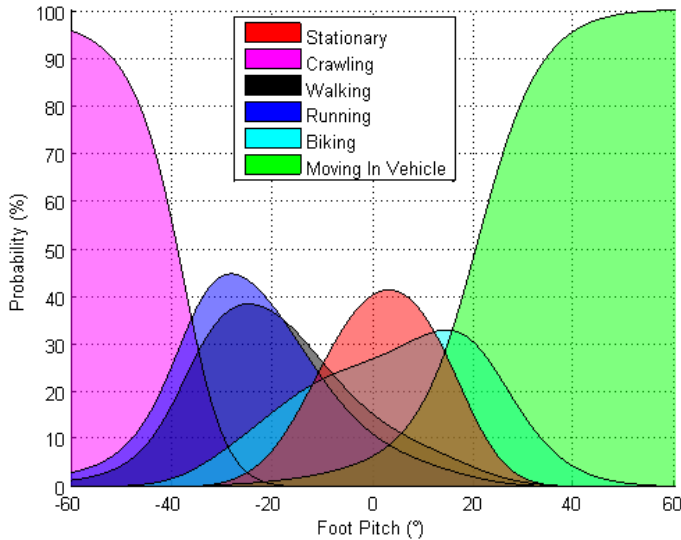

Figure 9. Probabilities Assigned to Activities Based on the Foot Pitch

Given that the inertial solution can provide a more robust elevation than single point GNSS, the change in elevation can be helpful to determine the vertical motion of the user. This feature is helpful in determining when stairs and elevators are used. Slope is the change in the local level vertical axis over the horizontal distance. Slope is computed as

$$m = \tan^{-1}\left(\frac{\Delta h}{\Delta d}\right)$$

(22)

where Δh is the change in height over the interval and Δd is the corresponding horizontal distance. The distributions are given in Table 2.

TABLE II.   TABLE 1 – DISTRIBUTIONS OF ACTIVITIES WITH SLOPE KNOWN

Source	Level	Up Stairs	Down Stairs	Up Elevator	Down Elevator
Slope (m)	$N(0,5)$	$N(30,10)$	$N(-30,10)$	$N(80,5)$	$N(-80,5)$

The normalized distributions for the slope are provided in Figure 10. There are some considerations to take into account in using the slope. Spiral staircases for example provide large height variations but small horizontal position changes. Thus the distance travelled is more appropriately computed by summing the step lengths rather than using two endpoints.
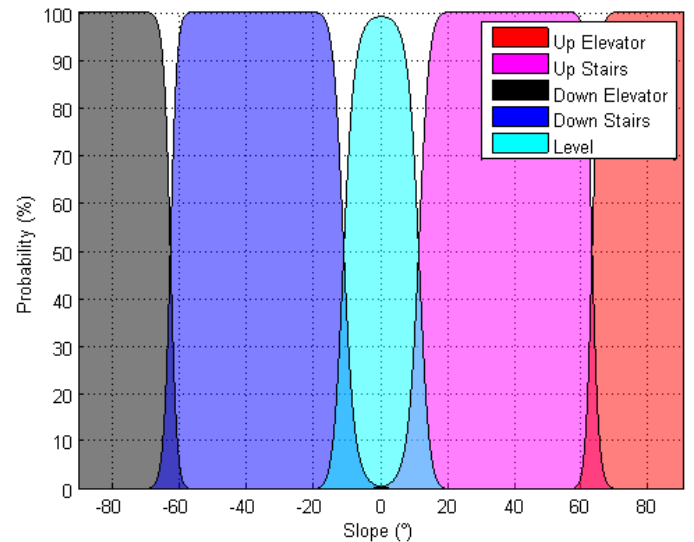

Figure 10. Probabilities Assigned to Vertical Movement Based on User's Slope

Determining the probability of being indoor or outdoor is performed in a similar manner using the number of satellites tracked (i.e. compared to the total number above the horizon) and average carrier-to-noise density (C/N$_o$). A large number of satellites tracked indicates less likelihood of large surrounding obstructions, while higher power indicates less material between user and satellite. Table 3 provides the distribution and Figure 11 shows the PDFs assigned. In this case the cumulative density function is used since the lower and upper bounds are unequal.

