공학석사학위논문

스마트폰에서의 UWB 기반 거리측정과 PDR을 이용한 실내 측위 알고리즘

UWB ranging and PDR combined indoor positioning algorithm in smartphone

2020년 2월

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이 논문을 공학석사 학위논문으로 제출함

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Abstract

UWB ranging and PDR combined indoor positioning algorithm in smartphone

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In this paper, an indoor positioning system that combines UWB positioning and PDR is introduced. The proposed scheme improves the performance of PDR using UWB ranging data. Length estimation and step detection in traditional PDR are substituted with speed estimation, which is based on deep learning. Heading calculation in traditional PDR is calibrated by UWB ranging data. Finally, improved PDR is combined with UWB ranging. Noble UKF-based algorithm which considers NLOS environment is used for combination. We prove that the performance of UWB ranging-PDR combined algorithm is better than simple UWB positioning or improved PDR algorithm through experiments.

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Keywords : Indoor positioning system (IPS), Ultra wide band (UWB) positioning, Pedestrian dead reckoning (PDR), Inertial sensor

measurement unit (IMU), Deep learning, Long short term memory (LSTM), Unscented Kalman filter (UKF)

***Student Number* : 2018-28618**

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Chapter 1
Introduction

Location based services (LBS) such as smartphone navigation, location-aware smart museum guide become popular over the last years [1], [2]. Those LBS are based on the user's current location. Thus, the quality of LBS is highly dependent on the accuracy of localization [3]. A lifestyle of modern people, which spends most of time indoor, makes LBS targeting indoor and indoor localization important field of study.

In outdoor positioning, GPS is so successful that it meets localization requirements for outdoor LBS. But in indoor positioning, GPS is not quite useful because of attenuation of GPS signal by the buildings [4]. Indoor positioning system (IPS) can be categorized into two groups. One is infrastructure-free IPS, and the other is infrastructure-based IPS. PDR is a well-known infrastructure-free IPS. Pure inertial sensor-based PDR doesn't need any wireless access point or fingerprinting data. PDR can be implemented with IMU sensors. Thus, PDR is relatively free from environmental influences than other IPS. PDR generally consists of three steps, including step detection, stride length estimation and heading calculation. PDR calculates the current position by keep adding traveled distance to the known starting point.

Because of this, PDR is vulnerable to accumulative error [5].

On the other hand, UWB positioning is a well-known infrastructure-based IPS. UWB positioning needs the anchor nodes to be deployed in advance for positioning. It uses time of arrival (ToA) ranging between the anchor nodes and the tag node. When the tag nodes get ranging results from more than four anchors, the position of the tag node can be calculated by the trilateration. UWB signal is short pulses over a large bandwidth, which makes it resistant to multipath. Because of this property, UWB positioning is very accurate when LOS between the anchor node and the tag node is present. However, In NLOS environment, the result of UWB positioning gets inaccurate [6].

The UWB positioning error in NLOS environment can be corrected by PDR and the accumulative error of PDR can be corrected by UWB positioning. There are a lot of studies that try to combine PDR and UWB. In [7], an integrated positioning method of UWB and PDR is proposed. It shows good dynamic performance, but it uses a foot-mounted IMU sensor for PDR so that it is not widely available. In [8], A UWB/PDR EKF fusion positioning method on smartphone is proposed. It only uses IMU sensors on the smartphone, but Its PDR algorithm is almost the same with traditional PDR even though there is room for improvement by using UWB ranging data.

In this paper, UWB ranging and PDR combined indoor positioning algorithm on smartphone is proposed. Firstly, PDR is improved by UWB ranging data. Deep learning model for speed estimation is trained with smartphone IMU sensor data (input) and UWB positioning data (output). Also, heading estimation is calibrated by UWB positioning data. Secondly, UWB

ranging result and PDR result are combined using unscented Kalman filter (UKF). It is proven that the performance of the combined algorithm is better than that of simple UWB positioning or improved PDR algorithm through experiments.

