Pedestrian tracking using an IMU array

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***Abstract*—Ubiquitous and accurate tracking of pedestrians are an enabler for a large range of emerging and envisioned services and capabilites. To track pedestrians in prevailing indoor environments, inertial measurement units (IMUs) may be used to implement foot-mounted inertial navigation. Today emerging ultra-low-cost IMUs are taking a leading role in the advancement of the IMU performance-to-cost boundary. Unfortunately, the performance of these IMUs are still insufficient to allow extended stand-alone tracking. However, the size, price, and power consumption of single-chip ultra-low-cost IMUs makes it possible to combine multiple IMUs on a single PCB, creating an IMU array. The feasibility of such hardware has recently been demonstrated. On the other hand, the actual gain of using such multi-IMU systems in the pedestrian tracking application is unclear. Therefore, based on an in-house developed IMU array, in the article we demonstrate that foot-mounted inertial navigation with an IMU array is indeed possible and benefitial. The error characteristics of the setup and different ways of combining the inertial measurements are studied and directions for further research are given.**

I. Introduction

Ubiquitous and accurate tracking of pedestrians are an enabler for a large range of emerging and envisioned services and capabilities. The currently available position dependent services primarily relying on satellite based positioning systems, e.g. GPS, and less frequently on cellular and Wifi based localization, have already significantly changed many aspects of our daily lives. Unfortunately, the radio infrastructure based pedestrian localization solutions have insufficient stand-alone accuracy and robustness for many applications in prevailing indoor environment. Consequently, inertial sensors and magnetometers are typically combined with motion models to implement pedestrian dead reckoning to improve performance and to cover up for the former technologies when they are unavailable [1]. Motion models/heuristics can allow a rather free placement of the inertial sensors (i.e., the use of built in inertial sensors and magnetometers in smart phones or similar products) but may also make the tracking performance limited by the validity of the model rather than the performance of the sensors. Further, the dependence on magnetometers for heading tracking is problematic since magnetometers are easily disturbed in indoor environments. To remedy this and to improve the tracking performance, the inertial sensors may be mounted on the feet to implement foot-mounted inertial navigation, rendering simple and general motion models in the form of zero-velocity-updates (ZUPTs) applicable. Remarkable tracking performance has been demonstrated with such a setups without the use of magnetometers [2]. However, most of the foot-mounted inertial navigation research systems are based on inertial measurements units significantly more expensive and with a significantly larger foot-print than the ultra-low-cost single-chip IMUs of typical consumer products.

Fig. 1. Multi IMU platform pulled out from the sole of a shoe. The platform provides pedestrian tracking through ZUPT-aided inertial navigation. The measurements from the individual single-chip IMUs seen on the PCB are combined to achieve improved pedestrian tracking performance. Close-up of the platform can be found in Fig. 2 and tracking results in Fig. 3.

A few foot-mounted inertial navigation systems built with ultra-low-cost IMUs can be found in the literature [3,4]. However, they exploit magnetometers to cover up for the shortcomings of the IMUs. Due to the large market size, the ultra-low-cost IMUs are taking a leading role in terms of the advancement of the performance-to-cost ratio. Therefore, we would still like to use these sensors for foot-mounted inertial navigation. Their performance is steadily improving but is currently still insufficient for long term stand-alone pedestrian tracking. However, the purposes they are made for make size, price, and power consumption main objectives of their development. Consequently, we may exploit these properties to circumvent their insufficient performance. The size, price and power consumption of single-chip ultra-low-cost IMUs makes it possible to combine multiple IMUs on a single PCB, creating an IMU array. The feasibility of such hardware has recently been demonstrated [5,6,7]. Since the inertial sensors are attached to each other they will sense the same motion. Consequently, their measurements can be combined to mitigate independent stochastic errors. (See [5] for a summary of fundamental gains using an IMU array.) However, actual test of pedestrian tracking by stand-alone foot-mounted inertial navigation is still lacking. Further, there are many conceivable dependent error sources. Consequently, the gain of using an IMU array for foot-mounted inertial navigation is unclear. Therefore, based on an in-house developed multi-IMU platform, in this article we demonstrate that foot-mounted inertial navigation with an IMU array is indeed possible and beneficial but that fundamental difficulties remains in the combination of the inertial measurements, preventing the potential performance gain to be attained. We give initial results on the characteristics of different methods for combining the inertial measurements. In particular we look at the effect on random and systematic errors of different strategies for combining the measurement from multiple IMUs.