TABLE III.   TABLE 2 – DISTRIBUTION OF THE ENVIRONMENT GIVEN SATELLITE TRACKING PARAMETERS

Source	Outside	Inside
Satellites Tracked (n)	$\int_0^\infty N(6, 2.5)$	$1\text{-P}_{outside}$
Mean C/N$_o$ (p)	$\int_0^\infty N(28, 5)$	1-P_{inside}

Figure 11 shows the distribution for the probability of being outside. The mean power levels are subject to different receiver and antenna combinations and internal tracking settings.
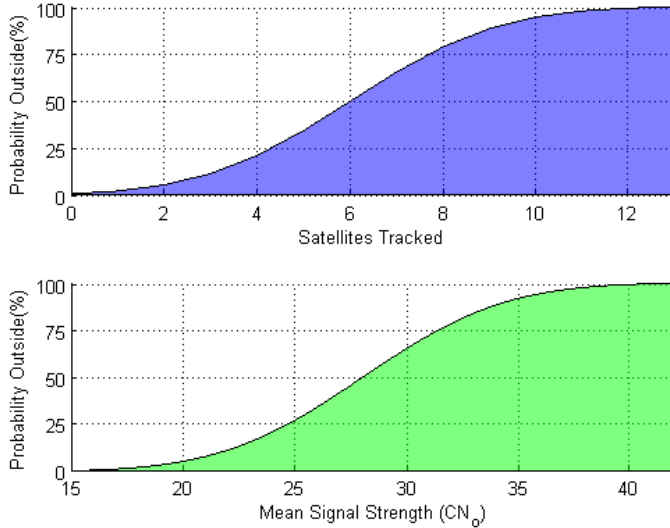

Figure 11. Probability Assigned to Environment Based on GPS Signal Tracking

IV.   DATA COLLECTION AND RESULTS

Data collections were performed in and around the University of Calgary campus. During data collection, a GoPro camera was mounted on the head of the subject and on the dashboard of the car in order to determine the true activity and environment during each interval of the test. The video camera was synchronized by displaying GPS time from a consumer-grade GPS receiver at the start of the test.

The test subject progressed through all activities in each environment while wearing the NavCube [10]. The subject wore two inertial sensors on his foot, one being an Analog Devices ADIS16488 MEMS IMU mounted on the top of the ankle, and the other being a 3-Space sensor by Yost Engineering Inc. mounted on the top of the foot near the toe. A u-blox 6 GPS receiver was used alongside a NovAtel OEM628 receiver. The u-blox patch antenna was attached to the ADIS16488 on the subject's ankle and a survey grade antenna was on the shoulder strap of the backpack. Both receivers are housed inside the NavCube, which also records the data from the ADIS16488. The 3-Space sensor logged data independently. Figure 12 shows the configuration of the data collection.

Figure 12. Subject's Foot with Two IMU's and Antenna

During the tests, the subject stood, crawled, walked and ran both in the indoors and outdoors. He also walked upstairs and downstairs, went up and down an elevator, biked and drove a car. The tests lasted for approximately 30 minutes.

The IMU and GPS data was first processed in a standard INS filter incorporating zero velocity updates during the stance phase of the gait. The filter details are provided in [11], but any estimation scheme could be used, provided the output included step length and duration. Although barometer and magnetometer data was collected, this information has not been used herein.

Results were compiled and processed in Matlab to show a video representing the user's view and activity and the probability of success. Figure 13 shows an example of the probabilities for each activity during the test (two more examples are provided in the Appendix). This screen shot occurs at 7.5 minutes into the data collection and 0.6 s into the 10 s test segment for which the activity is determined. Since no GPS satellites are tracked the probability of being inside is 100 %. As the individual is walking up stairs, the probability of walking is 98% and the probability of going up stairs is 100 %. In the majority of classifications, the probability is optimistically 100 % (rounded to the nearest percent).

