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Indoor Positioning System Based on Chest Mounted IMU

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Abstract: Nowadays, the demand on indoor navigation system is increasing rapidly. As a cost-effective choice, inertial measurement unit (IMU) based pedestrian dead reckoning (PDR) systems have been researched for years. The IMU is a unit which contains an accelerometer and a gyroscope. Different from the radio frequency identification (FRID), bluetooth low energy (BLE) and WiFi based systems, IMU based PDR systems are infrastructure-free, which do not require any additional hardware to be installed in the space. In this paper, we propose a PDR system based on chest mounted IMU. Since the IMU is mounted on upper body, the zero velocity update (ZUPT), which is normally used in foot based PDR systems, can not be used. Therefore, we propose a novel step length estimation to correctly compute the step displacement. To improve the positioning accuracy, we propose an efficient map matching algorithm based on particle filter. In addition, different from most existing algorithms, our algorithm is designed for 3D navigation, which can be used in a multi-floor building. The components of our map are carefully designed, which can represent the building floor information clearly. In our system, the altitude is updated by the barometer. With proposed algorithm implemented, our navigation system got second place in the IPIN 2018 Competition Track 2, achieving mean error 5.2 meters after a 800 meters walking. Our system is open source, the code can be found at `https://github.com/rairyuu/PDR-with-Map-Matching`.

Keywords: Barometer, IMU, Indoor Localization, Map Map Matching, Particle Filter, PDR

1. Introduction

In outdoor positioning systems, GPS and magnetometers are assembled to estimate positions and orientations of a system with respect to the Earth coordinate system. Normally, their positioning error is about 10 meters in well-conditioned situations. However, the accuracy becomes less reliable in indoor situations because walls block signals of GPS and additional magnetic fields from some devices make some noises. Therefore, localization using such devices works in outdoor situations only.

However, nowadays, the demand on indoor navigation system is increasing rapidly. Generally, the indoor navigation systems can be separated to two classes, infrastructure-free systems and non-infrastructure-free systems. Non-infrastructure-free systems require to install additional hardware into the buildings, which costs many resources. Radio frequency identification (RFID) [7], [12], bluetooth low energy (BLE) [11], WiFi [21], [24] based systems belong to this class. Infrastructure-free systems, which do not require any additional hardware to be installed, are more cost-effective. Camera based simultaneous localization and mapping (SLAM) and inertial measurement unit (IMU) based pedestrian dead reckoning (PDR) [8] systems belong to this class. With the development of hardware, the SLAM based navigation systems have the ability to work in real time. However, the camera based systems require a good illumination, which sometimes cannot be fulfilled. Although the accuracy is not as good as SLAM systems, the IMU based PDR systems have no requirement to outside environment, which are much stabler.

Fig. 1: Mount IMU on foot.

The IMU can be mounted on different body parts to adapt to various conditions. In most situations, the IMU is mounted on foot to utilize zero velocity update (ZUPT) [13], [14]. Owing to the sensor noise, the computed velocity drifts away from the actual value over time. ZUPT is a technology to reduce this error as follows. During walking, the velocity of human's foot is zero when the foot is on the ground. By detecting these periods and reset the velocity to zero, the error on velocity can be reduced. Generally, for other body parts, the ZUPT can not be used. However, those kinds of systems are usually more convenient to use. For example, the hand hold IMU based systems can be implemented in smart-phones [1]. The head mounted ones can be implemented in smart-glasses [25]. The chest mounted ones can be used in body suits, etc. Also, some systems can recognize

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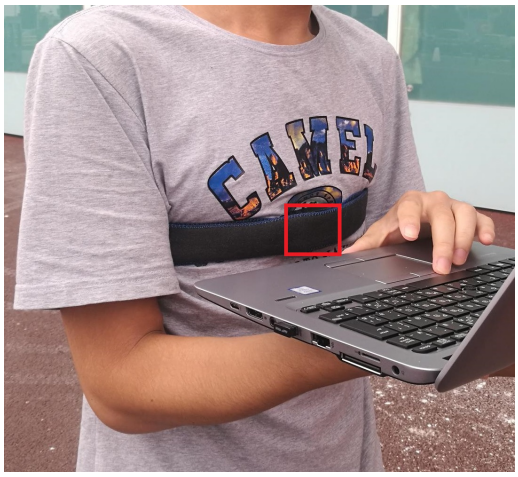


Fig. 2: Mount IMU on chest.

