Zero Velocity Detection in Foot-mounted Inertial Sensors: Novel method for generating zero velocity labels and a comparative analysis of data driven methods

Ashwani Kumar, Nishita Singh, Deepak Kumar Singh and Salil Goel
Geoinformatics, Dept. of Civil Engineering, IIT Kanpur, India

Key words: Inertial navigation, IMU, machine learning, zero-velocity detection, UWB, pedestrian dead reckoning, dataset

SUMMARY

Foot mounted inertial navigation is a hotspot problem in the field of indoor localization nowadays. It has various applications like navigation, indoor mapping, first responder positioning, gait analysis etc. In foot mounted inertial navigation, sensors such as Inertial measurement units (IMU) are installed on the feet of a user to utilize it for localization of the user. For user localization initial position, attitude of the user and current IMU sensor observations are used to find the current position of the user. However, IMU sensors used in indoor localization are low-cost sensors hence they suffer from various errors and biases which leads to drift in the final position estimation of the user. To bound the error growth, zero velocity update (ZUPT) is used which requires a crucial step of zero velocity detection. In zero velocity detection, time interval at which the foot of the user is firmly placed on the ground is evaluated and is referred to as zero velocity interval (ZVI). During ZVI it is assumed that the velocity of the foot is zero and this information is used as an update in the Kalman filter, referred to as ZUPT which in turn helps to reduce the error in position. Zero velocity detectors (ZVD) such as: ARED, SHOE etc. uses fixed threshold to perform zero velocity detection but fails in case of dynamic motion. To counter this problem, data driven ZVD which depends on learning-based models such as: CNN, LSTM, SVM, LSTM-CNN etc. are developed. But these detectors require large amount of data for training the models. Currently, the amount of publicly available datasets for training and testing of these models are quite few. Another problem is that the datasets which are available do not contain proper labelling of ZVI and the approach used to perform ZVI labelling in those datasets is quite computationally expensive. The performance of the learning-based detectors relies solely on the quality of the dataset. This paper proposes a novel approach to capture and automatically label the IMU observations needed for ZVD algorithms. In this approach, foot mounted IMU is proposed to be integrated with a dual foot mounted UWB (Ultra-Wide Band) sensor and periodicity of the UWB distance observations (between the feet) is used to detect and automatically label the ZVI. The quality of the labelled dataset thus, collected is discussed and analyzed.

The second part of the paper assesses and compares the performance of various ZVD algorithms including SHOE, SVM, LSTM, CNN, LSTM-CNN on the pyshoe dataset. The preliminary results demonstrate that conventional algorithms (such as ARED, AMVD and SHOE) can yield accuracy of the order of 85-90%, while other algorithms such as LSTM, CNN and LSTM-CNN may perform better albeit at the cost of increased efforts in training the networks. The main contributions of this paper are: (1) a new methodology for labelling the dataset by using an

additional UWB sensor, (2) comparison of existing zero velocity detection approaches on the publicly available dataset.

Zero Velocity Detection in Foot-mounted Inertial Sensors: Novel method for generating zero velocity labels and a comparative analysis of data driven methods

Ashwani Kumar, Nishita Singh, Deepak Kumar Singh and Salil Goel
Geoinformatics, Dept. of Civil Engineering, IIT Kanpur, India

1. INTRODUCTION

Inertial sensors are quite widely used for pedestrian positioning nowadays (Kone et al., 2020; Qian et al., 2021; Wagstaff and Kelly, 2018). Foot mounted systems are quite popular for pedestrian positioning (Wu et al., 2019). In these systems inertial sensors are mounted on user's foot & Inertial Navigation system (INS) based approach is used to find user's position at each time stamp. Inertial sensors used for pedestrian positioning consist of low-cost accelerometer and gyroscope sensors which are highly prone to errors and biases (Groves, 2013). These errors and biases lead to drift in the final positioning estimates obtained through INS. To reduce the drift in the positioning estimates a technique known as zero velocity update (ZUPT) is used (Foxlin, 2005). ZUPT uses pseudo observations of zero velocity which are compared with the system output to find the error which is then utilized to reduce the drift in navigation estimates (Foxlin, 2005; Skog et al., 2010).The process of finding the zero velocity points is referred to as zero velocity detection (ZVD). The existing zero velocity detection algorithms use accelerometer and gyroscope observations to detect the zero velocity points (Wahlstrom and Skog, 2021). These approaches can be subdivided into fixed threshold-based methods (Skog et al., 2010) and data driven methods (Chen et al., 2022; Wagstaff and Kelly, 2018). Fixed threshold-based methods use a fix threshold on the statistics obtained from accelerometer and gyroscope observations and use that threshold value to find zero velocity point. Although these methods are simplistic in nature, their major drawback is that they cannot account for variability in the motion types, gait cycles or the user. On the other hand, data driven methods can work quite easily for variable motions, cycles or different users and works better than fixed threshold-based methods however they require large amounts of data for training the model so that it can perform zero velocity detection accurately. As of date and to the best of author's knowledge, Pyshoe dataset (Wagstaff et al., 2020) provided by University of Toronto Institute for Aerospace Studies (UTIAS) is the only publicly available dataset (Wagstaff et al., 2020). Unavailability of large amount of data for training these data driven methods is a bottleneck for data driven methods for zero velocity detection. Another problem is that the label generation step used by various authors requires a large number of computational resources as most of the authors generated the ground truth labels by either using minimizing the closed loop error (Ma et al., 2018) or minimizing the total distance travelled (Bai et al., 2020). In this paper, we propose a novel setup and method for generation of foot-mounted inertial dataset and automatic labelling of the same. This setup uses a dual foot mounted UWB sensor, along with the foot mounted inertial sensor. Through preliminary experiments, we demonstrate how the proposed setup can be used for automatic labeling of IMU data and hence, allow generation of labeled datasets needed for various data driven methods. In the second part of this paper, we compare various ZVD algorithms on the Pyshoe dataset and evaluate their performance on various measures such as accuracy, sensitivity, and specificity. The results demonstrate that deep learning methods outperform conventional methods, specifically combination of CNN (Convolutional Neural Network) with LSTM (Long Short-Term Memory) yields the highest accuracy. The major contributions of this paper include: (1) A novel setup and methodology for generation and automatic labelling of IMU dataset needed for various data driven methods, (2) comparison of existing ZVD algorithms on a publicly available dataset. This paper is divided into five sections. Section 2 presents a brief overview of the literature. The methodology proposed in the paper and experimental setup is explained in section 3. Results and their discussion are presented in section 4, and conclusions of the paper and future scope of work are given in section 5.

2. LITERATURE REVIEW

This section is divided into two major parts. Section 2.1 reviews the publicly available datasets in the area of foot mounted inertial sensors and discusses the associated challenges. Section 2.2 reviews various ZVD algorithms and discusses how they have been used for detection of zero velocity points.

