Learning of Zero-Velocity Detection for Inertial Pedestrian Navigation

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Abstract. The detection of zero-velocity states is the vital prerequisite for zero-velocity update in the foot-mounted inertial pedestrian navigation system. The previous zero-velocity detector determines zero-velocity states by comparing measured inertial data with a calibrated threshold. The calibration of the threshold is inconvenient for this kind of the zero-velocity detector because the threshold is variable corresponding to different people and locomotion. The best threshold needs to be tuned corresponding to different situations. In essence, the detection of zero-velocity states is a binary classification problem. As the success of deep learning in image classification and speech recognition, it is possible to design an adaptive zero-velocity detector based on it. A Siamese network is designed to learn the metric of distinguish zero-velocity states. This method can adaptively get the most likely correct results without threshold tuning. Experiments are conducted and results show that the matching degree is about 96.31% and the navigation accuracy can reach within 4m in 20min.

1. Introduction

Achieving high-precision navigation and positioning is the pursuit of human beings. The research in pedestrian navigation which can provide continuous and accurate navigation information in all scenarios, has been going on for decades [1]. GPS has provided users with more accurate positioning information. However, GPS will fail when users are in scenarios such as indoor and forest due to the blocking and attenuation of the signal. The foot-mounted inertial pedestrian navigation using Micro Electro Mechanical Systems (MEMS) can still work in scenarios without pre-installed infrastructure or prior map information [2]. Zero-velocity update (ZUPT) is an efficient method to solve the divergence of inertial navigation. ZUPT includes two main parts: the zero-velocity detector (ZVD) and the Kalman filter. The performance of the ZVD plays an important role in the navigation result corrected by the Kalman filter [3]-[5].

The previous ZVDs determine zero-velocity states by the comparison of a certain threshold. These kinds of detectors include: Acceleration or Angular Rate Moving Variance or Moving Average Detector (AMVD), Acceleration Magnitude Detector (AMD), Angular Rate Energy Detector (ARED) and Stance Hypothesis Optimal Detector (SHOE) [3]-[7]. The performance of the ZVD depends on the calibration of the threshold. If the threshold is too large, some non-zero-velocity states may be determined as zero-velocity states falsely. If the threshold is too small, some zero-velocity states may be missed. It will cost much work to calibrate the optimal threshold. The optimal threshold depends on several factors such as the type of bipedal locomotion, the placement of MEMS and the difference of people. Adaptive-threshold ZVD has been studied in these years. The optimal threshold is usually decided by a velocity
or motion mode classification in the adaptive-threshold ZVD [8]-[13]. However, it is hard to build a
general velocity or motion mode classification due to the complexity and diversity of bipedal locomotion.

To solve the problems of traditional ZVDs, an adaptive ZVD is designed in our work based on deep
learning. The inertial data of MEMS mounted on the foot is processed and its features are trained by the
convolutional neural network. Then the Siamese network will compare the features. This network can
learn the inner features and the difference between the zero-velocity states and non-zero-velocity states
automatically so that it can detect zero-velocity states accurately.

2. Analysis of inertial data in bipedal locomotion

2.1. The inertial data in bipedal locomotion

Bipedal locomotion includes walking, jogging, running, jumping, etc. Bipedal locomotion always has a
stage of contacting with the ground and the feet in contact with the ground will be static. As shown in
Figure 1, this is a piece of data measured by MEMS mounted on foot during walking. The grey part is
the phase where the foot is moving and the purple part is the phase where the foot is static. The static
state is a good observation and can be used to correct navigation error by Kalman Filter.

![Figure 1. The inertial data in walking.](image)

2.2. The distribution of inertial data in bipedal locomotion

The zero-velocity state occurs periodically in the process of bipedal locomotion and is distributed
regularly in the space of inertial data. As shown in Figure 2, it is the scatter diagram of acceleration
norm and angular rate norm in low dynamic and high dynamic. Figure 2-b and Figure 2-d are partial
enlargements of Figure 2-a and Figure 2-c respectively. The zero-velocity states are calculated by SHOE
with corresponding optimal thresholds. The figure intuitively indicates that the acceleration norm is
close to the gravity value and the angular rate norm is close to 0. In theory, the acceleration norm should
be equal to the gravity value and the angular rate should be equal to the earth rotation rate which could
be considered as 0 as it merges in the measurement noise.

Based on the above analysis, the inertial data point can be considered to be still when the acceleration
norm is close to the gravity value and the angular rate norm is close to 0. However, it is difficult to get
an accurate and constant value which can determine if the measured data is close to the target value.

