Ramp Detection with a Foot-Mounted IMU for a Drift-Free Pedestrian Position Estimation

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***Abstract*—The localization of persons in indoor spaces is nowadays an open problem. There are partial solutions based on the deployment of a network of sensors (Local Positioning Systems or LPS). Other solutions only require the installation of an inertial sensor on the person's body (Pedestrian Dead-Reckoning or PDR). PDR solutions integrate the signals coming from an Inertial Measurement Unit (IMU), which usually contains 3 accelerometers and 3 gyroscopes. The main problem of PDR is the accumulation of positioning errors due to the drift caused by the noise in the sensors. This paper presents a PDR solution that incorporates a drift correction method based on detecting the access ramps usually found in buildings. The ramp correction method is implemented over a PDR framework that uses an Inertial Navigation algorithm (INS) and an IMU attached to the person's foot. Unlike other approaches that use external sensors to correct the drift error, we only use one IMU on the foot. To detect a ramp, the slope of the terrain on which the user is walking, and the change in height sensed when moving forward, are estimated from the IMU. After detection, the ramp is checked for association with one of the existing in a database. For each associated ramp, a position correction is fed into the Kalman Filter in order to refine the INS-PDR solution. Drift-free localization is achieved with positioning errors below 2 meters for 1000-meter-long routes in a building with ramps.**

***Index Terms*—Indoor localization, IMU, INS, Drift elimination.**

I. Introduction

Different approaches can be used to eliminate the positioning drift in *Pedestrian Dead Reckoning* (PDR) solutions [1]: 1) Integration with external sensor systems, such as radio-based LPS (it implies additional costs for the installation of the infrastructure), 2) The use of other sensors onboard the person, such as, barometers, compasses, cameras, etc.. [2] (they reduce drift but do not totally eliminate it), or 3) Methods that apply movement constraints, for example: straight-line path assumptions [3], fitting the position to accesible areas in the environment (map-matching) [4], or *action recognition* methods that classify the type of activity of the person [5].

Action recognition can be used to get clues about where a person could be located, allowing to make position corrections to eliminate drift. This approach is the one that we exploit in this work. In particular, we propose to detect with an IMU if the person is on a *ramp*, and if so, correct the PDR estimated position with the position of that ramp (see Fig. 1 for a person walking on a ramp in our building).

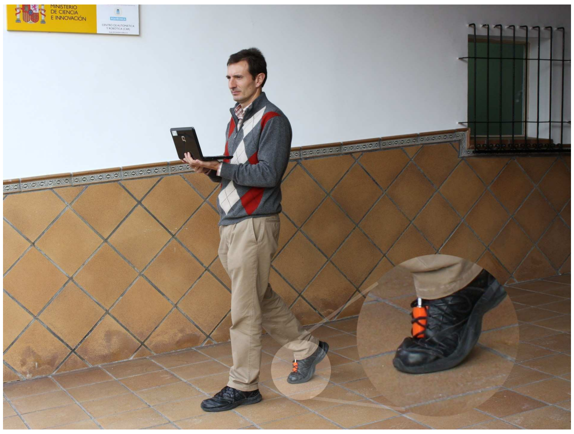

Fig. 1. Location of persons with inertial sensors and drift correction by detecting ramps. The IMU is attached to the right foot with the shoe's laces (orange color box).

The works in the literature that are closer to our contribution, since they propose a position correction based on the recognition of actions that only can occur at particular locations, are the ones by Gusenbauer [6] and Kourogi [7]. In [6] the detection of elevators and escalators using the readings from an IMU is proposed. The method, named "Activity based map-matching", applies positioning corrections in a direct Kalman filter whenever the person is detected on an escalator or elevator. The position correction is made with the position of the closest stair or lift. In [7] the detection of actions such as still, lateral walk or going up/down-stairs is used to improve the PDR algorithm. Besides, the improved position estimate is used to better detect the actions. No implementation details are given in any of these references.