2.1. Datasets

Various public datasets are available which contains data obtained from inertial sensors such as pyshoe (Wagstaff et al., 2020), WISDM (Kwapisz et al., 2011), RIDI (Yan et al., 2017), RuDaCoP (Bayev et al., 2019), Foot SLAM data (Wahlstrom et al., 2020) etc. But there are certain problems with these datasets. First of all datasets such as WISDM, RIDI, RuDaCoP are smartphone based datasets not foot mounted inertial datasets due to which it cannot be used to train a model for zero velocity detection of foot mounted inertial sensor dataset. FootSLAM dataset is obtained from foot mounted inertial sensor configuration but it does not contain ground truth labels for stance phase hence cannot be used for training of deep learning-based approaches. Currently, only pyshoe dataset is available which can be used to train a deep learning model for zero velocity detection as it contains ground truth labels and is taken from a foot mounted inertial sensor. In pyshoe dataset, 56 samples of trajectories are available which contains running and walking motions. To generate labels for each sample they have used both fixed threshold-based approaches and detectors that utilized velocity estimates from high-accuracy reference systems. For each motion trial, they found out the optimal approach and the optimal threshold. In this way they generated labels for each motion trial. However, the problem is that this process is highly computationally expensive. Another problem is that the amount of dataset is very limited in the number of motion classes covered which cannot be effectively used for new data driven approaches as for walking and running motions only few motion trials is given. Pyshoe dataset also does not contain examples for non-trivial motions like backward motions or sideways motions hence we can say that the dataset is not highly comprehensive. Some authors have used additional sensors for generating ground truth labels such as from camera tracking systems (Kone et al., 2020; Zhao et al., 2019), ultrasonic ranging of the distance between the shoe and the floor (Zhu et al., 2019), manual annotation of inertial measurements (X. Yu et al., 2019). But those datasets are not publicly available. Hence, we can say that there is a scarcity of better and comprehensive datasets which can be used to train new data driven approaches.

2.2. Zero velocity detection approaches

To find the time instant when the velocity of foot is zero, various zero velocity detection approaches are generated. These approaches include using thresholding based approaches (Skog et al., 2010), learning based approaches (Chen and Pan, 2021; Wagstaff and Kelly, 2018) & gait cycle segmentation approaches (Park and Suh, 2010). In a threshold based approach, various features like acceleration magnitude & variance (Krach and Robertson, 2008), angular rate magnitude & variance (Feliz et al., 2009) and their combination (Zeng et al., 2017) are compared against a threshold value which can be either fixed or modelled according to various motion types (Wagstaff et al., 2017), gait frequency (Tian et al., 2016) or motion speeds (N. Bai et al., 2020). In a learning based approach, usually motion classification is performed followed by zero velocity classification (Kone et al., 2020) while some researchers directly perform zero velocity classification using learning based classifiers (Yu et al., 2019). Classifiers used for motion classification include SVM (Park et al., 2016), random forest (Kone et al., 2020), CNN (Zhu et al., 2019) while for zero velocity classification SVM (Park et al., 2016), LSTM (Zhu et al., 2019) and CNN (Chen et al., 2020) are used. Gait cycle segmentation is also used to perform zero velocity detection. Gait is basically referred to as the manner or style of walking. Division of gait into various phases or states is referred to as gait cycle segmentation. Various models such as Hidden markov models (Zhao et al., 2019), finite state machines (Ren et al., 2016) etc. are used to perform segmentation of lateral direction gyroscope data to perform zero velocity detection.

3. ANALYSIS of SENSORS USED AND EXPERIMENTAL SETUP

3.1. Data Analysis of Inertial and UWB sensor

3.1.1. ANALYSIS OF INERTIAL SENSOR DATA FOR WALKING

Gait analysis is an important step in foot mounted inertial navigation in which various phases of gait cycle are detected. Gait is usually referred to as the manner or style of walking while gait cycle refers to the repetitive pattern which involves steps and strides (Loudon et al., 2008). Some authors divided the gait cycle simply into two phases as stance phase and swing phase (Muhammad et al., 2014). Here stance phase refers to the time period when the foot touches the ground while swing phase is referred to as the time period when the foot is off the ground. Some of the authors have used upto eight phases (Wu et al., 2019). Eight phases used are shown in figure 1.

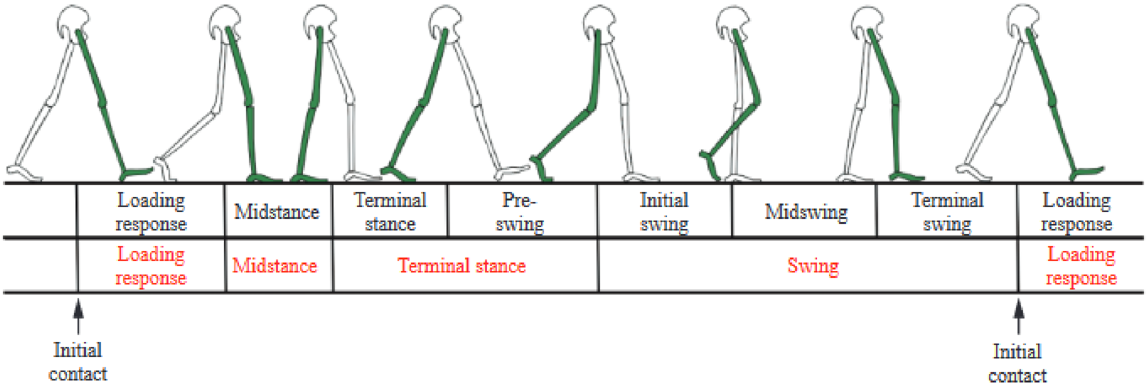

Figure 1: Eight phases of gait cycle (Source: Wahlstrom and Skog et al., 2020)

Out of these phases former four constitutes the stance phase while the latter four phases constitute the swing phase. In stance phase, midstance phase is the most important phase for us as it is basically referred to as the zero-velocity point by most of the authors (Wahlstrom and Skog, 2021). Midstance phase is the phase when one foot is lying flat on ground while other is in mid air also knoen as single support interval. In the subsequent paragraph, various phases extracted from inertial sensor data is explained. Most important information which can help to divide the gait cycle into various phases is contained in accelerometer observation along z direction and gyroscope observation along y direction (Tian et al., 2016). If we extract accelerometer and gyroscope observation for a particular gait cycle then we can manually see properties of various phases occurring in a gait cycle. If we look at the figure 2 which contains a single gait cycle extracted from pyshoe dataset, we can clearly see various phases. From figure 2 it is clear that during midstance phase the value of acceleration along z direction is close to acceleration due to gravity at the location while the gyroscope observation during midstance phase is close to zero. In the next section we will explain the analysis of UWB data for walking and will show that the variation of UWB is such that during each step there exists a minimum and a maximum that has a correlation with the IMU data and can be used for automatic labelling, as proposed in this paper.