Using the video, it was possible to determine the true activity and environment during each interval of the test, which was then compared with the results. Figure 14 provides the error plot indoor/outdoor estimation. This changing environment's classification is among the most challenging since GPS observation quality and quantity vary vastly between environments. The largest error of 60 % during the 3 to 5 minute interval occurred beside trees and near a metal building while crawling. At this point the antenna is pointed downward (note that the patch antenna is not isotropic) and therefore the C/N$_o$ decreased substantially. This leads to indecision as to whether the user was indoors or out. While indecisions are not desirable, the system appears to have safely detected the impossibility of making a decision, which is better than an incorrect one.
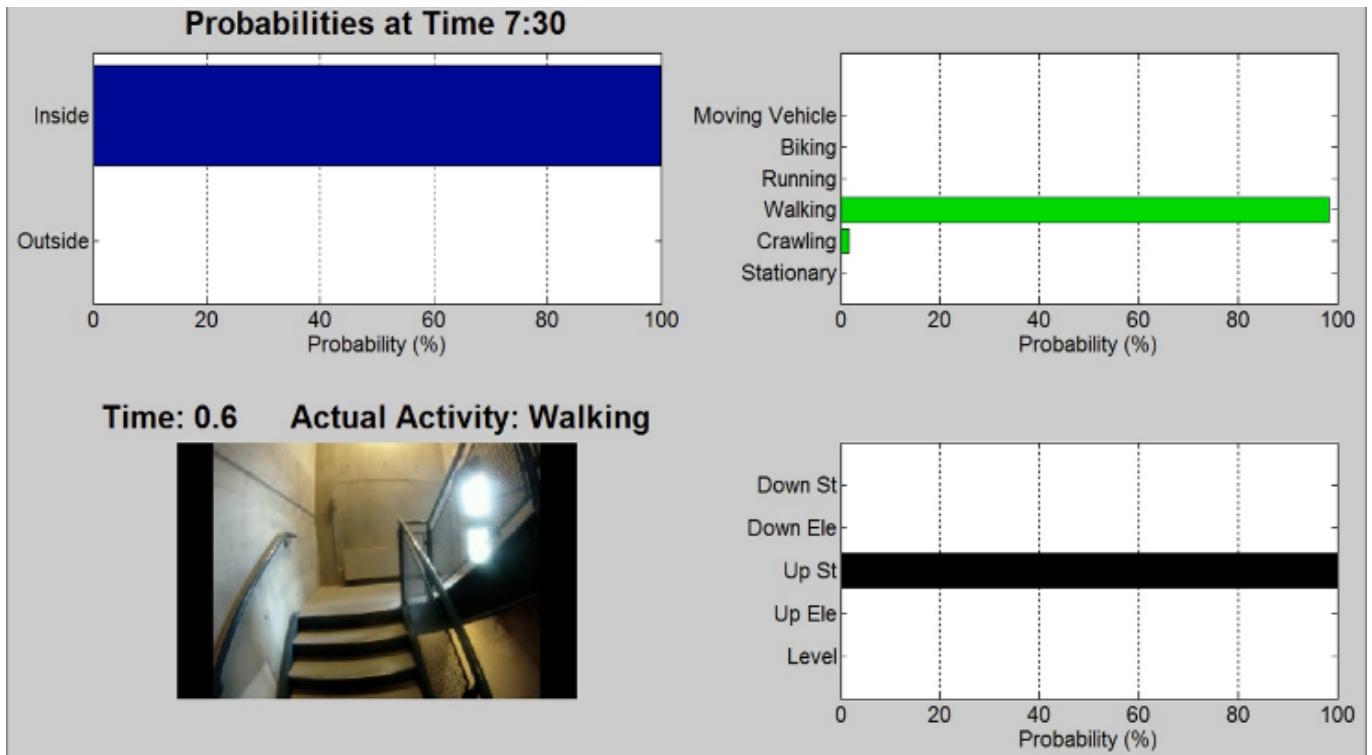
Figure 13. Sample Video Frame from Indoor Walking Upstairs Section of Test

During the 5 to 8 minute interval, the subject is deep indoors, which makes it the easiest situations to detect. During the 8 to11 minute interval, the user returns outside and the receiver takes a few minutes to reacquire all signals and thus the error falls below 10 percent in about one minute. Re-acquisition time is a function of several parameters, including antenna, mounting configuration, signal acquisition method and whether A-GPS is used or not.

