GiPStech

Indoor Positioning made simple and cheap

Brief Technology Description

March 2017

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Basics of geomagnetic localization algorithm

MCL algorithms can be included in the category known as "brute force" or exhaustive research that addresses specific types of problems systematically generating, at each iteration, a set of possible candidates and then testing whether or not these candidates may be a feasible solution to the problem under consideration. If at the n-th iteration there is only one candidate (or a set of selected very similar candidates) then one has found the solution, conversely, the algorithm provides to disrupt the set of candidates, to extend it generating new possible candidates, to re-test the new set releasing only the best candidates and to reiterate.

The fundamental idea behind the indoor localization technology developed by GiPStech is to use as input signals for the MCL the map of the geomagnetic field of the building together with "guiding" signals from a proprietary inertial module used to evolve the system.

The geomagnetic field is a natural phenomenon on the Earth and, in summary, we can say that it is locally constant. However inside closed environments this constancy is not realized due to the presence of ferromagnetic materials (cables, pipes etc.) that interfere with the field and alter the value. This characteristic is exploited by our tracking system to locate the user.

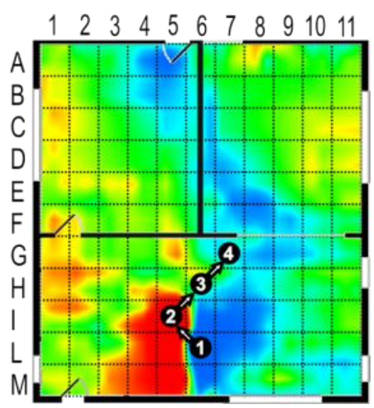

Figure 1 - Magnetic map of building

The plan in Figure 1 shows an example closed space, complete with an ideal grid, with a color representation of the values of the local geomagnetic field where one can observe the anomalies induced by the presence of ferromagnetic materials: areas with the highest field strength (red), and areas with a lower intensity (blue). If, during the iterations of the algorithm-driven inertial system we prefer candidates who in addition to not breaking geometric constraints (collisions with walls, leaving the perimeter of the building etc.) also have a value of magnetic field on the map very similar to that measured from the smartphone of the user to localize, then we will have the opportunity to improve the operation of MCL excluding at each iteration many more particles than in the case of sole use of the map without the presence of the magnetic field measurement.

As an example, suppose that the user who intends to be localized is in the position 1 (cell L6) of the map in Figure 1. From this position he then moves as indicated by the points 2, 3 and 4 in the same Figure.

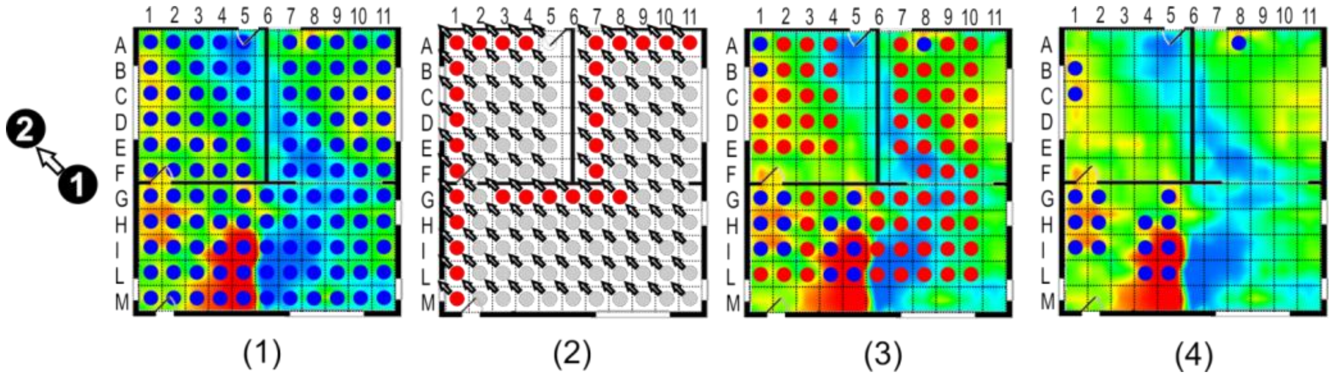

Figure 2 - First Iteration localization algorithm

At the beginning, for the localization system, the user's location is unknown. With reference to Figure 2:

- The system is initialized by placing the particles in each grid cell of the map (Figure 2 - 1).
- The first movement of the user is used to perturb the particles that are moved in the same direction. Some of these are eliminated from the solution since the permissible displacement causes a collision with the walls of the building (the particles in red).
- Particles that survive (red and blue) are further processed and sorted in accordance with a probability function that relates the value of the geomagnetic field of the cell where the particle is with that measured by the user's smartphone. In our case the user is in cell I5 with the value of the geomagnetic field measured by the magnetic sensor of the smartphone very intense (red), it is therefore possible to eliminate all the current from iteration particles with field values on the map very different from that measured by the user.
- Eliminated all particles are in red (3) and thus survive the end of the first iteration only the particles shown in (4).

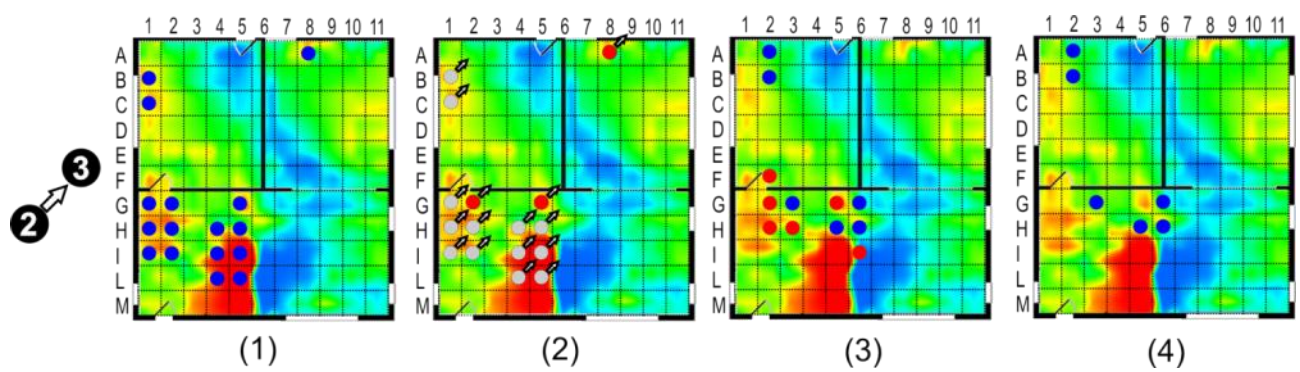

Figure 4 - Second iteration of the algorithm localization

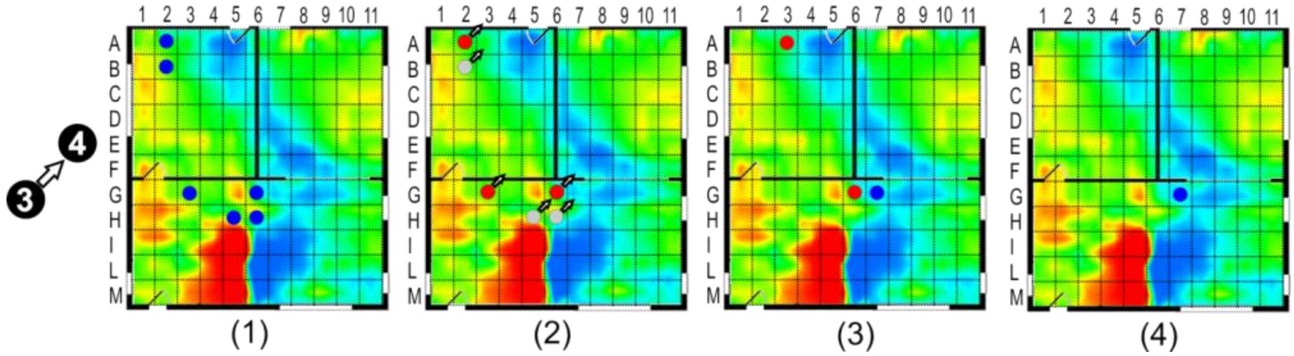

Figure 5 - Third iteration, user location in G3

Based on the subsequent movements of the user, the algorithm iterates the calculation arriving in two steps (Figure 4 and Figure 5) to correctly locate the user in the cell G7 and in the subsequent steps succeed therefore in tracking it correctly on the map. This description is greatly simplified. In the actual implementation of the algorithm various problems have been resolved in a proprietary way using techniques different from those reported in the literature, which we believe go beyond the state of the prior art and allow us to make significant improvements in the performance of the tracking system.