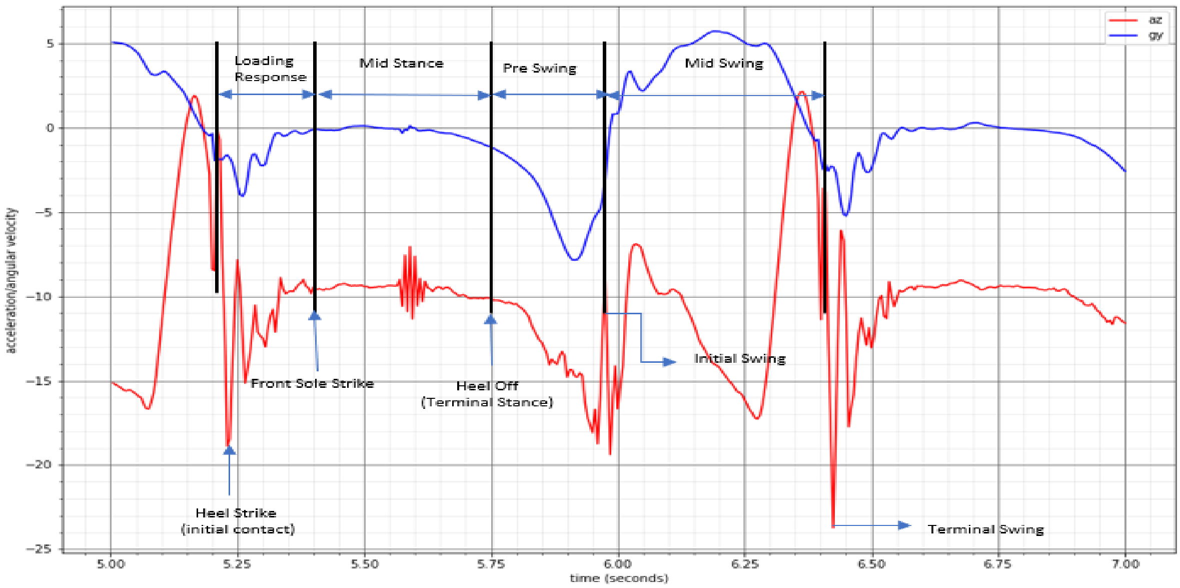

Figure 2: Gait cycle extracted from pyshoe dataset (Source: Wagstaff et al., 2018)

3.1.2. ANALYSIS OF UWB DATA FOR WALKING

UWB sensors poses benefits such as a relatively high time resolution, wide bandwidth, and a capability to work under NLoS (Non-Line of Sight) scenarios (Chen et al., 2022). It has been used in cooperative navigation scenarios where range between pedestrian is used to improve the localization accuracy of foot mounted INS (Zhu and Kia, 2018). UWB sensors are also used for motion body capture (Hamie et al., 2014), body tracking (Sharma et al., 2015) etc. When UWB sensors are mounted on user’s foot (one on each), two way ranging (TWR) protocol is used which gives us distance between the foot at a certain frequency. In this paper we have used decawave DWM 1001 UWB sensor which gives us data at the rate of 10 Hz. A snippet of dataset obtained for a user who walks four laps of 10 steps on the ground is shown in figure 3. Red circles denote the maxima while green circles denote minima.

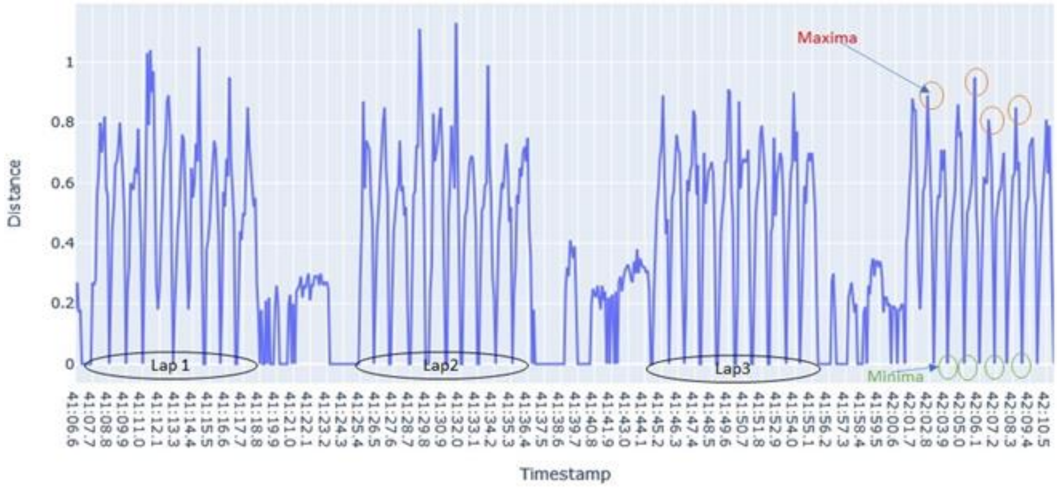

Figure 3: UWB data obtained for 4 laps of 10 steps each

In figure 3 we can clearly distinguish different laps and if we count the number of local minimum then it turns out to be equal to 10. So, from figure 3 it is clear that the number of steps taken is equal to the number of minima present.

3.2. EXPERIMENT SETUP

In the sensor setup, one Decawave DWM 1001 (UWB sensor) is mounted on each forefoot and Lord Microstrain 3DM-GX5-AHRS (inertial sensor) on heel of left foot. X-axis of inertial sensor points in opposite direction of the direction of gravity while Y-axis points towards the right foot and Z-direction points into the foot. To perform ranging between the two UWB sensors mounted on each foot, one of the device acts as an anchor while the other device acts as tag. The tag is connected to the computer using USB connection for retrieving data at the rate of 10 Hz while the anchor is connected to a powerbank which gives power to the sensor. To retrieve data from UWB sensor universal asynchronous receiver transmitter (UART) shell mode is used. UWB sensor gives distance observation at the rate of 10 Hz. Lord Microstrain 3DMGX5-AHRS inertial sensor is also connected to the same computer using USB connection. Sensorconnect software provided by microstrain official website is used to retrieve the data from the sensor at the rate of 100 Hz. Sensor setup assembly is shown in figure 4. By using the above sensor setup data from three persons (for person demographics refer table 1) is collected. For collecting ground truth data of midstance phase, manual procedure is followed in which a timer which is operated manually is used. When the person is walking another person used that timer to find the timestamps at which the midstance phases occur. Two experiments are conducted to perform a preliminary analysis of the hypothesis. Experiments and their results are discussed in section 6.