Table 1: Specifications of our IMU.

	range	resolution	sampling rate
accelerometer	$\pm 16g$	$490\mu g$	$400Hz$
gyroscope	$\pm 2000°/s$	$0.06°/s$	$400Hz$
barometer	$30 \sim 110kPa$	$0.18Pa$	$25Hz$
size	$56 \times 39 \times 18mm$		
weight	$46g$		

where the IMU is mounted and apply proper processes [6], [23]. In these body parts, the chest has fewest unexpected movements. In PDR based positioning systems, unexpected movements can introduce errors, decrease positioning accuracy and are difficult to handle. Therefore, the movement of chest is most simple and stable.

In this paper, we propose an indoor positioning system with map matching using a chest mounted IMU. Our motivation is to create a body suit to support the work in multi-floor buildings. Since the movement of human chest is most simple and stable, we decided to mount the IMU on chest. The input data of our system is acceleration, angular velocity and barometric pressure. The specifications of our IMU[*1] is listed in Table 1. To reduce the error accumulation on position and heading, we designed an efficient map matching algorithm based on particle filter. The components of our map are carefully designed, which can represent the building floor information clearly. With proposed algorithm implemented, our navigation system got second place in the IPIN 2018 Competition[*2] Track 2, achieving mean error 5.2 meters after a 800 meters walking.

2. Related Work

Generally, a positioning system consists of three parts, step detection, step length estimation and map matching. In this section, we review the past works on these therr parts.

The input data is a sequence of acceleration and angular velocity. Owing to the sensor noise, the computed displacement contains error. To avoid the error accumulation, step detection was proposed. For foot mounted IMU, Ojeda et al. proposed two empirical rules to separate steps [13], [14]. Madgwick et al. proposed a step detection algorithm based on filtering and thresholding, which only requires the norm of acceleration [4], [10]. For hand hold IMU, since the hand motion is complex and various, step detection is more difficult. To deal with this problem, Susi et al. proposed an adaptive algorithm which first recognize the motion type, then apply proper methods [19]. For head or chest mounted IMU, as implemented by Zhang et al., filtering and thresholding based algorithm is still a good choice [25].

Step length estimation is the process to compute the displacement of each step. The displacement consists of two parts, length and direction. Therefore, this process can be classified into two classes, computing the length and direction separately or not. Using a fixed step length works well in most situations. However, in some cases, this method may fail. To improve the accuracy, Weinberg et al. proposed an empirical equation to compute the step length for upper body mounted IMU [20]. The step direction can be computed from IMU pose. For foot mounted IMU, double integration can compute the length and direction together. However, simply applying double integration can not fit all motions. To settle this problem, Shin et al. proposed an adaptive step length estimation algorithm [18]. For hand hold IMU, Renaudin et al. proposed an adaptive algorithm based on motion mode classification [15]. Yan et al. proposed a regression model to compute the step displacement [23].

Utilizing the step detection and step length estimation can reduce the error on each step. However, the error on position still accumulates over time. Moreover, these processes cannot reduce the error on orientation. To solve these problems, particle filter based map matching algorithm has been proposed [16], [17], [22]. The particle filter is particularly good for dealing with non-linear and non-Gaussian estimation problems [2]. By implementing the particle filter based map matching algorithm to the navigation system, the positioning accuracy can be improved significantly. Davidson et al. showed how the particle filter improve the performance of indoor navigation [5]. By combining the backtracking particle filter with different level of 2D building plan detail, Widyawan et al. achieved high accuracy indoor navigation [9]. Bojja et al. proposed a 3D map matching algorithm in order to navigate in the 3D space [3].