Chapter 2

UWB ranging-PDR combined indoor positioning algorithm

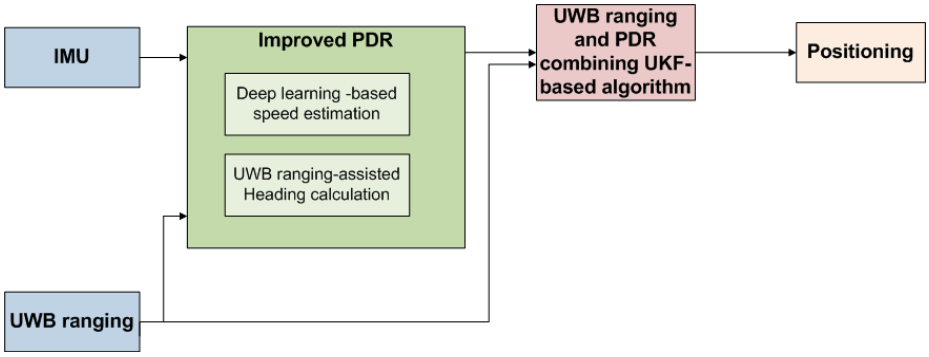

Figure 1. System overview

An overview of the UWB ranging-PDR combined indoor positioning algorithm in a smartphone is illustrated in Figure 1. In the traditional PDR method, only the data from IMU is used for step detection, stride length estimation and heading estimation. In improved PDR of the proposed algorithm, step detection and stride length estimation are substituted with deep learning-based speed estimation. In deep learning-based speed estimation, a deep learning model that estimates current speed is trained in the offline phase. The IMU data is fed into LSTM moedl as an input. The speed data which can be obtained based on UWB ranging data is fed into LSTM as an output. The UWB ranging-assisted heading calculation uses heading calculated from UWB ranging data to calibrate the heading estimated using gyroscope and magnetometer. Next, the UKF-based algorithm is used to fuse the result of the

improved PDR and the result of UWB ranging.

Chapter 2.1

Improved PDR

In traditional PDR, current position is calculated as equation below.

$$\begin{pmatrix} X_{k+1} \\ Y_{k+1} \end{pmatrix} = \begin{pmatrix} X_k \\ Y_k \end{pmatrix} + \begin{pmatrix} l_k \cos\theta_k \\ l_k \sin\theta_k \end{pmatrix} \qquad (1)$$

$\begin{pmatrix} X_{k+1} \\ Y_{k+1} \end{pmatrix}$ is current position, $\begin{pmatrix} X_k \\ Y_k \end{pmatrix}$ is previous position, l_k is the step length and θ_k is the heading at kth step. The accelerometer is used to count the number of steps and estimate the step length. The gyroscope and magnetometer are used to calculate the heading.

Unlike traditional PDR, current position is calculated as equation (2) in improved PDR.

$$\begin{pmatrix} X_{t+1} \\ Y_{t+1} \end{pmatrix} = \begin{pmatrix} X_t \\ Y_t \end{pmatrix} + \begin{pmatrix} S_t \cos\theta_t \Delta t \\ S_t \sin\theta_t \Delta t \end{pmatrix} \qquad (2)$$

$\begin{pmatrix} X_{t+1} \\ Y_{t+1} \end{pmatrix}$ is current position, $\begin{pmatrix} X_t \\ Y_t \end{pmatrix}$ is previous position, S_t is the speed, Δt is a constant time variance and θ_t is the heading at the time point t. In improve PDR, the step detection is not used. Instead, the state of user is separated based on constant time variance t. The speed is estimated by deep learning-based speed estimation and the heading is estimated by UWB ranging-assisted heading calculation. The detail of each algorithm is described below.

