SVM-based Motion Classification Using Foot-mounted IMU for ZUPT-aided INS

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***Abstract*—Zero-velocity-UPdaTe (ZUPT)-aided Inertial Navigation Systems (INS) is a promising self-contained positioning solution for localizing firefighters and first responders while navigating in extreme environments. This paper reports on a Support Vector Machine (SVM) algorithm for classifying 19 different pedestrian activities based on a foot-mounted Inertial Measurement Unit (IMU). Such classifications are necessary to define correctly the velocity threshold in the ZUPT algorithm. The trained SVM had a classification accuracy of 75.23%. The SVM was demonstrated to enhance the ZUPT-aided INS by adjusting the threshold used in the Stance Hypothesis Optimal dEtection (SHOE) detector and variances of zero-velocity measurements for each classified locomotion. In a pedestrian indoor navigation experiment of traveling 87.8m with a combination of walking, fast walking, jogging, running, sprinting, walking backward, jogging backward, and sidestepping, the ZUPT-aided INS using the SVM-enhanced SHOE detector had a displacement error of 2.4m, outperforming navigation accuracy of a standalone INS by $134.71\times$, and a fixed threshold ZUPT-aided INS by $1.43\times$.**

***Index Terms*—Foot-mounted IMU, ZUPT, SVM, EKF.**

I. Introduction

The development of an accurate and reliable positioning system for firefighters and first responders is critical in environments where the Global Navigation Satellite Systems (GNSS) have degraded performance or fail [1]. In such situations, Pedestrian Dead-Reckoning (PDR) systems implementing an Inertial Navigation Systems (INS) aided by a Zero-velocity UPdaTe (ZUPT) algorithm based on foot-mounted Inertial Measurement Units (IMUs) have been considered as a preferable option [2]–[5]. A traditional ZUPT-aided INS algorithm detects when the human foot is stationary and updates the velocity estimates with pseudo measurements of zero-velocity during this period in an Extended Kalman Filter (EKF) framework. This approach has been demonstrated to significantly improve navigation accuracy when compared with a standalone INS [6].

The performance of ZUPT-aided INS is sensitive to the accuracy of the zero-velocity detector [7]. A traditional approach for detecting ZUPT intervals is based on the Generalized Likelihood Ratio Test (GLRT), which compares a test statistics computed from IMU readouts with a pre-defined threshold [8]. However, it has been reported that the optimal value of the pre-defined threshold is different when a pedestrian performs different types of activities, including walking, jogging, running, and sprinting [9]. Moreover, optimal noise parameter settings in the EKF can be distinct in each case [10]. Therefore, it is crucial to differentiate between different pedestrian activities and optimize the navigation accuracy, accordingly. Although previous studies have demonstrated that enhancing the ZUPT-aided INS with an activity classifier could greatly improve navigation accuracy [11]–[13], these works considered limited types of motions and did not utilize adaptive EKF parameter settings.

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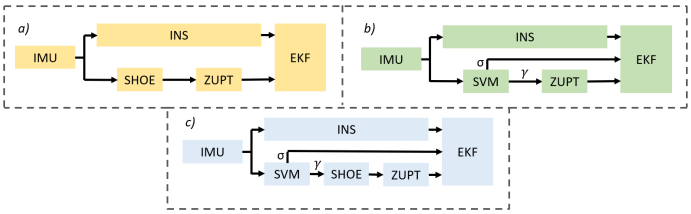

Fig. 1. (a) Traditional ZUPT-aided INS. (b) ZUPT-aided INS with SVM detector. (c) ZUPT-aided INS with SVM-enhanced SHOE detector. γ stands for the threshold used in the SHOE detector and σ is the variance of zero-velocity measurements.