3. Method

3.1 Step Detection

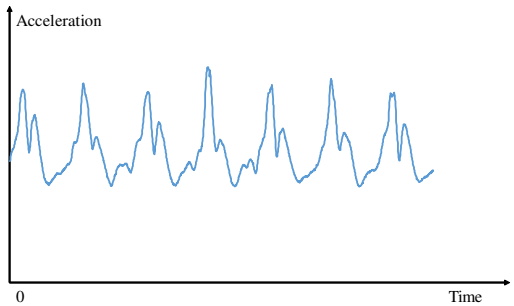
As shown in Figure 3, we use the filtering and thresholding to detect steps. First, as shown in Figure 3a, we compute the norm of 3D acceleration. To remove the noise, we apply a low pass filter to the norm. We define the interval from a peek to next peek as one step. The peek of norm corresponds to the moment that the foot hits ground, where the acceleration is maximum. The result of step detection is shown in Figure 3c.

3.2 Step Length Estimation

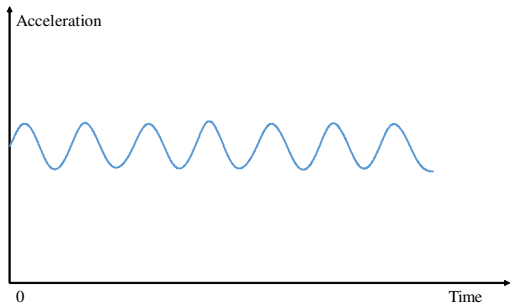
To compute current position, we first transform the 3D acceleration data from sensor frame to the world frame. The transformation matrix is computed from the IMU pose. In our system, the IMU pose is updated by Madgwick's algorithm [10].

In experiment, we found the displacement of one step can be computed by:

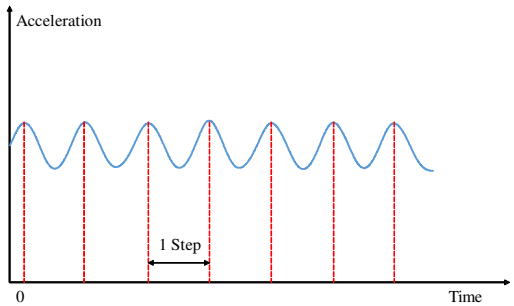
*1 http://x-io.co.uk/ngimu/
*2 http://ipin2018.ifsttar.fr/competition/about/



(a) Norm of 3D acceleration

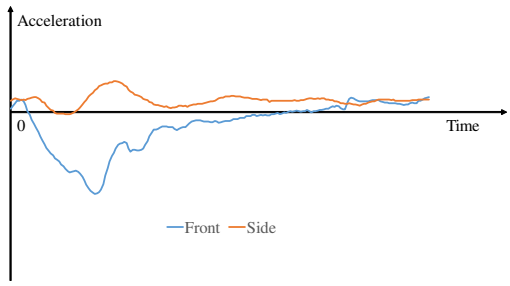


(b) Apply low pass filter

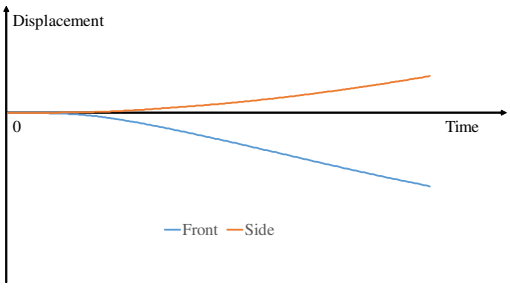


(c) Detected steps

Fig. 3: Process of step detection.



(a) 2D acceleration data



(b) Double integration

Fig. 4: Data of one step.