Chapter 2.1.1

Deep learning-based speed estimation

When people walk at varying speeds, the distinctive patterns appear on IMU data [9]. Thus, we can train the deep learning model, which estimates the speed from the IMU data. In traditional PDR, parameters for speed estimation is tuned manually for each pedestrian. But if we use the proper deep learning model, we can make a personalized speed estimation model without extra effort.

For training of the proposed model, appropriate input and output data are needed. For input data, we can use the raw IMU data. IMU data consists of a 3-axis accelerometer value, a 3-axis gyroscope value and a 3-axis magnetometer value. The size of the time window should be long enough to contain a meaningful pattern. The data sampling rate should be fast enough to track the steps. The proper size of the time window and data sampling rate is selected based on a few trials. The size of the time window for input data is 1 second.

IMU data is sampled at 50 Hz, so the size of input data is $50 * 9$.

For output data, we need traveled distance per unit time (dt), speed. We can use UWB ranging data to get speed. The transformation from UWB ranging data to speed data is illustrated in Figure 2.

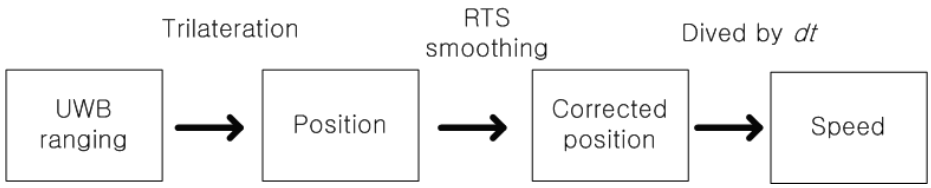

Figure 2 The transformation from UWB ranging data to speed data

First, the position is calculated by trilateration. The result from the trilateration algorithm contains an error, so it needs a little correction. The correction is done by RTS smoothing. The speed can be calculated by Euclidean distance between the current position and the previous position for unit time.

The deep learning model which can learn the correlation between the IMU sensor data and speed is proposed here. The IMU sensor data is time-series data, so we used the long short-term memory (LSTM) model, which is known to show good performance for time-series data analysis. The structure of the LSTM model used here is illustrated in Figure 3.

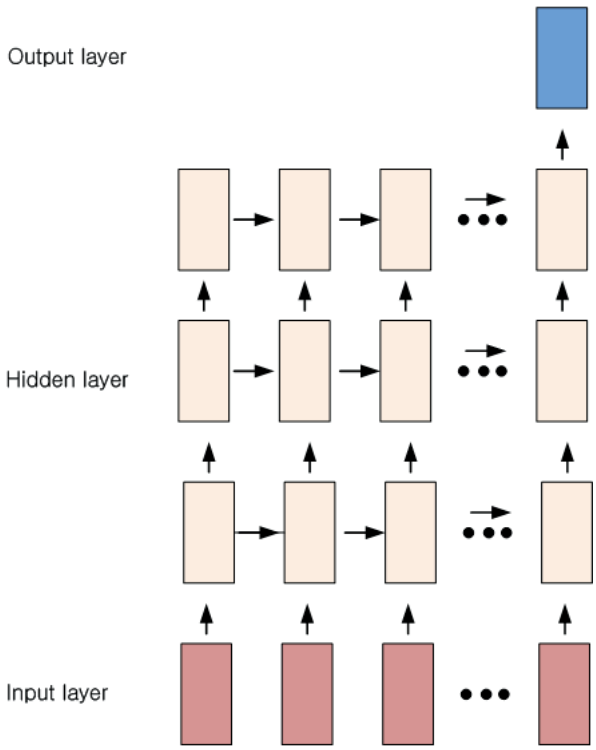

Figure 3 Structure of the LSTM model

It is many-to-one model. It consists of one input layer, 3 hidden layers and one output layer. Model is trained using aforementioned input and output data in offline phase. In online phase, the real-time speed of the pedestrian is estimated by the trained model and raw IMU data. The overall process is illustrated in Figure 4.