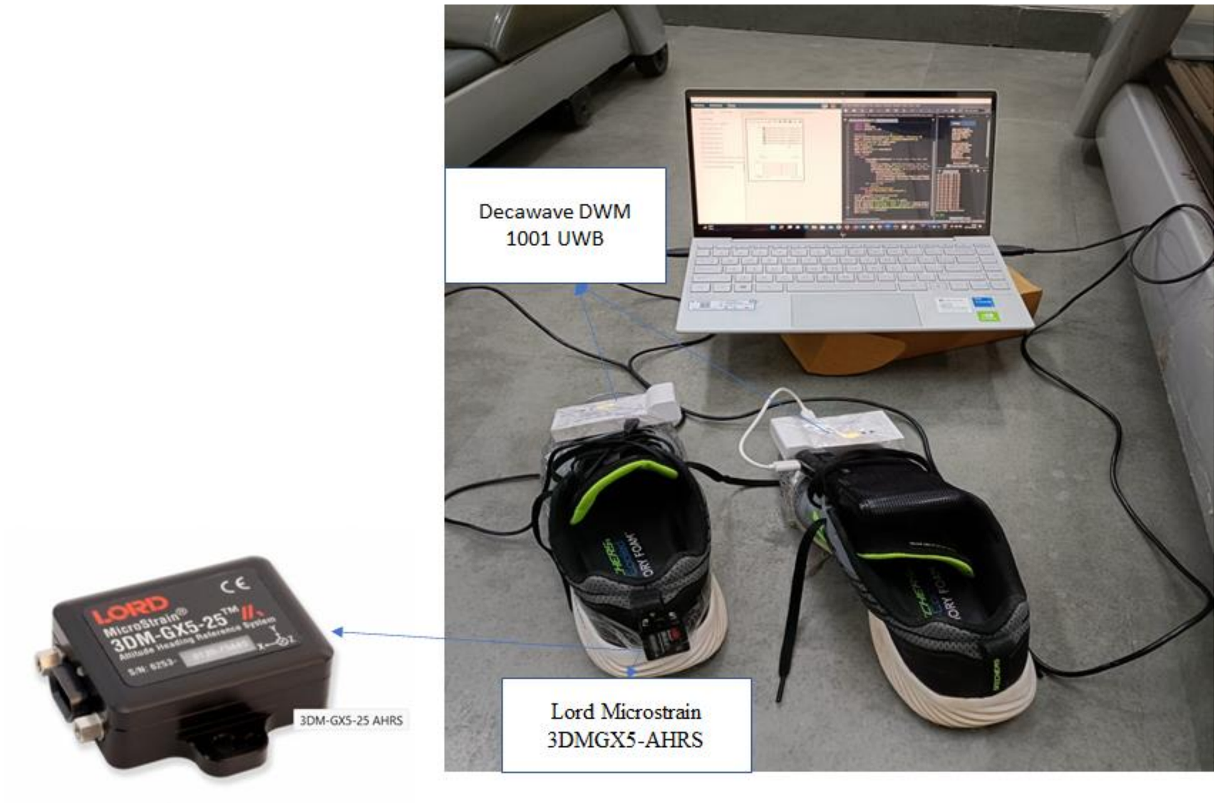

Figure 4:Sensor setup used (HP Envy Computer, Lord Microstrain AHRS, Decawave DWM 1001UWB)

Table 1: Demographics of subjects that performed experiments

SUBJECT	SEX	HEIGHT (CM)
1	Male	168
2	Female	150
3	Male	175

4. RESULTS and DISCUSSION

This section is broadly divided into two subsections. In the first section the results obtained for comparative study between fixed threshold-based methods and data driven methods are discussed. In the subsequent section the experiments performed to validate the hypothesis are discussed in detail.

4.1. Comparison of fixed threshold-based methods with data driven methods

For comparing fixed threshold methods with data driven methods one method from fixed threshold-based methods is selected and four methods from data driven methods are selected. From fixed threshold-based method stance hypothesis optimal estimation (SHOE) detector and from data driven methods we selected SVM, LSTM, CNN, CNN-LSTM are used. Four measures are used to compare these methods and the obtained results are tabulated in table 2. From table 2 it appears that data driven methods have a little inferior performance as compared to fixed threshold method. However, authors have already shown that data driven methods perform better than fixed threshold methods (Kone et al., 2020; Wagstaff and Kelly, 2018). The results shown below can be due to the reason that the training example used to train the deep learning models are same as fixed threshold-based methods which is quite few in number, also in data driven methods a large number of hyperparameters to tune are quite large in number which require a large amount of data. So, due to these reasons there is a need to further investigate the optimal set of hyperparameters which can lead to better results. So, it also stresses on the point that there are very less publicly available labelled datasets and there is a need to generate more labelled dataset so that we can truly use the potential of data driven methods.

Table 2: Comparison table for fixed threshold based methods and data driven methods

Metrics (%)	LSTM	CNN	CNN-LSTM	SVM	SHOE
Accuracy	92.3%	93.08%	94.64%	89.89%	97.62%
Precision	93.04%	94.19%	94.99%	78.42%	98.93%
Recall	92.19%	92.43%	94.26%	90.83%	94.47%
F1-score	92.2%	92.4%	94.3%	84.17%	96.65%

4.2 Experiments for validation of hypothesis

For validation of hypothesis two experiments are conducted in which the sensor setup is mounted on three subjects one by one. For first experiment they walked a distance of 20-30m (approximately) that is marked on a flat surface while for second experiment they walked for 2-3 minutes over a treadmill. The step length is known in advance and the number of step taken by a subject are counted manually. The demographics of the subjects for experiment 1 and 2 are given in table 3 and 4. Subject 1 and Subject 2 took normal steps while subject 3 deliberately took long steps due to which the step length shown above for subject 3 is larger despite her small height in experiment 1. .Figure 5, 6 & 7 shows the plots generated for IMU data overlayed with manually annotated stance phase, UWB data overlayed with manually annotated stance phase & IMU, UWB & manually annotated stance phase overlayed on each other respectively for experiment 1. Similarly, figure 8,9 & 10 represents the same for experiment 2. Since X direction of IMU is pointing in the opposite direction of gravity and from our earlier discussion we know that most of the information in contained in the direction pointing towards or opposite to the direction of gravity. That’s why accelerometer data in x direction is overlayed with the manually annotated stance phase. In figure 5 we can see that the manual annotated stance phases occur during the midstance phase (enclosed in black boxes) as well as during the swing phase. This is due to the reason that the IMU is mounted on one foot and we have marked the stance phases for both foot so we can say that alternate manually annotated stance phase markers represents one of the timestamps of midstance phase. From figure 6 it is clear that the minimum value of the UWB occurs close to the manually annotated stance phases for almost all the subjects.

Table 3: Demographics of subject and steps taken by each subject (Experiment 1)

Person	Sex	Height	Steps Taken	Step Length
Subject 1	Male	168 cm	53	55 cm
Subject 2	Male	175 cm	43	65 cm
Subject 3	Female	150 cm	36	60 cm

Table 4:Demographics of subjects, time taken & steps taken (Experiment 2)

Person	Sex	Height	Steps Taken	Avg. Step Length	Time taken
Subject 1	Male	168	107	60 cm	3 minutes
Subject 2	Male	175	97	45 cm	2 minutes
Subject 3	Female	150	170	40 cm	3 minutes