In this communication, we present a method to correct the estimated position of a person based on the detection of ramps using only an inertial sensor. Employing the algorithmic framework for inertial-based PDR navigation proposed by Foxlin [8] and Jiménez [9], we add a ramp detection method that triggers position corrections whenever a person is detected on one of the ramps of the building. This work assumes that there exist access ramps in the building to connect floors at different height levels, and it provides drift corrections in PDR without having to employ additional external absolute positioning sensors. Our algorithm detect ramps by measuring the ramp's slope and the change in height between consecutive steps. Then, ramps are evaluated for association with one ramp with similar features in a database. We believe that we are the first authors to propose the detection of ramps using an IMU attached to the foot of a person.

The section II presents the PDR method, including the ramp detection and the association algorithms. The section III shows the evaluation results for several indoor navigation tests. Finally, in the last section, we give the main conclusions drawn from this work.

II. The IMU-based PDR Method with Ramp Detection

A. The Inertial Framework for PDR

The PDR algorithm that we use to integrate the IMU readings is the one recently proposed by Jiménez et al. [9], named IEZ+. As Foxlin [8] proposed, the use of a complementary Extended Kalman Filter (EKF) and a foot-mounted IMU have many benefits in PDR, such as Zero Velocity Update corrections (ZUPT) every time the foot is motion-less (stance phase). It provides position estimates with a limited drift, even using MEMS sensors.

The Extended Kalman Filter (EKF) works with a 15-element error state vector: $\mathbf{X} = [\delta\mathrm{At}, \delta\omega^b, \delta\mathrm{Po}, \delta\mathrm{Ve}, \delta\mathrm{a}^b]$. This vector contains the estimated bias of accelerometers and gyroscopes ($\delta\mathrm{a}^b$ y $\delta\omega^b$, respectively), as well as, the 3D errors in attitude (δAt), position (δPo), and velocity (δVe). Fig. 2 represents a block diagram of the IEZ+ method, with some additional blocks (light-gray color) for ramp detection.

The IEZ+ PDR method, using only inertial information from one IMU, has proved to be very reliable with an accumulation of positioning errors of about 1-2% of the Total Traveled Distance (TTD) [9] [8]. However, as any integrating or dead-recknoning method, even with this small error, the accumulated error can be very significant for long distance routes (e.g. 10 meter error for 1000-meter-long paths).

B. Position Correction with Ramps

We correct the drift by detecting when the user is located on a ramp, then identifying the ramp and consequently its position, and finally generating a position correction in the EKF used in our PDR implementation. As it can be seen in the light-gray blocks in Fig. 2, a database contains the location of the ramps, their dimensions, orientations and slopes. The blocks termed "Ramp Detector" and "Ramp Association" are described in detail next:

1) Ramp detection: By definition a ramp can be distinguished from a leveled terrain by its slope. Also, when walking along a ramp there should be a change in height (an ascent or descent). However, it is not so straightforward to detect a ramp while a person is walking by simply using a foot-mounted IMU. Some of the challenges are to detect low-slope ramps with noisy IMU signals, or to distinguish between inclinations coming from real ramps, and those due to irregular stances over uneven terrain.

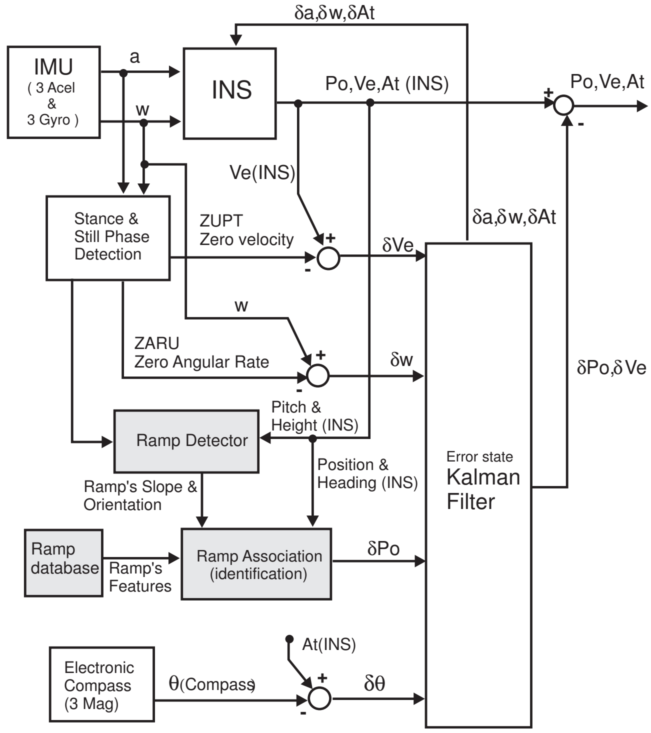

Fig. 2. Block diagram of the PDR method with position corrections at ramps.