![Figure 2. The distribution of inertial data in walking.](image)
3. Deep learning of zero-velocity detection

3.1. The framework of Siamese network

Siamese network is a similarity measurement method, which can be used to identify and classify categories when the number of categories is large. Siamese network learns a similarity measure from the data and uses the learned metric to compare and match new unknown samples. In the practical application of ZUPT, it is needed to take some time to stand still for initial alignment before locomoting. This will provide the inertial data during still state. These data can be used as the reference value for detecting other zero-velocity states. $X^k_{\text{still}}$ is the measured inertial data at instance $k$ during initial static state. $X^k_{\text{Anchor}}$ is the average value of $X^k_{\text{still}}$

$$X^k_{\text{still}} = \begin{bmatrix} \text{acc}_x^k & \text{acc}_y^k & \text{acc}_z^k \\ \text{gyr}_x^k & \text{gyr}_y^k & \text{gyr}_z^k \end{bmatrix},$$

$$X^k_{\text{Anchor}} = \text{mean}(X^k_{\text{still}}), k = 1, 2 \cdots n$$

As shown in Figure 3, it is the Siamese network of zero-velocity detection. $X^k_{\text{sample}}$ is the other inertial data. By training this network, we can get a network determining zero-velocity states.

![Figure 3. The Siamese network of zero-velocity detection](image)

3.2. The design of Siamese network

The net is shown in Figure 4. It contains two convolution layers and two fully connected layers.

![Figure 4. The design of net](image)
\[ D_u'(X_{\text{Anchor}}, X_i) = \left \| \text{net}(X_{\text{Anchor}}) - \text{net}(X_i) \right \| \]

\[ \text{loss}_w^i = \frac{Y(D_u')^2}{2} + \frac{(1-Y)}{2} \left \{ \max (0, m - D_u') \right \} \]

\[ \text{loss} = \sum_i \text{loss}_w^i \]  

Where, \( D_u' \) is defined as the Euclidean distance between the outputs of \( X_{\text{Anchor}} \) and \( X_i \) in the Siamese network; \( Y \) is 1 when \( X_{\text{Anchor}} \) and \( X_i \) are with the same label; \( Y \) is 0 when \( X_{\text{Anchor}} \) and \( X_i \) are with the different label; \( m \) is the margin value.

4. Experiments

4.1. Training of the network

As Figure 5 shown, it is the experimenter’s foot with the MEMS. A dataset is set up for training this neural network, including 5 training sets and 10 test sets. The optimal thresholds for the dataset are calibrated by SHOE and the labels for the dataset are also got by it. The training platform is Nvidia RTX2060.

Figure 5. MEMS mounted on the foot

After 1000 iterations of training, the loss converges to about 6.642 in Figure 6. To evaluate the performance of the net, the results of the net will be compared with the results by SHOE with the optimal threshold. As shown in formula (3):

\[ MD = \frac{\sum (z_{\text{shoe}} \cap z_{\text{net}})}{\sum z_{\text{shoe}}} \]  

Where, \( z_{\text{shoe}} \) is the result of SHOE with the optimal threshold; \( z_{\text{net}} \) is the result of the net; \( MD \) is the matching degree.

The statistical results are shown in Table 1. We get the matching degree in test sets to evaluate the performance of the net. The average matching degree is about 96.31%.
Table 1. The results of this net in test sets.

| Test set | Optimal threshold | Matching degree | Test set | Optimal threshold | Matching degree |
|----------|-------------------|-----------------|----------|-------------------|-----------------|
| 1        | 1e5               | 96.54%          | 6        | 1.4e5             | 95.04%          |
| 2        | 3.3e4             | 98.74%          | 7        | 2.5e5             | 96.92%          |
| 3        | 5e4               | 97.31%          | 8        | 5.8e4             | 95.77%          |
| 4        | 8.6e4             | 95.95%          | 9        | 9.5e4             | 96.69%          |
| 5        | 7e5               | 93.91%          | 10       | 1.2e5             | 96.24%          |

4.2. Performance evaluation on pedestrian tracks

We conduct five experiments and each experiment time is over 20 min. The performance of the net is shown in Table 2. The average error is about 3.89m

Table 2. The navigation results of the net.

| Time(s) | Distance(m) | Error of the net(m) |
|---------|-------------|---------------------|
| 1       | 1205.56     | 1489.16             | 3.87     |
| 2       | 1212.98     | 1598.68             | 3.56     |
| 3       | 1392.61     | 1607.79             | 3.25     |
| 4       | 1914.04     | 1919.59             | 4.67     |
| 5       | 1820.91     | 1857.26             | 4.12     |

Figure 7. Trajectories of SHOE and the net

As shown in Figure 7, it is the results from the first experiment. Figure 7-a is the navigation trajectory calculated by SHOE with optimal threshold 2.3e5 and Figure 7-b is the navigation trajectory calculated by net. The navigation error of SHOE is about 4.13m and the navigation error of the net is about 3.87m. The net can perform as well as SHOE with the optimal threshold.

5. Conclusion

This adaptive detector by learning can detect zero-velocity accurately without threshold tuning. This method can improve the applicability of ZUPT. The experiments show that navigation accuracy can reach within 4m in 20min by this method.

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