INS and GNSS Fusion Enhancement based on a Weighted Reliabilities Approach

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***Abstract*—The maturity of outdoor positioning systems based on satellites encourages indoor positioning research to focus on radio technologies. However, specific infrastructures often have to be deployed in this case. Then, inertial sensors appear to be a good relay to radio systems. A system fusing INS and GNSS could thereby compute a position anywhere. Yet, taking advantage of each sensor requires to know which one is the most reliable in real-time. Therefore, a quantification of the sensors' reliability is introduced in this paper. This approach aims at running both outdoors and indoors. Moreover, the complexity of algorithms is carefully studied here to fit the user mobility requirements. Experiments are conducted in reproducible situations and results show that taking reliabilities into account benefits the hybridization of INS and GNSS for positioning in both convenient and constrained environments.**

***Index Terms*—INS (Inertial Navigation System) and GNSS (Global Navigation Satellite System) Fusion, Pedestrian Navigation, Weighted Reliabilities, Hybrid positioning.**

I. Introduction

The massive integration of Global Navigation Satellites Systems (GNSS) in smartphones and cars over the last decade has increased the demand for Location Based Services (LBS) [1]. So far, outdoor positioning technologies have demonstrated their efficiency for consumers and transport industries. Whereas numerous applications require reliable and accurate indoor positioning services, localization devices designed for outdoors are inefficient indoors most of the time. As an example of application field in industries, rescue squads can be interested in protecting lone workers. In the context of handicap, blind people could be assisted for safer indoor navigation. For contextual awareness in applications, developpers working on social networking or augmented reality attempt to use an indoor positioning function. Consumers are not left out in such considerations, as they spend most of their time in buildings and malls. Thus, the need for positioning services is not limited to outdoor applications.

Much research has been devoted to address the indoor context with wireless technologies including RFID, Ultra Wide Band, WiFi, Bluetooth, Ultra High Frequency, Ultrasound, InfraRed or DECT phones [2]. Those technologies, though attractive indoors, are not commonly used outdoors. New trends show that indoor positioning and indoor navigation are challenging topics of research, especially if the proposed solutions are compatible with outdoor use. Transition between outdoors and indoors should become possible. More generally, the continuity of service issue [1] concerns transitions between convenient and constrained environments. Consequently, a truly global positioning system should be efficient in those different environments. As a matter of fact, GNSS-based techniques can already cover outdoor areas and are implemented in the hardware of many mobile devices. Hence, indoor GNSS appears to be a relevant candidate to address a wide variety of environments.

However, infrastructure issues limit the deployment of indoor radio technologies. Therefore, fully covering indoors with radio is not feasible at this point in time. Scalability is an important specification as well as accuracy, precision, complexity and robustness [2]. Among other techniques independent from infrastructure, Inertial Navigation Systems (INS) allow an easy integration in mobile devices using MicroElectroMechanical Systems (MEMS) and digital processors [3]. But, the position of the pedestrian is not directly observable from the MEMS output. Dead reckoning algorithms based on a standalone INS have already been developped to locate pedestrians indoors [4]. Besides, drifts are caused by the numerical integration of the output of the sensors. Though, stochastic filtering can be implemented but algorithms often become computationally complex [5]. Furthermore, the possible need to know experimental specifications *a priori*, such as the step length [6], can be deterrent to reproduce experiments.

A common and respectable approach for the fusion of INS and GNSS consists of highlighting their obvious complementarities [7]. Indeed, GNSS provide absolute positioning and provide long-term reliability compared to INS but still depend on the radio waves propagation and on a synchronization with a specific infrastructure [8]. On the other hand, INS is autonomous, independent of changes in the environment and can potentially return an attitude but suffers from long-term drifts. Beyond, INS only provides a localization relative to a known starting point. Consequently, a system combining INS and GNSS seems to be an expedient candidate for a global positioning system reliable anywhere, according to the literature.

Fusion is considered appropriate for GNSS augmentation with INS, in order to avoid satellites visibility issues, to smooth

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trajectories in dead reckoning situations [9] or to process long numerical integrations on radio codes [10]. Secondly, inertial drifts, due to noisy and biased measurements [11] from the Inertial Motion Unit (IMU), can be compensated with GNSS as a reference, by observing the propagation of covariance errors in stochastic filters [9], or by estimating the position error. Therefore, existing techniques often consider one system as the reference for the other to estimate imprecisions during the whole experiment.

Besides, multisensor fusion [5] is adopted in situations where system variables are not observable and allows the reduction of uncertainty, noise rejection or unavailability tolerance. Several methods can be implemented such as inference, classification or estimation. Nonetheless, it has some limitations like assumptions on the statistical distribution of noises or biases, computational cost or lack of transparency. Consequently, a low cost integration of such an hybrid system [3] requires a reduction in complexity.

II. Paper contributions

Fig. 1. Our results are based on reproducible experiments, with shoe mounted sensors: a strap-down INS (XSens) and a GPS antenna (uBlox).

The proposed approach aims at positioning pedestrians on the move. The difficult task of determining whether the radio receiver is located in a zone where data are reliable or not [7] motivates the introduction of a reliability function. Furthermore, outliers should be discarded before the fusion process, or at least carefully treated [5]. In addition, one of the successes of GPS is its ability to provide a real-time estimation of the positioning error [8], contrary to INS. Moreover, radio signal and IMU measurement error sources randomly affect the efficiency of the position computation. Thereby, determining whether radio or inertial measurements are more reliable than the other is also a difficult task. In order to benefit from their complementary advantages, INS and GNSS should be permanently combined in the fusion process. From the light of those observations, a reliability criterion for INS needs to be introduced, and the estimation of the GPS positioning error should be adapted for fusion. Those real-time criteria can then be used as weights for inertial and radio data fusion.