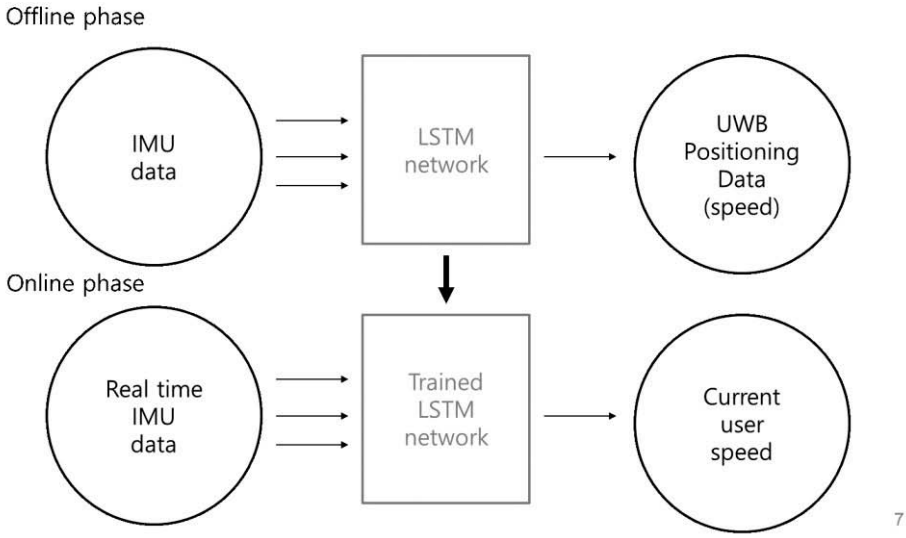

Figure 4. Deep learning-based speed estimation

Chapter 2.1.2

UWB ranging-assisted heading calculation

The heading of a smartphone can be calculated based on a magnetometer and gyroscope. In traditional PDR, the heading of a pedestrian is considered to be the same with the heading When the pedestrian holds the device with a little tilt, the result can be inaccurate because of inconsistency between the device heading and the actual heading.

This kind of error can be calibrated using the UWB ranging data. UWB ranging data can be used to calculate the actual heading of the pedestrian, not the device heading. We can calculate the actual heading of the pedestrian using UWB ranging data when the pedestrian walks straight for enough time.

In the proposed algorithm, inertial heading, ih_t is calculated in the same way that the traditional PDR calculates heading, using gyroscope and magnetometer. When the difference between previous inertial heading and current inertial heading is smaller than threshold ih_τ, the pedestrian is considered to walk straight. Thus, we can detect the $lSection$, which represents the section where the pedestrian walks straight. For $lSection$, we collect the UWB positioning data, P_t. Simultaneously, UH is calculated by subtracting the position already added in the $lSection$ from the position newly added to $lSection$. UH is the vector representation of UWB heading. uh is the scalar representation of UWB heading and calculated as $\arctan(UH[1]/$

$UH[0]$). Bias, b is calculated as $uh - ih_t$ When $lSection$ becomes long enough. The length threshold for $lSection$ to calculate b is l_τ. Finally, we can get the heading value as $ih_t + b$. The Figure 5 shows the proposed heading calculation algorithm in detail.

```
lSection = []
b = 0
for t=1,2,... do
    if ih_t − ih_{t−1} ≤ ih_τ then
        lSection.append(P_t)
        for E in lSection do
            UH+ = P_t − E
            uh = arctan(UH[1]/UH[0])
        end
    end
    else
        lSection=[]
    end
    if length(lSection)≥l_τ then
        b = uh − ih_t
    end
    Heading = ih_t + b
end
```

Figure 5 UWB ranging-assisted heading calculation

Chapter 2.2

UWB ranging and PDR combining UKF-based algorithm

Although the result from improved PDR is more accurate than traditional PDR, basically it is still vulnerable to accumulative error. But this error can be corrected using the absolute positioning of UWB. Also, UWB positioning error in NLOS environment can be corrected by the relative positioning of improved PDR. The results from each algorithm are combined by the UKF-based algorithm to overcome the shortcomings of each algorithm. In proposed algorithm, the state vector at time t, X_t is defined as equation (3).