II. FOOT-MOUNTED INERTIAL NAVIGATION

The rigid body dynamics dictates that the velocity $\mathbf{v}_k^{(i)}$ of the i:th IMU is physically connected to the acceleration via its temporal derivative, and the position $\mathbf{p}_k^{(i)}$ to the velocity via its derivative. Similarly, the orientation $\mathbf{q}_k^{(i)}$ (the quaternion describing the orientation of the system) can be related to the angular rate $\boldsymbol{\omega}_k^{(i)}$ through a simple differential equation. A first order discrete approximation (ignoring the motion of the earth) of the relations are given by

$$\begin{bmatrix}\mathbf{p}_k^{(i)}\\ \mathbf{v}_k^{(i)}\\ \mathbf{q}_k^{(i)}\end{bmatrix} = \begin{bmatrix}\mathbf{p}_{k-1}^{(i)}+\mathbf{v}_{k-1}^{(i)}dt\\ \mathbf{v}_{k-1}^{(i)}+(\mathbf{q}_{k-1}^{(i)}\mathbf{f}_k^{(i)}\mathbf{q}^{(i)\star}_{k-1}-\mathbf{g})dt\\ \boldsymbol{\Omega}(\boldsymbol{\omega}_k^{(i)}dt)\mathbf{q}_{k-1}^{(i)}\end{bmatrix}, \qquad (1)$$

where k is a time index, dt is the time difference between measurement instances, $\mathbf{f}_k^{(i)}$ is the specific force which is measured by the accelerometers, and $\mathbf{q}_{k-1}^{(i)}\mathbf{f}_k^{(i)}\mathbf{q}^{(i)\star}_{k-1}-\mathbf{g}$ is the acceleration in the navigation coordinate frame where $\mathbf{g}=[0,0,g]$ is the local gravity. The triple product $\mathbf{q}_{k-1}^{(i)}\mathbf{f}_k^{(i)}\mathbf{q}^{(i)\star}_{k-1}$ denotes the rotation of $\mathbf{f}_k^{(i)}$ by $\mathbf{q}_k^{(i)}$ and $(\cdot)^\star$ is the conjugate transpose. Further, $\boldsymbol{\Omega}(\cdot)$ is the quaternion update matrix. Refer to [8] for a detailed treatment of inertial navigation.

The measurements of the specific force $\tilde{\mathbf{f}}_k^{(i)}$ and the angular rate $\tilde{\boldsymbol{\omega}}_k^{(i)}$ can be modelled by

$$\begin{aligned}\tilde{\mathbf{f}}_k^{(i)} &= \mathbf{f}_k^{(i)}+\delta\mathbf{f}_k^{(i)}+\mathbf{v}_k^{(i)}\\ \tilde{\boldsymbol{\omega}}_k^{(i)} &= \boldsymbol{\omega}_k^{(i)}+\delta\boldsymbol{\omega}_k^{(i)}+\mathbf{w}_k^{(i)},\end{aligned} \qquad (2)$$

where $\delta\mathbf{f}_k^{(i)}$ and $\delta\boldsymbol{\omega}_k^{(i)}$ denotes deterministic non-zero-mean errors due to imperfect calibration, e.g., g-sensitivity, voltage level induced gain errors, amplifier saturation, etc., and $\mathbf{v}_k^{(i)}$ and $\mathbf{w}_k^{(i)}$ are zero-mean stochastic errors. Starting from initial estimates of the position, velocity, and orientation and by running the recursion (1) with measurements of the specific force $\tilde{\mathbf{f}}_k^{(i)}$ and the angular rate $\tilde{\boldsymbol{\omega}}_k^{(i)}$ provided by an IMU, estimates of the position, velocity, and orientation $\begin{bmatrix}\hat{\mathbf{p}}_k^{(i)} & \hat{\mathbf{v}}_k^{(i)} & \hat{\mathbf{q}}_k^{(i)}\end{bmatrix}^\top$ for all time instances k are obtained. Unfortunately, the errors in (2) will inevitably accumulate in the estimates leading to a rapid error growth.