Real-time and user mobility requirements suggest to develop computationnaly efficient algorithms. This is why INS positions are computed recursively using Zero velocity UPdaTe (ZUPT) [12] and gravity corrections in order to mitigate the impact of biases. No stochastic filter is being implemented, which enables the mastering of all parameters of the computation, and keeps the complexity low. This also makes the proposed weighted reliabilites approach a good reference to evaluate the performance of future developments.

The main contributions described in this paper are:

- **A basic inertial positioning algorithm** to decrease complexity and computational cost.
- **Radio and inertial reliability criteria** to fuse data while limiting the impact of aberrations.
- **Experimental results outdoors** to evaluate the performance of the proposed algorithm.

III. Inertial Navigation System

A. IMU description

The experimental device considered in this paper is a XSens MTx composed by a 3-axis accelerometer and a 3-axis gyrometer respectively returning accelerations and angular rates of the inertial reference frame ($\mathcal{R}^c$) with respect to the navigation reference frame ($\mathcal{R}^n$) expressed in $\mathcal{R}^c$. This IMU allows us to sample measurements at a frequency of $f_s = 100Hz$.

Angular rates are noted ω_x (roll rate), ω_y (pitch rate), ω_z (yaw rate). The acceleration vector in $\mathcal{R}^c$ is $\vec{a}^c = [a_x^c \ a_y^c \ a_z^c]^T$.

B. Dead reckoning concept

The localization should be computed in $\mathcal{R}^n$ in order to deliver pieces of information understandable by the user. Gyrometers are used to process the change of coordinate frame thanks to angular rate measurements which are integrated with a quaternion based method. Accelerations expressed in $\mathcal{R}^n$ are integrated to locate the pedestrian. Its attitude at each time is known too.

Placing the IMU in the shoe, and using the so-called ZUPT technique, enables us to estimate the speed with respect to $\mathcal{R}^n$ each time the foot is put on the floor. The impact of biases [12] are drastically mitigated by this assumption. The described method, namely dead reckoning, consists of the following steps:

a) Initial conditions: The initial acceleration is assumed to be $\vec{a}_0^c = \vec{a}_0^n = \vec{g}$, where $\vec{g}$ is the known gravity field. The initial position can be chosen as $\vec{r} = [0 \ 0 \ 0]^T$. The inertial quaternion of attitude should be $\bar{q}_0 = [1 \ 0 \ 0 \ 0]^T$, assuming that the initial attitude is horizontal in the heel of the shoe.

b) Gyrometers calibration: We assume the foot to be placed on the floor motionless for a predefined duration $\Delta t_i = 10s$. In fact, during this period, effective angular rates should be zero.

As the noise is assumed to be additive white Gaussian zero centered, the average value of measurements during Δt_i, as shown in Fig. 2, should lead to an estimation of the biases of the gyrometers. The assumptions made here are that the biases of the gyrometers will not change during the experiment and that $n_i = \Delta t_i f_s$ samples are enough to statistically estimate those biases.

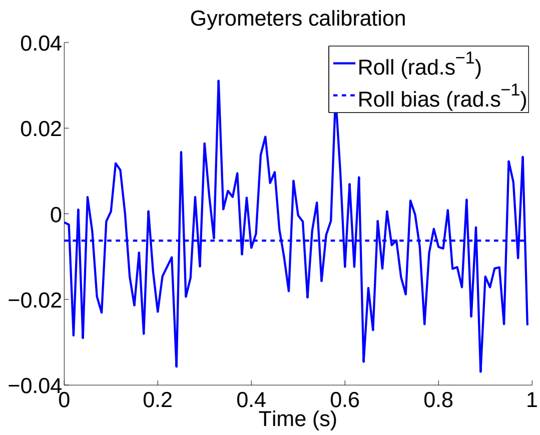

Fig. 2. At the beginning of the experiment, during a period $\Delta t_i = 10s$, the foot is assumed to be motionless on the floor. The bias of each gyrometer is evaluated by averaging the measured values in order to eliminate the impact of noise, while observing the impact of bias.

c) Step detection: This step detection method is based on the norm of the acceleration, which is expected to stay constant, *i.e.* equal to gravity, when the shoe is placed on the floor, as shown in Fig. 3. Nevertheless, a threshold detection applied at each time to the signal is not robust to noise. This is why the acceleration norm is averaged over a time window of $\Delta t_d = 0.3s$, during which the foot appears to be motionless, as in Fig. 3. The obtained norm mean $\tilde{a}_k^c$ at time k is compared afterwards with a given value, such as $a_t = 11m.s^{-2}$ which is a bit more than the gravity norm. The choices to be dealt with here are the width Δt_d of the time window and the acceleration threshold a_t above which the foot is moving.