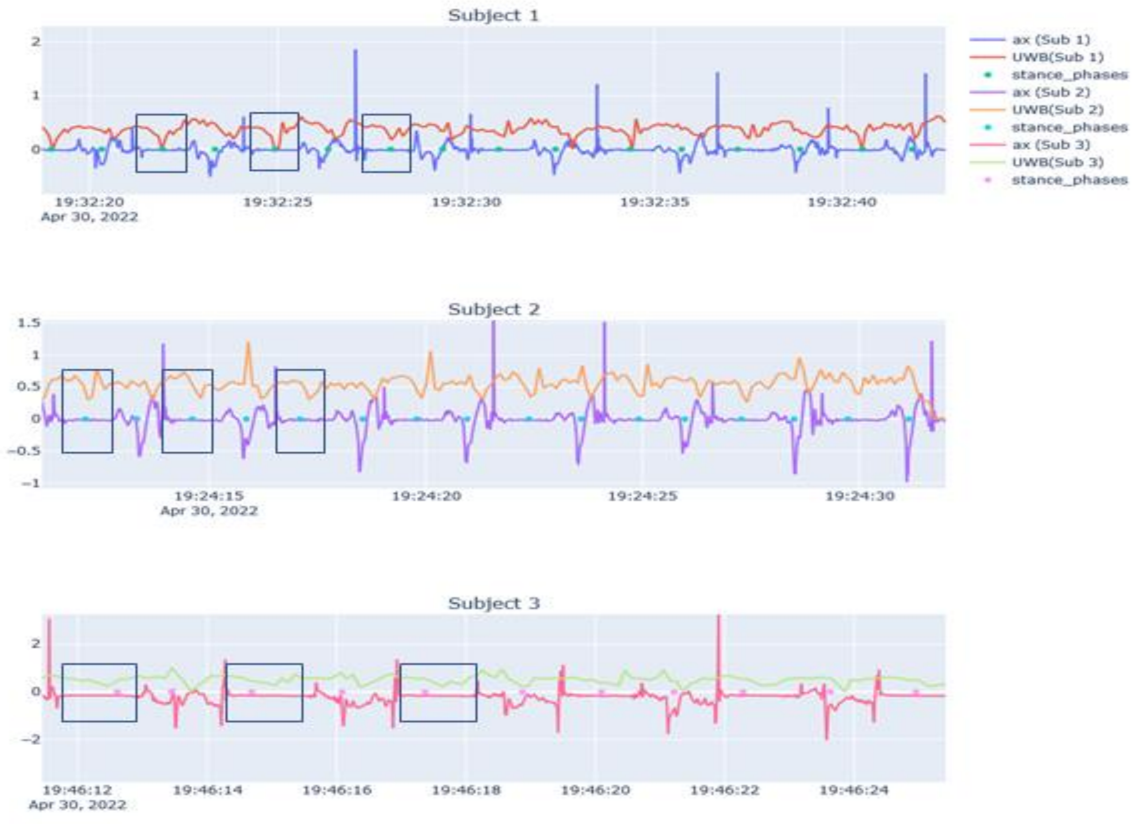

Figure 5: IMU data overalyed with manually annotated stance phase (Experiment 1)

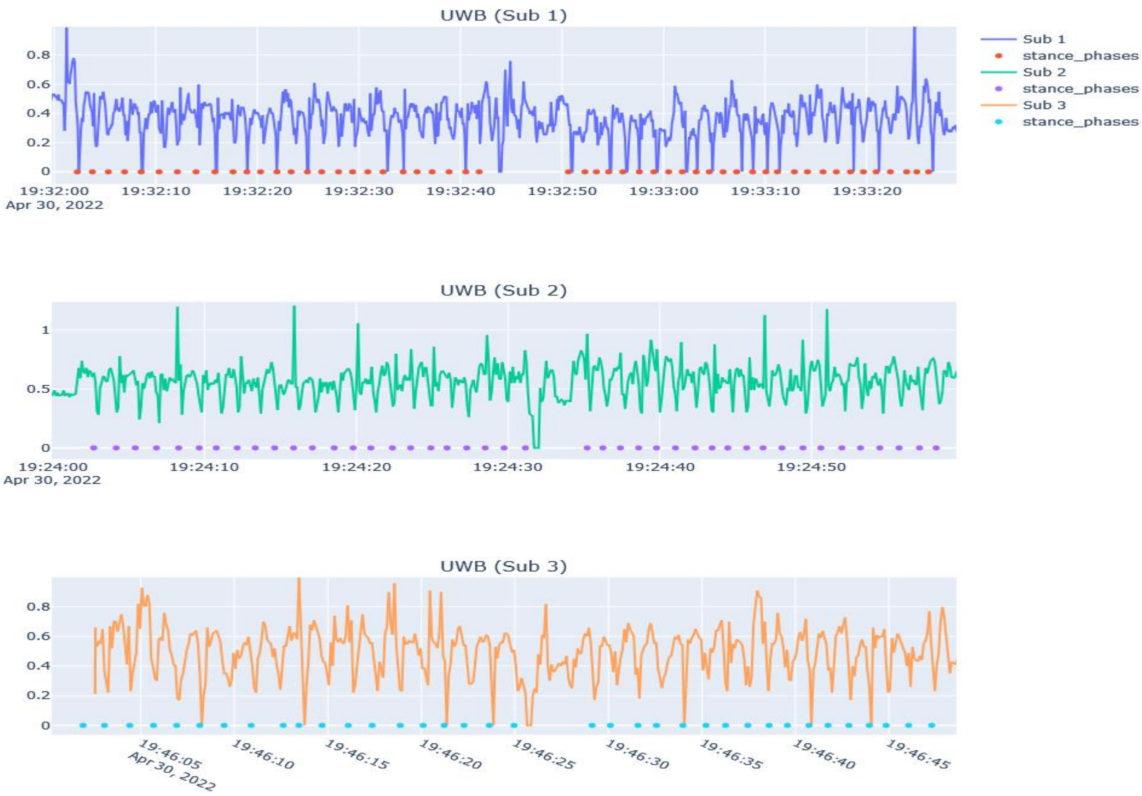

Figure 6: UWB observations are overlayed with manually annotated stance phase observations for all subjects

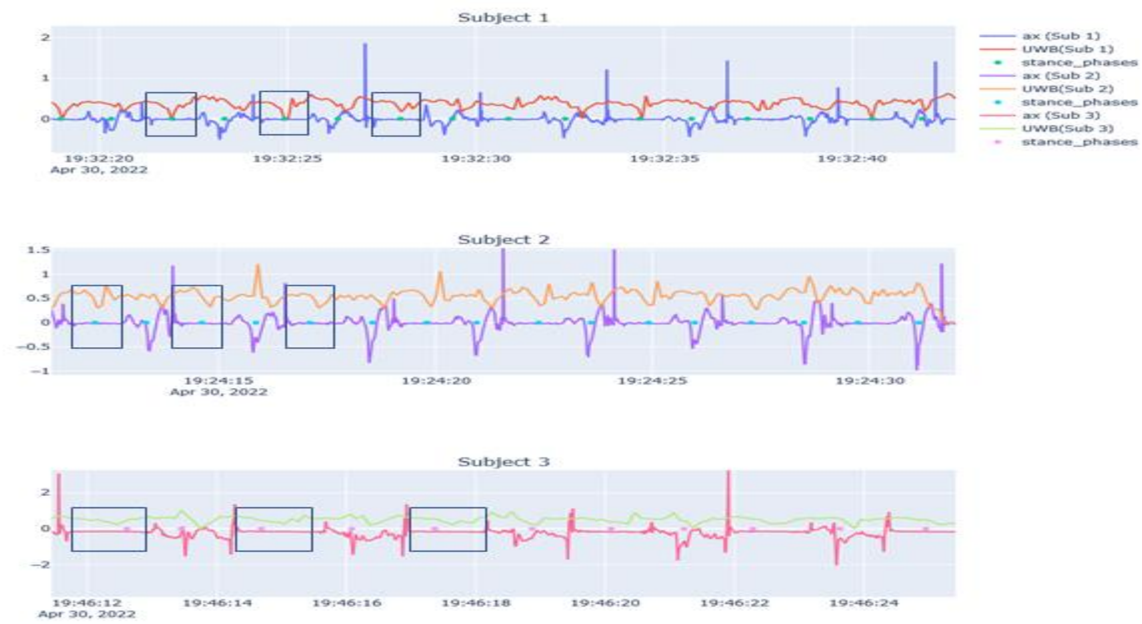

Figure 5: UWB,IMU and manually annotated stance phases overlayed for 3 subjects

From figure 7 it is clearly visible that the minimum value of UWB occurs one during the swing phase and one during the midstance phase due to the reason that the IMU is worn only on one foot. So, if we ignore the minimum values in the swing phase then we can see that the minimum value between the foot lies close to the manually annotated stance phase and also in the midstance phase of the IMU observation (marked by black boxes in figure 7). So, from this observation we can infer that the UWB observations can be used to detect the midstance phase in an IMU data if both of them are used together. Results obtained in experiment 2 also follows the same trend as experiment 1. So, the above experiments give us a preliminary validation that the UWB observation could be used to mark the midstance phase in IMU observation by using the hypothesis that the minimum distance between the foot occurs during the midstance phase.