The rapidly growing errors would soon render the free-inertial navigation position estimates useless. Fortunately, the error accumulation can be cut and the errors partially compensated for by applying feedback from motion models. With the IMU placed on the foot, a general model imposing a minimum of motion constraints can be applied via so called zero-velocity updates (ZUPTs). In essence, the foot is assumed stationary if linear motion is detected. See [9,10] for further details. The ZUPTs are applied by making the reassignment

$$\begin{bmatrix}\hat{\mathbf{p}}_k^{(i)}\\ \hat{\mathbf{v}}_k^{(i)}\\ d\boldsymbol{\theta}_k^{(i)}\end{bmatrix} \Leftarrow \begin{bmatrix}\hat{\mathbf{p}}_k^{(i)}\\ \hat{\mathbf{v}}_k^{(i)}\\ 0\end{bmatrix} + \mathbf{K}_k\hat{\mathbf{v}}_k^{(i)} \quad \text{and} \quad \hat{\mathbf{q}}_k^{(i)} \Leftarrow \boldsymbol{\Omega}(d\boldsymbol{\theta}_k^{(i)})\hat{\mathbf{q}}_k^{(i)}, \qquad (3)$$

where the feedback $\mathbf{K}_k$ is provided by the Kalman gain, and $d\boldsymbol{\theta}_k^{(i)}$ is the correction in orientation. With the ZUPTs, positions estimates with systematic $\delta\mathbf{p}_k^{(i)}$ and random errors $\mathbf{w}_k^{(i)}$ are archived [11]

$$\hat{\mathbf{p}}_k^{(i)} = \mathbf{p}_k^{(i)}+\delta\mathbf{p}_k^{(i)}+\mathbf{w}_k^{(i)}.$$

The systematic error will originate from $\delta\mathbf{f}_k^{(i)}$ and $\delta\boldsymbol{\omega}_k^{(i)}$ and systematic errors induced by imperfections in the ZUPTs, while the stochastic errors will originate from $\mathbf{v}_k^{(i)}$ and $\mathbf{w}_k^{(i)}$. The primary interest of this article is the two terms $\delta\mathbf{p}_k^{(i)}$ and $\mathbf{wv}_k^{(i)}$ and how these are affected by different ways of combining the inertial measurements from multiple IMUs.

III. INERTIAL NAVIGATION WITH AN IMU ARRAY

Unfortunately, the ZUPTs cannot completely compensate for the accumulated errors from (2). First, the heading and position errors will not be observable [12] and secondly, the implicity motion model of the ZUPTs will not be perfect [11, 13], making (3) introducing new errors. In summary, there will be three remaining error sources in the position estimates of the foot-mounted inertial navigation: 1) Errors introduced by the ZUPTs 2) remaining errors from $\delta\mathbf{f}_k^{(i)}$ and $\delta\boldsymbol{\omega}_k^{(i)}$; and 3) remaining errors from $\mathbf{v}_k^{(i)}$ and $\mathbf{w}_k^{(i)}$.