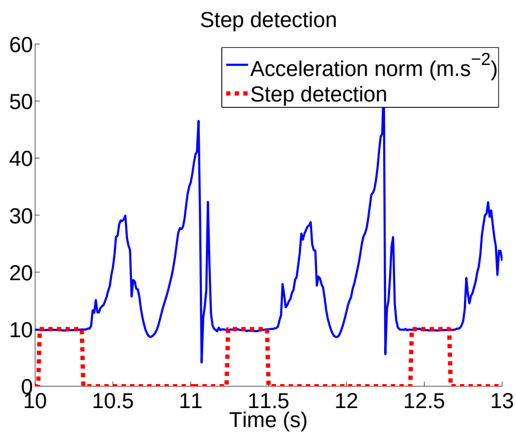

Fig. 3. Step detection method based on averaging over a certain duration the norm of the acceleration, which is expected to remain constant, *i.e.* equal to gravity, when the shoe is placed on the floor.

d) Inertial to navigation coordinate frame: The transition matrix $\mathbf{P_c^n}$ from $\mathcal{R}^c$ to $\mathcal{R}^n$, as a function of the quaternion of attitude $\bar{q}$, is

$$\mathbf{P_c^n} = \begin{pmatrix} 2(q_2^2+q_1^2)-1 & 2(q_3q_2+q_4q_1) & 2(q_4q_2-q_3q_1) \\ 2(q_3q_2-q_4q_1) & 2(q_3^2+q_1^2)-1 & 2(q_4q_3+q_2q_1) \\ 2(q_4q_2+q_3q_1) & 2(q_4q_3-q_2q_1) & 2(q_4^2+q_1^2)-1 \end{pmatrix} \quad (1)$$

where

$$\bar{q} = [q_1 \ q_2 \ q_3 \ q_4]^T$$

e) Navigation equations: The well-known inertial equations used here, from [13], are

$$\dot{\bar{q}} = \frac{1}{2}\mathbf{\Omega}\bar{q} = \frac{1}{2}\begin{pmatrix} 0 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 0 & -\omega_z & \omega_y \\ \omega_y & \omega_z & 0 & -\omega_x \\ \omega_z & -\omega_y & \omega_x & 0 \end{pmatrix}\bar{q} \quad (2)$$

$$\vec{v}^n = \begin{cases} \vec{0} \text{ if foot on the floor} \\ \displaystyle\int \mathbf{P_c^n}\vec{a}^c dt \text{ otherwise.} \end{cases} \quad (3)$$

$$\vec{r}^n = \int \vec{v}^n dt \quad (4)$$

f) Recursive integration: The first order differential equation (2) can be integrated, at time k, as

$$\bar{q}_k = expm(\frac{1}{2}\mathbf{\Omega}dt)\bar{q}_{k-1} \quad (5)$$

where

$$dt = \frac{(k)-(k-1)}{f_s}$$

Since $\bar{q}_k$ has been well defined, the acceleration in $\mathcal{R}^n$ is

$$\vec{a}_k^n = \mathbf{P_c^n}(\bar{q}_k)\vec{a}_k^c \quad (6)$$

As well, the speed is found by integrating the acceleration,

$$\vec{v}_k^n = \begin{cases} \vec{0} \text{ if foot on the floor at time } k \text{ (ZUPT),} \\ \vec{v}_{k-1}^n + dt\vec{a}_{k-1}^n \text{ otherwise.} \end{cases} \quad (7)$$

Finally, the position of the user in $\mathcal{R}^n$ is

$$\vec{r}_k^n = \vec{r}_{k-1}^n + dt\vec{v}_{k-1}^n \quad (8)$$

g) Recursive estimation of the acceleration biases: Each time the foot is motionless on the ground, $\vec{a}^n$ in Eq. 6 should be equal to gravity. This leads to a dynamic evaluation of acceleration biases, as shown in Fig. 4 for the x-axis. Biases related to the change of frame computation by $\mathbf{P_c^n}$ are included in this estimation.

$$\forall k, \begin{cases} \vec{a}_k^n = \vec{g}_0 \\ \vec{b}_{a,k} = \vec{g}_0 - \mathbf{P_c^n}(\bar{q}_k)\vec{a}_k^c \end{cases} \quad (9)$$

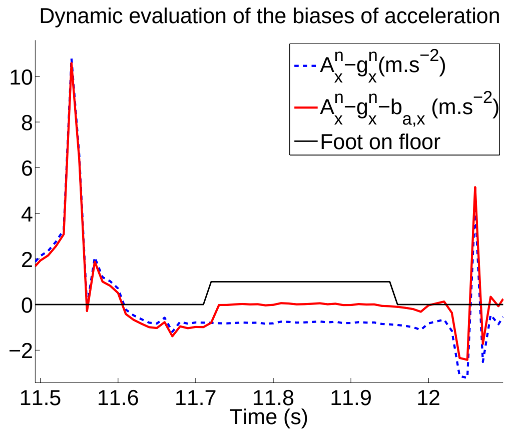

Fig. 4. Each time the foot is motionless on the ground, which is known thanks to the step detection, the acceleration minus gravity in $\mathcal{R}^n$ should be null. The difference between the expected value and the measured one enables us to dynamically evaluate the biases.

C. Added value of this algorithm

No Kalman filter has been implemented in this algorithm, resulting in no need for *a priori* knowledge of statistical information. Computation costs are reduced to a minimum, the algorithm remains recursive and is online compatible, which is compatible with user mobility constraints. However, a step detection algorithm is necessary to determine whether the shoe is motionless on the floor and a ZUPT-based positioning algorithm involves that the IMU cannot be placed easily in a smartphone. Finally, the recursive estimation of biases can be used as information on the INS reliability.

IV. Global Navigation Satellite System

A. Indoors issues and solutions

The computed indoor position of a user is not accurate with a standard GPS receiver. Indeed, multipath effects and attenuation due to walls and floors degrade the signal quality. A-GPS combined with HS-GPS [10] is a possible solution. Another quite intuitive approach is to repeat the signals through a receiving antenna on the roof of the building for instance, and the so-called repeaters as shown in Fig. 5.