Inertial system and offset resolution

As described above the localization system requires adequate input signals. It is therefore necessary to estimate the user motion length and direction to use these measures to drive the iterations of the location engine.

It is known in literature that it is possible to estimate the direction of motion of a moving object if you can use an inertial measurement unit (IMU) consisting of accelerometer, gyroscope and compass that is firmly anchored to the moving object, and for which is known the offset in alignment between the reference system of the IMU and the reference system of the object that moves. These techniques could also be applied in the case of a user where a smartphone would replace the IMU and the smartphone be securely anchored to the user with offset pre-determined.

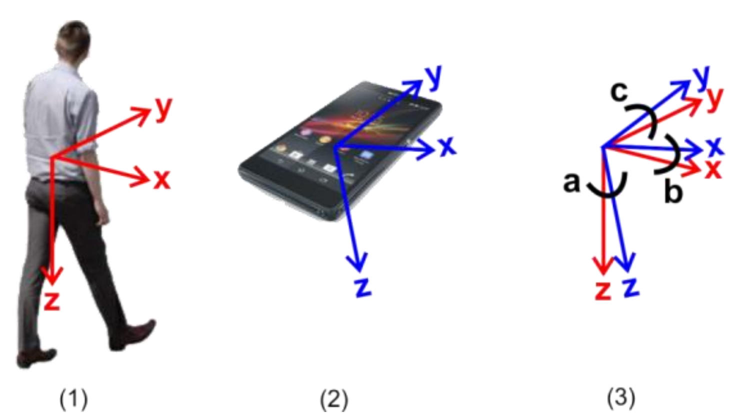

Figure 6 - Reference systems and smartphone user

If these assumptions were verified it would be possible to use known techniques, for example to calculate the angle which expresses the user's direction of travel with respect to the reference system fixed to the map (Figure 7, angle Ψ) and the other two angles of pitch and roll.

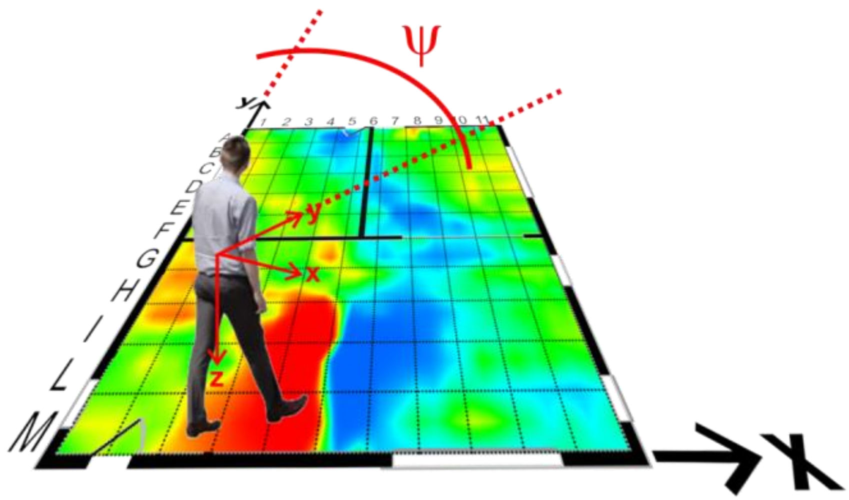

Figure 7 - angle Ψ representative of the direction of movement of the user

In reality any user that intends to be located has his smartphone in his hands and may move it during his journey or during his activities. Consequently it is no longer possible to know in static mode the offset angles a, b, c of Figure 6.

The implemented **inertial engine uses a proprietary technique to solve this problem**, **estimating the moving direction angle (angle of yaw) without constraining the relative orientation of smartphone and user.** Moreover our engine uses a proprietary technique for the estimation of the angles of pitch and roll.