$$X_t = [x_t, vx_t, y_t, vy_t]^T \quad (5)$$

x_t is x coordinate, y_t is y coordinate, vx_t is x component of velocity, vy_t is y component of velocity at time t. The state transition equation and the state transition matrix F for the proposed algorithm is defined as equation (4) and equation (5).

$$\begin{cases} x_{t+1} = x_t + vx_t \Delta t \\ y_{t+1} = y_t + vy_t \Delta t \end{cases} \quad (6)$$

$$F = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (7)$$

The initial position is assumed to be known. Initial velocity is calculated using improved PDR. In the prediction step, we predict the position of the next time point using the above equations. In the update step, we use the result of improved PDR as input for vx_t and vy_t as equation (6).

$$\begin{cases} vx_t = S_t \cos \theta t \\ vy_t = S_t \sin \theta t \end{cases} \quad (6)$$

Also, we use the UWB ranging calibrated by improved PDR result for position in update step, instead of using raw UWB ranging because raw UWB ranging result can be incorrect in non-line-of-sight environment. We can rule out incorrect ranging result using improved PDR result.

First, predicted position, PP_t is calculated from state vector X_{t-1}. Then, we compare ur_i and pr_i. ur_i is the UWB ranging from anchors. pr_i is Euclidean distance between PP_t and anchors. A_i is ith anchor deployed and N is the number of anchors. In a non-line-of-sight environment, ur_i is always longer than the actual range. If there is any case in which pr_i is longer than ur_i, it means that PP_t is inaccurate. Thus, ur_i can not be calibrated based on the PP_t, so calibrated range, cr_i is same with ur_i. If not, PP_t is thought to be accurate. Then, we compare ur_i and pr_i again. If ur_i is too longer than pr_i, cr_i is set to pr_i. Else, cr_i is set to ur_i. Finally, we can get the position by trilateration of cr_is, and use it as a position input for the update step, UP_t.

Figure 6 shows proposed UWB ranging and PDR combining UKF-based algorithm in detail.

```
PP_t = UKF.predict(X_{t-1})[0, 2]
isPredictedPositionCorrect = true
for i in N do
    pr_i = euclideanDistance(PP_t, A_t)
    if ur_i - pr_i ≤ 0 then
        isPredictedPositionCorrect = false
    end
end
if isPredictedPositionCorrect == false then
    for i in N do
        cr_i = ur_i
    end
end
else
    for i in N do
        if ur_i - pr_i ≥ r_τ then
            cr_i = pr_i
        end
        else
            cr_i = ur_i
        end
    end
end
UP_t = trilaterate(cr)
```

Figure 6. UWB ranging and PDR combining UKF-based algorithm

Chapter 3

Experimental results

In this study, improved PDR and UWB ranging fusion algorithm is proposed. Experiments are designed to evaluate the performance of the proposed algorithm precisely. First, to verify the performance of deep learning-based speed estimation of improved PDR, the speed estimation accuracy of the proposed algorithm and traditional PDR algorithms are compared. Second, to evaluate the performance of the proposed heading calculation method, the calibrated heading and uncalibrated heading are compared. Finally, UWB ranging and PDR combining UKF-based algorithm is compared with the improved PDR algorithm and the simple UWB positioning algorithm.

In experiments, the subject walks, holding a smartphone attached with a UWB tag module at chest height. The eight anchor nodes are deployed at the experiment place in advance. The smartphone and UWB module used here is Samsung Galaxy S7 and Decawave's DWM1001. Samsung Galaxy S7 has a 9-axis inertial sensor inside. DWM1001 uses UWB channel 5, which is a 6.5Ghz channel with a bandwidth of 500Mhz. Its ranging accuracy is within 10cm in line of sight condition [10].