A drawback introduced by using repeaters is that the whole set of received signals and codes from satellites is repeated at the same time, which creates interference between carriers and between codes. The near-far effect [14] also leads to signal-to-noise ratio issues concerning the received signal. A solution to both problems would be to allow repeaters to only send a signal one after the other [15]. Unfortunately, phase jumps are introduced in the signals each time the system switches the emission from one repeater to another. Consequently, phase measurements, and decimetric accuracy, are not possible.

Another solution would be to reproduce a local constellation of pseudo-satellites, the so-called pseudolites. Typically designed to improve vertical accuracy positioning for landing planes [8], or to enhance performances in opencast mines, they can act as additional satellites to the GPS constellation. The system is based on a local set of emitters of GPS codes, as shown in Fig. 5. However, pseudolites do not benefit from the GPS ground segment, used to synchronize satellites. A drawback by using them is that the emitters are not synchronized if there is no master unit.

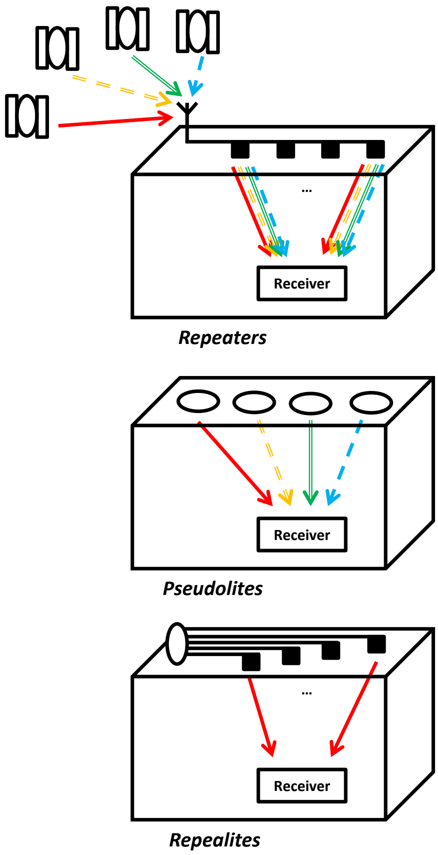

Fig. 5. Indoor-GNSS techniques: Repeaters benefit from the native synchronization of satellites but generate interference or phase jumps; Pseudolites enable phase measurements for a decimetric accuracy but suffer from a lack of synchronization; Repealites try to take advantage of the two previous techniques by allowing phase measurements and synchronization. The several kinds of arrows symbolize the different GPS codes.

Finally, repealites are introduced to take advantage of both repeaters and pseudolites. They are synchronized thanks to a single code generator linked to all emitters, as shown in Fig. 5. In like manner, interference is mitigated by establishing a propagation delay through the length of cables, chosen so that code cross-correlations are minimized between transmitters. To conclude, as summarized in Table I, the use of repealites seems to be unavoidable if we intend to reach decimetric accuracy indoors. The synchronization is an advantage of this architecture but a possibly inconvenient infrastructure must be deployed. Indeed, optical fibers must be used between the central code generator and the emitters. Moreover, multipath and near far effects still have to be mitigated with some specific techniques [16], especially trying to locate somebody who moves indoors.

TABLE I
A SYNTHESIS OF INDOOR GNSS TECHNIQUES

System	*Synchronization*	*Phase Measurements*
Repeaters	**Yes** All codes repeated	**No** Emission one at a time
Pseudolites	**No** Each emitter sends its code	**Yes** Simultaneous emission
Repealites	**Yes** Known delay between emitters	**Yes** Simultaneous emission

So far, we have not experimented with the proposed fusion algorithm with repealites, which will be part of our future work. Indeed, it was necessary to give a proof of concept with an existing efficient system such as GPS outdoors. Results and enhancements are described in the following sections.

B. Outdoor positioning enhancement

GPS is not always available, nor reliable, for example in urban canyons or near buildings, due to unavailability, dilution of precision and multipath. This motivated our research to extend the advantages of a fusion of inertial and radio sensors outdoors.

Addressing the issue of transition between indoors and outdoors [7] in a transparent way for the end user would be another enhancement for user mobility outdoors. As different environments are numerous, it seems more suitable to consider the reliability of each sensor taking into account the experimental situation rather than systematically switching between GNSS for outdoors and INS for indoors. Thereby, reliability coefficients for GNSS and INS should be introduced for efficient fusion.

V. RELIABILITY CRITERIA

A. Inertial coefficient

Any measurement is noisy, but it is not necessarily a major issue depending on the experiment. In our consideration, noise is not the main issue. Added to that, Kalman filters could optimally mitigate the impact of white Gaussian noise [5] if necessary. Besides, the major drawback of an IMU that is identified here concerns biases and their estimation. Indeed, biases of gyrometers may lead to estimate a curved trajectory because the transition matrix from $\mathcal{R}^c$ to $\mathcal{R}^n$ isn't correctly estimated. Biases of accelerometers may cause drifts on speed and position estimates. Thus, biases are considered as the main flaw with INS, whereas Gaussian noise issues could be handled with some well-known stochastic filters.

As described in section III, bias evaluation is possible each time the foot lays on the floor. Assuming biases will not change while the shoe is moving, we have permanently access to bias values.

