Gait Classification Using Wavelet Descriptors in Pedestrian Navigation

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BIOGRAPHIES

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Mr. Joel A. Hesch is a Ph.D. candidate in the Department of Computer Science and Engineering at the University of Minnesota. He has been awarded the UMN Doctoral Dissertation Fellowship (2011-12), the Honeywell International Innovator Scholarship (2010), the NIH Neuro-physical-computational Sciences Fellowship (2007-09), and the UMN CSE Excellence in Research award (2007). His primary research focuses on designing and improving nonlinear estimation algorithms for autonomous ground and aerial vehicles in GPS-denied scenarios. In particular he is interested in characterizing and improving the consistency of Vision-aided Inertial Navigation (V-INS). He is an IEEE student member.

ABSTRACT

The design of pedestrian navigation systems for use in GPS-denied scenarios has received significant attention from research community in recent years. Numerous target applications exist, including localization for groups of firefighters, first responders, or soldiers. In these applications, the safety and efficiency of the entire team relies on the availability of accurate position and orientation (pose) estimates of each team member. One approach is to equip each person with a body-mounted Inertial Measurement Unit (IMU). As the person moves, the linear acceleration and rotational velocity measurements can be integrated to obtain a pose estimate. However, the integration of both sensor noise and unknown bias causes the pose estimates to drift quickly. To mitigate the inertial drift errors, an aiding sensor can be employed such as a camera or laser scanner, which provides exteroceptive information about the environment. The person´s pose can be estimated by fusing the integrated IMU signals with environmental cues, such as the locations of nearby landmarks, in order to improve pose-estimation accuracy. While these aiding sensors are typically considered to be essential for accurate, GPS-denied navigation, they often require additional infrastructure (e.g., radio beacons), which increases the complexity, cost, and power requirements of the personal navigation system.

In contrast, we exploit the wealth of information available from human gait motion in order to improve localization accuracy. Specifically, we employ wavelet signatures computed from the raw IMU signals (tri-axial gyroscope and tri-axial accelerometer measurements) in order to classify the current gait of the person (e.g., walking, running, crawling) and utilize stochastic constraints on the person's motion, available from trained motion models, in order to correct their pose estimates. We have tested our approach both in simulation and experimentally to validate its correctness and accuracy in real-time personal navigation scenarios.

The key benefits of our approach are that it is computationally inexpensive, flexible amongst many users, and extensible to a wide variety of gaits. Moreover, we do not require any additional sensors, hence reducing the cost, weight, and power requirements of our system.

I. INTRODUCTION

Numerous pedestrian navigation applications have been proposed [1], including localization for a coordinating group of firefighters [2], first responders [3], or soldiers [4]. In these applications, the safety and efficiency of the entire team relies directly on the position and orientation estimates of each team member. A challenging scenario arises in GPS-denied environments when the team operates inside a building, in the urban canyon (i.e., next to tall buildings), underground, in foliage, or under the forest canopy.

As an industry leader in navigation technologies, Honeywell has been researching and developing personal navigation equipment. For instance, a dead-reckoning system based on the fusion of IMU and compass information termed the DRM™ 4000, is currently commercially available. This system is low-cost and capable of GPS-denied navigation in the absence of large magnetic disturbances. Moreover, Honeywell has been developing advanced techniques for aiding personal navigation by estimating displacements using gait models. In the work of Soehren and Keyes [5], a human motion model (based on gyroscope and accelerometer measurements) is employed to infer the distance and direction of a motion type. This generates a displacement estimate that is blended with the result of IMU integration to estimate position. In addition, to study the effect of adding additional aiding sensors on the pose estimate accuracy, Honeywell developed a positioning system under the DARPA individual Precision Inertial Navigation System (iPINS) program that uses an IMU, GPS, barometer, and motion classification to estimate a person's pose in both indoor and outdoor environments.