The other input signal required by the localization engine is the distance that the user travels in his displacements, for example between two consecutive steps. Also in this case there are various techniques available in literature which allow determining the space covered by the object that moves if it firmly anchored to the IMU and is known the offset of alignment between the two reference systems. In reality, because of drifts and errors present on the accelerometer measures, calculating the distance through this simple formula causes errors of the order of a few meters per minute of use, and therefore is not usable.

There is a second problem concerning the determination of the instants of time in which the user actually is moving and those in which the user is stationary. If the smartphone was fixed, for example to the user's foot measuring acceleration would be very defined. In this case (Figure 8) it would be relatively simple to identify both the instants of time with the transitions still-motion and motion-still and to calculate the integrals to determine the distance traveled.

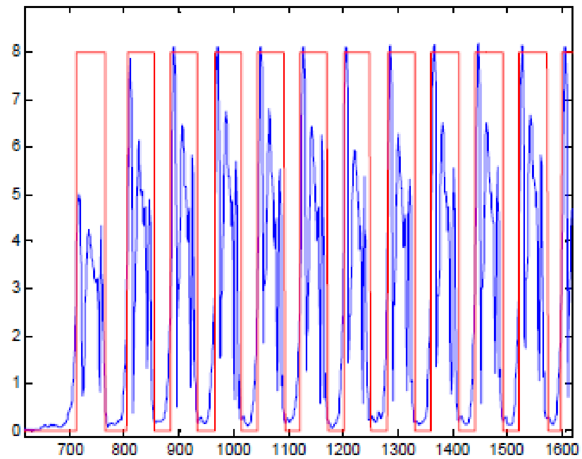

Figure 8 - Measurement of acceleration during walking user

In reality, the smartphone is not attached to the user and this in turn does not allow to use the readings of acceleration to simply discriminate the state of motion and still, as the user dynamic is measured coupled with other effects introduced by the absence of the bond of attachment (relative movements between user and smart phones on during the walk).

Our inertial engine implements a proprietary technique **that overcomes these problems** and allows us to **determine the times when the user is moving and / or still and the distance traveled regardless of the bond of attachment between smartphone and user**.

The estimates calculated by the inertial engine (moving direction, instants when the user is stationary and / or still, distance traveled) are used as input signals as described in the previous section for the location engine.

In particular, according to the previous description, it is possible to model the evolution of the state, i.e. position of the person, by means of a probability density function (also indicated hereinafter with the acronym pdf) which relates the state x_t to a measurement obtained from one or more sensors y_t.

The object is approximate the pdf on the basis of the measurements y_1, y_2, …, y_k made by the sensors at different instants of time.

This conditioned pdf, which here we indicate as $Bel(x_k)$, is expressible through the following relation between the state x and measurement y:

$$Bel(x_k) = p(x_k|y_k, y_{k-1}, \dots, y_o)$$

By calculating the probability $p(x_k|y_k, y_{k-1}, \dots, y_o)$, applying Bayes theorem and carrying out the appropriate transformations we obtain:

$$Bel(x_k) = p(x_k|y_k, y_{k-1}, \dots, y_o) = \frac{p(y_k, y_{k-1}, \dots, y_o|\, x_k)p(x_0|y_{k-1}, \dots, y_o)}{p(y_k|y_{k-1}, \dots, y_o)}$$

By transforming and further simplifying it is possible to obtain a recursive formulation of the previous one:

$$Bel(x_k) = \eta p(y_k|x_k) \int (x_k|x_{k-1}) Bel(x_{k-1})\, dx_{k-1}$$

The previous formulation enables to calculate the pdf recursively at each iteration *t* based on knowledge of the data measured by the sensors and the state of the previous iteration.

The previous expression cannot be evaluated analytically due to its non-linear nature and consequently it is necessary to use approximation techniques. For example, particle filters and Kalman filters belong to this set of techniques. For more details regarding particle filters, see *Sebastian Thrun et. al*, "**Probabilistic Robotics**", Publication Date: August 19, 2005 | **ISBN**-10: 0262201623, **ISBN-13**: 978-0262201629.

A particle filter estimates a posteriori approximation of the pdf which is substantially representable as a set of independent samples distributed in space and which take the name "particles".

Problems related to magnetometers calibration

Magnetometers are commonly used to measure Earth's local magnetic field vector so that to obtain the orientation of a body w.r.t. the magnetic North. One of the first magnetic compasses was proposed in China thousands of years ago; it was made of a bowl filled with water, used as a leveling platform, and a magnetic lodestone placed on a plate floating on the water.