Furthermore, a reliability coefficient should be dimensionless to allow comparisons. Then, a reference bias has to be identified in order to be compared with the estimated biases. The only constant bias measured by accelerometers is gravity, whatever the situation is at anytime. Based on this consideration, we establish a function of INS reliability f_{INS} as follows:

$$f_{INS} : \begin{cases} \mathbb{R}^+ \to \mathbb{R}^+ \\ t \mapsto \begin{cases} 100 * \dfrac{|\|\vec{g}^n\| - \|\vec{b}_{\vec{a}^n}(t)\||}{\|\vec{g}^n\|} \\ 0 \text{ if not available.} \end{cases} \end{cases} \tag{10}$$

Both accelerometers, gyrometers and process' biases are taken into account in the value of $\|\vec{b}_{\vec{a}^n}\|$, due to the change of frame. Furthermore, this function describes a kind of error between the gravity and the biases, which especially emphasizes the fact that if biases become more important than the gravity then the IMU is not even capable of correctly determining the vertical direction.

B. Radio coefficient

Radio measurements are subject to multiple sources of errors, such as multipath. In the current experiments, we use a uBlox LEA6T that can return an estimation of horizontal and vertical inaccuracies in meters. As the radio reliability coefficient should also be dimensionless, a reference distance accuracy must be considered.

Correlators are used in GPS receivers to process pseudoranges thanks to the auto-correlation method. Those pseudoranges are then used to compute the position of the receiver. Whatever the method of computation of the position, basic sources of errors in the receiver come from the correlators. As a result, we chose to refer to the minimal accuracy of commonly used correlators, which is $0.05T_C$ [17], where T_C is the chip duration. Finally, the reference distance accuracy that we chose is $d = c*(0.05T_C) = 0.05*293m$ for civil C/A codes. The function of GPS reliablity f_{GPS} is established as follows:

$$f_{GPS} : \begin{cases} \mathbb{R}^+ \to \mathbb{R}^+ \\ t \mapsto \begin{cases} 100 * \dfrac{|0.05 * 293 - hAcc(t)|}{0.05 * 293} \\ 0 \text{ if not available} \end{cases} \end{cases} \tag{11}$$

where $hAcc$ is the horizontal accuracy estimation in meters.

This reliability criterion can be used with repealites. Indeed, the computation of a position in a repealites-based system still allows the estimation of the positioning accuracy for each sample.

C. Possible improvements

Those functions are based on the comparison between the main error source of each sensor, and a characteristic quantity in the same unit. The choice of this reference quantity has been justified here, but any other justification could be discussed.

Moreover, the linearity of those criteria enables to compare the resulting number with common sense values in percentages. However, other functions of reliabilities such as exponential laws could amplify the rejection of outliers.

VI. Hybridization based on a weighted reliabilities approach

A. Overview of the approach

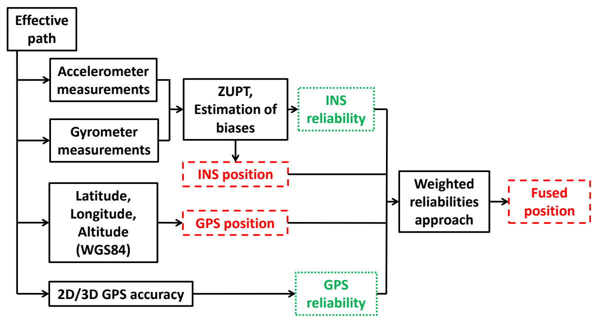

Fig. 6. The proposed fusion algorithm is based on a weighted reliabilities approach. The previously described functions of reliabilities allow us to grant a weight to measurements from each sensor before fusing the independently estimated positions.

The proposed fusion is based on a barycentric method applied to positions, which means we consider weights, α_{gps} and α_{ins}, based on the reliability functions, as follows:

$$\vec{r}_{fus} = \alpha_{gps}\vec{r}_{gps} + \alpha_{ins}\vec{r}_{ins} \tag{12}$$

with $\alpha_{gps} = \frac{f_{gps}}{f_{gps}+f_{ins}}$ and $\alpha_{ins} = \frac{f_{ins}}{f_{gps}+f_{ins}}$.

An advantage of using barycenters is that there is no exclusive use of GPS or INS. Each system is permanently used if available, but the impact of a non-reliable one on the computed position remains minimal.

A remaining issue concerns the nature of the vectors of position. Indeed, INS locates relatively to an initial position whereas GPS position is absolute in the WGS84 coordinate frame. Thus, a coordinate transformation on GPS estimated positions can be processed and the INS initial position and cap (or yaw) can be adapted.

B. GPS coordinates transformation

Positions computed by INS and GNSS must be expressed in the same coordinate frame before being fused with the weighted reliabilities approach. GPS positions are expressed in the WGS84 coordinate frame whereas INS positions are expressed in a local Cartesian coordinate frame. For comparison purpose and reading convenience, the computed trajectories are plotted in an East-North Cartesian frame, with axis scaled in meters. By computing the distances relative to the variations of latitudes ($\delta\phi$) and longitudes ($\delta\lambda$), GPS latitudes (ϕ) and longitudes (λ) can be transformed as follows:

$$\forall k \in [\![2;n]\!], \begin{cases} \delta\lambda_k = \frac{\pi}{180}(\lambda_k - \lambda_{k-1}) \\ \beta_k = cos^2(\frac{\pi}{180}\phi_k)sin^2(\frac{\delta\lambda_k}{2}) \\ x_k = x_{k-1} + \frac{2R_T}{|\delta\lambda_k|}atan(\sqrt{\frac{\beta_k}{1-\beta_k}}) \end{cases} \tag{13}$$

$$\forall k \in [\![2;n]\!], \begin{cases} \delta\phi_k = \frac{\pi}{180}(\phi_k - \phi_{k-1}) \\ \gamma_k = sin^2(\frac{\delta\phi_k}{2}) \\ y_k = y_{k-1} + \frac{2R_T}{|\delta\phi_k|}atan(\sqrt{\frac{\gamma_k}{1-\gamma_k}}) \end{cases} \tag{14}$$

where

$R_T = 6369.62875km$ is the Earth mean radius
x_k is the coordinate on the local West to East axis
y_k is the coordinate on the local South to North axis
n is the number of GPS acquisitions

The design of a global positioning system could impose the choice of the already used WGS84 coordinate frame. Then, instead of GPS positions, INS estimated positions should be transformed to the WGS84 coordinate frame with the reverse process. In this case, and for distances of hundreds of meters, the proportion between latitude or longitude variations and distances could be considered as not varying quickly.