With a suitable signal processing, two main parameters could be useful for ramp detection: 1) the pitch angle (ψ) of the IMU at each step, and 2) the difference in the vertical position (height) between two consecutive steps (δz or rise). At a ramp a positive rise has associated a negative pitch angle, and viceversa. So, we propose to detect a ramp when the product of both values (pitch and rise), which should be a negative number, is below a given threshold:

$$\mathrm{RampDetected}(k) = \begin{cases} 1 & \psi(k) \cdot \delta z(k) < \mathrm{Th} \\ 0 & \mathrm{Otherwise} \end{cases}, \qquad (1)$$

where k is the index of the step detected.

The pitch angle used in equation 1 (ψ) is obtained, after some additional processing, from the pitch angle ($\tilde{\psi}$) at the output of the INS mechanization. This angle ($\tilde{\psi}$) measures the terrain inclination but also a pitch that only depends on how the IMU was attached to the foot (a factor which should be removed). The calculations to obtain the pitch of interest are: 1) filter the pitch angle with a FIR filter over the last three step samples (which adds a group delay of one step), $\psi_f(k) = 0.33\tilde{\psi}(k) + 0.33\tilde{\psi}(k-1) + 0.33\tilde{\psi}(k-2)$; 2) compute the IMU's installation pitch as the average of the IMU pitch at each step with a first-order low-pass IIR filter, $\bar{\psi}(k) = 0.99\bar{\psi}(k-1) + 0.005\psi_f(k) + 0.005\psi_f(k-1)$ (we assume that the path is in its majority over a leveled surface); 3) Finally, we obtain the inclination angle of the terrain (independent of IMU installation) as:

$$\psi(k) = \psi_f(k) - \bar{\psi}(k). \qquad (2)$$

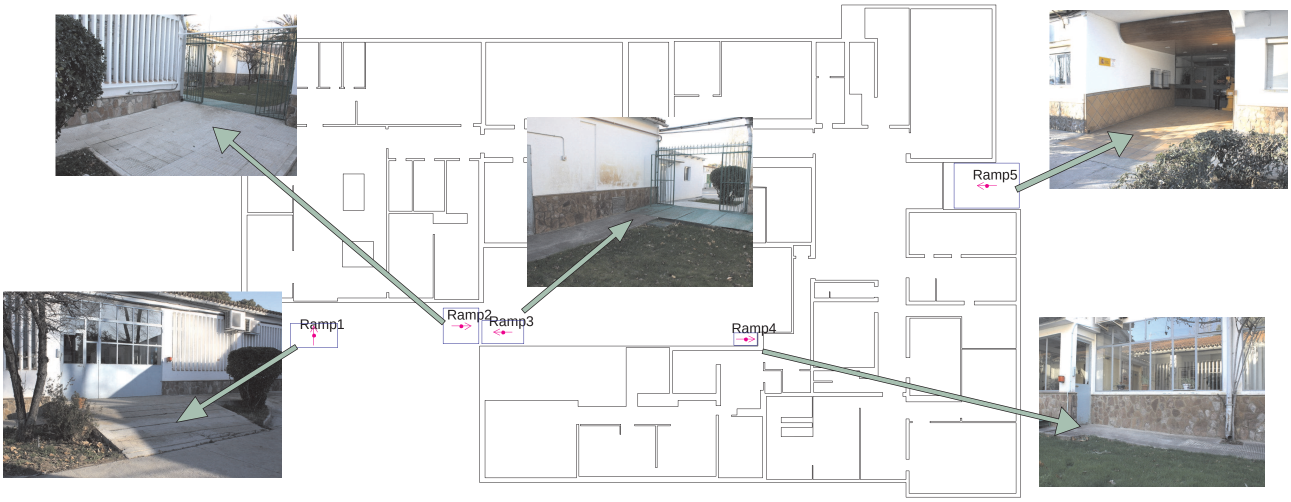

Fig. 3. Ramps to access the main building of CAR-CSIC center.