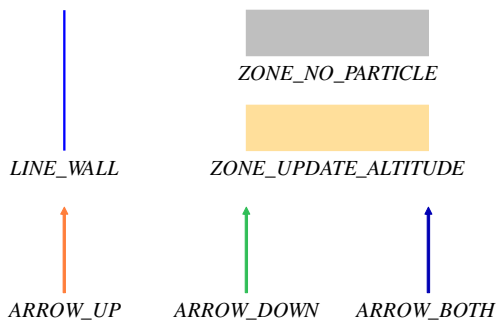


Fig. 5: The components of our map.

$$\boldsymbol{D} = K \cdot \iint \boldsymbol{a}(t)\, dt\, dt \tag{1}$$

where $\boldsymbol{a}(t)$ is the 3D acceleration of that step, K is a parameter which needs to be calibrated for each user. In this approach, the length and direction of one step can be computed at the same time. The 2D acceleration data (removed the up direction) of one step (moving forward) is shown in Figure 4a. By analyzing the data, we found that in one step, the decelerating phase is much more obvious than accelerating phase. Therefore, as shown in Figure 4b, the vector computed by double integrating the 2D acceleration is opposite to the forward direction. To transform it to correct direction and length, user parameter K is required. In our experiment, parameter K is in the range $[-5.0, -3.0]$. After calibration, the error on step length is in 10%. Note that the displacement on side is not zero. In normal, the steps are made by left foot and right foot alternately. Therefore, the upper body tends to left and right alternately. This is the reason that there is a side displacement in the step. Since the step made by left/right foot is usually followed with a step made by the other foot, the overall movement is forward.

For the PDR systems based on upper body mounted IMU, the step direction is usually difficult to compute. Most systems requires the step direction keep the same with IMU heading, which makes the systems inconvenient to use. In our approach, since the step displacement is computed from transformed acceleration, it does not depend on IMU heading. Therefore, our system has no restriction on the step direction or IMU heading, which is more user-friendly. However, there is a drawback. In experiment, we found that using this approach can not update the altitude correctly. Thence, we decide to use the barometer instead.

3.3 Map Matching

Our map matching algorithm is based on particle filter [16]. As shown in Figure 5, there are six components in our map. *LINE_WALL* corresponds to the wall, which can not be crossed. In *ZONE_NO_PARTICLE*, the particles will be deleted. Also, new particles can not be produced in *ZONE_NO_PARTICLE*. Only in *ZONE_UPDATE_ALTITUDE*, the altitude will be updated. In our map, the stair, escalator and elevator correspond to the same component, *ARROW*. *ARROW_UP* connects to upper floor, *ARROW_DOWN* connects to lower floor, *ARROW_BOTH* connects to both.

Each particle has three parameters, current position $\boldsymbol{P}_i$, current

heading h_i and scale s_i. Scale s_i is a scalar randomized from range [0.9, 1.1]. As discussed in Section 3.2, the error on step length is in 10%. Using this scale can cover the error of step length estimation. Final position $\boldsymbol{P}$ and heading h are computed by:

$$\boldsymbol{P} = \frac{1}{n} \cdot \sum_{i=1}^{n} \boldsymbol{P}_i \tag{2}$$

$$h = \frac{1}{n} \cdot \sum_{i=1}^{n} h_i \tag{3}$$

where n is the number of particles. For each particle, current position $\boldsymbol{P}_i$ is updated by:

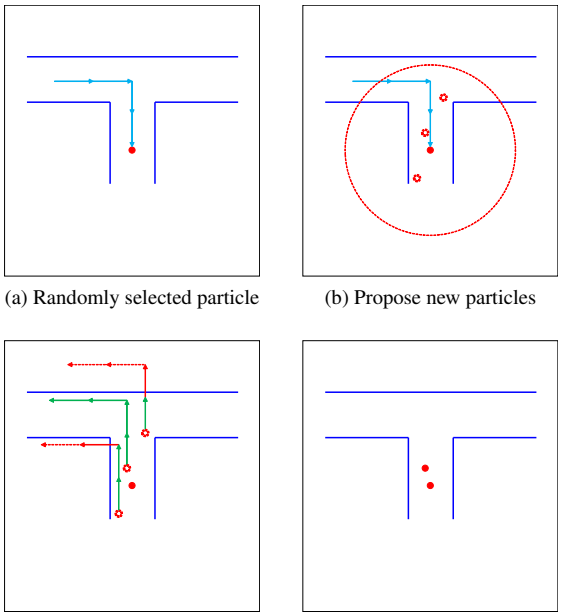
$$\boldsymbol{P}_i^{t+1} = \boldsymbol{P}_i^t + R(\boldsymbol{D}^t \cdot s_i, h_i) \tag{4}$$