With multiple IMUs attached to each other, assuming that measurements are transformed into a single reference frame, multiple measurements (2) are obtained. This means that the latter error $\mathbf{wv}_k^{(i)}$ (or the source of the latter error, $\mathbf{v}_k^{(i)}$ and $\mathbf{w}_k^{(i)}$) can be averaged out. In contrast, the systematic error $\delta\mathbf{p}_k^{(i)}$ (or the sources $\delta\mathbf{f}_k^{(i)}$ and $\delta\boldsymbol{\omega}_k^{(i)}$) can only be mitigated to some extent. This is because, e.g. dynamic induced systematic errors will not be zero-mean with respect to i [11]. Finally, the errors induced by (3) will not change. This is because in essence the signal to noise ratio for the zero-velocity detection is large [10], and therefore, using multiple IMUs will not significantly change the detection. In arriving at a joint state estimate $\begin{bmatrix}\hat{\mathbf{p}}_k & \hat{\mathbf{v}}_k & \hat{\mathbf{q}}_k\end{bmatrix}^\top$ we may either combine multiple measurements to produce a joint inertial measurement $\begin{bmatrix}\tilde{\mathbf{f}}_k & \tilde{\boldsymbol{\omega}}_k\end{bmatrix}^\top$ from which a joint state estimate is derived or combine multiple state estimate into a joint state estimate.[1] A linear combination with some weighting gives the two alternatives

$$\hat{\mathbf{p}}_k \Leftarrow \begin{bmatrix}\tilde{\mathbf{f}}_k\\ \tilde{\boldsymbol{\omega}}_k\end{bmatrix} = \sum_i \alpha^{(i)}\begin{bmatrix}\tilde{\mathbf{f}}_k^{(i)}\\ \tilde{\boldsymbol{\omega}}_k^{(i)}\end{bmatrix} \text{ or } \hat{\mathbf{p}}_k = \sum_i \beta^{(i)}\hat{\mathbf{p}}_k^{(i)}.$$

[1] It is assumed that the IMU array is calibrated. See [14] for further details.

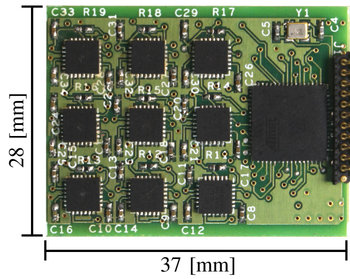

Fig. 2. The in-house constructed IMU array platform holding 18 MPU9150 IMUs (9 on the top side and 9 on the bottom side) and an AT32UC3C2512 microcontroller. The displayed photo is of the actual size of the platform.

Another nonlinear combination method is the median denoted by ${\mu_{1/2}}^i(\cdot)$ which gives

$$\hat{\mathbf{p}}_k \Leftarrow \begin{bmatrix} \tilde{\mathbf{f}}_k \\ \tilde{\boldsymbol{\omega}}_k \end{bmatrix} = \overset{i}{\mu_{1/2}} \left(\begin{bmatrix} \tilde{\mathbf{f}}_k^{(i)} \\ \tilde{\boldsymbol{\omega}}_k^{(i)} \end{bmatrix} \right) \text{ or } \hat{\mathbf{p}}_k = \overset{i}{\mu_{1/2}} \left(\hat{\mathbf{p}}_k^{(i)} \right).$$

Other non-linear combination methods are also conceivable. What weighting to use for the mean case is not obvious and will be discussed in the next section.

The different combination methods have different pros and cons. Combining inertial measurement to form a single measurement only works if the IMUs are rigidly attached to each other while combining state estimates allows for more flexibility. The former gives a computational cost which is independent of the number of IMUs while the latter gives a computational cost which is proportional to the number of IMUs. Our experience (see next section) is that the approaches gives similar results for short trajectories (the system is in essence linear [15] making them equivalent). However, the former approach is more practical for an implementation while the latter is easier to use for analysis. However, note that the latter method will break down for longer trajectories due to the nonlinearity of the orientation, i.e. non-linearity of the system. Consequently, in practice it would need to be applied on a step-wise basis (see [12]) or similar. Further, the median gives a statistically more robust combination than the weighted mean.

IV. Experimental pedestrian tracking results

To assess the feasibility of foot-mounted inertial navigation using arrays of ultra-low-cost IMUs and to examine the characteristics of different methods for combining the inertial measurements, an in-house developed IMU array platform was used. The platform contains 18 MPU9150 IMUs (9 on the top side and 9 on the bottom side) and an AT32UC3C2512 microcontroller. The platform is shown in Fig. 2. Details of the platform can be found in [5].