In this paper, a Support Vector Machine (SVM) classifier is reported. The classifier aims to predict 19 different classes of motion, including both swing and stance phases, while performing standing still, walking, fast walking, jogging, running, sprinting, walking backward, jogging backward, sidestepping leftward, and sidestepping rightward. This paper evaluates the navigation performance of ZUPT-based INS when using three different stance phase-detection mechanisms shown in Fig. 1: the Stance Hypothesis Optimal dEtection (SHOE) detector with a fixed threshold, SVM detector, and SVM-enhanced SHOE detector, referred to as ZUPT-SHOE, ZUPT-SVM, and ZUPT-SVM-SHOE, respectively, in the rest of this paper. In ZUPT-SVM and ZUPT-SVM-SHOE, SVM predictions are used to 1) vary the variance of the zero-velocity measurements used in the EKF and 2) directly and indirectly detect the zero-velocity event. In ZUPT-SVM, the ZUPT event is determined by the SVM stance phase predictions while in ZUPT-SVM-SHOE, the swinging and stance phases are combined as one motion. Thus, when the SVM predicts a motion, it was used to tune the optimal threshold in the SHOE detector.

II. Proposed Approach

The reported SVM was trained and evaluated with foot-mounted IMU measurements collected while performing different pedestrian activities listed in TABLE I. In this section,

the data collection process, dataset labeling, and structure of the SVM are discussed.

A. Data Collection

A VectorNav VN-200 IMU with frequency of 800Hz was used in this study. Fig. 4 (c) shows an experimental setup, where the IMU was mounted on a boot. This paper considers nine different types of motion: walk (∼60 Step Per Minute (SPM)) and fast walk (∼90 SPM), jog (∼120 SPM), run (∼150 SPM), sprint (∼180 SPM), walk backward (∼60 SPM), jog backward (∼90 SPM), and walk sideways to the right and to the left (∼90 SPM). The pace of each activity was approximately controlled for uniformity of events with respect to a metronome. One subject performed two identical trials for each type of locomotion. IMU measurements collected in the first trial were used as a training dataset and those in the second trial were used in the testing procedure. Thus, the test datasets were different from the dataset used to train. In all the experiments, the subject started by standing still for 10 seconds and then traveled a straight line on a flat surface for a nominal distance of 42.6m.

B. Dataset Labeling

This paper considers the swing phase and the stance phase of a pedestrian motion as two different activities. Ground truth labels of the two phases for each pedestrian motion were based on foot-mounted IMU measurements collected in the training dataset. Fig. 2(a) and (b) show an example of five steps of the recorded accelerometers' and gyroscopes' readings. The measurements were processed as follows.

The first step is to compute the linear acceleration and angular velocity magnitudes based on readings from three accelerometers and three gyroscopes as can be seen in Fig. 2(c) and (d). The resulting two magnitude signals of the vector of acceleration and angular velocity still present high noise, thus, a Simple Moving Average (SMA) window filter was applied to lessen the noise.

$$S_k^{SMA} = \frac{1}{k} \sum_{i=n-k+1}^{n} s_i$$

where S_k^{SMA} is the mean over the last window of k entries set to 50 for all the activities to smooth the signal. Let the considered magnitude data-points be s_i. The results of the signal processing algorithm can be seen in Fig. 2(c)(d). Analyzing both synthetic signals, we observe two clear zones:

- Flat zone (stance phase): when the foot is assumed to be on the ground. For example, in Fig. 2 (c) and (d), an area between the interval 31.4-32 seconds.
- Nonuniform (swing phase): when the foot is assumed to be in the air. For example, in Fig. 2 (c) and (d), an area between the interval 32-32.8 seconds.

To automatically determine the flat and nonuniform zones, this paper computes the local minimums of the collected IMU signals. Based on Fig. 2(c)(d), we observed that the values of local minimums of the flat and nonuniform zones have a larger difference in the case of the gyroscope than in the case of the accelerometer magnitude. This property is beneficial for detection of the two phases, and therefore, only the angular velocity magnitude was used in the following procedure.

The second step in the procedure is to find all local maxima and minima. To filter the maximums, a threshold had to be set and we only considered the first and the last maximum of the nonuniform region. For instance, the green vertical lines between the interval of 31.8-33 seconds from Fig. 2(e). Once the nonuniform is well defined, the minimum of the area compressed by two nonuniform zones is selected.

Analyzing the intervals containing a minimum (red vertical line) between two marked maximums (green vertical lines), a threshold can be defined for each minimum by multiplying it by a constant ratio. However, this ratio will change depending on the type of locomotion. As an example, in Fig. 2(f), it can be seen that the detected area varies when the foot is on the ground with each step.

Finally, in Fig. 2(f), the data points colored in red were labeled as the ground truth for the stance phase and the blue points, as the swing phase per each activity.