During the 11to13 minute interval, the user is outside under open skies and travels on a bicycle. From 13 to17 minutes the user is stationary beside the vehicle setting up the camera and data collection equipment for the vehicle portion of test. This results in a reduced visibility of the sky and increased signal tracking difficulty. From 17 to 26 minutes the user is driving the vehicle. Here the constraint of Equation (13) provides a low error in classification. Without this constraint the solution would have contained 40 - 50 % errors since the antenna was located near the vehicles pedals (not in direct line of sight to the satellites). This is what occurs from 26 to 27 minutes when the vehicle is stopped and the constraint is therefore not applicable.
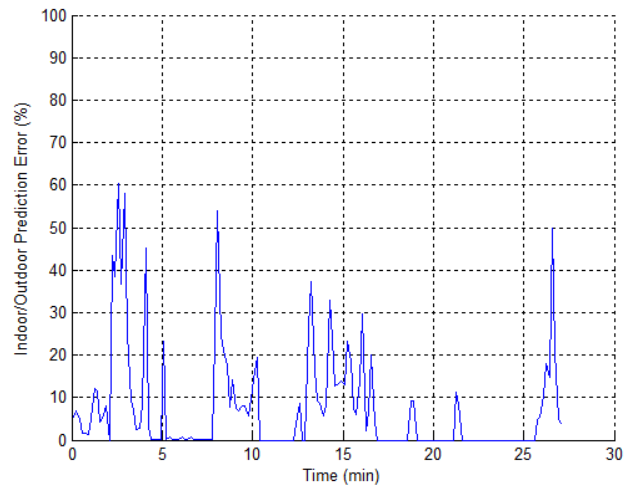

Figure 14. Environment Classification Errors

The activity classification has errors less than 1 percent some 99 % of the time. Figure 15 shows the activity classification errors. There are however seven discontinuities with high errors, sometimes 100 %. The four epochs reaching 100 % error occur simultaneously with a change in activity. Often an activity changes during the 10 s test interval. The true solution is considered at the end, while the proposed algorithm results use the entire 10 s. Thus the 100 % errors are simply due to an interpretation of activity during the true and estimated time.

Three other peaks occur at 5, 13 and 16 minutes, with errors of 30 to 50 %. These misclassifications are due to splits in the 10 s interval. For example, at 5 minutes the user transitioned from crawling to walking during the interval. Thus, the algorithm was split indicating a portion of time to walking and a portion to crawling. Similarly at 13 minutes the subject stopped walking and began a stationary period during the transition to the vehicle. At 16 minutes the vehicle began started and began moving. Thus each spike corresponds to a change in activity. The classification error may be considered a biased classification from another activity source being observed. Solving this may be impossible since the 10 s window is required to provide enough time to determine step information.
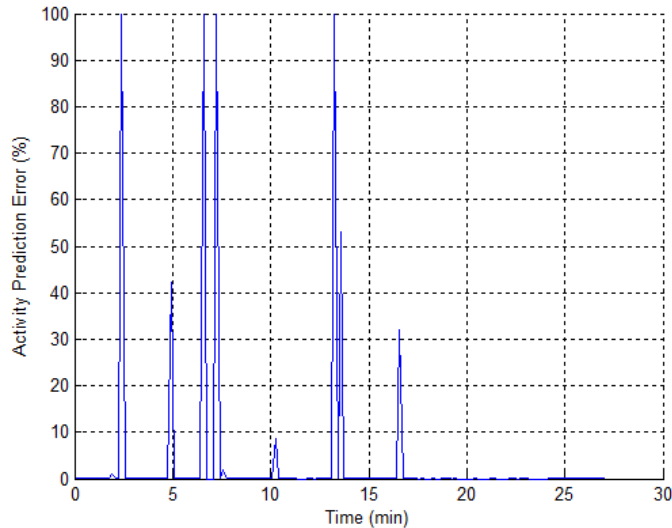

Figure 15. Activity Classification Errors

V.   CONCLUSIONS

A naïve Bayesian model can successfully be used to classify activities and the environment. While the PDFs of each feature may not exactly represent every individual or environmental scenario, the combination of several features and modeled constraints generally provides excellent reliability and accuracy. The classification is correct except when two activities are observed during the same interval. Indoor and outdoor detection also suffered some errors, but failed safely, typically providing a 50/50 split on whether the individual is inside or out. Some challenges occurred when the user was located outside but close to objects which shaded GPS signals.