Chapter 3.1

Deep learning-based speed estimation

For this experiment, training data is collected while the subject is wandering the hallway in the building for an hour. Thirty-six thousand samples are used for training. For the evaluation, the subject walks straight at 58.5m long hallway. The difference between the real distance traveled (58.5m) and distance estimated by the model was recorded. The experiment is done for three different speeds (slow, normal, fast). The experiment is ten times repeated per each speed, total 30. The results are shown in Table 1, and the unit is m.

estimation shows the best accuracy.

	Slow	Normal	Fast	Total
Proposed	2.93	4.32	4.11	3.33
Wonho Kang [11]	3.03	2.81	18.28	8.11
Weinberg [12]	10.22	9.12	9.40	9.95

Table 1. Speed estimation performance at variable speeds

The model used for comparison is a traditional function model, which has a difference between maximum acceleration and minimum acceleration while

walking as an input parameter. Wonho kang's model is $L_k = \begin{cases} \alpha\sqrt[4]{A_{pp,k}} + \gamma, \ for\ A_{pp,k} < A_\tau \\ \beta * \log(A_{pp,k}) + \omega, \ for\ A_{pp,k} \geq A_\tau \end{cases}$ and Weinberg model is $L_k = \alpha * \sqrt[4]{A_{pp,k}}$. L_k is a step length at step k and $A_{pp,k}$ is difference between maximum acceleration and minimum acceleration in step k. A_τ is a threshold. α,β, γ and ω are hyperparameters needs to be tuned. The model in [11] shows performance similar with proposed scheme at slow and normal speed. But it shows lower performance compared to proposed scheme at fast speed. The model in [12] always shows lower performance compared to proposed scheme at all different speeds. In conclusion, the deep learning-based speed shows the best accuracy.

Chapter 3.2

UWB ranging-assisted heading calculation

In this experiment, the subject walks along the rectangular line (5x31m). The experiment is four times repeated. The average error between reference heading and estimated heading is shown in Table 2 (unit is °).

Without calibration	16.2
With calibration	8.5

Table 2. Heading estimation performance with and without calibration

The error was smaller when calibration is applied.

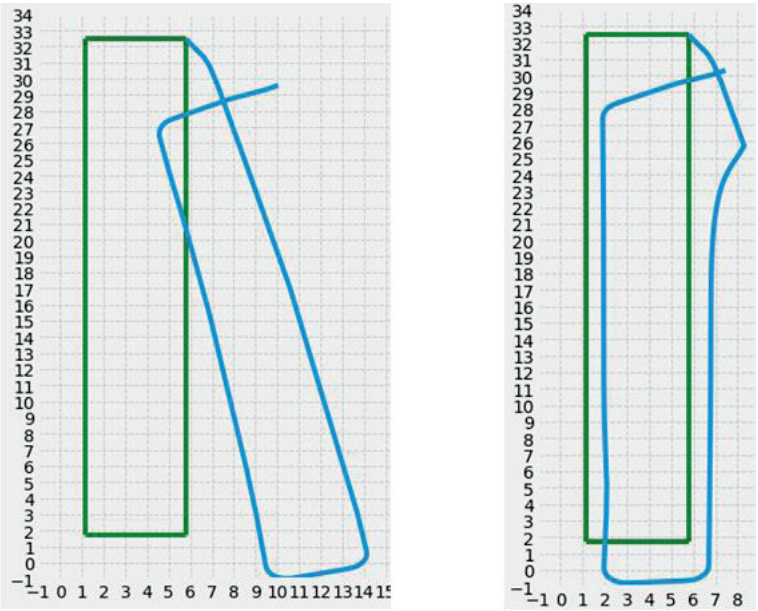

Figure 7. PDR result with and without heading calibration

In Figure 7, the figure left is PDR result without heading calibration and the figure right is PDR result with heading calibration. We can see that when the subject goes straight for a certain amount of time, calibration is applied and the positioning result gets more accurate.

