A Novel Adaptive Zero-Velocity Detector for Inertial Pedestrian Navigation Based on Optimal Interval Estimation

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ABSTRACT In the foot-mounted inertial pedestrian navigation system, the zero-velocity update (ZUPT) algorithm is an efficient way to bound the inertial error propagation. Therefore, a reliable and accurate zero-velocity detector (ZVD) that adapts to all kinds of locomotion and scenarios plays a vital role in achieving high-precision and long-term pedestrian navigation. The classical threshold-based ZVDs are susceptible to failures during dynamic locomotion due to the fixed threshold. Recent machine-learning-based ZVDs need a huge amount of data to support the model training and their generalization is limited in new testing scenarios. In this paper, we propose a novel adaptive ZVD using the optimal interval estimation. Two filters are used to process the angular rate, aiming at determining a gait cycle. In a gait cycle, the acceleration is mapped to the search space by a special convex function. Based on the features of the data in the search space, a zero-velocity benchmark is calculated for the following interval estimation. The zero-velocity benchmark and the hierarchical iterative search are used to estimate the optimal zero-velocity interval (ZVI). The experiments demonstrate the effectiveness and adaptability of this novel ZVD.

INDEX TERMS Pedestrian navigation, zero-velocity detector, search space, zero-velocity benchmark, hierarchical iterative search.

I. INTRODUCTION
The widespread use of the Global Navigation Satellite System (GNSS) enables localization to be available to general public. However, the navigation information of GNSS is unavailable in the indoor scenarios due to the problem of signal absorption and spurious reflections [1]. Indoor navigation needs other technical supports. The infrastructure-dependent localization systems, such as Wi-Fi, UWB, GSM and iBeacon, can provide accurate navigation information by the arrangement of the indoor environments in advance [2]–[4]. These systems are inflexible in real usages, and thus cannot realize autonomous navigation for users in new environments. In contrast, inertial sensor has the advantage of measuring self-motion in all environments, which means that inertial navigation owns the excellent ability to enable autonomous navigation in any given environments [5].

With the rapid development of Micro-Electro-Mechanical-System (MEMS) equipped with the inertial measurement unit (IMU), body-mounted inertial pedestrian navigation is possible [6], [7]. However, the sensor noise introduces navigation errors which will accumulate approximately proportional to the time cubic. To solve this problem, ZUPT-aided algorithm is proposed as an efficient and common compensation mechanism for the inertial pedestrian navigation system [8]. This algorithm takes the advantage of the stationary state of the foot-mounted IMU during the human bipedal locomotion and feeds the zero-velocity pseudo-measurement into the Kalman Filter to correct the navigation errors. The ZVD, which determines whether an IMU is stationary, is the most critical part of this algorithm [9]–[11]. The threshold-based ZVD and the machine-learning-based ZVD are currently two major approaches used in zero-velocity detection.

The threshold-based ZVDs are classical approaches to detect the stationary instances of bipedal locomotion. They depend on the pre-calibrated fixed thresholds and thus cannot adapt to different kinds of locomotion. The stance hypothesis optimal detector (SHOE), the acceleration moving variance detector (MV), the acceleration magnitude detector (MAG) and the angular rate energy detector (ARE) are four typical threshold-based ZVDs [12]–[17]. These ZVDs all use some math functions to calculate target values from the inertial data and then compare these values with a fixed threshold to determine the ZVIs. They work well when pedestrians
walk at a slow, periodic and stable speed. However, when facing high dynamic locomotion, e.g. running, their performance degrades and often produces a false or missed ZVI. To improve the usability of threshold-based ZVDs, researchers have tried to find adaptive threshold-based ZVDs. Johan et al. designed an adaptive ZVD by a Bayesian approach and used the posterior odds ratio to detect the ZVI [18]. Tian et al. proposed an adaptive ZVD by building a fitting mathematical model between the gait frequency and the threshold [19]. Wang et al. designed a ZVD making the threshold adaptive to gait patterns with different velocities [20]. It is hard to model the general relationship between thresholds and locomotion due to the complexity and diversity of human dynamics. Although these adaptive threshold-based ZVDs have acquired some good results in their papers, their effectiveness still needs more experiments to be verified.

Recently, machine learning can provide a new approach to design adaptive ZVDs. The core idea of machine-learning-based ZVDs is training a learning model between inertial data and the ZVIs. Wagstaff et al. trained a model by Support Vector Machine to classify six different motion types from the IMU data. The optimal threshold will be selected to detect the ZVIs based on the classified motion type. Meanwhile, a long short-term memory (LSTM) neural network is trained to directly detect the ZVIs [21], [22]. This ZVD has achieved real-time performance and pretty good results. Kone et al. used Histogram-based Gradient Boosting and Random Forest to classify two major motion types and reduce the computation cost. Then the ZVIs could be detected by two LSTM neural networks corresponding to the two major motion types [23]. The machine-learning-based ZVDs achieve much better effectiveness and adaptability in high dynamic locomotion. However, these ZVDs need abundant and representative datasets to train their models, which may cost considerable manpower and material resources. In addition, the existence of the over fitting in machine learning models can lead to poor generalization of these ZVDs in testing sets.