C. Initial position determination

As previously mentioned in section III, gyrometers are calibrated during a period $\Delta t_i = 10s$ when the user is assumed to be motionless. This time is an opportunity to average the available GPS positions in order to estimate an initial point, as follows:

$$\forall j \in [\![0;m]\!], \vec{r}_{ins,j} = \frac{1}{m}\sum_{k=0}^{m}\vec{r}_{gps,k} \tag{15}$$

where $m = \Delta t_i * f_{s,gps}$, and $f_{s,gps}$ is the gps receiver sample frequency.

D. Cap recursive adaptation

The estimation of the initial cap with GPS is not accurate enough to be used in computations. Indeed, GPS provides accurate tendencies on long-term trajectories, but it can provide a chaotic distribution of positions in a short period, which means an inaccurate cap based on position. Hence, our fusion also automates the cap determination.

One of the main characteristics of INS is that it doesn't drift during a short period. Accordingly, a straight line followed by the user can be identified thanks to inertial measurements, if l_k, defined in Eq. 16 is close to 1.

$$\forall k \in [\![2;n]\!], l_k = \frac{\vec{u}_k.\vec{v}_k}{\|\vec{u}_k\|\|\vec{v}_k\|} \tag{16}$$

where

$\vec{u}_k = \vec{r}_{ins,k-1} - \vec{r}_{ins,k-2}$ and $\vec{v}_k = \vec{r}_{ins,k} - \vec{r}_{ins,k-2}$

When a straight line is followed, the average cap of the INS based in the shoe is estimated relative to GPS measurements.

$$cap_j = atan2(x_{ins,j}, y_{ins,j}) - atan2(x_{gps,j}, y_{gps,j}) \tag{17}$$

$$cap_k = \frac{k-1}{k}cap_{k-1} + \frac{1}{k}cap_j \tag{18}$$

where j is the index describing times when a straight line is followed, and k the index describing the discrete time of the experiment.

Thus, the proposed method, to determine the cap between INS estimated trajectory and the GPS one, is interesting because it is recursive and attenuates possible high frequency mistakes by averaging the estimated cap. Long term drift of INS and short term chaotic results of GPS are moderated with this robust approach.

VII. Evaluation of performance based on experiments

For now, the proposed algorithm is tested outdoors, which allows us to benefit from a clear satellite view and a proven GPS receiver. Though, in urban canyon for example, outdoor situations are not always favorable for the GPS receiver. As well, relatively long path are not always favorable for INS.

A. *Comparative criteria used for the evaluation*

In order to be able to determine whether the proposed fusion algorithm based on weighted reliabilities is relevant or not, some comparative criteria have to be highlighted.

The determination of the effective path with our equipment is a relevant issue. Even if possible drawbacks are introduced such as distance errors, the "Add path" function of Google Earth allows us to draw a path on a satellite view. The associated kml file, readable by Matlab, is exported afterwards. Thus, one is capable of qualitatively comparing the shape of the estimated trajectories relative to the effective one.

The only quantitative result that can be used here as a comparative criterion is the distance between the final and the starting positions, since we know that the user always comes back to its original position during the experiments.

B. *Experiments in an open outdoor environment*

The aim of experimenting the weighted reliabilities approach in an open outdoor environment is to highlight the efficiency of the fusion in case the INS is not reliable, since we are assuming that the GPS remains reliable. The open outdoor environment is a municipal athletic field, where the racetrack is 400m long.

When INS and GPS are both in favorable conditions, Fig. 7 shows that the coefficients of reliability are similar in order of magnitude. Even if the nature of those coefficients do not describe the same physical phenomenon, that is to say biases for INS and multipath among other error sources for GPS, their dimensionless values are comparable.

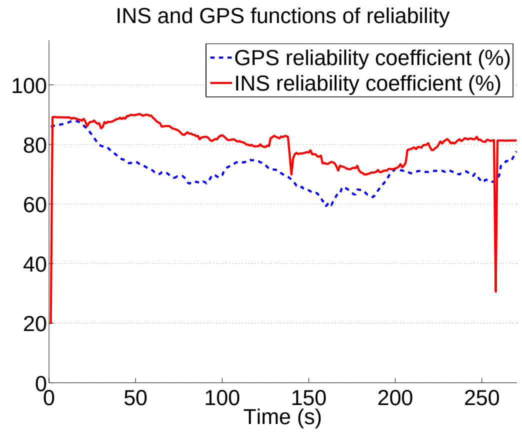

Fig. 7. Outdoor athletic field - Favorable case for INS and GPS

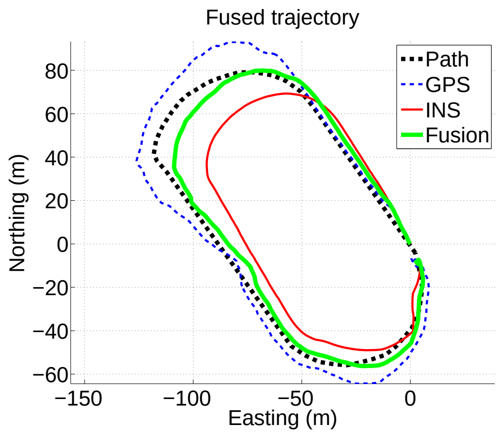

Fig. 8. Outdoor athletic field - Favorable case for INS and GPS

Whereas the set of positions computed with INS does not describe the wideness of the north curve as shown on Fig. 8, the recursive estimation of biases of acceleration seems to reduce the expected long-term drift.