In this paper, we continue our research for constraining inertial drift without relying on additional sensors. We present an approach that estimates the person's position and orientation using a dictionary of motion models, and a gait classifier that only relies on the IMU data. Specifically, we first detect the person's gait (e.g., walking, running, or crawling) using wavelet signatures computed from the IMU signals. Subsequently, a motion constraint is formulated based on a set of motion models which determine speed as a function of gait, frequency, and biometric information (e.g., leg length). Finally, we incorporate the motion constraint into the inertial navigation system to reduce pose estimate errors. The principal advantage of the proposed approach is that it works without requiring additional sensors, instead, it leverages domain information (i.e., how a person moves) and the already-available IMU measurements, in order to improve navigation accuracy.

The remainder of this paper is organized as follows: Section II reviews the relevant literature on personal navigation systems. Subsequently, we present our personal navigation prototypes in Section III. The approach for wavelet-based gait classification and method for updating the pose estimate is in Section IV. We present experimental results to validate our method in Section V. Finally we provide the summary in Section VI.

II. RELATED WORK

Personal navigation systems have relied extensively on the use of portable GPS devices, which are widely available today. The main limitation of GPS-based approaches is that they rely on line-of-sight to the satellite network for accurate navigation. This means that many environments preclude there usage, including indoors and in the urban canyon (i.e., next to tall buildings).

Other approaches use exteroceptive sensors such as cameras [6] and lidars [7, 8] in combination with an IMU for person navigation. The key idea is to measure the relative motion of the person with respect to the environment, in order to reduce IMU drift. This approach can also be accomplished using temporary beacons deployed in the environment [9], or mounted on other team members [3]. These methods have a myriad of limitations such as reliance on robustly detectable / uniquely identifiable environmental features, necessity to instrument the environment with radio-frequency identification (RF-ID) tags, or nearby collaborators who also have a good position estimate.

In contrast to the above approaches are those which seek to estimate pose using only an IMU with no additional sensors or external references. These methods are interesting because they significantly simplify the hardware requirements, and mitigate the need for complicated system calibration (e.g., calibrating the camera-to-IMU transformation [10]). These IMU-only approaches exploit knowledge about the motion of a person in order to improve estimation accuracy.

For instance, many authors have exploited so called "zero-velocity updates" (ZUPTs) to reset the IMU velocity errors during the stance phase of walking [7, 11]. Other approaches utilize inertial sensor data for motion classification, in addition to ZUPTs. For instance, Lau et al. [13] developed a small sensor unit, comprised of an accelerometer and a gyroscope, to detect shank and foot segment motion and orientation during different walking conditions. Qiu et al. [14] investigated a feature based method and a waveform based method with a low cost waist-mounted IMU.

More advanced techniques also exploit IMU signal characteristics (e.g., peaks and valleys in the acceleration signal induced by walking) to differentiate between walking and running. Using this information, they can also enforce constraints on the gait motion [12]. The number of gaits that can be detected is limited to walking forward, walking backward, running, and stationary. The running model was developed on a treadmill and outdoors. In our proposed method, we can expand the number of gaits to 10 or more.

In the current paper, we propose a new approach for classifying motion gaits that is flexible across a wide range of users. Instead of looking for specific features in the IMU signals, we employ the wavelet transformation in order to capture both frequency and time-domain information in a compact form. This method can be applied for a wide range of gaits, and requires virtually no manual tuning to adapt it to different gaits. Subsequently, we employ motion models, trained across a wide variety of subjects, to update pose based on the current gait.

III. SYSTEM BACKGROUND

Before presenting the details of our gait classification method, we provide a brief overview of the two personal navigation systems on which the proposed gait classification method has been tested.

The first testbed is an Emergency Responder Locator System developed by Honeywell for the Department of Homeland Security (DHS), under the Geospatial Location Accountability and Navigation System for Emergency Responders (GLANSER) program. The GLANSER system provides the situational awareness in indoor and GPS-denied environments by displaying first-responder locations on a 2D or 3D display. Honeywell's GLANSER system consists of portable geospatial locators that contain an Ultra-Wideband (UWB) ranging radio, a Micro Electronic Mechanical Systems (MEMS)-based IMU, a Doppler velocity radar, a barometric altimeter, and a processor module. Figure 1 shows the prototype geospatial locator unit (GLU), which is mounted on a backpack [15].

