Dual-GPS Fusion for Automatic Enhancement of Digital OSM Roadmaps

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***Abstract*—This paper presents a method to enhance digital OSM maps with roads inclination automatically. It relies on GPS data collected from two receivers. These data are fused with existing road map data by implementing the unscented Kalman filtering in a centralized scheme. We modeled the map data as a sensor that allows to account for its errors and uncertainties. The core of our method relies on a probabilistic map-matching approach that is used to manage the road network database through the computation of the Mahalanobis distance. We show experimental results from an extra-urban road network scenario in which the inclination of matched road segments is estimated to ensure a more reliable route planning.**

I. Introduction

This work concerns the automatic update of digital roadmaps in OpenStreetMap (OSM). OSM is an international community project for editing or creating free maps [1]. This is a free web-service that is continually updated from GPS traces that users can upload. It is now possible to record and view the location of roads and their various features (for instance, name, type, direction of traffic, position and inclination of the road). Other objects - as traffic lights, road signs, bus stops, etc. - can be easily geo-located in the digital roadmap. OSM is a completely free map database that is more and more used in the development of geolocation or route planning applications [2], [3].

An interesting application related to the management of GPS traces is the creation of routable maps for personal navigation devices (PND). The idea is to avoid the expensive purchasing of the several map updates originally supplied with the PND [4]. Biannually (or annually) updated using land-surveying or satellite images processing, these new maps do not accurately reflect the latest changes of the road network (opened or modified road, new roundabout, etc.). In contrast, OSM allows the visualization and extraction of the most recent and available maps. However, OSM deals with thousands of GPS traces, sometimes involving the same road segment, to reach a precise geolocation. Many attributes have yet to be completed manually, as the inclination of the road. This parameter can be extremely important to ensure the safety of specific road convoys [5].

The digital road network is usually described by a set of nodes. Nodes are the basic elements of the OSM database and are located by geographical coordinates. A path is an interconnection between two or more nodes characterizing a line (for instance, a street). A path is also described by uniform properties: the type of road (motorway, primary or secondary road, etc.), the traffic flow direction, the speed limit, the inclination, etc. Paths can be redrawn later if new properties appear. There is also, in the OSM database, the presence of isolated nodes to define points of interest (POI).

Our contribution is in the use and update of these digital road data. Indeed, the processing of traces from a single GPS receiver can be of poor quality, in terms of location, if the 3-D positioning was degraded by reflections of GPS signals. We focus here on two important attributes of roads: the location and inclination. Using an on-board multisensor system based on the fusion of data from two GPS-EGNOS receivers and a map database, we propose a method for automatic updating of digital roadmaps. This update applies to both refinement and completeness of the attributes of road location and inclination. The goal is to provide the most recent and complete digital road map for land-vehicle navigation systems. Our multi-sensor system that is equipped with two GPS receivers whose antennas are positioned on the vehicle appropriately to ensure better location accuracy [6]. We also fuse the existing road map data to ensure an accurate 2-D location of the vehicle on the map. In addition, we include in the fusion process, the map as an additional measurement equation which takes into account errors in the statistical of the associated noise. To solve this estimation problem, we implement a method of non-linear filtering: the unscented Kalman filter (UKF) that allows a direct processing of non-linear equations without using a linearization step of the state equations as is the case of extended Kalman filtering.

To validate the proposed method, we drive the instrumented vehicle in a context of urban traffic. We show experimental results for estimating inclination of each road segment traveled by the vehicle. We integrate these data to OSM and show that it is possible to automate the updating of the road inclination attribute in roadmaps.

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II. Problem modeling

The goal of the proposed approach is to give a theoretical framework for automatic enhancement of digital roadmaps. To this end, we use information from a global navigation satellite system (GNSS) and more particularly GPS measurements from multiple GPS receivers coupled with a digital road map which has to be updated. In this application context, the usual kinematic equations has been used to model its evolution. More complex dynamics model could be used but would not lead to significant benefits in the case of a standard vehicle.

Hence, we use a state-space modeling of the problem to describe the 3-D motion. The following characteristics describe the 3-D vehicle's dynamics: the acceleration γ, the velocity v and the position (given in UTM coordinates) are the components of the state vector along the coordinates x, y and z. Let $X_t = (x_t,\ v_t^x,\ \gamma_t^x,\ y_t,\ v_t^y,\ \gamma_t^y,\ z_t,\ v_t^z,\ \gamma_t^z)^T$ be the state vector.