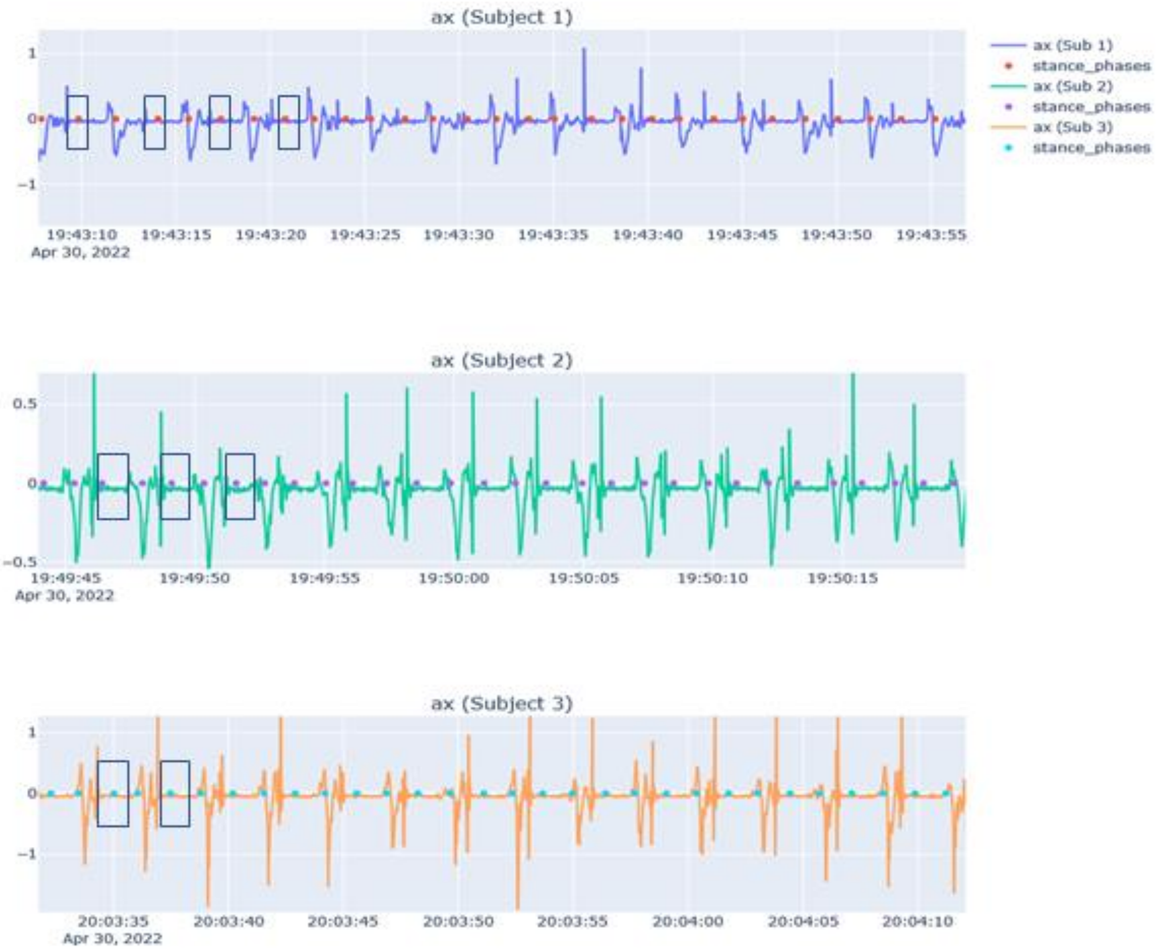

Figure 6: Accelerometer data obtained for all subjects overlayed with manually annotated stance phases on treadmill

Figure 7: UWB data overlayed with manually annotated stance phases on treadmill

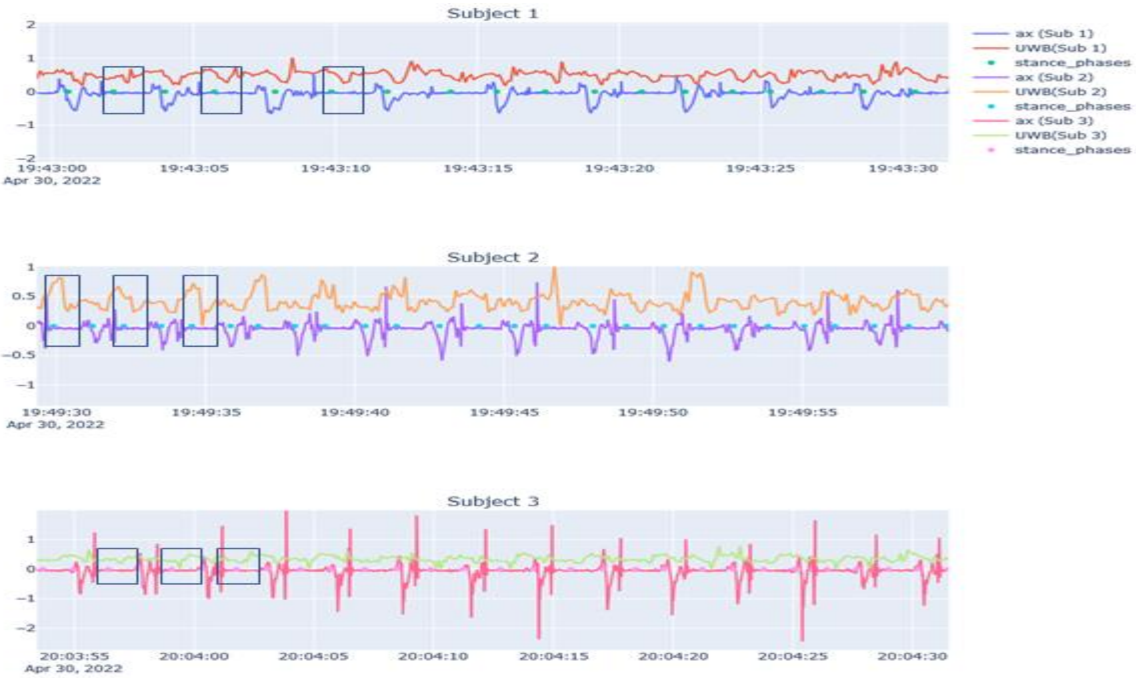

Figure 8: UWB, IMU and manually annotated stance phases overlayed for all subjects on treadmill

In figure 10, there is a particular offset between the minimum of UWB in each step. This offset occurs because the method of collecting time stamps for stance phase detection is performed manually. This means that we are not able to manually pinpoint the location manually when the distance between the foot is minimum. Hence, we require an automatic method by which we can clearly pinpoint the middle point of the midstance phase for ground truth generation.