Both kinds of ZVDs have some inherent deficiencies which may lead to poor performance under certain circumstances. To improve the adaptability and robustness of ZUPT, we propose a novel optimal-interval-estimation-based ZVD (OIE-ZVD) in this work. Our work aims at achieving a general ZVD for different people and different locomotion including walking, running and stair climbing/descending.

The remainder of the paper is organized as follows: Section II analyzes the statistical features of inertial data in a gait cycle; Section III describes our proposed OIE-ZVD; Section IV verifies OIE-ZVD through two kinds of representative experiments; the conclusions are given in Section V.

II. THE STATISTICAL FEATURES OF INERTIAL DATA IN A GAIT CYCLE

The velocity, position and yaw produced by the bipedal locomotion are the vital information in pedestrian navigation. Because of the complexity of human body structure and the diversity of each person, it is difficult to build an accurate kinematic model of bipedal locomotion for all pedestrians. But the inertial data in bipedal locomotion has some distinct features making it easier to be analyzed.

A. ANALYSIS OF BIPEDAL LOCOMOTION

Walking is a common form of bipedal locomotion. After a long course of research, the process of foot motion has been well summarized in a gait cycle. As shown in Figure 1, a gait cycle can be divided into the swing phase and the stance phase. During the stance phase, the foot is on the ground as a support and is commonly considered to be stationary [24], [25]. This phase is actually the ZVI in a gait cycle. The gait cycle of walking can also be divided into three continuous and sequential parts which are motion, rest and motion.

The whole process of foot motion during bipedal locomotion is composed of numerous, continuous and sequential ‘motion-rest-motion’. In this paper, a cycle of ‘motion-rest-motion’ is defined as One-Gait-Cycle (OGC). From the definition, OGC is also the basic unit of pedestrian navigation.

As shown in Figure 2, OGC is a model whose shape is like a sandwich. The two outer intervals of OGC are the motion parts and the inner interval is the rest part. The time length of each interval is determined by the corresponding locomotion. For example, in running situations, the length of the rest interval will be much shorter than that of the motion parts. In OGC, there is only one continuous rest interval. The ZVI is equal to the rest interval and the NZVI is equal to the motion interval.

B. THE FEATURES OF ACCELERATION AND ANGULAR RATE IN ZVI

The foot-mounted IMU measures the acceleration and angular rate, which makes it possible to distinguish the ZVI and NZVI. But it is still a challenge to get the accurate ZVI. The motion in NZVI is complex and irregular, and its inertial data fluctuates violently and randomly. However, the inertial data in the ZVI is relatively stable. Theoretically the acceleration magnitude should be equal to the gravity magnitude and the angular rate magnitude should be equal to 0 in the ZVI.

![Figure 1. Process of a gait cycle for walking.](image1)

![Figure 2. Model of OGC.](image2)
The inertial data of walking and running in OGC is shown in Figure 3. The variation of acceleration magnitude over time in the walking and running is shown in Figure 3-a and Figure 3-b. The color change of the lines represents the change of acceleration magnitude, and the black line represents the gravity magnitude. The red boxes correspond to the ZVIs. It can be seen that the acceleration magnitude fluctuates slightly around the gravity magnitude in the ZVI. In the NZVI, the acceleration magnitude has no fixed range and fluctuates greatly which is related to the actual foot motion.

The variation of angular rate magnitude over time in walking and running is shown in Figure 3-c and Figure 3-d. The color change of the lines represents the variation of angular rate magnitude and the red boxes correspond to the ZVIs. Angular rate magnitude fluctuates slightly around 0. In the NZVI, the angular rate magnitude has no fixed range and fluctuates greatly. We can deduce the theoretical features of acceleration magnitude.
and angular rate of the ZVI in OGC:

\[
\begin{align*}
OGC &= [T_0, T_1] \\
NZVI_1 &= [T_0, t_{z0}], \quad ZVI = (t_{z0}, t_{z1}), \\
NZVI_2 &= [t_{z1}, T_1] \\
E_{\text{acc}ZVI} &= \int_{t_{z0}}^{t_{z1}} acc(t)dt / (t_{z1} - t_{z0}) \to g \\
E_{\text{gyr}ZVI} &= \int_{t_{z0}}^{t_{z1}} gyr(t)dt / (t_{z1} - t_{z0}) \to 0
\end{align*}
\]  

where \(T_0\) and \(T_1\) are respectively the start time and the end time of the OGC; \(t_{z0}\) and \(t_{z1}\) are respectively the start time and the end time of the ZVI; The interval between \(T_0\) and \(t_{z0}\) is the NZVI. The interval between \(t_{z1}\) and \(T_1\) is the NZVI. \(E_{\text{acc}ZVI}\) and \(E_{\text{gyr}ZVI}\) are respectively the expectation of acceleration magnitude and angular rate magnitude in the ZVI.

### III. THE ALGORITHM OF OIE-ZVD

As shown in Figure 4, the algorithm of OIE-ZVD includes four major parts:

1. The detection of OGC: The angular rate magnitude is used to decide the OGC. This is the basic unit to get the ZVI.
2. The convex function: It is a nonlinear amplifier to amplify the difference between the ZVI and NZVI.
3. The zero-velocity benchmark: It is used to give the following rough search a criterion that will decide the NZVI.
4. The hierarchical iterative search: The rough search will eliminate NZVIs and get an inaccurate ZVI. The trim will process the inaccurate ZVI and finally get the accurate ZVI.