A. Dynamics of vehicle

We use a third order kinematic state model, which can be expressed along u-axis ($u = \{x, y, z\}$) as follows:

$$\begin{pmatrix} u_{t+1} \\ v_{t+1}^u \\ \gamma_{t+1}^u \end{pmatrix} = \underbrace{\begin{pmatrix} 1 & \Delta t & 0 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{pmatrix}}_{F_u} \begin{pmatrix} u_t \\ v_t^u \\ \gamma_t^u \end{pmatrix} + \begin{pmatrix} \Omega_t^u \\ \Omega_t^{v^u} \\ \Omega_t^{\gamma^u} \end{pmatrix} \quad (1)$$

where $(\Omega_t^u, \Omega_t^{v^u}, \Omega_t^{\gamma^u})^T$ are additive white Gaussian noises and Δt denotes the sampling rate. This equation can be extended to the three-dimensional case:

$$X_{t+1} = f(X_t, \Omega_t) = F X_t + \Omega_t \quad (2)$$

where F is the linear dynamics flow of the system:

$$F = \begin{pmatrix} F_x & \mathbb{O}_{3\times3} & \mathbb{O}_{3\times3} \\ \mathbb{O}_{3\times3} & F_y & \mathbb{O}_{3\times3} \\ \mathbb{O}_{3\times3} & \mathbb{O}_{3\times3} & F_z \end{pmatrix} \quad (3)$$

$\mathbb{O}_{3\times3}$ is a null matrix of dimension 3×3 and Ω_t is an additive white Gaussian noise with zero mean and Q_t covariance matrix:

$$Q_t = \begin{pmatrix} Q_t^x & \mathbb{O}_{3\times3} & \mathbb{O}_{3\times3} \\ \mathbb{O}_{3\times3} & Q_t^y & \mathbb{O}_{3\times3} \\ \mathbb{O}_{3\times3} & \mathbb{O}_{3\times3} & Q_t^z \end{pmatrix} \quad (4)$$

where [7]:

$$Q_t^u = \begin{pmatrix} \frac{\Delta t^5}{20} & \frac{\Delta t^4}{8} & \frac{\Delta t^3}{6} \\ \frac{\Delta t^4}{8} & \frac{\Delta t^3}{3} & \frac{\Delta t^2}{2} \\ \frac{\Delta t^3}{6} & \frac{\Delta t^2}{2} & \Delta t \end{pmatrix} q_t^u \quad (5)$$

q_t^u is here the dynamics noise covariance along u.

B. Measurements

1) GPS data: to enhance the map database, we dispose of GPS measurements from several GPS-EGNOS receivers mounted on the vehicle. These measurements are jointly used with the digital road map to be updated. The proposed approach needs first an estimation of the 3-D parameters of the vehicle from the collected GPS data, denoted $\mathcal{Z}_{t+1}^{\text{GPS},i}$, $i = (1, \dots, m_{\text{GPS}})$, m_{GPS} being the number of GPS units:

$$\mathcal{Z}_{t+1}^{\text{GPS},i} = \begin{pmatrix} x_{t+1}^{\text{GPS},i} \\ y_{t+1}^{\text{GPS},i} \\ z_{t+1}^{\text{GPS},i} \end{pmatrix} = h^{\text{GPS},i}(X_{t+1}) + \mathcal{V}_{t+1}^{\text{GPS},i} \quad (6)$$

where $h^{\text{GPS},i}$ is the (non-linear) measurement function of the GPS sensor #i and $\mathcal{V}_{t+1}^{\text{GPS},i} \sim \mathcal{N}(0, R_{t+1}^{\text{GPS}})$ is an additive white Gaussian noise. R_{t+1}^{GPS} is the GPS measurement noise covariance matrix.

2) Map data: to increase the accuracy of the 3-D parameters estimation, the GPS data are fused with the road map data from a geographic information system (GIS), if possible. Transitional nodes of arcs are the main features of the map database. These interconnected nodes define the road network and are composed of three attributes: the location information $(x_{t+1}^{\text{MAP}}, y_{t+1}^{\text{MAP}})$ and the orientation $\theta_{t+1}^{\text{MAP}}$ of the road segment.

$$\mathcal{Z}_{t+1}^{\text{MAP}} = \begin{pmatrix} x_{t+1}^{\text{MAP}} \\ y_{t+1}^{\text{MAP}} \\ \theta_{t+1}^{\text{MAP}} \end{pmatrix} = h^{\text{MAP}}(X_{t+1}) + \mathcal{V}_{t+1}^{\text{MAP}} \quad (7)$$

where h^{MAP} is the non-linear function that links the state vector components to the measurements and $\mathcal{V}_{t+1}^{\text{MAP}}$ is an additive white Gaussian noise with zero mean and R_{t+1}^{MAP} covariance matrix.

