Pedestrian dead reckoning (IMU integration in 3D)

Panteleimon Manouselis, p.manouselis@student.utwente.nl, s3084493, M-ROB
Mrinal Magar, m.b.magar@student.utwente.nl, s2689529, M-S&C
Yifan Cheng, y.cheng-2@student.utwente.nl, s3072517, M-ITech
Koen Freriks, k.freriks@student.utwente.nl, s2014637, M-ME

***Abstract* — In this report an experiment is described of the dead-reckoning of a pedestrian. The results are presented, and after it is discussed how they could be improved.**

***Keywords* —IMU, Dead-Reckoning**

I. INTRODUCTION

In this report, we present a detailed method for integrating IMU data to estimate the position and orientation of a pedestrian using a combination of linear acceleration and angular velocity measurements. The results are discussed based on the measure of drift and resemblance to the true path.

II. IMU DATA AND CALIBRATION

In total, four different experiments were done, executed by different team members. The experiment consists of walking a path in the hallway of a building while wearing a backpack equipped with two lidar's and a IMU. The path can be described as walking three circles around a certain point in the hallway and then returning to the starting position. The IMU data that was gathered consists of measurements from a 3-axis accelerometer and a 3-axis gyroscope, sampled at a rate of 200 Hz. The accelerometer measures the linear acceleration of the device in units of m/s^2. The gyroscope measures the angular velocity of the device in units of deg/s. The IMU data may be affected by biases and scale errors, which can be caused by factors such as temperature drift or manufacturing variations and noise, such as measurement noise or external disturbances.

The first step was data preprocessing. The Z-scores outlier removal technique was employed and data points that were significantly different from the dataset were removed. The threshold was set to 2.5 by trial-and-error and the Z-score for each data point was computed by the following equation:

$$Z = \frac{data - \mu}{\sigma}$$

where μ is the mean value and σ is the standard deviation of the channel.

Then we calibrate the IMU with the bias and scale factor values we obtained from the individual assignments. Here are the vectors we decided to use:

$$b_a = \begin{bmatrix} 0.002186 \\ 0.010954 \\ -0.012225 \end{bmatrix}, S_a = \begin{bmatrix} 0.000466 & 0 & 0 \\ 0 & -0.000398 & 0 \\ 0 & 0 & 0.000444 \end{bmatrix}$$

$$b_g = \begin{bmatrix} -0.003768 \\ 0.000648 \\ -0.001457 \end{bmatrix}, S_g = \begin{bmatrix} -1.000354 & 0 & 0 \\ 0 & -0.990428 & 0 \\ 0 & 0 & -0.982728 \end{bmatrix}$$

Calibration of angular velocity:

$$\omega^b = (\widetilde{\omega^b} - b_a)/(I + S_g)$$

Calibration of accelerometer readings:

$$f^b = (\widetilde{f^b} - b_a)/(I + S_a)$$

Here, the tilde operator on f and w represents the readings obtained from the sensor. And the f and w without the tilde operator are the true readings. We compared the data for each run and excluded the 4th run first because the bias offset of acceleration on z-axis is far different from the other runs. Then we calculated the mean of the rest of the runs. The scale factors of the angular rate are close to 1.0, we analyzed that our gyro did not measure the earth's rotation. So, other than using a wrong matrix, we chose not to use the scale factor to calibrate the angular velocity. $So,\ S_g = 0_{3x3}$

III. INTEGRATION METHOD

To estimate the position and orientation of the pedestrian based on the IMU data, we used a quaternion integration method. This method involves converting the acceleration and angular velocity measurements from the IMU data into quaternion form, and then integrating these quaternions to obtain the quaternion form of the position and orientation estimates at each time step.

To reduce the effects of noise and improve the accuracy of the position and orientation estimates, we also applied a low-pass filter to the IMU data and compensated for the gravitational acceleration by subtracting the gravitational acceleration from the acceleration measurements.

To estimate the velocity and displacement of the pedestrian, we used a similar integration approach. We extracted the acceleration measurements from the IMU data and compensated for the gravitational acceleration by subtracting the gravitational acceleration from the acceleration measurements. We then integrated the compensated acceleration measurements to update the velocity estimates at each time step and further integrated the velocity estimates to update the displacement estimates at each time step. A smoothing parameter (alpha) was used to smooth the estimates and reduce the effects of noise.