#### A. THE DETECTION OF OGC

The OIE-ZVD gets the ZVI after completing a step. So it is necessary to determine OGC at first. The angular rate is used to determine OGC.
The measurement noise exists in the raw signals of IMU, which will bring considerable difficulties to data analysis. The raw inertial data should be processed to reduce the sensor noise in advance. A weighted-average filter is used to process the raw angular rate signal to reduce the measurement noise. The filter is defined as:

\[
\text{Signal}_{\text{processed}}(k) = \sum_{i=k-w_{\text{size}}}^{k+w_{\text{size}}} \text{Signal}_{\text{raw}}(i) \cdot f(|i-k|) 
\]

(2)

\[
f(|i-k|) = \frac{w_{\text{size}} - |i-k|}{w_{\text{size}}^2}
\]

(3)

where \(w_{\text{size}}\) is the size of window which is a small integer; \(f(|i-k|)\) is the weight function corresponding to time; \(\text{Signal}_{\text{raw}}\) is the raw angular rate signal and \(\text{Signal}_{\text{processed}}\) is the processed angular rate signal.

After noise reduction, a sliding-window-averaging (SWA) filter is adopted to determine OGC. The window size for SWA is set to half of the IMU output frequency. The SWA is as follows:

\[
\text{Signal}_{\text{SWA}}_{\text{processed}}(k) = \frac{1}{2w+1} \sum_{i=k-w}^{k+w} \text{Signal}_{\text{processed}}(i)
\]

(4)

where the value of \(w\) is half of the IMU output frequency; \(\text{Signal}_{\text{SWA}}_{\text{processed}}\) is the final signal which is used to detect the OGC.

As shown in Figure 5, the blue curve is the raw angular rate signal and the green curve is the angular rate signal after SWA. It can be seen that the signal presents periodic fluctuation like sinusoidal signal, and the red dots represent the local peak points of the signal. The peak points are corresponded to the original signal, and the interval between two adjacent peak points is OGC. As shown in the figure, each OGC is separated by a red dotted line.
B. SEARCH SPACE MAPPING OF ACCELERATION

The first step in distinguishing the ZVI and the NZVI is to find a criterion. According to the analysis in the previous section, the gravity is a good criterion to distinguish the acceleration among the different intervals. Direct comparison of numerical values is not feasible due to the errors. Therefore, an approach is needed here to amplify the difference between the ZVI and NZVI so as to distinguish the two intervals accurately. In our work, a special convex function maps the acceleration magnitude to a search space, in which differences between two intervals are compared.

The local gravity magnitude is \( g \) which is known in advance. The acceleration magnitude obtained by IMU at the moment of \( k \) is \( \text{acc}(k) \) in OGC. The ratio between \( \text{acc}(k) \) and \( g \) is \( \text{ratio}(k) \) at sampling instance \( k \). It is calculated as:

\[
\text{ratio}(k) = \frac{\text{acc}(k)}{g}
\]  

(5)

The conclusion is obtained that \( \text{acc}(k) \) is closer to \( g \) in the ZVI in section II. This means \( \text{ratio}(k) \) should be closer to 1 in the ZVI. This gives a scale standard to compare. We need a method to greatly amplify \( \text{ratio}(k) \) if \( \text{acc}(k) \) is in the NZVI. Meanwhile, \( \text{ratio}(k) \) will be amplified little if \( \text{acc}(k) \) is in the ZVI. As shown in Figure 6-a, a special convex \( f(x) \) is proposed to amplify the difference:

\[
f(x) = e^x + e^{1/x}, \quad x \in (0, \infty)
\]  

(6)

The derivative of \( f(x) \) is:

\[
f'(x) = e^x - e^{1/x} / x^2, \quad x \in (0, \infty)
\]  

(7)

As shown in Figure 6-b, \( f'(x) \) is a monotonic increasing function. \( f'(x) \) is only equal to 0 when \( x = 1 \).

From the analysis of \( f'(x) \), \( f(x) \) has the minimum value when \( x = 1 \). \( f(x) \) changes slowly when \( x \) is near 1 and changes extremely fast when \( x \) is far away from 1. \( f(x) \) meets the requirements of amplifying \( \text{ratio}(k) \). \( \text{ratio}(k) \) is mapped to the search space by \( f(\text{ratio}(k)) \). In the search space, if \( \text{acc}(k) \) is in the NZVI, \( f(\text{ratio}(k)) \) will become very large.
As shown in Figure 7, the acceleration magnitude in Figure 3 is mapped to the search space. In Figure 7, the data is very stable in the ZVI. However, it fluctuates greatly in the NZVI. This is extremely obvious in running as shown in Figure 7-c and the difference reaches seven orders of magnitude. Figure 7-b and Figure 7-d are respectively the enlarged parts of Figure 7-a and Figure 7-c. The value of the red horizontal lines in both figures is about 5.4366 which is much larger than 0.1845 which corresponds to the measurement error percentage of the accelerometer.

\[ e^{1+20\%} + e^{1/(1+20\%)} - e^1 - e^1 \approx 0.1845 \]  

The data of the ZVI in the search space is more stable. By this method, we can identify \( acc(k) \) which is much larger than \( g \). It cannot be in the ZVI and should be eliminated.