The following experiment was conducted: An agent equipped with the IMU array in the sole of his shoe walked in a 200 [m] straight line. The initial heading was set by first letting him walk 8 [m] between two plates with imprints for the shoes (colored circles in Fig. 3). The estimated translation was then used as a base line, defining zero heading direction. The walk and heading initialization was repeated 10 times.

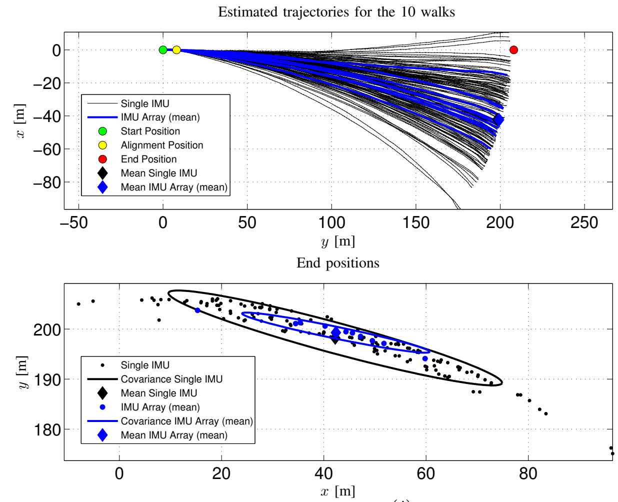

Fig. 3. Estimated individual trajectories, i.e. $\hat{\mathbf{p}}_k^{(i)}$ (black) and trajectories $\hat{\mathbf{p}}_k$ (blue) resulting from taking the mean value of all measurements to construct a joint inertial measurement.

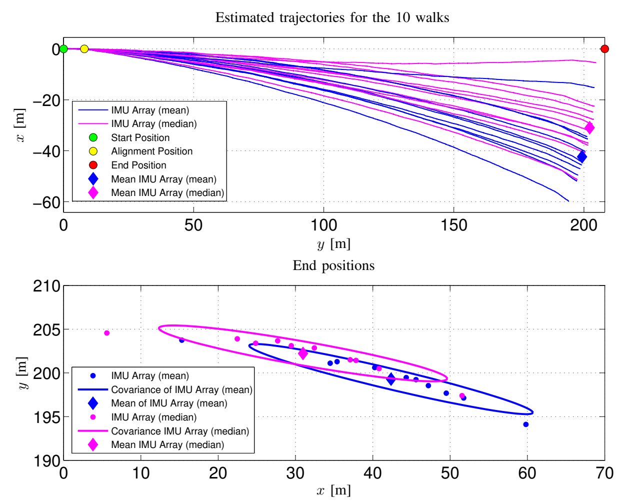

Fig. 4. Estimated trajectories $\hat{\mathbf{p}}_k$ (magenta) resulting from taking the median of the inertial measurements rather than the mean (blue).

The estimated individual trajectories $\hat{\mathbf{p}}_k^{(i)}$ are shown in black in Fig. 3. Further, the resulting trajectories from taking the mean value with uniform weighting of all measurements to construct a joint inertial measurement are displayed in blue. This demonstrates the feasibility of foot-mounted inertial navigation by an IMU array and the basic gain in using multiple IMUs. The negligible difference between the mean of the single IMU trajectories and the mean of the result of the full IMU array shows that the system is essentially linear for this trajectory. The result from applying the median of the inertial measurements rather than the mean is seen in Fig. 4 where the resulting trajectories are plotted on top of those produced by taking the mean. The median is seen to mitigate the effect of some outliers.