where $\boldsymbol{D}^t$ is the 2D displacement of current step, $R(\boldsymbol{X}, y)$ is a function which rotates vector $\boldsymbol{X}$ angle y. Hereafter, our system apply the collision detection to the particles. If the line from $\boldsymbol{P}_i^t$ to $\boldsymbol{P}_i^{t+1}$ hits the $LINE_WALL$s, the ith particle will be deleted. At last, our system produce new particles and wait for next step. The process of producing new particles is shown in Algorithm 1. The position of $NewParticle$ is randomized from the circle with center $Particle$ and radius $Radius$. The heading of $NewParticle$ is randomized around the final heading h. The scale of $NewParticle$ is randomized in the range [0.9, 1.1]

Algorithm 1 Produce new particles

```
ParticleNumberMax = 256
TryTimeMax = 8
Radius = 3.0
ParticleNumber = n
while ParticleNumber ≤ ParticleNumberMax:
    Particle = SelectRandomParticle()
    TryTime = 1
    while TryTime ≤ TryTimeMax:
        NewParticle = ProposeNewParticle(Particle, Radius)
        if BacktrackingTest(NewParticle) == PASS:
            AppendParticle(NewParticle)
            ParticleNumber = ParticleNumber + 1
            break
        TryTime = TryTime + 1
```

When producing new particles, one problem is that the particles may be produced in impossible positions. This problem decreases the positioning accuracy, sometimes even crashes the map matching module. Inspired by the backtracking particle filter proposed by Widyawan et al. [9], we apply a backtracking test to new particles. In Figure 6, blue arrows corresponds to recent steps. First, new particles are randomly proposed around a randomly selected particle. As shown in Figure 6c, new particles go back recent steps and apply the collision detection. If the particle hits the walls, it will be deleted. As shown in Figure 6d, only particles passed this test are left. By applying the backtracking test, most new particles are produced around the correct position. This helps our system achieve higher accuracy. Moreover, this algorithm could also be used when the map matching failed to track the user. By applying the backtracking test to the randomly selected points around last estimated position, it is possible to find correct current position and restore the system.



(a) Randomly selected particle (b) Propose new particles

(c) Apply backtracking test (d) Result

Fig. 6: Process of backtracking test. Blue arrows are recent steps.

As discussed in Section 3.2, we use the barometer to update the altitude. Delta altitude Δa can be computed by:

$$\Delta a = \Delta p \cdot -0.09 m/Pa \tag{5}$$

where Δp is the delta pressure. Even in indoor situation, the barometric pressure varies over time. To update the altitude correctly, we introduce $ZONE\_UPDATE\_ALTITUDE$ to the map. Only in this zone, the altitude can be updated. Also, all $ARROW$s are defined in this zone. Since the user does not stay in this zone for a long time, this approach usually works well. When the delta altitude Δa is closed to the floor height, our system will match current position to the export of the nearest $ARROW$ and produce new particles. Every time the floor changes, the positioning error of our system can be reduced.

4. Evaluation

In this section, we present quantitative experiment results of our system. Basically, we followed the evaluation approach in IPIN 2018 Track 2. In each experiment, the user is asked to walk along a given route. Several key-points are set in the route before the experiment, the position of these key-points is known. The user is asked to stop at each key-point and record the estimated position output by our system. Error e^i of the i-th key-point is defined by following equation:

$$e^i = D_{xy}(\boldsymbol{P}_g^i, \boldsymbol{P}_e^i) + D_z(\boldsymbol{P}_g^i, \boldsymbol{P}_e^i) \tag{6}$$

$$D_{xy}(\boldsymbol{P}_g^i, \boldsymbol{P}_e^i) = \sqrt{(\boldsymbol{P}_g^i.x - \boldsymbol{P}_e^i.x)^2 + (\boldsymbol{P}_g^i.y - \boldsymbol{P}_e^i.y)^2} \tag{7}$$

$$D_{xy}(\boldsymbol{P}_g^i, \boldsymbol{P}_e^i) = |\boldsymbol{P}_g^i.z - \boldsymbol{P}_e^i.z| \cdot p_z \tag{8}$$

where $\boldsymbol{P}_g^i$ is the real position and $\boldsymbol{P}_e^i$ is the estimated position. Position $\boldsymbol{P}^i$ has three elements, x, y and z. Element x and y are in meters, whereas element z is a scalar which represents current floor. p_z is the penalty on floor, which is set to 15.