However, a very common problem with magnetometers is related to measurements distortions due to external perturbations on the magnetic field. As a consequence, the measurements provided by IMU systems, are affected by magnetic distortions and non ideal sensor effects like nonorthogonality and general time-varying bias. In a realistic point of view, each magnetometer is affected by distortions related to sensor fabrication issues like axes misalignment and different sensitivity on each sensor axis, this anomaly is denoted as soft iron. Moreover the obtained magnetic field measurements are also corrupted by a measurement bias, denoted as hard iron perturbation, due to distortions related to sensor fabrication issues and the magnetic deviations induced by the host platform [11]. These distortions are created by objects that produce a constant magnetic field. For instance permanent magnet, speakers or pieces of magnetized material will cause a hard iron distortion. If the magnetized material is physically attached to the same reference frame as the sensor, then this type of hard iron distortion will cause a constant offset in the sensor output. Hard iron bias magnitude can easily be 10 times or greater compared to earths magnetic field. These issues hinder the sensor usability and motivate several calibration techniques to be performed before they are used.

Let $\widetilde{m}(t)$ be the real earth field which should be measured by the magnetometer, the obtained measurement by the sensor can be modeled as:

$$m^*(t) = A(\widetilde{m}(t) + b) \qquad \text{Eq. 1}$$

where $m^*(t) \in R^3$ is a constant vector representing the hard iron bias affecting the sensor measurement and $A \in R^{3x3}$ is a matrix representing the axes misalignment, the measurement scaling w.r.t. the magnetic field module and the sensitivities on each sensor axis. The problem of magnetometer calibration consists in defining a procedure able to obtain an estimation $\widehat{A}, \widehat{b}$ as more coherent as possible with the real couple A, b so that by computing

$$\widehat{m}(t) = \hat{A}^{-1}m^*(t) - \hat{b} \qquad \text{Eq. 2}$$

the obtained measurement is $\widehat{m}(t) \approx \widetilde{m}(t)$.

Let now m_0 be the reference magnetic vector in the North-East-Down (NED) reference frame (note that this vector is locally constant on the earth' plane). Given the transformation matrix R(t) representing the rotations, at time t, from the sensor reference frame to the NED reference frame, by rotating the measurements from the sensor to NED reference frame and using (Eq. 1) it follows that:

$$m_0 = R(t)(A^{-1}m^*(t) - b)$$

Since the matrix A is assumed to be known thanks to a starting calibration performed in a traditional way, in the following, for the sake of notation simplicity, let $m(t) = A^{-1}m^*(t)$ yielding to

$$\mathrm{m_0 = R(t)(m(t) - b)} \qquad \text{Eq. 3}$$

Starting from the above model, by deriving both sides w.r.t. time it follows that:

$$0 = \dot{R}(t)(m(t) - b) + R(t)\dot{m}(t) \qquad \text{Eq. 4}$$

and finally:

$$S_\omega(t)b = S_\omega(t)m(t) + \dot{m}(t) \qquad \text{Eq. 5}$$

Where $S_\omega(t)$ is a 3x3 matrix constructed by angular rotations coming from a gyroscope.

Let T_w be the observation time of the acquired measurements. This time is divided into N sub intervals of $T = \frac{T_w}{N}$ seconds. For each time interval $q = 1, \dots, N$, defined by $t \in [(q-1)]T, qT]$, by applying the inner product to the equation (5) it follows that:

$$[\int_0^T \phi_K(\tau)S_\omega(\tau + (q-1)T)d\tau]\, b = \int_0^T \phi_K(\tau)\big(S_\omega\,(\tau + (q-1)T)m(\tau + (q-1)T) + \dot{m}(\tau + (q-1)T)\big)\,d\tau \qquad \text{Eq. 6}$$

After some transformations is possible to rewrite the previous formulation before as:

$$\int_0^T \phi_K(\tau) S_\omega(\tau + (q-1)T) d\tau] b$$
$$= \int_0^T \phi_K(\tau) S_\omega(\tau + (q-1)T) m(\tau + (q-1)T) d\tau + - \int_0^T \dot{\phi}_K(\tau) m(\tau + (q-1)T) d\tau \qquad \text{Eq. 7}$$