$$\mathcal{Z}_{t+1}^{\text{MAP}} = \begin{pmatrix} x_{t+1} \\ y_{t+1} \\ \arctan\left(\frac{v_{t+1}^y}{v_{t+1}^x}\right) \end{pmatrix} + \begin{pmatrix} \mathcal{V}_{t+1}^{\text{MAP,x}} \\ \mathcal{V}_{t+1}^{\text{MAP,y}} \\ \mathcal{V}_{t+1}^{\text{MAP},\theta} \end{pmatrix} \quad (8)$$

It must be noticed that this state-space modeling of the map leads to the possibility to include statistical aspects related to uncertainties and errors on land-surveying in the term $\mathcal{V}^{\text{MAP}}$. Moreover, inhomogeneities in the accuracy of land-surveying depending on the geographic region can be considered.

III. Automatic map enhancement

The proposed modeling define a theoretical framework to automatically enhance the road map data. Based on Eqs. 2, 6 and 8, we propose a solution to this estimation problem that relies on the unscented Kalman filtering. The benefits of such methods in dealing with non-linear state equations are well-known [8].

We detail below the general structure of the proposed solution, based on the usual steps in dynamic estimation: prediction and correction of the state vector. The general principle of the UKF relies on the use of sigma-points which are statistical sampling points of the conditional probability density function related to the estimate. The adopted filtering structure is a sequential processing of GPS and road map measurements (see Eqs. 6 and 8).

A. Correction with GPS measurements

The unscented Kalman filtering approach needs to augment the n-dimensional state vector X_t with the dynamics and GPS measurement noise components:

$$\begin{aligned} X_t^a &= \left[\begin{array}{ccc} X_t^T & \Omega_t^T & \mathcal{V}_t^{\text{GPS},i\,T} \end{array}\right]^T \\ \widehat{X}_{t|t}^a &= \left[\begin{array}{ccc} \widehat{X}_{t|t}^T & 0_\Omega^T & 0_{\mathcal{V}^{\text{GPS}}}^T \end{array}\right]^T \\ \widetilde{P}_{t|t}^a &= \left[\begin{array}{ccc} \widetilde{P}_{t|t} & 0 & 0 \\ 0 & Q_t & 0 \\ 0 & 0 & R_t^{\text{GPS}} \end{array}\right] \end{aligned} \tag{9}$$

$\widetilde{P}_{t|t}^a$ is the estimation error covariance matrix of the augmented state. $\widetilde{P}_{t|t}$ is the estimation error covariance matrix of the state vector X_t. 0_Ω and $0_{\mathcal{V}^{\text{GPS}}}$ are null vectors whose dimension is equal to the dimension n_Ω of Ω^T and $n_{\mathcal{V}^{\text{GPS}}}$ of $\mathcal{V}^{\text{GPS},i}$. T denotes the transpose operator.

We define the sigma-points which are associated to the augmented state as:

$$\chi^{a,\text{GPS}} = \left[\begin{array}{ccc} \chi^{\text{X}\,T} & \chi^{\Omega\,T} & \chi^{\nu^{\text{GPS},i}\,T} \end{array}\right]^T \tag{10}$$

where $\chi^{a,\text{GPS}}$ is a $n_a \times (2n_a+1)$ matrix. n_a is the dimension of the augmented state vector:

$$n_a = n + n_\Omega + n_{\mathcal{V}^{\text{GPS}}} \tag{11}$$

The sigma-points set is computed as follows [9]:

$$\chi_{t|t}^{a,\text{GPS}} = \left[\widehat{X}_{t|t}^a \quad \widehat{X}_{t|t}^a \pm \left(\sqrt{(n_a+\lambda)\,\widetilde{P}_{t|t}^a}\right)^k_{k=\{1,\ldots,n_a\}} \right] \tag{12}$$

λ is a parameter of the transform. Then, the sigma-points evolve according to the dynamics flow of the system (see Eq. 2):

$$\chi_{t+1|t}^{j,\text{X}} = f(\chi_{t|t}^{j,\text{X}}, \chi_{t|t}^{j,\Omega}) \tag{13}$$

where $\chi_{t+1|t}^{j,\text{X}}$ is the j^{th} column of $\chi_{t+1|t}^{\text{X}}$. So, we get:

$$\widehat{X}_{t+1|t} = \sum_{j=1}^{2n_a+1} w_j \chi_{t+1|t}^{j,\text{X}} \tag{14}$$

The weights w_j are computed as follows:

$$\begin{cases} w_1 = \dfrac{\lambda}{(n_a+\lambda)} \\ w_{2k} = \dfrac{1}{2(n_a+\lambda)},\ w_{2k+1} = \dfrac{1}{2(n_a+\lambda)} \end{cases} \tag{15}$$

where $k=\{1,...,n_a\}$. w_{2k} and w_{2k+1} are the weights which are associated to the k^{th} column of $\sqrt{(n_a+\lambda)\,\widetilde{P}_{t|t}^a}$.