Figs. 3 and 4 shows that there is clearly a gain in combining multiple IMUs. In Fig. 5 the mean variance over all IMU combinations and the variance for the worst IMU combination, of the end position as a function of the number of IMUs

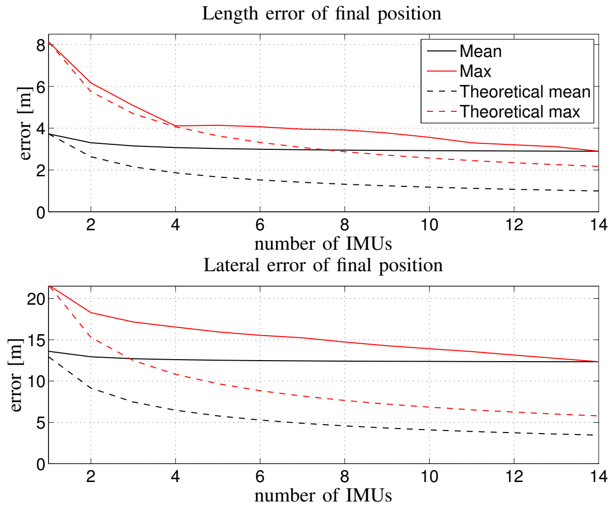

Fig. 5. Performance (root-mean-square error) as a function of the number of IMUs in length and lateral directions. Clearly, the errors (solid lines) does not fall off as the square root of the number of trajectories (dashed lines) as would have been the case if the errors were IID. However, the worst case errors (red) improves more than the mean (black) errors.

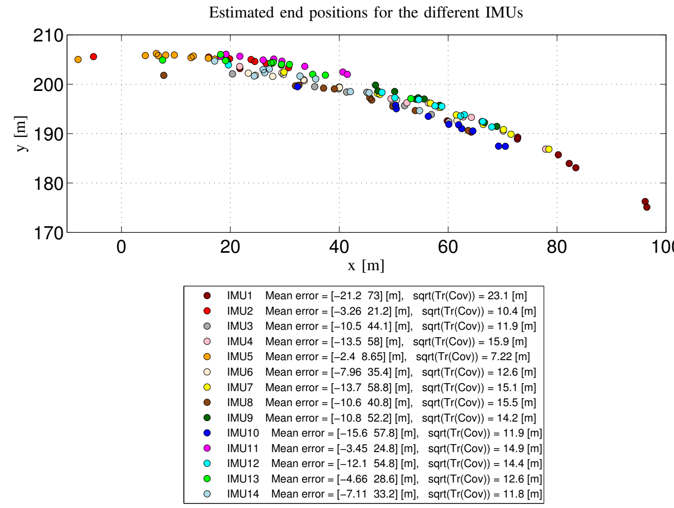

Fig. 6. Estimated end points and in the legend mean erros and spread for individual IMUs. The varying systematic errors of the IMUs are clearly seen.

is shown. If all error sources hade been independent and identically distributed (IID) the lines should have overlapped and the variance of the mean should drop as the inverse of the square root of the number of, IMUs indicated by the dashed lines in Fig. 5. This is clearly not the case and is primarily due to the systematic error terms $\delta \mathbf{p}_k^{(i)}$. Fig. 6 shows the estimated end points for different IMUs. It can clearly be seen that the errors are dominated by the systematic components (mean error), which vary significantly between different IMUs. To get the expected performance gain, the different IMUs need to be weighted by the error variance of the final position estimate. The problem is that this is not known *a priori* and the effect of the systematic errors $\delta \mathbf{f}_k^{(i)}$ and $\delta \boldsymbol{\omega}_k^{(i)}$, and consequently the error variance, will vary with the trajectory. An alternative is to use a weighting with the sample variance of the individual IMU from multiple calibration runs. This will minimize the sample variance of $\hat{\mathbf{p}}_k$ and the systematic errors will have to be delt with in some other way. How to perform the weighting is subject to future research.

V. Conclusions

Using an array of ultra-low-cost IMUs is a feasible approach to improve performance for foot-mounted inertial navigation systems. The naive approach of combining the inertial measurements by taking the mean value is possible but gives suboptimal performance. Potentially, the weighted mean could also be used to combine measurements but how to weight the measurements is not clear.

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