The rise or change-in-height value between two consecutive steps, $\delta z(k)$, is computed similarly to the pitch angle (in terms of filtering). In this case, the real height change has to be distinguished from the rise caused by the vertical drift at the INS output. The detrended change in height between two consecutive steps is:

$$\delta z(k) = \delta z_f(k) - \bar{\delta z}(k), \tag{3}$$

where $\delta z_f(k)$ is the rise between two steps computed as: $\delta z_f(k) = z_f(k) - z_f(k-1)$, and $\bar{\delta z}(k)$ is the estimated drift in height.

2) Ramp Association: Once a ramp is detected with the above-mentioned method, it is necessary to identify the particular ramp where the person is located. To do that, the estimated position of the person (from the INS output) is compared with the ramps positions contained in the database. In order to avoid ambiguities, the association is done with the closest ramp in the database with an orientation or heading similar to the direction of movement of the person (within $\pm 30^{\text{o}}$). The ramp's orientation (marked with a magenta arrow in Fig. 3) defines the direction of ascension along the ramp, and the pedestrian's direction of ascension is known from the parameter (δz) that indicates whether the person is going up or down.

3) Position Correction: After the ramp association, the pre-stored position of the ramp in the database, Po_{ramp}, should coincide with the estimated position at the INS output (Po). However, in general, due to the typical PDR drift both positions will differ from each other. This difference is the positioning error (δPo) used to feed the EKF (Fig. 2):

$$\delta\text{Po}(k) = \text{Po}(k-1) - \text{Po}_{\text{ramp}}(k), \tag{4}$$

where the correction is done with the position of the last detected step, because the ramp detector added a one-step delay at the FIR filter.

The certainty that we have on the correction error measurement (δPo), depends on several factors such as: the ramp size, the similitude between the heading of movement and the orientation of the ramp, or even their slope similitudes. In this work, in a first approach, we use a standard deviation that is proportional to the size of the ramp ($\sigma_{\delta\text{Po}} = \text{SizeRamp}/4$). This means that the smaller ramps are the ones with higher certainty.

III. Experimental Evaluation

A. Test Conditions

The inertial sensor used is the model MTi from XSens. It is configured to output data from each triad of accelerometers, gyroscopes and magnetometers at 100 Hz. This IMU is mounted on the user's foot (requirement to use the IEZ+ algorithm), attaching it to the right shoe with its own shoe's laces.

The tests were performed in the main building of our working place, the Center for Automation and Robotics (CAR-CSIC), which has several access ramps at the transitions from indoor to outdoors. In Fig. 3 there is a floor plan of the building with the location of the ramps.

B. Ramp Detection Performance

The evaluation tests indicate that it is possible to detect each of the 5 ramps in the database, including those with low slopes (ramps number 3 and 4). In the graph of Figure 4 the capacity to detect the ramps 2, 3 and 4, along a cyclic route repeated twice is shown. The individual values of the estimated slope (ψ) and rise (δz) is also shown, as well as, the product of both values that is used for thresholding. Several ramp detections can occur on the same ramp, as many a right-foot stances on a particular ramp. False detection of ramps occurs in some cases (e.g. due to irregular stances over the border of a carpet), but in almost all cases, these false ramps are rejected during the association, and therefore not used to update the Kalman filter.