C. Motion classification

Support Vector Machines (SVMs) are supervised machine learning algorithms that are used both for classification and regression [14]. The SVM model represents different classes in a multidimensional space and finds hyperplanes that distinctly classify the data points. In this case, the datasets used to train and test the SVM model had six input features (three accelerometers and three gyroscopes readings), and the labels were obtained using the signal processing techniques discussed in Section II-B. The six-dimensional data was divided by a Radial Basis Function (RBF) kernel [15] with hyperparameters C = 100 and γ = 0.058. The SVM variables were chosen because they resulted in the highest classification accuracy during the hyperparameter tuning process. A ConFusion Matrix (CFM)

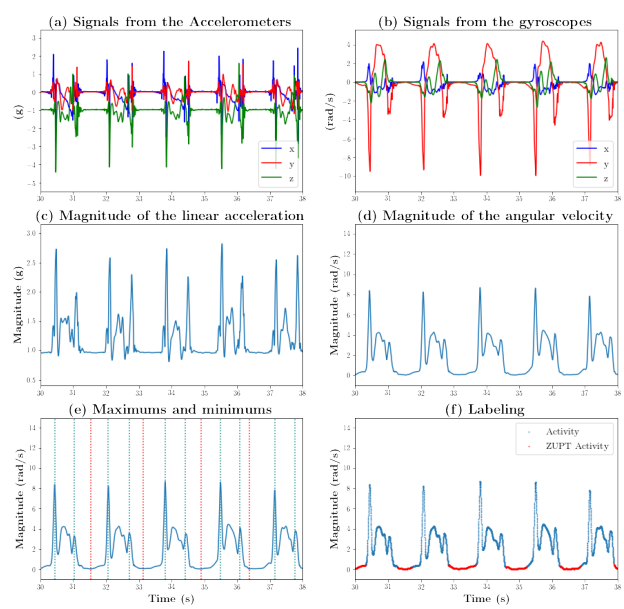

Fig. 2. Labeling detection algorithm for five steps when a pedestrian is walking at 60 SPM.

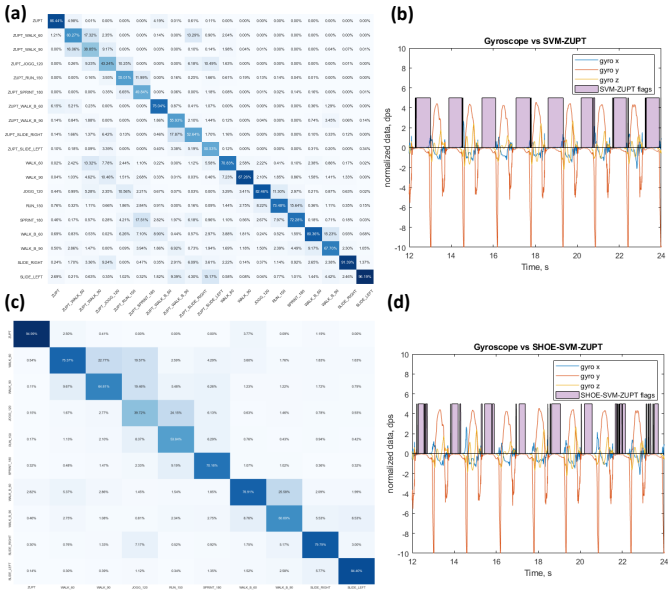

Fig. 3. (a) Confusion matrix of the SVM model which predicts the swing and stance phase for each type of motion. (b) Example of the SVM model prediction. (c) Confusion matrix of the SVM model predicting 9 types of motion. (d) Example of SVM aided stance hypothesis optimal detection (SHOE).

for the ZUPT-SVM algorithm of the testing results is shown in Fig. 3(a) and for the ZUPT-SVM-SHOE in (c), yielding an overall accuracy of 75.23% and 77.86% respectively.

III. Experimental Validation

This paper uses the trained SVM to enhance ZUPT-aided INS when performing different pedestrian activities. An independent experiment was conducted to validate the navigation performance. In this experiment, the same subject used the experimental setup, shown in Fig. 4, and traveled along a straight line of a nominal distance of 87.8m with different types of motions, during which periods were marked by different colors.

