IMU-based localisation literature review

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***Abstract*—Determining exact locations has become a topic of significant interest and numerous experiments have been conducted to investigate various strategies. While some methods like GPS were ineffective in some environments, to address this challenge, the Inertial Measurement Unit (IMU) device has been adapted. In this literature review, we particularly focus on the role of step detection in tracking movements and explore a range of alternative IMU-based localisation approaches.**

I. Introduction

In recent years, the need for accurate and real-time localisation techniques has become important, especially with the rapid advancement in robotics, autonomous vehicles, and augmented reality applications. The IMU, an electronic device designed to measure velocity, orientation, and gravitational forces has emerged as an invaluable asset in localising devices and vehicles in both indoor and outdoor environments, where other traditional methods such as GPS fail. This literature review provides a comprehensive overview of IMU-based localisation, exploring its mechanisms and evaluation criteria. While some research emphasises the role of step detection, others introduce alternative approaches in localisation methods. In the subsequent sections of this paper, section 1 offers a review of three key studies on step detection based on IMU-based localisation techniques. Section 2 discusses another distinct method and Section 4 focuses on different evaluation methodologies. Finally, Section 5 provides the conclusion.

II. Step detection approach

There has been a lot of research on step-detection methods for localisation. Three notable works, [1], [2], and [3], leverage Inertial Measurement Units (IMU) sensors to identify human steps for this purpose.

A. *Step detection and IMU sensor fusion*

[1] discusses a position estimation algorithm for indoor localisation. It emphasises the inefficiencies of traditional systems like GPS for indoor environments, primarily due to weak signal reception. Moreover, relying solely on IMU sensor data has challenges like errors that accumulate over time and interference from external magnetic fields. To address this, [1] introduces an algorithm that combines accelerometer, magnetometer, and gyroscope data from an IMU sensor to estimate position.

In [1], pitch and roll values from the accelerometer and gyroscope are estimated using sensor fusion via Kalman filter to integrate data from these sensors, obtaining more accurate pitch and roll estimates. Then, the pitch value derived from the sensor fusion is used for detecting steps and estimating their length. A valid step is detected based on specific peaks (maxima and minima) within the pitch data. If the maximum or minimum peaks exceed a noise threshold, the step count is increased with predefined thresholds to avoid false detections. After detecting a step, how far each step travels is determined. The model uses the difference in pitch values (between the highest and lowest peaks) to estimate the step length via a linear regression model. Then the direction (heading) of a person is estimated using magnetometer and gyroscope data, and to address sensor inaccuracies, a Kalman filter is applied to provide a more precise orientation measurement. Upon determining the step length and heading, the algorithm calculates an individual's position. This is achieved by multiplying the step length with the total number of steps taken and then aligning this result according to the estimated direction (heading).

One of the notable strengths of the algorithm is that the strengths of each sensor are combined, mitigating their weaknesses. For example, while the gyroscope provides short-term accuracy but drifts over time, the accelerometer provides reliable long-term data but can be noisy in the short term. By fusing data from these sensors, the proposed algorithm aims to provide accurate indoor position estimates.

B. *PILoT System*

[2] introduces a Precise Indoor Localisation Technique (PILoT), which is designed to address the limitation of Dead Reckoning (DR) techniques and emphasises robustness to random position changes and error resetting. Similarly to how [1] incorporates a Kalman filter to combine data from the accelerometer, gyroscope, and magnetometer readings, the PILoT system also employs a Kalman filter for merging data from accelerometer and gyroscope. This assists in estimating pitch, roll, and heading. This study also emphasises that the Kalman filter approach provides a better estimation over individual sensor data.

While [1] detects steps by only analysing pitch maxima and minima derived from the sensor fusion, the PILoT system utilises the Continuous Wavelet Transform. This helps in identifying the patterns of human bipedal motion to accurately detect steps. The human walking motion is divided into four main phases in [2]; the stance phase, the heel take-off phase, the swinging phase and the heal touch-down phase. Furthermore, [2] categorises smartphone placement into two types: stride orientation and step orientation. The PILot system can discriminate between these two orientations, improving its reliability. For the step detection phase, the approach used in [2] is the same as [1], using noise threshold and the maximum and minimum peaks. To estimate step length, [2] utilises a static estimator that computes length as L = H x K1, where H represents an individual's height and K1 is a gender-specific calibration constant. (0.415 for males and 0.413 for females)

For the orientation and heading estimation, the combined data of the accelerometer, gyroscope, and compass data are used with the Kalman filter. While the accelerometer data is used to determine device orientation and both gyroscope and compass data are used for heading estimation.

Unlike [1], which does not work on error correction, [2] incorporates a map-awareness technique. This method recalibrates the user's location using recognisable patterns from floor plans, specifically focusing on the turning events. This allows for occasional correction of accumulated errors in dead reckoning.