C. ZERO-VELOCITY BENCHMARK

By mapping the acceleration magnitude to the search space, we can intuitively distinguish the approximate range of the ZVI and the NZVI. However, an accurate range of the ZVI is required for ZUPT. In order to determine the range of the ZVI accurately, it is necessary to find a zero-velocity benchmark, which can be used as a representative of other points in the ZVI. The zero-velocity benchmark will provide a criterion for the next rough search.

The zero-velocity benchmark must be in the ZVI, which should have the features of the ZVI. Its acceleration magnitude should be close to \( g \). Actually there are also some points satisfying this feature in the NZVI, which are required to be excluded. It is assumed that the maximum measurement error percentage of the accelerometer is \( P_{MEP} \) which should be calibrated in advance. The IMU is set stationary for a long time and the magnitude of acceleration is \( acc_s(k) \) at sampling instance \( k \). \( P_{MEP} \) is calculated:

\[ bias(k) = abs(acc_s(k) - g) \quad k = 1, 2, 3 \cdots \]
\[ P_{MEP} = \max(bias(k))/g \]  

A set containing several intervals is obtained by the following:

\[ x_i = f(acc(i)/g) \quad i \in OGC = [T_0, T_1] \]
\[ SESP = \{x_1, x_2 \cdots x_i \cdots \} \]  

\[ V_{ZVB} = f(1 + P_{MEP}) \]
\[ itv_k = \{x_{m}, x_{m+1}, x_{m+2} \cdots x_{m+s}/s_{m+s} \leq V_{ZVB}, s = 0, 1 \cdots f \} \]  

\[ Sitv = \{itv_1, itv_2 \cdots itv_n \cdots \} \]
\[ itv_1 \cap itv_2 \cdots \cap itv_{n-1} \cap itv_n = \emptyset \]

where \( SESP \) is the search space and \( x_i \) is the data at the moment of \( i \) in it; \( V_{ZVB} \) is the value of \( (1 + P_{MEP}) \) in the search space; \( Sitv \) is the set of intervals meeting the condition and \( itv_n \) is the nth interval. One of elements in \( Sitv \) contains the ZVI. In fact, there are few \( x_i \) whose acceleration magnitude close to \( g \) in the NZVI. Therefore, if the \( itv \) contains the ZVI, it will be much denser than the others without the ZVI. From the above analysis, the zero-velocity benchmark can be determined by the mean and median of the positions of all \( x_i \) in \( itv_n \), as shown in the formulas:

\[ p_{ave} = \text{Mean} \left( \sum_{k=1}^{n} \sum_{s=m}^{m+j} \text{position}(x^k_i) \right) \]
\[ p_{mid} = \text{Median} (\text{position}(x^k_i)) \]
\[ x^k_i \leftrightarrow x_i, \quad i \in OGC = [T_0, T_1] \]
\[ i = \text{position}(x^k_i) \]
\[ p_{benchmark} = \text{INT} ((p_{ave} + p_{mid})/2) \]  

where \( p_{ave} \) is the average position of the points in \( itv \); \( p_{mid} \) is the median position of the points in \( itv \); \( p_{benchmark} \) is the position of the zero-velocity benchmark.
TABLE 1. Statistics of ZVIs for three experimenters.

|          | Number of IMU samples | ZVIs | Percentage | ZVIs | Percentage | ZVIs | Percentage |
|----------|-----------------------|------|------------|------|------------|------|------------|
| N1er     | 596297                | 285516 (1e)  | 48.38%     | 260256 | 43.64%     | 270627 | 45.38%     |
| N2er     | 587399                | 268975 (3.3e) | 45.79%     | 277843 | 47.30%     | 272552 | 46.40%     |
| N3er     | 589582                | 272864 (5e)  | 46.30%     | 258547 | 43.87%     | 266276 | 45.18%     |

FIGURE 15. Comparison of the detected ZVI by Adaptive-SHOE, OIE-ZVD and SHOE with corresponding the optimal thresholds.

FIGURE 16. The calculated horizontal trajectories of the three experimenters by SHOE with different thresholds in experiment I.

Figure 8-a is the OGC of walking. The red line in the black rectangle is the \( itv \) calculated by formula (10) and formula (11). We can get four intervals \( (itv_1, itv_2, itv_3 \) and \( itv_4 \)) in this OGC. It can be seen from the figure that the interval \( (itv_2) \) containing the ZVI is dense, and the intervals \( (itv_1, itv_3 \) and \( itv_4) \) excluding the ZVI are sparse. The green dot in the figure is the zero-velocity benchmark obtained by formula (13). We can set a rough value \( V_{MEP} \) corresponding to \( P_{MEP} \) (the maximum measurement error percentage of the accelerometer) in the search space.

\[
V_{MEP} = \max(e^{1+P_{MEP}} + e^{1/(1+P_{MEP})}, e^{1-P_{MEP}} + e^{1/(1-P_{MEP})})
\]

D. HIERARCHICAL ITERATIVE SEARCH FOR ZERO-VELOCITY OPTIMAL INTERVAL

When the zero-velocity benchmark is determined, the ZVI can be accurately determined in OGC. The hierarchical iterative method is adopted to search ZVI in the search space. The first step determines an approximate range of the ZVI by the rough search. The second step adopts the method of trim to determine the ZVI with high precision. The ZVI can be detected accurately by the two steps.