This first experiment thereby emphasizes that the expressions of the reliabilities and their use to weight the estimated positions are coherent with a use in convenient conditions. This is why, the proposed algorithm is tested afterwards in disadvantageous conditions for INS and for GPS.

The next presented experiment was selected among others because INS drift was significant. Environmental conditions are quite similar with the previous experiment, which is the reason why the reliability in GPS measurements stays between 60 and 80%, as shown in Fig. 9, similarly with the previous experiment. However, reliability in INS drastically falls from about 80% to 50%, as shown in Fig. 9, which is coherent with an observation of the trajectory estimated by INS on Fig. 10. Even if curves are detected, their lengths are not long enough compared with the effective path.

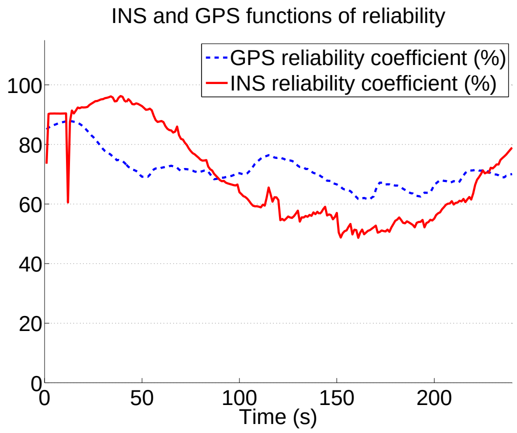

Fig. 9. Outdoor athletic field - INS drifting

The main observation in Fig. 10 is that the set of positions estimated with the proposed fusion algorithm still remains quite close to the effective path. Nonetheless, it is necessary to soften this result by observing that GPS and INS errors in position are approximately opposed referring to effective path. We do not have results where errors accumulate even if this situation is theoretically possible.

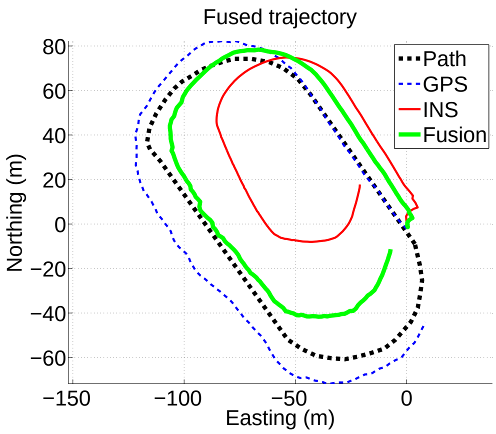

Fig. 10. Outdoor athletic field - INS drifting

To conclude, the weighted reliabilities approach seems to compensate for an INS defection if GPS is reliable enough.

C. Experiments in an urban canyon

The aim of experimenting the weighted reliabilities approach in an urban canyon is to highlight the efficiency of the fusion in case GPS is not reliable. The so-called urban canyon is the perimeter of a square in the shadow of a building.

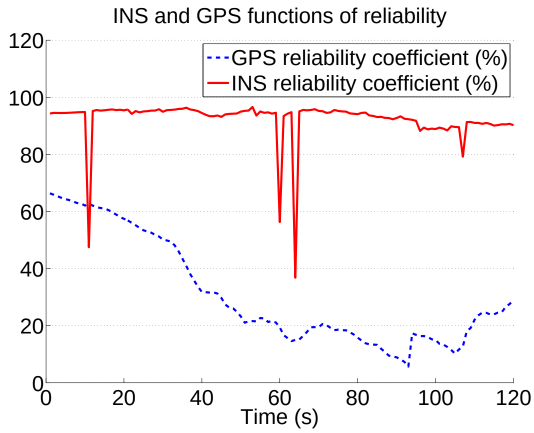

Fig. 11. Urban canyon - GPS affected by errors

As observable in Fig. 11, INS remains quite reliable during the experiment (2 minutes), with a mean of over 90% reliability. However, the reliability of the INS suffers from four steep drops. They can be interpreted as the four corners of the effective path. Indeed, when the user sharply turns, values from the gyrometers vary more than with a straight line, which has an impact of the transition matrix from $\mathcal{R}^c$ to $\mathcal{R}^n$ and then an impact of the estimated biases of acceleration. Moreover, the first drop happens after 10 seconds from the beginning of the experiment, which corresponds to the end of the period Δt_i when the user is motionless for calibration.