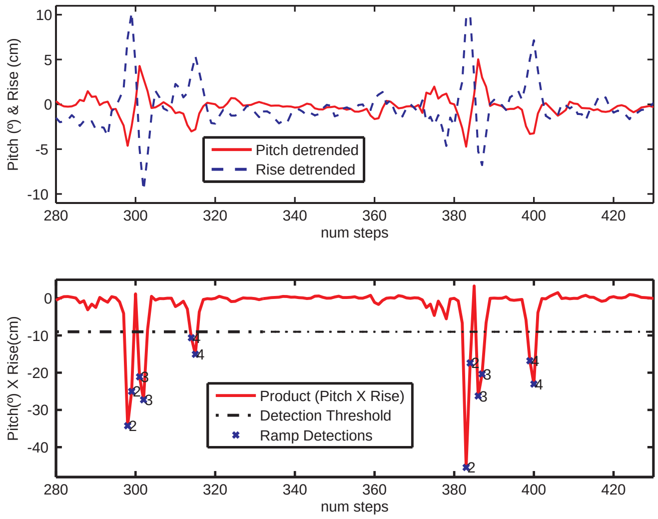

Fig. 4. Ramp detections and associations, for 2 repetitions of a test visiting ramps 2, 3 and 4. Top graph: Estimated Pitch and Rise. Bottom graph: Ramp detections (crosses) and the identification of ramps after the association (marked with the number of the associated ramp).

C. Drift Corrections in Position

Several closed routes have been repeated until a significant positioning drift was accumulated, using only the IEZ+ PDR method without ramp aiding (i.e. a pure dead-reckoning solution). When the algorithms proposed in this paper were activated to use the ramp corrections, we obtain almost a perfect elimination of the accumulative positioning errors, as can be seen in Fig. 5 for a route that is 1000 meters long (in this particular test, ramps 1 and 5 were not detected since they do not lie in the route). The correction is effective with a frequent ramp visit, however the final positioning error depends on the walked distance since the last detected ramp.

IV. Conclusions

We have presented an algorithm that detects *access ramps* in buildings and, with that information, corrects the positioning drifts in PDR solutions. It only requires the use of one IMU attached to the foot of a person. We know that the proposed method is a "partial" solution to the problem of drift elimination in PDR, because it assumes that a building must have some ramps in frequently-visited places. However, our proposal should be a very useful complement in a final PDR solution that integrates multiple methods to compensate drift (e.g. integrated with map-matching, Radio-based or ultrasonic LPS, GPS, etc.), since we believe that the definitive solution to the accurate and continuous indoor localization, will require the integration of multiple technologies and algorithms in a hybrid location system.

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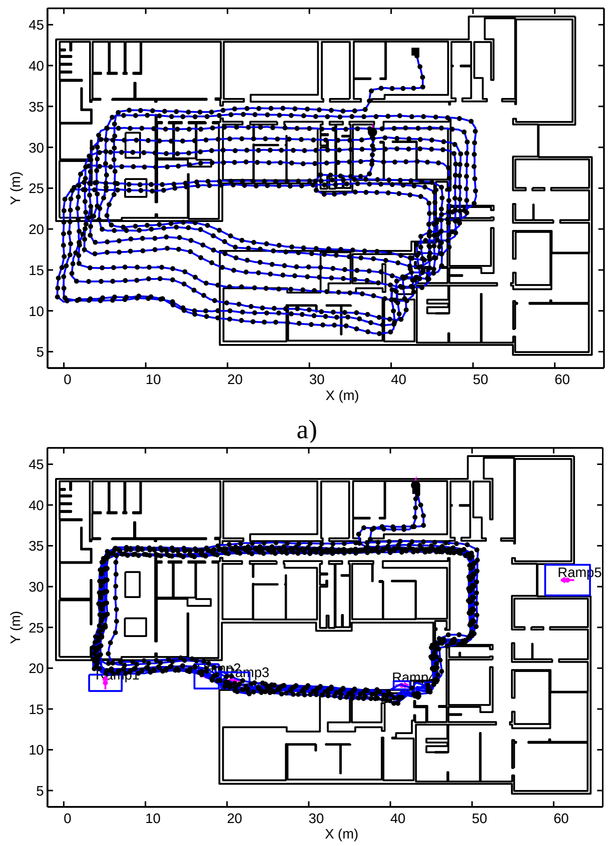

Fig. 5. Closed route repeated 8 times, for a trajectory with a total length of 1000 meters. The trajectory is along the main corridors in the CAR-CSIC building, going temporarily to an exterior yard to finally enter again in the building. a) PDR estimation with IEZ+ algorithm (a significant drift is observed). b) Ramp-assisted PDR estimation (the drift is eliminated).

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