And after a second rewrite we have:

$$G_q b = \zeta_q \qquad \text{Eq. 8}$$

Where

$$G_q = [\int_0^T \phi_K(\tau) S_\omega(\tau + (q-1)T_w) d\tau]$$
$$\zeta_q = \int_0^T \phi_K(\tau) S_\omega(\tau + (q-1)T_w) m(t) d\tau - \int_0^T \dot{\phi}_K(\tau) m(\tau + (q-1)T_w) d\tau$$

The following matrices can be now defined:

$$\boldsymbol{G} = \begin{bmatrix} G_1 \\ \vdots \\ G_N \end{bmatrix}, \boldsymbol{Z} = \begin{bmatrix} \zeta_1 \\ \vdots \\ \zeta_N \end{bmatrix}$$

yielding to:

$$Gb = Z \qquad \text{Eq. 9}$$

The solution:

$$\hat{b} = G^+ Z \qquad \text{Eq. 10}$$

represents a solution to the problem of magnetometer calibrations in terms of a least mean square approximation of the hard iron bias.

Resolution of errors in measuring

The sensors present on the smartphone (accelerometer, gyroscope, compass) are used by the inertial engine to estimate the input signals for the tracking system. These sensors are, however, imprecise and typically introduce errors of variable intensity and variable in time. In part, these errors are filtered by the inertial motor, however it is not possible to totally eliminate them and therefore the estimates are affected by errors with the same characteristics.

The developed localization system overcomes this problem by using proprietary techniques that seek to definitely correct both the estimate of the angle of motion direction (Ψ) and the distance traveled by the user during the phase of motion (d). Without entering into details for obvious reasons of confidentiality, our statistical filter at each iteration not only performs what described in previous sections, but also for each particle estimates a value Ψ_p and a value d_p substantially allowing each particle to evolve autonomously and independently from the other. In this way the particle is no longer bound to the movement resulting from the values defined by the inertial measurements in input but has an amount of "intelligence" which enables it to move a distance and in a direction that are functions of its history and the intrinsic "importance" of the particle in comparison with others. This technique allows achieving remarkable performance in the localization phase.

Integration with existing RF solutions

Our technology has no limits of integration with other techniques and we are in fact developed a version that integrate our technology based on geomagnetic anomalies with techniques based on RF wifi patterns (Bluetooth and WIFI).

From literature it is well-known that localization precision achievable via wifi patterns ranges from 2 to 4m if the mapping has been performed “one shot” (once and for all as per our technique) to 5-7m if the mapping is performed “SLAM”(simultaneous localization and mapping) respectively. On the other hand wifi techniques allow for a rapid localization of objects thanks to the presence of a known “constellation” of signal emitters.

Our geomagnetic-based localization can by contrast reach precisions of 1m or less, depending on the location intensity of geomagnetic anomalies. On the other hand initial localization may prove difficult due to the lack of a reference point to define a neighborhood in which to operate the MCL algorithm and the consequent need of sizable computing efforts to run the algorithm on large areas.

To integrate the best aspects of the two technologies we are developing solutions that employ them "hierarchically", where wifi techniques will periodically provide the gross estimate of user location, and geomagnetic techniques refine the search in the defined neighborhood. This combination is poised to provide an efficient solution: the initial “gross” localization is performed immediately using wifi signal; the “refined” localization is performed immediately thereafter by geomagnetic techniques applied to a smaller area; required computational resources are limited.

Product line

We have currently developed several vertical application that includes:

- a web map editor to upload building maps
- a app to fingerprint the map and locate the user on the map
- the algorithm, complete with inertial engine and localization engine (geomagnetic only)
- a server basic infrastructure to support the system

The technology works efficiently reaching extraordinary localization performances: up to few centimeters accuracy. On the other hand, we invested our limited resources on building the basic system with the less time-consuming tools, and therefore optimization is still needed to reach the final architecture and get to the commercial version of it.

We are available to show the functionality of the technology at any time upon request.

From the market adoption standpoint, we had a chance to discuss the integration of our technology into apps with small and medium worldwide app developers. Their response has always been very warm, generally requesting us to start immediately the co-development of one or more apps.

Patents

Currently GiPStech has filed five patents at world level protection (PCT).