Figure 1: GLANSER GLU prototype, which is a backpack-mounted personal navigation system

The second testbed is the Honeywell ePINS – enhanced Personal Inertial Navigation System. ePINS facilitates GPS-denied navigation by fusing the measurements from a MEMS-grade IMU with advanced motion classification algorithms. Figure 2 depicts the ePINS system attached via a belt on the lower back of the user.

Figure 2: Honeywell ePINS prototype

In both personal navigation systems (ePINS and GLANSER), the HG1930 MEMS IMU (see Figure 3) is used to provide inertial measurements for strapdown navigation. It is an ideal sensor for personal navigation applications due to its small size (< 4 cu. in.), high performance (< 1°/hr bias), low power (< 3 watts), and low cost. We note that this IMU provides the only data used during the online portion of the proposed gait classification method.

Figure 3: HG1930 Inertial Measurement Unit

IV. PROPOSED METHOD

We decompose the task of aiding an INS for personal navigation using only motion-model information into three subproblems. First, we describe how to classify gaits in a wavelet-domain feature space. This process is generic enough to allow new gaits to be added to the classification scheme easily, and robust enough to ensure that gaits are not misclassified. Second, we describe a step-length model training approach wherein we characterize the step length of each gait as a function of frequency and biometric information of the person (e.g., height). Lastly, we must form an EKF update using the step length calculated from the trained model to correct the navigation solution, which requires characterizing the model uncertainty.

A. Gait Classification

The task of determining which gait a person is executing is inherently a classification problem. Given a variety of gaits (e.g., walking, running, crawling) and data describing the current motion (i.e., accelerometer and gyroscope measurements), we must determine the person's current gait. The challenge is that raw IMU data is multi-dimensional, noisy, and recorded in a time-varying frame of reference which changes uniquely for each person. Thus, relying on “features” in the raw time-domain signal is error-prone and few unique features exist (e.g., the foot-strike spike in the z-axis accelerometer that occurs during walking), which can be used to reliably disambiguate between gaits.

Although we perform gait classification in the wavelet domain, we first need to segment the data into individual steps using the time-domain data. The segmentation process begins by analyzing the peaks and valleys of a particular gait in order to determine when a single step starts and stops (see Figure 4). We partition the signal using the maxima/minima at the start/end of each step.

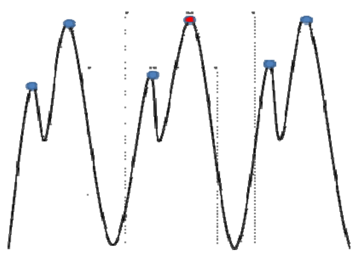

Figure 4. An example of three cycles for a given gait. The blue dots represent local maxima. The red dot is the global peak within a sliding time window, which separates the second and third cycles. (one full step include two cycles)

The results of the step-segmentation routine are displayed in Figure 5, where we use the y-axis acceleration channel. In this case, all the peaks are highlighted using a pink star ‘*’, and the valleys are denoted using a pink box.

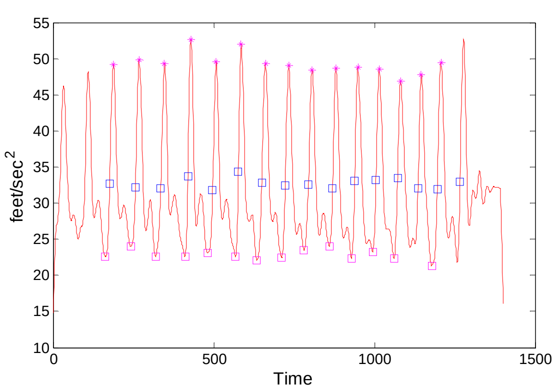

Figure 5: Segmentation of the IMU data using the y-axis accelerometer signal

After segmenting the IMU data, we examine the regularity for different individuals executing a specific gait. Figure 6 displays the results for two different peoples’ walking style (in red and blue) across approximately 15 example steps. As is evident from the graph, walking has some characteristics which are common across people, e.g., the sharp peaks in the z-axis acceleration due to foot-ground impacts. However, there is also variability amongst people in terms of the magnitude and time of occurrence of certain time-domain features within the IMU signals. This suggests that attempting to classify gaits based on the time-domain IMU signals is a formidable task that may require significant hand tuning for each individual. To overcome these issues, we decided to examine the IMU data in a different feature space. In particular, we noted that both frequency and time-domain characteristics of the IMU signals play an important role in differentiating gaits. Hence, a natural approach is to examine the IMU signals in the wavelet domain.