1) ROUGH SEARCH OF THE ZVI

The core idea of the rough search is to find \( acc(k) \) which cannot be in the ZVI. \( acc(k) \) in the NZVI should have significant difference from \( g \), which is extreme obvious in the search space. We can set a rough value \( V_{MEP} \) corresponding to \( P_{MEP} \) (the maximum measurement error percentage of the accelerometer) in the search space.

\[
V_{MEP} = \max(e^{1+P_{MEP}} + e^{1/(1+P_{MEP})}, e^{1-P_{MEP}} + e^{1/(1-P_{MEP})})
\]
of $x_{\text{benchmark}}$, the interval in front of $x_d$ should be considered as the NZVI according to the time order. If $x_d$ is behind $x_{\text{benchmark}}$, the interval behind $x_d$ should be considered as the NZVI according to the time order. As the NZVI is determined, we can eliminate it from the SESP and get a new SESP. Then we should repeat these steps in the new SESP until $\max SEPS$ is less than $V_{MEP}$. The rough search is a greedy and fast method to determine the approximate range of the ZVI. After the rough search, we will carry out the trim on the remaining interval to get the accurate ZVI.

2) TRIM OF THE ZVI

The core idea of the trim is to find an optimal interval that most accords with the statistical feature of acceleration in the ZVI. In the search space, the theoretical expectation of the data in the ZVI is $2e$. If there is an interval in the search space, its expectation is approximate to $2e$, and the elimination of any point in this interval has little influence on the expectation. This interval can be considered as the ZVI.

In the model of OGC, $acc(k)$ in the NZVI should be at both ends of the remaining interval after the rough search. We compare the values of the two endpoints in the search space. The point with the larger value should be eliminated as the possible $acc(k)$ in the NZVI. Based on this method, the expectation of the interval before elimination is $E_{\text{pre}}$ and the expectation of the interval after elimination is $E_{\text{cur}}$. The ratio of $E_{\text{pre}}$ and $E_{\text{cur}}$ can be mapped to another search space by the same convex function, as shown in the formula:

$$p_E = \frac{E_{\text{cur}}}{E_{\text{pre}}}$$

$$f(p_E) = e^{p_E} + e^{1/p_E}$$  \hspace{1cm} (15)

The optimal ZVI can be determined by the convergence in the search space. After several iterations in the trim, there will be a termination when convergence condition is reached in both cases, as show in the formula:

$$|f(E/g) - 2e| < \epsilon$$

$$|f(E_{\text{cur}}/E_{\text{pre}}) - 2e| < \epsilon$$  \hspace{1cm} (16)

where $\epsilon$ is the convergence criteria.

The flow chart of hierarchical iterative search is shown in Figure 9. The left part is the rough search and the right part is the trim.

As shown in Figure 10, the red lines represent $2e$ which is the theoretical convergence value. After several iterations, the data in the search space converges to the vicinity of $2e$.

Examples of the hierarchical iterative search are shown in Figure 11. The red lines represent the NZVI eliminated by rough search and the green lines represent the NZVI eliminated by the trim. The blue lines represent the estimated optimal ZVI. After the rough search and the trim, the accurate ZVI is acquired.

IV. EXPERIMENTS AND ANALYSIS

In order to evaluate the effectiveness of OIE-ZVD, two kinds of experiments in different scenarios and locomotion

![FIGURE 17. The calculated horizontal trajectories of the three experimenters by OIE-ZVD, Adaptive-SHOE and SHOE in experiment I.](image)

| TABLE 2. The horizontal position errors. |
|-----------------------------------------|
|                            | SHOE(m) | 3.3e^6 | 5e^6 | 1e^7 | ADAPTIVE-SHOE(m) | OIE-ZVD(m) |
| N1er | ESEP | MEAN | RMS | ESEP | MEAN | RMS | ESEP | MEAN | RMS | ESEP | MEAN | RMS | ESEP | MEAN | RMS | ESEP | MEAN | RMS |
| N2er | 2.18 | 5.07 | 8.98 | 29.32 | 51.23 | 82.46 | 19.03 | 40.19 | 67.73 | 1.19 | 5.11 | 9.23 | 1.38 | 4.83 | 7.45 |
| N3er | 22.67 | 74.21 | 96.58 | 2.76 | 10.06 | 16.87 | 14.26 | 69.68 | 79.12 | 2.49 | 9.91 | 15.42 | 2.14 | 9.32 | 14.61 |

![FIGURE 18. The experiment of three different kinds of locomotion by the same experimenter.](image)
were conducted. We use SHOE and Adaptive-SHOE [18] to compare with OIE-ZVD. SHOE is a fixed threshold-based ZVD. Adaptive-SHOE is an adaptive threshold-based ZVD. The online code of Adaptive-SHOE is located at http://www.openshoe.org/?page_id=54.