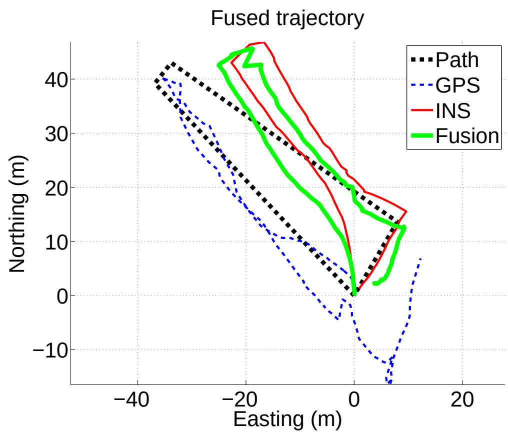

Fig. 12. Urban canyon - GPS affected by errors

On the other hand, the reliability of GPS is varying around 20%, which is three times less than on the athletic field. So, the coefficient of reliabilities provide correct information about the expected situation where GPS is not reliable, probably due to multipath in urban canyons, and the INS remains reliable because the path of experiment is short and almost straight.

Fig. 12 especially shows that GPS estimations are not reliable, expect concerning the global cap followed. This information seems to be correctly integrated in the proposed fusion because one can see the initial cap being oriented to North, whereas the tendency is more directed to North-West. Positions resulting from fusion are progressively reoriented to follow the effective cap, until the last straight line (the small one on the right of Fig. 12) matches the effective path in terms of cap and distance. The weighted reliabilities fusion appears to support GPS deficiencies with the help of INS estimations. However, the correction seems to be efficient only after a certain duration, which is not instantaneous.

D. Experimental results synthesis

TABLE II
STANDARD DEVIATION OF THE EFFECTIVE ACCELERATION

Experiment	A_x	A_y	A_z
Stadium, Favorable (388m, 5min)	0.07g	-0.08g	0.01g
Stadium, INS drifting (388m, 5min)	0.03g	0.26g	0.05g
Urban canyon, GPS errors (125m, 2min)	-0.04g	-0.01g	0.01g

For information purpose about the quality of the acceleration computed by the inertial algorithm, Table II summarizes the standard deviation of effective accelerations along each axis of the navigation frame. Besides, those values are not computed from measurements but from already processed acceleration. The gravity unit is chosen to facilitate the comparison with the gravity considered as the only constant bias over time. The maximum value of standard deviation is normally observed in the experiment when INS is drifting. The minimum values are observed in the experimented used to observe the impact of GPS errors.

TABLE III
ERRORS BETWEEN THE ESTIMATED FINAL AND STARTING POSITIONS

Experiment	*GPS*	*INS*	*Fusion*
Stadium, Favorable (388m, 5min)	6.6m	9.2m	7.8m
Stadium, INS drifting (388m, 5min)	44.8m	27.5m	13.4m
Urban canyon, GPS errors (125m, 2min)	14.0m	1.5m	4.5m

Table III summarizes the quantitative results based on the distance from estimated to effective final positions. The error from the fusion algorithm is always smaller than the error from the least reliable sensor. One of the main difficulties with fusion is to know when a sensor is reliable or not, especially if no environmental data is known in the fusion process as it is the case here. Thus, even if fusion does not improve INS and GPS in the same time, it allows us to permanently combine them, taking advantage of the most efficient sensor without any other information than the coefficients of reliability. Consequently, transitions between outdoors and indoors can possibly be handled with the proposed solution without map-matching.

VIII. DISCUSSION

The inertial positioning algorithm is recursive and computationally efficient. It has been designed to mitigate the impact of drifts and to be compatible with user mobility requirements. However, the initial period during which the foot lays motionless on the ground in order to calibrate gyrometers, the width of the time windows and the trigger for step detections still have to be tuned to address issues in a general context.

The computation cost has been largely considered here but nothing has been presented concerning the optimal sample frequency nor the minimal precision required for inertial measurements in order to correctly estimate the user position. Moreover, the position computation from IMU measurements is not based on the commonly used Kalman filtering, assuming that it allows a better control on the algorithm parameters. Hence, the approach simplicity benefits to user mobility but an optimal use of the measurements still has to be dealt with.

On the other hand, INS and GNSS have complementary advantages, but the time when a sensor is more reliable than the other is not easily found. So, functions of reliabilities were introduced. The choice of those functions is subjective because any other reference error source could be chosen to be compared with estimated errors as far as it is justified by experimentation. Moreover, we implemented a basic error ratio whereas many other functions could be used. The exponential law, for example, has not been detailed here but provides interesting properties to reject errors.

The case when the two systems are not reliable can happen for a short duration. The fusion result is not exposed here because shapes and distances are not properly estimated. Our algorithm works in real-time without prediction, which nears that the position computed from fusion cannot enhance both systems at the same time. Thus, the proposed fusion allows a real-time enhancement of INS or GPS if the other is reliable, and neither GPS nor INS is always taken as a reference for the other.

Even if other experimental results tend to support the efficiency of the proposed fusion, we are aware that results in many more situations still have to be evaluated. To conclude, the INS and GPS fusion outdoors in optimal and constrained conditions has been processed without rising any obstacle for an INS and repealites fusion indoors, which is part of future work.

IX. CONCLUSION AND FUTURE WORK

This paper presented an INS and GNSS fusion enhancement based on a weighted reliabilities approach. The preliminary evaluation of performance shows that the fusion algorithm is operable on INS and GPS outdoors, but we aim at fusing INS and repealites indoors as well. The introduction of reliability criteria and the implementation of a recursive cap estimation enable us to permanently combine the radio and inertial systems in a way that benefits from their complementary advantages. This reciprocal enhancement provides the opportunity to handle with the issue of transition between outdoors and indoors without *a priori* knowledge on the environment. The basic approach described here will be used to evaluate performance of future developments. Biases have been mitigated and used to provide informations on inertial reliability in this paper. The presented approach can be compared and possibly combined with Kalman filtering in future work in order to precisely evaluate the impact of white gaussian noise.

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