Chapter 3.3

UWB ranging and PDR combining UKF-based algorithm

Finally, the performance of the UWB ranging and PDR combining UKF-based algorithm is evaluated. In this experiment, subject walks along the rectangular line (5x31m). Experiment is four times repeated.

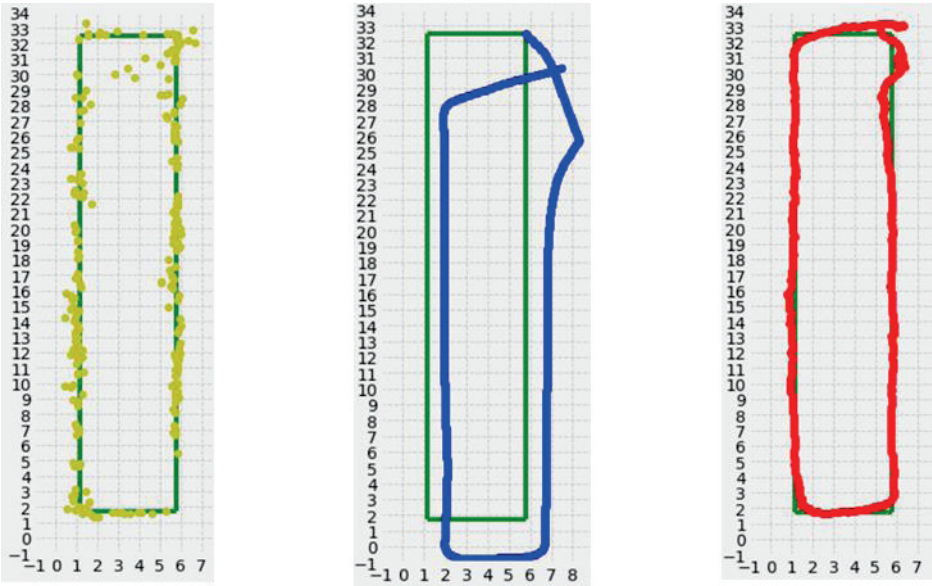

Figure 8. Positioning results from simple UWB positioning, improve PDR and fusion algorithm

In Figure 8, the figure left is the result of simple UWB positioning. It is just the trilateration of UWB ranging results. It has a few points which are far from the reference line. This is due to non-line-of-sight environment. The figure middle is the result of Improved PDR. It is getting inaccurate as time goes by because of accumulative error. The figure right is UWB ranging and PDR combining UKF-based algorithm, and it shows the most accurate result. It is almost free from the non-line-of-sight error of simple UWB positioning and accumulative error of PDR.

UWB positioning only	0.29
Improved PDR only	1.15
UWB and PDR combined	0.21

Table 3. Performance of simple UWB positioning, improved PDR and fusion algorithm

Table 3 shows the average error of each algorithm. UWB ranging and PDR combining UKF-based algorithm shows the best performance.

Chapter 4

Conclusion

In this paper, a noble UWB ranging-PDR combined indoor positioning algorithm is proposed. UWB ranging, which recently becomes available in a smartphone, is an attractive option for indoor localization due to its high ranging accuracy. But its ranging result gets affected by non-lineof-sight environment. There are a lot of objects which can block the UWB signal in an indoor environment. So the error caused by non-line-of-sight environment is a major obstacle to the spread of UWB. The proposed algorithm effectively solved this problem by combining a PDR algorithm with UWB ranging. This might be helpful for the widespread of UWB ranging for indoor positioning.

Also, the improved PDR algorithm proposed here takes full advantage of UWB ranging infrastructure. The data collected from UWB ranging infrastructure is used for making the personalized PDR algorithm. Moreover, the proposed algorithm can be easily implemented on smartphone. This property makes our algorithm more available. Because of its high accuracy and availability, the proposed algorithm is expected to be used as a base indoor positioning method for a lot of LBS.