The gyroscope bias repeatability of the IMU is 1.5°/s, and the in-run bias stability is 10°/h. The accelerometer bias repeatability of IMU is 5mg, and the in-run bias stability is 0.05mg. The sampling rate of the IMU is 400Hz. The winsize is 5 and the \( w = 200 \) which is the half of IMU sampling rate. The \( P_{MEP} \) calibrated in advance is about 13% and the \( \varepsilon = 0.01 \). These parameters are used in all experiments. The IMU is mounted on to the front of a shoe as shown in Figure 12.

**A. EXPERIMENT I: ADAPTABILITY TO DIFFERENT PEOPLE**

As shown in Figure 13, this experiment is conducted by three experimenters on the outdoor playground. This experiment aims at verifying the availability of OIE-ZVD for different people. The weight and height of the three experimenters are different. They walked around the playground four times. The real trajectory on the Google Maps is shown in Figure 14. The green dots are four benchmarks which are set to compare the navigation error. The total walking time is about 1490.74s (24min50.74s) and the total walking distance is about 1871.58m. The start point and the end point of the experiment is the same point for each person.

1) ZVI DETECTION RESULTS

Different people have different thresholds to detect the ZVI. The thresholds tuning is required to get the correct ZVI by SHOE. This is time-consuming and inconvenient. After tuning, we obtain the optimal thresholds for each experimenter. \( 1 \times 10^{-5}, 3.3 \times 10^{-4} \) and \( 5 \times 10^{-4} \) are respectively the optimal thresholds to the No.1 experimenter (N1er), the No.2 experimenter (N2er) and the No.3 experimenter (N3er).

The accuracy of the ZVI detection is very important for the following Kalman Filter. If the detected number of ZVIs is much more than the true number, it will bring extra errors by Kalman Filter. If the detected number of ZVIs is much less than the true number, Kalman Filter cannot correct errors well.

As shown in Table 1, the total number of IMU samples for N1er is 596297. The total number of IMU samples in ZVIs is 285516 by SHOE with the optimal threshold \( 1 \times 10^{-5} \) and accounts about 48.38%. The total number of IMU samples in ZVIs is 260256 by Adaptive-SHOE and accounts about 43.64%. The total number of IMU samples in ZVIs is 270627 by OIE-ZVD and accounts about 45.38%. The statistics of N2er and N3er is also shown in Table 1.

The number of ZVIs calculated by different method is similar for the same person. This is very obvious in Figure 15. In Figure-15a, SHOE detects some short ZVIs which Adaptive-SHOE and OIE-ZVD cannot detect. The acceleration magnitude in the short ZVIs is not as stable as in the long ZVIs. These short ZVIs are suspicious. The reason is that the threshold is tuned manually and the existence of the threshold errors is inevitable. However, these errors have little influence on the system.

From the results of Table 1 and Figure 15, OIE-ZVD can perform as well as Adaptive-SHOE and SHOE with the optimal threshold in walking. OIE-ZVD does not need thresholds tuning like SHOE.

2) NAVIGATION RESULTS

The navigation results are shown in Figure 16 and Figure 17. The horizontal errors between the start point and the end point (ESEP) are shown in Table 2.

As shown in Figure 16-a, the red line represents the horizontal trajectory by SHOE with the optimal threshold \( 1 \times 10^{-5} \) for N1er. The horizontal error between the start point and the end point of the red line is about 2.28m. The calculated trajectory...
is well fitted with the real one. However, the error of the blue line ($3.3 \times 10^4$) is about 18.41 m and the error of the green line ($5 \times 10^4$) is about 14.52 m. The blue line and the green line are not fitted well with the real trajectory. The similar results are shown in Figure 16-b and Figure 16-c and the statistics is shown in TABLE 2. Through the analysis, different people may have different thresholds and the fixed threshold-based ZVD is inconvenient in real.

As shown in Figure 17, the horizontal trajectories of experimenters are calculated and shown by OIE-ZVD, Adaptive-SHOE and SHOE with the optimal threshold for each person. OIE-ZVD and Adaptive-SHOE can directly get the appropriate results without tuning thresholds. Their horizontal errors between the start point and the end point are shown in TABLE 2.

As shown in Figure 14, four benchmarks are set to estimate the errors. In TABLE 2, the mean (MEAN) and the root mean square (RMS) of the horizontal errors are calculated compared to the four benchmarks. The accuracy of navigation results have a direct connection with the thresholds for SHOE. Although the maximum horizontal RMS error (16.87 m) accounts for about 0.91% after tuning the thresholds, the fixed threshold-based ZVD is not convenient in application. The maximum horizontal RMS error (14.61 m) of OIE-ZVD accounts for about 0.80%. OIE-ZVD can detect the ZVI accurately and adaptively like Adaptive-SHOE in walking.

**B. EXPERIMENT II: ADAPTABILITY TO DIFFERENT LOCOMOTION**

As shown in Figure 18, the experiment was conducted by the same experimenter with three different kinds of locomotion. This aims at verifying the adaptability and robustness of OIE-ZVD under the condition of different locomotion. Adaptive-SHOE can work well in walking and will still need to be used with motion classifiers that enable adaptive parameter tuning in the future [18]. Adaptive-SHOE may have poor performance in this experiment.