5. CONCLUSION & FUTURE WORKS

In this paper, we first compared fixed threshold-based methods with data driven methods by using pyshoe dataset and concluded that for data driven methods we require a large amount of dataset which can be used to train the data driven approaches. So, to generate a new dataset a new hypothesis is tested. The hypothesis states that the distance between the feet will be minimum during mid stance phase. To test this hypothesis, two experiments were conducted over 3 subjects in which UWB and IMU sensors are mounted on subject's foot. Experiments were conducted on a flat surface for fixed distance & for fixed time over a treadmill. Results shown in figure 7 & 10 conclusively prove that the distance between the feet is minimum when the foot of the subject is in stance phase. The above result gives us preliminary evidence that our hypothesis is correct. However, there are some of the problems with our analysis which needs further improvements.

In future we will try to remove some of the problems of our analysis like manually collecting the stance phases. Since, our hypothesis appears to be correct and by using UWB observation we got only one point of the midstance phase. In future we will try to improve this idea to retrieve the complete midstance phase by using the sensor setup used in this experiment. The proposed setup will also be used to perform extensive labelled data collection, all of which will be made available publicly and will be important for data-driven methods.

REFERENCES

Bayev, A., Chistyakov, I., Derevyankin, A., Gartseev, I., Nikulin, A., Pikhletsky, M., 2019. RuDaCoP: The Dataset for Smartphone-based Intellectual Pedestrian Navigation, in: 2019 International Conference on Indoor Positioning and Indoor Navigation (IPIN). Presented at the 2019 International Conference on Indoor Positioning and Indoor Navigation (IPIN), IEEE, Pisa, Italy, pp. 1–8. https://doi.org/10.1109/IPIN.2019.8911823

Chen, C., Jao, C.-S., Shkel, A., Kia, S., 2022. UWB Sensor Placement for Foot-to-foot Ranging in Dual-foot Mounted ZUPT-aided INS. IEEE Sens. Lett. 1–1. https://doi.org/10.1109/LSENS.2022.3145750

Chen, C., Zhao, P., Lu, C.X., Wang, W., Markham, A., Trigoni, N., 2020. Deep Learning based Pedestrian Inertial Navigation: Methods, Dataset and On-Device Inference. arXiv:2001.04061 [cs].

Chen, Z., Pan, X., 2021. Learning of Zero-Velocity Detection for Inertial Pedestrian Navigation. Presented at the Journal of Physics: Conference Series. https://doi.org/10.1088/1742-6596/1846/1/012055

Feliz, R., Zalama, E., García-Bermejo, J.G., 2009. Pedestrian tracking using inertial sensors 3, 9.

Foxlin, E., 2005. Pedestrian Tracking with Shoe-Mounted Inertial Sensors. IEEE Comput. Grap. Appl. 25, 38–46. https://doi.org/10.1109/MCG.2005.140

Groves, P.D., 2013. Principles of GNSS, inertial, and multisensor integrated navigation systems, 2nd ed. ed, GNSS technology and application series. Artech House, Boston.

J. Hamie, B. Denis, M. Maman, 2014. On-body localization experiments using real IR-UWB devices, in: 2014 IEEE International Conference on Ultra-WideBand (ICUWB). Presented at the 2014 IEEE International Conference on Ultra-WideBand (ICUWB), pp. 362–367. https://doi.org/10.1109/ICUWB.2014.6959008

J. Zhu, S. S. Kia, 2018. A Loosely Coupled Cooperative Localization Augmentation to Improve Human Geolocation in Indoor Environments, in: 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN). Presented at the 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 206–212. https://doi.org/10.1109/IPIN.2018.8533806

Kone, Y., Zhu, N., Renaudin, V., Ortiz, M., 2020. Machine Learning-Based Zero-Velocity Detection for Inertial Pedestrian Navigation. IEEE Sensors J. 20, 12343–12353. https://doi.org/10.1109/JSEN.2020.2999863

Krach, B., Robertson, P., 2008. Integration of foot-mounted inertial sensors into a Bayesian location estimation framework, in: 2008 5th Workshop on Positioning, Navigation and Communication. Presented at the 2008 5th Workshop on Positioning, Navigation and Communication (WPNC), IEEE, Hannover, Germany, pp. 55–61. https://doi.org/10.1109/WPNC.2008.4510357

Kwapisz, J.R., Weiss, G.M., Moore, S.A., 2011. Activity recognition using cell phone accelerometers. SIGKDD Explor. Newsl. 12, 74–82. https://doi.org/10.1145/1964897.1964918

M. N. Muhammad, Z. Salcic, K. I. Wang, 2014. Subtractive Clustering as ZUPT Detector, in: 2014 IEEE 11th Intl Conf on Ubiquitous Intelligence and Computing and 2014 IEEE 11th Intl Conf on Autonomic and Trusted Computing and 2014 IEEE 14th Intl Conf on Scalable Computing and Communications and Its Associated Workshops. Presented at the 2014 IEEE 11th Intl Conf on Ubiquitous Intelligence and Computing and 2014 IEEE 11th Intl Conf on Autonomic and Trusted Computing and 2014 IEEE 14th Intl Conf on Scalable Computing and Communications and Its Associated Workshops, pp. 349–355. https://doi.org/10.1109/UIC-ATC-ScalCom.2014.114

Ma, M., Song, Q., Gu, Y., Li, Y., Zhou, Z., 2018. An adaptive zero velocity detection algorithm based on multi-sensor fusion for a pedestrian navigation system. Sensors 18, 3261. https://doi.org/10.3390/s18103261

N. Bai, Y. Tian, Y. Liu, Z. Yuan, Z. Xiao, J. Zhou, 2020. A High-Precision and Low-Cost IMU-Based Indoor Pedestrian Positioning Technique. IEEE Sensors Journal 20, 6716–6726. https://doi.org/10.1109/JSEN.2020.2976102

Park, S.K., Suh, Y.S., 2010. A zero velocity detection algorithm using inertial sensors for pedestrian navigation systems. Sensors (Basel) 10, 9163–9178. https://doi.org/10.3390/s101009163

Park, S.Y., Ju, H., Park, C.G., 2016. Stance Phase Detection of Multiple Actions for Military Drill Using Foot-mounted IMU. International Conference on Indoor Positioning and Indoor Navigation 4.