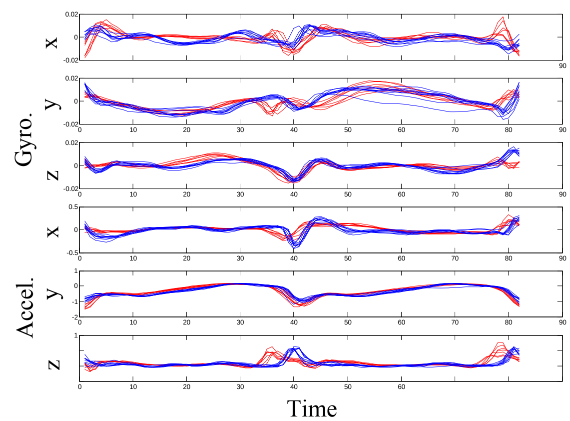

Figure 6: Sample steps for two subjects (red) and (blue).

Specifically, we compute the wavelet transform of each channel over a sliding time window of length m, from t_{k-m} up to t_{k-1}. Subsequently, we build-up a wavelet descriptor for each gait by concatenating the channels that exhibit the most information in the wavelet domain. By computing different wavelet descriptors for each gait at different frequencies and phase shifts, we encapsulate a wide variety of information about each gait that is suitable for input to a classifier.

For the online phase, we calculate the wavelet descriptor of the incoming IMU data and we use a k-nearest-neighbor classifier to determine the gait. After the candidate class has been identified, we can further validate the result by examining the quality of the classification. We score each classification decision based on the strength of the match (i.e., $\alpha > t_{match}$) and the ratio of the best match to the next best match (i.e., $\alpha/\beta > t_{ratio}$).

For more discriminative classification results we also evaluated a one-class support vector machine (SVM) approach. The goal of one-class SVM is to find a region in the input space where the data predominantly lies (or the unknown probability density is 'large'), as shown in Figure 7. This is known as the problem of single class learning, because all training samples are from one class. We employ a radial basis function (RBF) to map the input space to a high dimensional space, where we perform classification. We construct each gait model using the training data belong to a particular gait. So each one-class RBF SVM captures the distribution of the training data for a particular gait.

After training each gait classifier, we can use the entire bank of SVMs online, very efficiently. Specifically, as the person moves around (using any of the learned gaits), we compute the wavelet descriptor for the current motion over the past m IMU measurements. We then score the current gait descriptor using each of the gait classifiers in the bank to obtain a decision on which gait is currently being executed. By selecting how often the classification procedure is performed, and how many classification results to take into account before declaring a decision, we can adaptively tune the classifier performance online.

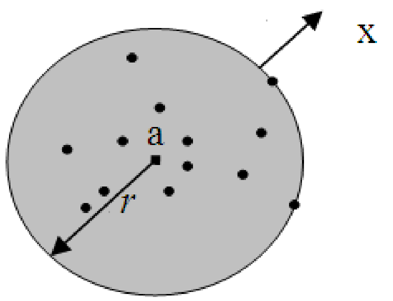

Figure 7. Single class SVM using a hypersphere boundary, which is specified by the center point a, and the radius *r*. The black dots denote training points, while X denotes a query point.

B. Step-Length Modeling

Once we have determined a person's gait, the step-length modeling task can be formulated as a regression over the frequency currently being executed and person's biometric information. Given the wide variety of factors relating a gait to the actual motion, we determined it necessary to construct accurate step-length models for each gait. For example, for the walking motion class, each person may walk with a different stride length or velocity profile, depending on their biometric characteristics (e.g., height, thigh length, and weight) as well as the frequency of walking (i.e., a person walking fast may tend to take longer strides than a person strolling casually).