Further enhancements to the algorithm include using both differences in heading and course over ground and the pitch to determine if an individual is driving rather than a passenger in a moving vehicle. Other activities such as walking on a moving vehicle and kicking could be detected. Additional work is required to improve the process when the navigation solution fails over extended time periods (i.e. hours).

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APPENDIX A - EXAMPLE VIDEO FRAME DURING BICYCLE SECTION OF TEST
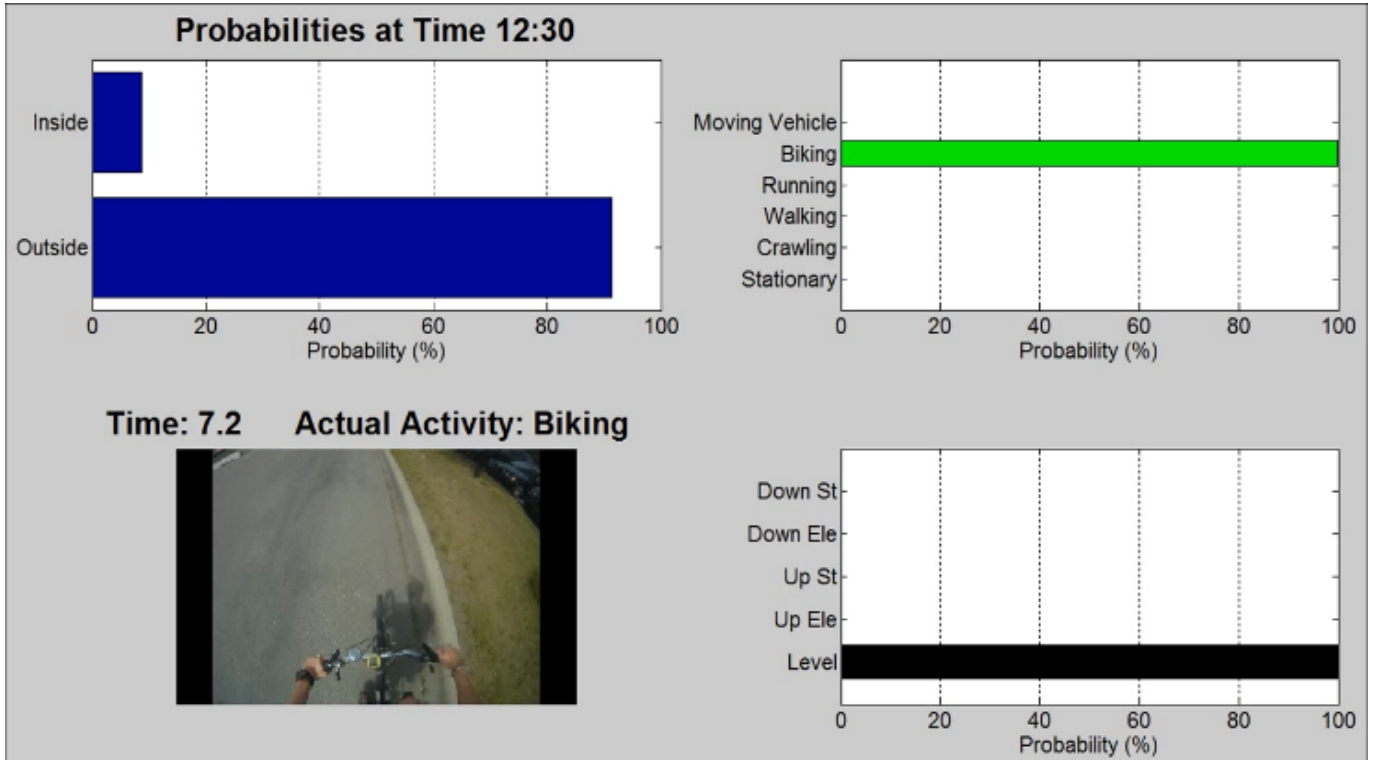
APPENDIX B - EXAMPLE VIDEO FRAME DURING DRIVING SECTION OF TEST