Qian, W., Zhu, Y., Jin, Y., Yang, J., Qi, P., Wang, Y., Ma, Y., Ji, H., 2021. A Pedestrian Navigation Method Based on Construction of Adapted Virtual Inertial Measurement

Unit Assisted by Gait Type Classification. IEEE Sensors J. 21, 15258–15268. https://doi.org/10.1109/JSEN.2021.3074392

Ren, M., Pan, K., Liu, Y., Guo, H., Zhang, X., Wang, P., 2016. A Novel Pedestrian Navigation Algorithm for a Foot-Mounted Inertial-Sensor-Based System. Sensors 16, 139. https://doi.org/10.3390/s16010139

Sharma, M., Parini, C., Alomainy, A., 2015. UWB Sensor Nodes for Tracking of Human Motion in Medical and Rehabilitation Applications, in: Proceedings of the 5th EAI International Conference on Wireless Mobile Communication and Healthcare - "Transforming Healthcare through Innovations in Mobile and Wireless Technologies." Presented at the 5th EAI International Conference on Wireless Mobile Communication and Healthcare - "Transforming healthcare through innovations in mobile and wireless technologies," ICST, London, Great Britain. https://doi.org/10.4108/eai.14-10-2015.2261745

Skog, I., Handel, P., Nilsson, J.O., Rantakokko, J., 2010. Zero-Velocity Detection—An Algorithm Evaluation. IEEE Trans. Biomed. Eng. 57, 2657–2666. https://doi.org/10.1109/TBME.2010.2060723

Tian, X., Chen, J., Han, Y., Shang, J., Li, N., 2016. A Novel Zero Velocity Interval Detection Algorithm for Self-Contained Pedestrian Navigation System with Inertial Sensors. Sensors 16, 1578. https://doi.org/10.3390/s16101578

Wagstaff, B., Kelly, J., 2018. LSTM-Based Zero-Velocity Detection for Robust Inertial Navigation. 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN) 1–8. https://doi.org/10.1109/IPIN.2018.8533770

Wagstaff, B., Peretroukhin, V., Kelly, J., 2020. Robust Data-Driven Zero-Velocity Detection for Foot-Mounted Inertial Navigation. IEEE Sensors J. 20, 957–967. https://doi.org/10.1109/JSEN.2019.2944412

Wagstaff, B., Peretroukhin, V., Kelly, J., 2017. Improving foot-mounted inertial navigation through real-time motion classification, in: 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN). Presented at the 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), IEEE, Sapporo, pp. 1–8. https://doi.org/10.1109/IPIN.2017.8115947

Wahlstrom, J., Markham, A., Trigoni, N., 2020. FootSLAM meets Adaptive Thresholding. IEEE Sensors J. 1–1. https://doi.org/10.1109/JSEN.2020.2987813

Wahlstrom, J., Skog, I., 2021. Fifteen Years of Progress at Zero Velocity: A Review. IEEE Sensors J. 21, 1139–1151. https://doi.org/10.1109/JSEN.2020.3018880

Wu, Y., Zhu, H.-B., Du, Q.-X., Tang, S.-M., 2019. A Survey of the Research Status of Pedestrian Dead Reckoning Systems Based on Inertial Sensors. International Journal of Automation and Computing 19.

X. Yu, B. Liu, X. Lan, Z. Xiao, S. Lin, B. Yan, L. Zhou, 2019. AZUPT: Adaptive Zero Velocity Update Based on Neural Networks for Pedestrian Tracking, in: 2019 IEEE Global Communications Conference (GLOBECOM). Presented at the 2019 IEEE Global Communications Conference (GLOBECOM), pp. 1–6. https://doi.org/10.1109/GLOBECOM38437.2019.9014070

Yan, H., Shan, Q., Furukawa, Y., 2017. RIDI: Robust IMU Double Integration. arXiv:1712.09004 [cs].

Zeng, Z., Liu, S., Wang, W., Wang, L., 2017. Infrastructure-free indoor pedestrian tracking based on foot mounted UWB/IMU sensor fusion, in: 2017 11th International Conference on Signal Processing and Communication Systems (ICSPCS). Presented at the 2017 11th International Conference on Signal Processing and Communication Systems (ICSPCS), IEEE, Surfers Paradise, QLD, pp. 1–7. https://doi.org/10.1109/ICSPCS.2017.8270492

Zhao, H., Wang, Zhelong, Qiu, S., Wang, J., Xu, F., Wang, Zhengyu, Shen, Y., 2019. Adaptive gait detection based on foot-mounted inertial sensors and multi-sensor fusion. Information Fusion 52, 157–166. https://doi.org/10.1016/j.inffus.2019.03.002

Zhu, T., Pan, X., Zhang, S., 2019. A Zero Velocity Detection Method for Soldier Navigation Based on Deep Learning. Journal of Physics 9.

BIOGRAPHICAL NOTES

Ashwani Kumar is currently pursuing his P.hD. in geoinformatics from Department of CIVIL Engineering, IIT Kanpur. His research interests include sensor fusion, inertial navigation & deep learning. He received his B.Tech degree in Civil Engineering from NIT SRINAGAR in 2017. In 2019, he received M.Tech degree in GIS and Remote Sensing from MNNIT ALLAHABAD where he worked on the topic of estimation of tree morphological parameters using LiDAR data.

Nishita Singh is currently pursuing her M.Tech in Geoinformatics from Department of Civil Engineering, IIT Kanpur. Her fields of interests include inertial navigation, machine learning and Deep Learning. She received her B.Tech Degree in Civil Engineering from HBTU, Kanpur in 2020.

Deepak Kumar Singh is currently pursuing his M.Tech in Geoinformatics from Department of Civil Engineering, IIT Kanpur. His field of interest is sensor-based navigation using Deep learning and his thesis topic is Zero Velocity Detection using Foot Mounted IMU. He received his B.Tech degree in Civil Engineering from the University of Mumbai, Maharashtra.

Salil Goel is an Assistant Professor in the Department of Civil Engineering, Indian Institute of Technology Kanpur, India. He earned his PhD jointly from The University of Melbourne, Australia and IIT Kanpur, India in the year 2017 as a Melbourne India Postgraduate Academy (MIPA) Scholar under the Joint PhD Agreement between the two institutions. He earned his B.Tech and M.Tech (specialization in Geoinformatics) from Department of Civil Engineering, IIT Kanpur under the B.Tech-M.Tech Dual Degree Program in 2011. His research interests involve use and fusion of sensors such as LiDAR, Camera, Inertial and GNSS to solve problems related to localization, mapping and tracking involving a variety of platforms including but not limited to terrestrial and UAV platforms. He is actively working in the area of indoor positioning and navigation, wherein his team is exploring new methods of fusion of various sensors and developing algorithms to carry out localization and mapping in GNSS denied and challenging environments.

CONTACTS

Ashwani Kumar
IIT Kanpur
Geoinformatics, Department of Civil Engineering, IIT Kanpur
Kanpur
INDIA
+91 9044253685
Email: kashwani@iitk.ac.in

Nishita Singh
IIT Kanpur
Geoinformatics ,Department of Civil Engineering,IIT Kanpur
Kanpur
INDIA
+91 8795833459
Email: nishita20@iitk.ac.in

Deepak Kumar Singh
IIT Kanpur
Geoinformatics, Department of Civil Engineering, IIT Kanpur
Kanpur
INDIA
+91 9167622916
Email: dksingh20@iitk.ac.in

Salil Goel
IIT Kanpur
Geoinformatics, Department of Civil Engineering, IIT Kanpur
Kanpur
INDIA
+91 9695256600
Email: sgoel@iitk.ac.in