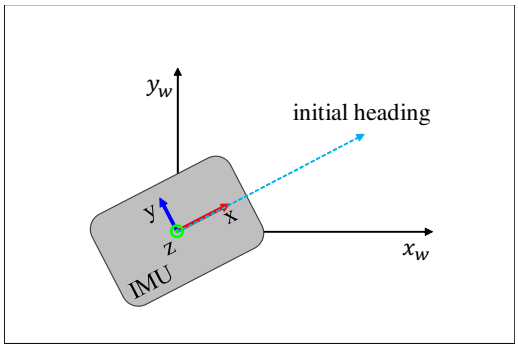


Fig. 7: Calibrate the IMU pose with initial heading.

Table 2: Experiment 1: the distribution of error

travelled distance: 432.22m	
key-point number: 25	
	our system
mean	0.78m
median	0.51m
75th percent	0.76m
standard deviation	0.92m

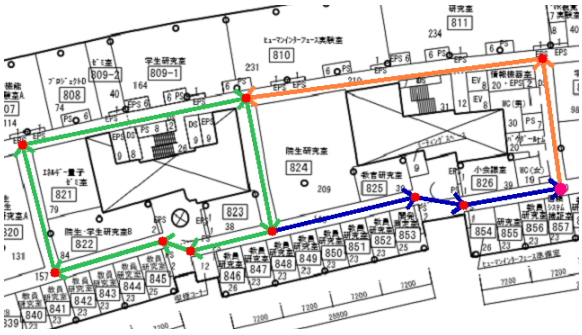
Table 3: Experiment 2: the distribution of error

travelled distance: 792.49m	
key-point number: 70	
	our system
mean	5.2m
median	3.6m
75th percent	5.7m
standard deviation	5.0m

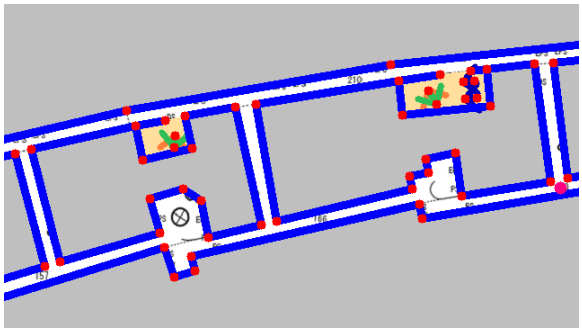
In the experiment, initial position and heading are given to setup the system. The process of setup is: 1. open the IMU and launch our system software; 2. connect the IMU to the computer; 3. calibrate the IMU pose with initial heading (as shown in Figure 7); 4. attache the IMU on the user's chest; 5. start tracking.

In first experiment, we evaluate our system in the campus building with different configurations. As shown in Figure 8a, the user is asked to start at the pink point, go along the orange arrows, walk around the green route for three times and walk back to start point along the blue arrows. There is no open space in the route, the width of corridors is $2-3$ meters. Therefore, we use 256 particles in this experiment. The travelled distance is 432.22 meters. The red points represent to key-points. The estimated routes of our system are shown as Figure 8c and Figure 8d. At the beginning of the route, the system without map matching still works well. However, the drift on heading is getting larger over time. Therefore, the result becomes worse. In our system with map matching, since the estimated position and heading are calibrated dynamically, the result is much more accurate and stable. The detailed results are shown in Figure 9 and Table 2.