Finally, we calculated the magnitude of drift, which is the difference between the final displacement estimate and the initial displacement estimate. The drift represents the error or deviation in the displacement estimates over the duration of the data collection and can be used to evaluate the accuracy of the process.

IV. RESULTS

Since the smoothing parameter reduces the effects of noise, it can improve the accuracy of the drift calculation. As listed below, different alpha results in different drifts. It was found that the found trajectory was best in the region of alpha ranging from 0.985 to 0.995. When comparing the drift values in this range using Table 1, it can be seen that the drift is minimal for 0.985 and gets significantly higher towards 0.995. However, Figure 1 indicates that using a higher alpha, the obtained trajectory is smoother. There seems to be a tradeoff between accuracy and noise reduction. From visual inspection it is concluded that the second measurement raised the result that was most similar to the true path. From comparing with the other trajectories, using Figure 2, it can be concluded that there is still significant run-to-run bias present and therefore the estimated position is not yet accurate.

Alpha	Drift 1	Drift 2	Drift 3	Drift 4
0.985	2.01893	2.05028	2.00094	2.04582
0.900	4.52249	4.60413	4.48908	4.59639
0.995	18.16178	18.48682	17.8938	18.41584

Table 1: Drifts of each run with different parameter alpha

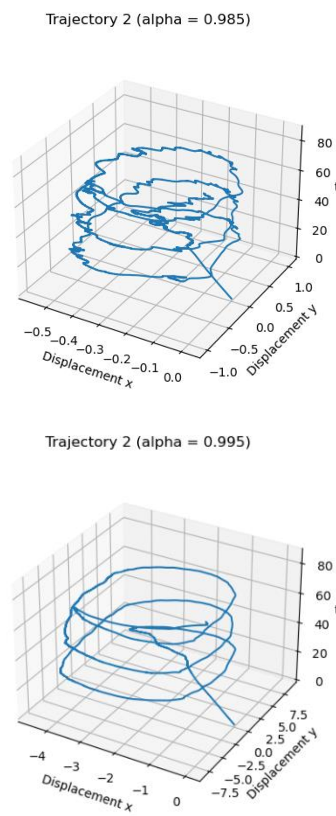

Figure 1: Trajectory of 2nd run with alpha = 0.985 and alpha = 0.995

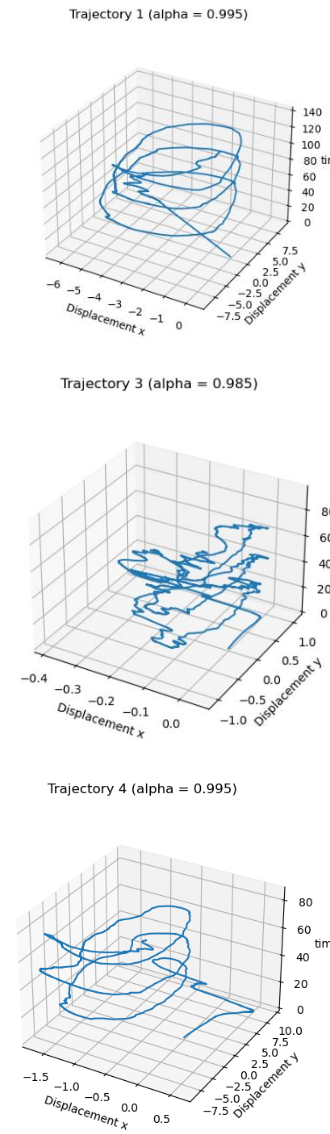

Figure 2: Trajectory of 1st, 3rd and 4th run with alpha = 0.995

V. DISCUSSION

When comparing the different trajectories, it is seen that they do not seem to be very similar, this indicates inaccuracy of the measurement. The same conclusion can be drawn from the fact that there is still some amount of drift present in all the measurements.

VI. CONCLUSION

An experiment was described where the position of a pedestrian is estimated by integrating IMU data. A path was found and improved using a smoothing parameter. Since different trajectory's do not seem to be very similar due to the run-to-run bias, in addition to the fact that a significant amount of drift remains in the results, it is concluded that further processing of the data is needed. This will be done in the future using Lidar-Inertial fusion.

References

[1] A. Noureldin, T. B. Karamat and J. Georgy, Fundamentals of Inertial Navigation, Satellite-based Positioning and their Integration, London : Springer, 2013.