The first locomotion (LM1) is walking. The total locomotion time is about 1120.56 s (18 min 40.56 s) and the total distance is about 1154.07 m. The second locomotion (LM2) is stair climbing/descending. The total locomotion time is about 960.48 s (16 min 0.48 s) and the total distance is about 517.28 m. The third locomotion (LM3) is combination of walking, jogging and running. The total locomotion time is about 1020.51 s (17 min 0.51 s) and the total distance is about 1247.21 m. The experimenter started and finished the locomotion at the same position in all experiments.

1) ZVI DETECTION RESULTS

Different locomotion needs different thresholds to detect the ZVI for SHOE. After tuning, we obtain the optimal thresholds for each locomotion. $7e^5$, $1.4e^5$ and $8.6e^4$ are the optimal thresholds for LM1, LM2 and LM3.

As shown in TABLE 3 and Figure 19, OIE-ZVD, Adaptive-SHOE and SHOE all can perform well in walking...
as the results in the experiment I. However, Adaptive-SHOE performs badly in the other locomotion. In Figure 19-b and Figure 19-c, it cannot detect ZVIs correctly for LM2 and LM3. OIE-ZVD can still detect ZVIs correctly. The statistics in TABLE 3 shows obvious difference in the total number of IMU samples in ZVIs. In LM2, Adaptive-SHOE, SHOE and OIE-ZVD respectively account 56.39%, 62.37% and 61.23%. The total number of IMU samples in ZVIs by Adaptive-SHOE is much less than that by SHOE or OIE-ZVD. In LM3, Adaptive-SHOE, SHOE and OIE-ZVD respectively account 47.48%, 53.11% and 53.35%. Adaptive-SHOE misses more ZVIs in LM2 and LM3.

In LM3, the number of IMU samples in ZVIs by SHOE is close to that by OIE-ZVD. But their detection accuracy is different. In Figure 19-c, SHOE misses ZVIs compared to OIE-ZVD. These ZVIs are detected by OIE-ZVD. OIE-ZVD can still perform well in different locomotion.

2) NAVIGATION RESULTS
The navigation results are shown in Figure 20 and Figure 21. Figure 22 is the real trajectory of walking. The experimenter walked indoors and outdoors. The walking navigation results are shown in Figure 20-a and Figure 21-a. Like the former analysis, SHOE with the optimal threshold, Adaptive-SHOE and OIE-ZVD performs well. In TABLE 4, the horizontal position errors between the start point and the end point are all less than 5m for them in walking.

Figure 20-b and Figure 21-b are the height results of LM2. Although the horizontal error between the start point and the end point is about 2.09m by Adaptive-SHOE, the vertical error diverges in Figure 21-b and the vertical error is about 18.18m in TABLE 5. This means that Adaptive-SHOE cannot work well in LM2. OIE-ZVD can still work well and get the accuracy similar to SHOE with the optimal threshold. However, the optimal threshold is required to be tuned in advance. OIE-ZVD is a more efficient method.

V. CONCLUSION
A novel adaptive zero-velocity detector based on optimal interval estimation is proposed in this work. According to the features of the inertial data, OGC is taken as the basic unit of bipedal locomotion. In OGC, the features of the ZVI and the NZVI are different. To amplify the difference between the intervals, a convex function is used to map the acceleration to the search space. The optimal ZVI is estimated through the zero-velocity benchmark and the hierarchical iterative search in the search space. This algorithm can find the ZVI without setting thresholds.

We conducted extensive experiments to evaluate OIE-ZVD across different people, different scenarios and different locomotion. Compared with SHOE which has the optimal threshold, OIE-ZVD can achieve the same level of accuracy. In walking, OIE-ZVD can perform as well as Adaptive-SHOE. When Adaptive-SHOE is unusable in other locomotion, OIE-ZVD can still work well. OIE-ZVD has the advantage of higher convenience and efficiency. The horizontal error of the navigation results only accounts for less than 1% in the experiment I by OIE-ZVD. In the experiment II, OIE-ZVD has accurately detected the ZVI under different locomotion. The horizontal error is within 0.3% and the vertical error is corrected. Experimental results indicate the effectiveness and reliability of OIE-ZVD.

Some future work is required to be done. More kinds of locomotion in different scenarios should be tested to verify
the robustness of OIE-ZVD in the future. The algorithm of OGC detection can be improved. Meanwhile, the application of OIE-ZVD in real time is the target for us.

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REFERENCES

[1] S. Godha, G. Lachapelle, and M. E. Cannon, “Integrated GPS/INS system for pedestrian navigation in a signal degraded environment,” in Proc. ION GNSS, Fort Worth TX, USA, Sep. 2006, pp. 26–29.

[2] M. Sun, Y. Wang, S. Xu, H. Qi, and X. Hu, “Indoor positioning tightly coupled Wi-Fi FTM ranging and PDR based on the extended Kalman filter for smartphones,” IEEE Access, vol. 8, pp. 49671–49684, 2020.

[3] H. Benzerrouk and A. V. Nebylov, “Robust IMU/UWB integration for indoor pedestrian navigation,” in Proc. 25th St Petersburg Int. Conf. Integ. Navigat. Syst. (ICINS), St. Petersburg, Russia, May 2018, pp. 1–5.

[4] V. Andrushchak, T. Maksymyuk, M. Klymash, and D. Ageyev, “Development of the iBeacon’s positioning algorithm for indoor scenarios,” in Proc. Int. Symp. Practice. Problems Infocommunications. Sci. Technol. (PIC S&T), Kharkiv, Ukraine, 2018, pp. 741–744.