In particular, we studied a number of factors affecting the motion profile by monitoring the gaits of a wide variety of subjects at Honeywell Labs. Each subject executed 10 different gaits at 3~5 frequencies for each gait, using a ground-truth system consisting of a laser range finder and ultra-wide band (UWB) radios to triangulate the person's true position as they moved. All the IMU data was labeled using the truthing system to obtain a gait label, position, and velocity for each segment of IMU data. We evaluated the accuracy of several regression techniques, including both global regression (linear and quadratic models) and local regression (local linear and Gaussian kernel models). For each regression model, we determined step length as a function of frequency and biometric information. The frequency is calculated as the inverse of the average gait cycle time (i.e., time to complete one step). Figure 8 shows the four regression models for the right shuffle gait of test subject 1.

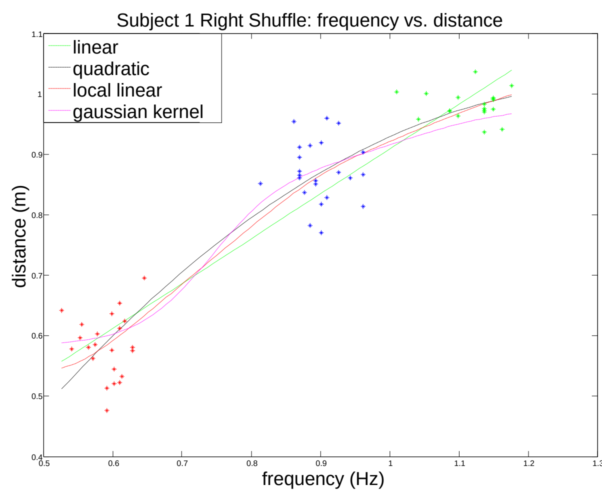

Figure 8: Step length vs. frequency for the right shuffle gait of subject 1

After adding the biometric information of the person, the regression model will be a function of two or more dimensions. The step length model can be trained online as well by adding the model parameters to the state of the extended Kalman filter (EKF), and estimating them over time.

C. Motion-Model Aided Personal Navigation

After training the motion classifier and building the step-length model for each gait, we can examine the performance of our system online during the operational phase. Specifically, we compute the wavelet transform of the IMU data to determine the gait mode and frequency. Subsequently, we obtain the estimated step length from the motion model. The calculated step length is compared with the position difference computed from the strapdown navigation, and incorporated into the Honeywell personal navigation EKF as a measurement update. We compute the Jacobian of the measurement equation, **H**, and the noise covariance, **R**, based on an error characterization of the gait model. In order to prevent misclassifications from affecting the filter estimates, we employ a probabilistic threshold to gate each measurement. We compute the measurement residual **r**, and the corresponding covariance of the residual $\mathbf{S} = \mathbf{H}\mathbf{P}\mathbf{H}^T + \mathbf{R}$, and we accept the measurement if $\mathbf{r}^T \mathbf{S}^{-1} \mathbf{r} < t_{mahal}$.

V. EXPERIMENTAL RESULTS

In this section, we describe our experimental trials that validate the correctness and accuracy of the proposed solution.

Experimental result 1: In the first set of experimental trials, we evaluated the discriminative capability of wavelet-based gait classification by evaluating five different gaits (walking, running, duck walking, military crawling, and knee crawling) across different frequencies and phase shifts. In particular, we computed the wavelet descriptor for each gait, and stored a bank of templates corresponding to different phase shifts and frequencies of the gait. Subsequently, using query data of a known gait, we performed nearest-neighbor classification to see which gait template most closely matched the query (see Figure 9). Table 1 depicts the cumulative results obtained over all queries. We note that using wavelet descriptors allowed the correct gait to be identified 100% of the time. This suggests that wavelet descriptors are a powerful tool for disambiguating gaits. Determining the correct frequency proved less accurate, particularly for military crawl, where only 44% of the queries returned the correct solution. It should be noted however, that even in this case, 95% of the queries returned a frequency which was within 0.1 of the true. A similar level of accuracy was attained for phase where for the military crawl, the correct phase shift (i.e., 0 deg) was selected only 81% of the time.