This dataset was evaluated using three different implementations of the ZUPT-aided INS: 1) ZUPT-SHOE with a fixed threshold of e^5; 2) ZUPT-SVM where the stance phase was determined when the trained SVM predicts a stance phase in any activities as Fig. 3(a) shows; and 3) ZUPT-SVM-SHOE

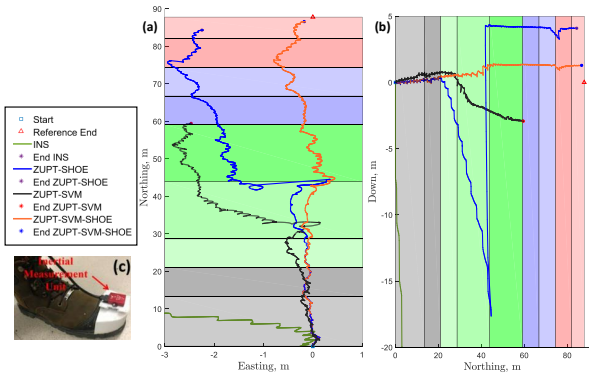

Fig. 4. (Green) Navigation solution with standalone INS. (Blue) Navigation solution with an optimized fixed threshold. (Black) Navigation solution using the just the SVM predictions. (Red) Navigation solution combining the SVM prediction with the SHOE detector.

TABLE I
EKF parameters and threshold of stance phase detection

Activities	Metronome (step per min)	Threshold (log)	Uncertainty (m/s)	Error (m)
Walk	60	3	0.02	0.69
Fast-Walk	90	4.2	0.02	0.79
Jog	120	6.89	0.1	1.31
Run	150	7.8	0.1	1.31
Sprint	180	8.7	0.1	7.01
Walk backward	60	3	0.02	0.33
Jog backward	90	5.4	0.02	0.41
Side-step right	90	5.4	0.05	0.41
Side-step left	90	5.4	0.05	0.29

where stance phase and swing phase for the same activity predicted by the SVM were combined as a single motion as is shown in Fig. 3(c), and the result of the motion prediction of the SVM model was used to tune the threshold used in the SHOE detector and variance of the Extended Kalman Filter according to the values listed in TABLE I. The values of the threshold and the variances listed in TABLE I were selected to minimize position errors of the ZUPT-aided INS in the experiments. Fig. 1(a), (b), and (c) present a block diagram of each implementation. Details of the ZUPT-aided INS were documented in [16].

Fig. 4 illustrates horizontal (a) and vertical (b) trajectories estimated by the three implementations of ZUPT-aided INS. This paper evaluates the numerical errors in position at the destination. The errors of the standalone INS, ZUPT-SHOE, ZUPT-SVM, and ZUPT-SVM-SHOE were 733.47m, 7.77m, 27.53m, and 5.44m, respectively. Three remarks can be made about the experimental results. First, it could be observed in Fig. 4 that the ZUPT-SHOE had a maximum displacement error of 17.64m. The maximum error occurred during jogging, running, and sprinting because the fixed threshold used in the SHOE detector in this experiment could not detect the stance phases in these activities. As a result, velocity estimates were not corrected, leading to large position errors. Second, the ZUPT-SVM solution underestimated trajectory length. This phenomenon could be explained by the fact that the trained SVM detector had a few false alarm instances. The false alarms led the ZUPT algorithm to incorrectly reset the velocity to zero when the foot was moving, resulting in position errors. Third, the ZUPT-SVM-SHOE had the minimum navigation error, as compared to the other two approaches.

IV. Conclusions

In this paper, an SVM classifier is reported which was trained and used to classify 19 classes, including both stance and swing phases while walking, fast walking, jogging, running, sprinting, walking backward, jogging backward, sidestepping, and standing still. The trained SVM achieved a classification accuracy of 75.23%. Navigation errors of standalone INS, ZUPT-SHOE, ZUPT-SVM, and ZUPT-SVM-SHOE were 733.47m, 7.77m, 27.53m, and 5.44m, respectively, in an 87.8m straight-line pedestrian navigation experiment involving different activities. The experimental results showed that it is advantageous to enhance ZUPT-aided INS with the reported SVM.

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