Bibliography

[1] D. Ahmetovic, C. Gleason, K. M. Kitani, H. Takagi, and C. Asakawa, "Navcog: turn-by-turn smartphone navigation assistant for people with visual impairments or blindness," W4A '16: Proceedings of the 13th Web for All Conference, no. 9, pp. 1–2, April 2016.

[2] S. Alletto, R. Cucchiara, G. D. Fiore, L. Mainetti, V. Mighali, L. Patrono, , and G. Serra, "An indoor location-aware system for an iot-based smart museum," IEEE INTERNET OF THINGS JOURNAL, vol. 3, no. 2, pp. 244–253, April 2016.

[3] S. Chan1 and G. Sohn, "Indoor localization using wi-fi based fingerprinting and trilateration techiques for lbs applications," ISPRS International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVIII-4/C26, pp. 1–5, June 2012.

[4] L. A Latiff, A. A. Abdullah, O. Chia-Ching, and N. Fisal, "Development of an indoor gps-free self-positioning system for mobile ad hoc network (manet)," vol. 2, 12 2005, p. 6 pp.

[5] Y. Wu, H.-B. Zhu, Q.-X. Du, and S.-M. Tang, "A survey of the research status of pedestrian dead reckoning systems based on inertial sensors," International Journal of Automation and Computing, vol. 16, pp. 1–19, 10 2018.

[6] A. Alarifi, A. Al-Salman, M. Alsaleh, A. Alnafessah, S. Alhadhrami, M. Al-Ammar, and H. Al-Khalifa, "Ultra wideband indoor positioning technologies: Analysis and recent advances," Sensors, vol. 16, pp. 1–36, 05 2016.

[7] P. Chen, Y. Kuang, and X. Chen, “A uwb/improved pdr integration algorithm applied to dynamic indoor positioning for pedestrians,” Sensors, vol. 17, p. 2065, 09 2017.

[8] X. Li, Y. Wang, and K. Khoshelham, “Uwb/pdr tightly coupled navigation with robust extended kalman filter for nlos environments,” Mobile Information Systems, vol. 2018, pp. 1–14, 12 2018.

[9] J. Kang, J. Lee, and D.-S. Eom, “Smartphone-based traveled distance estimation using individual walking patterns for indoor localization,” Sensors, vol. 18, p. 3149, 09 2018.

[10] DWM1001 System Overview, Decawave, 2017, version 1.0.

[11] H. Weinberg, “Using the adxl202 in pedometer and personal navigation applications,” 2002, norwood, MA, USA: Analog Devices.

[12] W. Kang and Y. Han, “Smartpdr: Smartphone-based pedestrian dead reckoning for indoor localization,” IEEE Sensors Journal, vol. 15, pp.

요 약

본 논문에서는 UWB 측위 기법과 Pedestrian dead reckoning (PDR)을 함께 이용하는 새로운 실내 측위 알고리즘을 제시하였다. 제시된 알고리즘은 PDR의 성능을 UWB 측위 결과를 이용하여 향상시켰다. 전통적인 PDR에서 보폭 추정과 걸음 감지는 본 논문의 알고리즘에서는 속도 추정으로 대체되었으며, 본 논문의 속도 추정은 딥러닝 모델을 이용해서 이루어 졌다. 또한 이동 방향은 UWB 측위 데이터를 이용하여 보정되었다. 최종적으로 향상된 PDR의 결과와 UWB ranging의 결과를 unscented Kalman filter를 이용하여 합쳤다. 본논문에서 제시된 PDR의 성능은 기존의 PDR보다 좋은 성능을 보였다. 또한 UWB ranging과 improved PDR을 합친 알고리즘이 각각을 독립적으로 사용했을 때보다 더 좋은 성능을 보여주었다.

주요어 : 실내측위, UWB 기반 측위, PDR, 관성센서, 딥러닝, LSTM, UKF
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