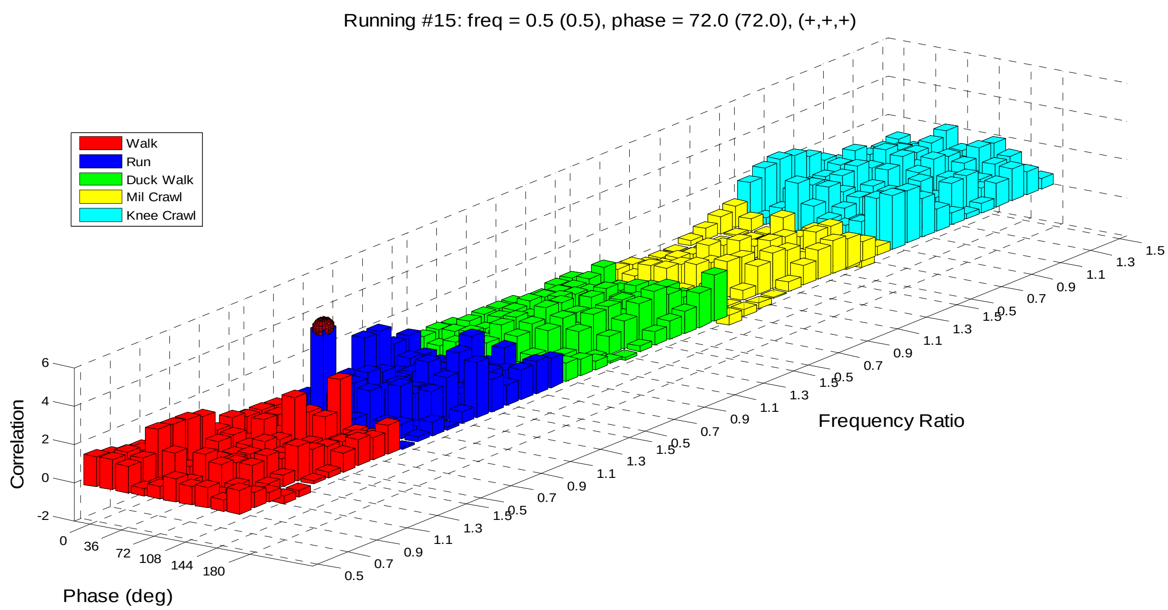

Figure 9: Classification results from a query of running at a certain frequency and phase (depicted by the dark sphere). The height of each bar denotes the likelihood of the query data matching that gait, frequency, and phase. As is evident from this trial, the nearest-neighbor approach correctly classifies gait, phase, and frequency.

Table 1: Results from the query data across different phases and frequencies. The true query gaits are depicted across the columns, each one was executed at 0 deg phase shift and frequency scale 1. The horizontal direction denotes the query data, while the vertical direction denotes the classification result.

		queried gait (freq = 1, phase = 0)				
		Walk	Run	Duck Walk	Mil. Crawl	Knee Crawl
classified gait	Walk	100%	0	0	0	0
	Run	0	100%	0	0	0
	Duck Walk	0	0	100%	0	0
	Mil. Crawl	0	0	0	100%	0
	Knee Crawl	0	0	0	0	100%
classified frequency	0.5	0	0	0	0	0
	0.6	0	0	0	0	0
	0.7	0	0	0	0	0
	0.8	0	0	0	6%	0
	0.9	0	0	12%	38%	0
	1	100%	100%	77%	44%	98%
	1.1	0	0	12%	13%	0
	1.2	0	0	0	0	0
	1.3	0	0	0	0	0
	1.4	0	0	0	0	2%
	1.5	0	0	0	0	0
classified phase shift (deg)	0	100%	100%	92%	81%	98%
	36	0	0	0	3%	0
	72	0	0	0	0	0
	108	0	0	0	0	2%
	144	0	0	0	0	0
	180	0	0	0	0	0
	216	0	0	0	0	0
	252	0	0	0	0	0
	288	0	0	0	0	0
	324	0	0	8%	16%	0

Experimental result 2: We present the results obtained from training one-class RBF SVMs, which captures the distribution of the wavelet descriptors for each gait. Figure 10 shows the histogram of the score of the seven gait models using all the six channels. We perform classification by appropriately selecting a threshold for each axis. We can clearly see that the 'not in class' query (Figure 10, right) is well separated from the 'in class' query (Figure 10, left), thus threshold selection is straight forward.