We also evaluated our system in the IPIN 2018 Competition Track 2. The competition is hold in a huge shopping mall which contains several open spaces. The evaluation route crosses three floors, consists of indoor and outdoor spaces. In indoor spaces, the width of corridors is $10-20$ meters. Therefore, we use 512 particles in this experiment. During the competition, the shopping mall is crowded by customers. Our result is shown in Figure 10. In outdoor spaces, since the map matching can not work, our result is not so good. When we went indoor, the result became acceptable, where error is generally less than 5 meters. As shown in Table 3, the mean error of our system is 5.2 meters. The IPIN competition evaluates the 75th percent error. Therefore, our final score is 5.7 meters, which is 0.2 meters worse than the champion. In 10 teams who participated in this track, we got the second place. The detail of the competition and our result can be found at `http://ipin2018.ifsttar.fr/competition/about/`.

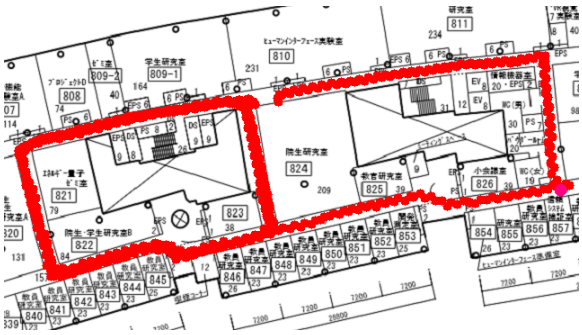


(a) Experiment route



(b) Input map

(c) Result of our system, without map matching



(d) Result of our system, with map matching

Fig. 8: Experiment 1: evaluation on our system with different configurations.

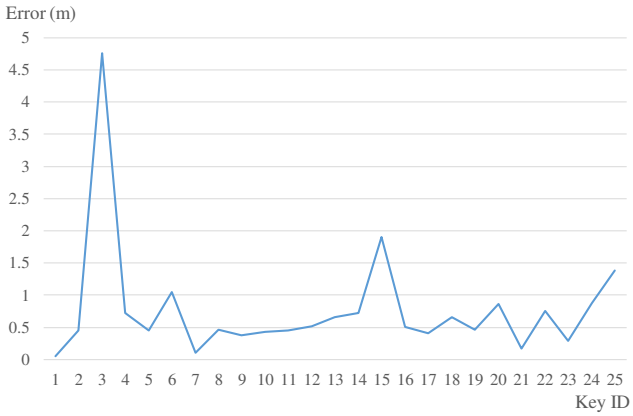


Fig. 9: Experiment 1: the error on each key-point.

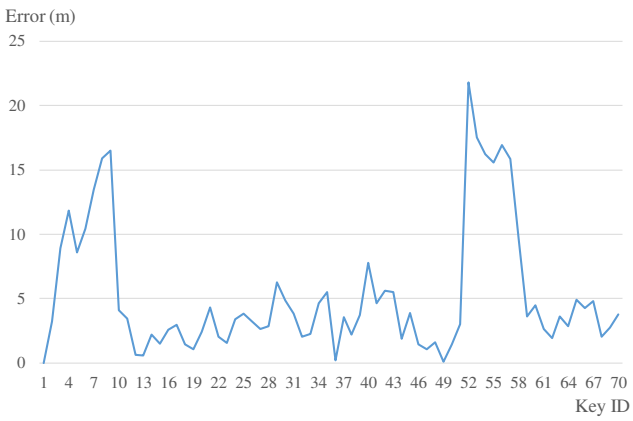


Fig. 10: Experiment 2: the error on each key-point.

5. Conclusion

In this paper, we proposed a novel indoor positioning system with map matching. In our system, the IMU is mounted on chest where the movement is most simple and stable. To reduce the error accumulation on position and heading, we designed an efficient map matching algorithm based on particle filter. Different from most existing algorithms, our map matching algorithm is designed for 3D navigation, which can be used in multi-floor buildings. With carefully designed components (wall, stair, escalator, elevator), our map can represent the building floor information clearly. With proposed algorithm implemented, our navigation system got second place in the IPIN 2018 Competition Track 2, achieving mean error 5.2 meters after a 800 meters walking. In our future work, we are improving the accuracy of the step length estimation. Also, as mentioned in our motivation, we are designing a body suit to support indoor work.

Acknowledgement

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