C. Refined step detection and stride estimation

[3] also introduces an indoor positioning method that leverages IMU for continuous indoor tracking, pointing out the common shortcomings of GPS indoors. The primary algorithm is the Pedestrian Dead Reckoning (PDR), which incorporates accelerometers and gyroscopes to detect steps, strides, and headings. [3] emphasises the limitations of the traditional PDR, which detects steps based on threshold values of vertical impact. This approach may need to be revised due to foot inclination. While [1] and [2] propose a comprehensive algorithm combining data from accelerometers, magnetometers, and gyroscopes to estimate position including techniques such as sensor fusion, step detection, and step length estimation, [3] focuses on improving step detection and stride estimation by analysing the vertical and horizontal acceleration of the foot while walking.

[3] proposes an improved step detection using pattern recognition derived from the vertical and horizontal acceleration of walking. By analysing the walking patterns, they can recognise steps more reliably. Similar to [2], the walking activity is broken down into two stages in [3]: the standing and the swing phases. Then, the swing part is further divided into two phases, the foot is behind the body's centre of gravity and the foot is in front. They can be detected by observing changes in the body's centre of gravity and analysing the foot's acceleration components, both vertically and horizontally.

For step recognition, while [1] and [2] counted a step whenever a certain acceleration threshold was exceeded, [3] highlights that individual differences and external vibrations can lead to errors. Their proposed alternative solution uses an acceleration signal pattern to accurately determine when a step has occurred. Differing from other studies that depend on step frequency for stride calculation, which can be influenced by various factors like obstacles or visibility issues, [3] suggests a method that correlates stride directly with acceleration rather than walking frequency. Their findings indicate a relationship between stride length correlates and the amount of vertical force experienced during a step, which can be measured through acceleration. In terms of determining direction (heading), instead of solely depending on gyroscopes which can drift off or contain biases over time, it combines gyroscopes with magnetic compasses. The gyroscope corrects the compass's inaccuracies, while the compass adjusts the gyroscope's drift, providing an initial orientation.

III. NON STEP DETECTION APPROACH (IMU AND MILPS INTEGRATION)

Unlike [1], [2], and [3], [4] concentrates on integrating IMU with the Magnetic Indoor Local Positioning System (MILPS) to overcome IMU limitations rather than employing step-detection approaches. [4] states that the IMU solution by itself suffers from sensor drifts and nonlinear integration errors, which compromise its long-term stability. Therefore, it presents a solution that integrates IMU and Magnetic Indoor Local Positioning System (MILPS) to enhance indoor object localisation, especially for kinematic applications.

MILPS operates using quasi-static DC magnetic fields, which can penetrate obstructions such as walls and furniture. While magnetic fields from known positioned coils can be generated and their intensities can be captured with a mobile sensor to get an object's position, Earth's magnetic field can impact these signals. To encounter this, [4] proposes to switch the current direction in each coil at a specific frequency, calculating the differences between positive and negative sample clusters aids in determining the object's distance from the coil. However, MILPS has limitations. For 2D position determination, it requires signals from at least two coils, and its accuracy decreases if an object is in line with the coils.

The IMU sensor offers high-frequency position determination using its factory-calibrated sensors. It undergoes a factory calibration that corrects readings from its components and stores this data in its flash memory. The sensor provides three-dimensional data on acceleration, angular rates, and magnetic fields. By combining its readings with the magnetic fields from MILPS, this configuration provides high-frequency localisation by merging relative positioning data from the IMU with external updates from MILPS. The Kalman Filter (KF) was adopted in [4] for a linear fusion of IMU and MILPS measurements and for nonlinear applications, the Extended Kalman Filter (EKF) was used. Then, the Iterated Kalman Filter (IKF) further refined the process, eliminating linearisation errors arising from inaccurate predictions.

IV. EVALUATION

To assess the efficacy of the proposed algorithm in [1], several experiments were carried out, simulating real-world scenarios. In all these tests, the smartphone was held in hand. Each experiment aimed to measure the algorithm's accuracy in tracking pedestrian movement in different patterns. During the Rectangular Motion Experiment, the participants walked in a rectangular path, while in the Straight-line Motion Experiment, they walked in a linear direction. For the Circular Motion Experiment, the pedestrian walked a circle of 9m radius. In each of these tests, the proposed algorithm consistently showed significant positional accuracy of the proposed algorithm. The performance was quantified using displacement and root mean square error. In [2], tests were carried out 10 times, involving 50 steps each, where the smartphone was randomly shifted between hand and pocket. In [4], a defined indoor path measuring 8 x 6 metres was set up. A handcart equipped with a horizontally-set IMU was used to collect data, which was subsequently logged in MATLAB with timestamps. The system's calculated trajectories were contrasted with the actual path at eight specific track points.

V. CONCLUSION

In conclusion, the need for precise indoor had led to the emergence of innovative IMU-based techniques, as highlighted in this literature review. From leveraging sensor fusion and step detection to integrating other systems like MILPS, researchers have made significant improvements in addressing the challenges of indoor positioning. As technologies like robotic continue to evolve, these advancements in IMU-based localisation will play an important role in enhancing accuracy and reliability in localisation and navigation scenarios.

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