Experimental result 3: Table 2 presents the classification results using the GLANSER GLU on seven motion classes for one subject using the k-nearest-neighbor classifier. This classification result may improve the vertical-axis position estimates. For example, the person's vertical motion profile can fall into one of three classes, i.e., no vertical change, upward motion, or downward motion. In this example, the 'no vertical change' class includes 'walk forward', 'walk backward', 'run', 'crawl forward', and 'duck walk'. If the 'upward motion' class is detected, we know that the corresponding vertical change is about 7 inches, which is the vertical rise of a single step on the stair case.

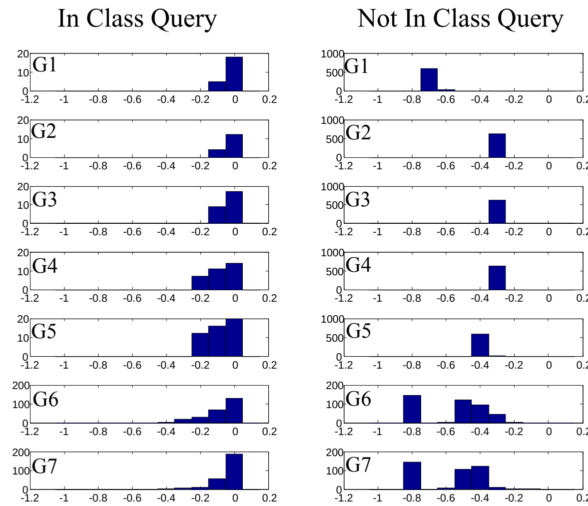

Figure 10: Histogram of the score for seven gait models using the 'in class' query (left) and 'not in class' query (right) for one-class RBF SVMs. Gaits are: G1: walking, G2: running, G3: duck walking, G4: military crawl, G5: knee crawl, G6: left shuffle, and G7: right shuffle. A score close to 0 denotes a close match, a score close to -1 is not a close match.

The barometric altimeter for estimating altitude indoors is sensitive to pressure changes induced by heating and ventilation systems. We can reduce this effect by constraining the person's altitude when they are traversing a single floor of the building (i.e., when executing any of the 'no vertical change' gaits). If the classification results are either 'walking upstairs' or downstairs, we can form a vertical position measurement to improve the navigation estimate computed by the strapdown navigation system.

Table 2: Classification accuracy using the GLANSER GLU prototype

	Classification accuracy	steps
Walk forward	91.7%	72
Walk backward	97.2%	36
Run	100%	11
Up stairs	100%	9
Down stairs	77.8%	9
Crawl forward	93.4%	61
Duck walk	100%	32

VI. SUMMARY

In conclusion, we have presented a new method for motion classification (gait classification) using wavelet descriptors of IMU data. The proposed motion classification method is robust to different frequencies and phases for a wide variety of motion types. For each classified motion type, we can estimate the step length based on the person's gait frequency, as well as biometric information such as height or leg length. The step length is formulated as a velocity measurement that the extended Kalman filter employs to correct the inertial drift in the strapdown navigation solution. We examined the accuracy of both k-nearest-neighbor classification and support vector machine classification using radial basis functions. The results depicted that the RBF SVM provided a more descriptive mechanism for capturing the distribution of each gait class. In our future work, we are examining methods for more robust signal segmentation methods, which will help for reducing the template storage in the motion dictionary. Also we are integrating the online step-length training capability for the personal navigation system.

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REFERENCES

[1] C. J. Matthews, Y. Ketema, and D. Gebre-Egziabher, "Dead Reckoning and Personal Navigation Based on a Kinetic Model for Human Gait," UMN Technical Report, AEM Report 2010-1.