[5] R. Harle, “A survey of indoor inertial positioning systems for pedestrians,” IEEE Commun. Surveys Tuts., vol. 15, no. 3, pp. 1281–1293, 3rd Quart., 2013.

[6] E. Foxlin, “Pedestrian tracking with shoe-mounted inertial sensors,” IEEE Comput. Graph. Appl., vol. 25, no. 6, pp. 38–46, Nov. 2005.

[7] S. Godha and G. Lachapelle, “Foot Mounted Inertial System for Pedestrian Navigation,” Meas. Sci. Technol., vol. 19, no. 7, pp. 1–9, Jul. 2008.

[8] I. Skog, P. Handel, J. O. Nilsson, and J. Rantakokko, “Zero-velocity detection—An algorithm evaluation,” IEEE Trans. Biomed. Eng., vol. 57, no. 11, pp. 2657–2666, Nov. 2010.

[9] Z. Wang, H. Zhao, S. Qiu, and Q. Gao, “Stance phase detection for ZUPT-aided foot-mounted pedestrian navigation system,” IEEE/ASME Trans. Mechatronics, vol. 20, no. 6, pp. 3170–3181, Dec. 2015.

[10] J.-O. Nilsson, A. K. Gupta, and P. Handel, “Foot-mounted inertial navigation made easy,” in Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN), Busan, South Korea, Oct. 2014, pp. 24–29.

[11] J.-O. Nilsson, I. Skog, and P. Handel, “A note on the limitations of ZUPTs and the implications on sensor error modeling,” in Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN), May 2012, pp. 1–4.

[12] R. Zhang, F. Hoflinger, and L. Reindl, “Inertial sensor based indoor localization and monitoring system for emergency responders,” IEEE Sensors J., vol. 13, no. 2, pp. 838–848, Feb. 2013.

[13] S. Y. Park, H. Ju, and C. G. Park, “Stance phase detection of multiple actions for military drill using foot-mounted IMU,” in Proc. IEEE Int. Conf. Indoor Positioning Indoor Navigat., Alcala de Henares, Spain, Oct. 2016, pp. 54–58.

[14] Y. Li and J. J. Wang, “A robust pedestrian navigation algorithm with low cost IMU,” in Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN), Sydney, NSW, Australia, Nov. 2012, pp. 1–7.

[15] D. Arden, “Indoor pedestrian navigation with foot-mounted strapdown inertial navigation and cooperative sensor fusion for indoor positioning,” in Proc. Int. Tech. Meet. Int. Navig., San Diego, CA, USA, Jan. 2010, pp. 89–98.

[16] X. Yu, B. Liu, X. Lan, Z. Xiao, S. Lin, B. Yan, and L. Zhou, “AZUPT: Adaptive zero velocity update based on neural networks for pedestrian tracking,” in Proc. IEEE Global Commun. Conf. (GLOBECOM), Waikoloa, HI, USA, Dec. 2019, pp. 1–6.

[17] J. Bird and D. Arden, “Indoor navigation with foot-mounted strapdown inertial navigation and magnetic sensors [emerging opportunities for localization and tracking],” IEEE Wireless Commun., vol. 18, no. 2, pp. 28–35, Apr. 2011.

[18] J. Wahlstrom, I. Skog, F. Gustafsson, A. Markham, and N. Trigoni, “Zero-velocity detection—A Bayesian approach to adaptive thresholding,” IEEE Sensors Lett., vol. 3, no. 6, pp. 1–4, Jun. 2019.

[19] X. Tian, J. Chen, Y. Han, J. Shang, and N. Li, “A novel zero velocity interval detection algorithm for self-contained pedestrian navigation system with inertial sensors,” Sensors, vol. 16, no. 10, p. 1578, Sep. 2016.

[20] Y. Wang and A. M. Shkel, “Adaptive threshold for zero-velocity detector in ZUPT-aided pedestrian inertial navigation,” IEEE Sensors Lett., vol. 3, no. 11, pp. 1–4, Nov. 2019.

[21] T. Feigl, S. Kram, P. Walter, R. H. Siddiqui, M. Philipsen, and C. Mutschler, “A bidirectional LSTM for estimating dynamic human velocities from a single IMU,” in Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN), Pisa, Italy, Sep. 2019, pp. 1–8.

[22] B. Wagstaff and J. Kelly, “LSTM-based zero-velocity detection for robust inertial navigation,” in Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN), Nantes, France, Sep. 2018, pp. 24–27.

[23] Y. Kone, N. Zhu, V. Renaudin, and M. Ortiz, “Machine learning-based zero-velocity detection for inertial pedestrian navigation,” IEEE Sensors J., vol. 20, no. 20, pp. 12343–12353, Oct. 2020, doi: 10.1109/JSENS.2020.2998963.

[24] C. W. Chan and A. Rudins, “Foot biomechanics during walking and running,” Mayo Clin. Proc., vol. 69, no. 5, pp. 448–461, 1994.

[25] C. L. Vaughan, B. L. Davis, and J. C. O’Connor, “The three dimensional and cyclic nature of gait,” in Dynamics of Human Gait, 2nd ed. Western Cape, South Africa: Kiboho, 1992, pp. 11–12.

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