[2] M. Angermann, M. Khider, and P. Robertson, "Towards operational systems for continuous navigation of rescue teams," *In Proc. of the IEEE/ION Position, Location and Navigation Sym.*, pp. 153-158, Monterey, CA, May 5-8, 2008.

[3] J. R. Guerrieri, M. H. Francis, P. F. Wilson, T. Kos, L. E. Miller, N. P. Bryner, D. W. Stroup, and L. Klein-Berndt, "RFID-Assisted Indoor Localization and Communication for First Responders," *In Proc. of the European Conf. on Antennas and Propagation,* pp. 1-6, Nice, France, Nov. 6-10, 2006.

[4] A. K. Brown and P. Olson, "Urban/Indoor Navigation using Network Assisted GPS," *In Proc. of the ION Annual Meeting*, pp. 1131-1136, Cambridge, MA, 2005.

[5] W. Soehren and C. Keyes, "Human-Motion Based-Navigation Algorithm Development", *In Proc. of the IEEE/ION Position, Location and Navigation Sym.*, San Diego, CA, Mar. 13-16, 2000.

[6] A. I. Mourikis, N. Trawny, S. I. Roumeliotis, A. Johnson, A. Ansar, L. Matthies: "Vision-Aided Inertial Navigation for Spacecraft Entry, Descent, and Landing," *IEEE Trans. on Robotics*, 25(2), pp. 264-280, Apr. 2009.

[7] J. A. Hesch, F. M. Mirzaei, G. L. Mariottini, and S. I. Roumeliotis, "A 3D Pose Estimator for the Visually Impaired," *In Proc. of the IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, pp. 2716-2723, St. Louis, MO, Oct. 11-15, 2009.

[8] J. A. Hesch, F. M. Mirzaei, G. Luca Mariottini, and S. I. Roumeliotis, "A Laser-aided Inertial Navigation System (L-INS) for Human Localization in Unknown Indoor Environments," *In Proc. of the IEEE Int. Conf. on Robotics and Automation*, pp. 5376 – 5382, Anchorage, AK, May 3-7, 2010.

[9] V. Kulyukin, C. Gharpure, J. Nicholson, and S. Pavithran, "RFID in Robot-assisted Indoor Navigation for the Visually Impaired," *In Proc. of the IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, pp. 1979–1984, Sendai, Japan, Sept. 28–Oct. 2, 2004.

[10] F. M. Mirzaei and S. I. Roumeliotis, "A Kalman filter-based Algorithm for IMU-camera Calibration: Observability Analysis and Performance Evaluation," *IEEE Trans. on Robotics*, 24(5), pp. 1143-1156, Oct. 2008.

[11] L. Ojeda and J. Borenstein, "Personal Dead-reckoning System for GPS-denied Environments," *In Proc. of the IEEE Int. Work. on Safety, Security, and Rescue Robotics*, Rome, Italy, Sept. 27-29, 2007

[12] W. Soehren and W. Hawkinson, "A Prototype Personal Navigation System," *In Proc. of the IEEE/ION Position, Location and Navigation Sym.*, pp. 539-546, San Diego, CA, Apr. 25-27, 2006,.

[13] H. Lau, K. Tong, and H. Zhu, "Support Vector Machine for Classification of Walking Conditions Using Miniature Kinematic Sensors," *Med. Biol. Eng. Comput.* 46(6):563-73, Mar. 2008.

[14] D. Qiu, J. Litton, and C. Yang, "Vector Intelligent Sensor for Human Motion Detection and Navigation," *In Proc. of the ION International Technical Meeting*, pp. 670-677, San Diego, California, Jan. 24-26, 2011.

[15] R. McCroskey, P. Samanant, W. Hawkinson, S. Huseth, and R. Hartman, "GLANSER - An Emergency Responder Locator System (ERLS) for Indoor and GPS-Denied Applications," *In Proc. of the Int. Technical Meeting of the Satellite Division of ION (GNSS),* pp. 2901-2909, Portland, OR, Sept. 21-24, 2010.