The error covariance matrix $\widetilde{P}_{t+1|t}$ must also be computed using the $2n_a+1$ sigma points:

$$\widetilde{P}_{t+1|t} = \sum_{j=1}^{2n_a+1} w_j (\chi_{t+1|t}^{j,\text{X}} - \widehat{X}_{t+1|t})(\chi_{t+1|t}^{j,\text{X}} - \widehat{X}_{t+1|t})^T \tag{16}$$

The predicted GPS measurement $\widehat{\mathcal{Z}}_{t+1|t}^{\text{GPS},i}$ of the sensor #i can be derived from Eqs. 13 and 15:

$$\widehat{\mathcal{Z}}_{t+1|t}^{\text{GPS}} = \sum_{j=1}^{2n_a+1} w_j (z_{t+1|t}^{\text{GPS},i})^j \tag{17}$$

where $(z_{t+1|t}^{\text{GPS},i})^j$ is the j^{th} column of:

$$z_{t+1|t}^{\text{GPS},i} = h^{\text{GPS},i}(\chi_{t+1|t}^{\text{X}}) + \chi_{t+1|t}^{\nu^{\text{GPS},i}} \tag{18}$$

The state vector and error covariance matrix are updated using the GPS measurement:

$$\begin{cases} K_{t+1}^{\text{GPS}} = \widetilde{P}_{X_{t+1}\mathcal{Z}_{t+1}^{\text{GPS}}} \widetilde{P}^{-1}_{\mathcal{Z}_{t+1}^{\text{GPS}}\mathcal{Z}_{t+1}^{\text{GPS}}} \\ \widetilde{P}_{t+1|t+1}^{\text{GPS}} = \widetilde{P}_{t+1|t} - K_{t+1}^{\text{GPS}} \widetilde{P}_{\mathcal{Z}_{t+1}^{\text{GPS}}\mathcal{Z}_{t+1}^{\text{GPS}}} K_{t+1}^{\text{GPS}\,T} \\ \widehat{X}_{t+1|t+1}^{\text{GPS},i} = \widehat{X}_{t+1|t} + K_{t+1}^{\text{GPS}} (\mathcal{Z}_{t+1}^{\text{GPS},i} - \widehat{\mathcal{Z}}_{t+1|t}^{\text{GPS},i}) \end{cases} \tag{19}$$

where $\widetilde{P}_{X_{t+1}\mathcal{Z}_{t+1}^{\text{GPS}}}$ and $\widetilde{P}_{\mathcal{Z}_{t+1}^{\text{GPS}}\mathcal{Z}_{t+1}^{\text{GPS}}}$ are error covariance matrices which are computed as follows:

$$\widetilde{P}_{X_{t+1}\mathcal{Z}_{t+1}^{\text{GPS}}} = \sum_{j=1}^{2n_a+1} w_j (\chi_{t+1|t}^{j,\text{X}} - \widehat{X}_{t+1|t})((z_{t+1|t}^{\text{GPS},i})^j - \widehat{\mathcal{Z}}_{t+1|t}^{\text{GPS},i})^T \tag{20}$$

$$\widetilde{P}_{\mathcal{Z}_{t+1}^{\text{GPS}}\mathcal{Z}_{t+1}^{\text{GPS}}} = \sum_{j=1}^{2n_a+1} w_j ((z_{t+1|t}^{\text{GPS},i})^j - \widehat{\mathcal{Z}}_{t+1|t}^{\text{GPS},i})((z_{t+1|t}^{\text{GPS},i})^j - \widehat{\mathcal{Z}}_{t+1|t}^{\text{GPS},i})^T \tag{21}$$

$\widehat{X}_{t+1/t+1}^{\text{GPS},i}$ denotes the estimate of the state vector (3-D positioning, velocity and acceleration) of the vehicle at time instant $t+1$ using the GPS measurements until the sensor #i. These equations are then iterated for each GPS sensor #i, $i=(1,\ldots,m_{\text{GPS}})$.

B. Map-based correction

The map is used here as an additional sensor that corrects the GPS-based estimate. With such a modeling, the map uncertainties and inaccuracies can be modeled in a natural way. Using the UKF, we proceed to a new augmentation of the state vector:

$$\begin{aligned} X_{t+1}^a &= \left[\begin{array}{ccc} X_{t+1}^T & \Omega_{t+1}^T & \mathcal{V}_{t+1}^{\text{MAP}\,T} \end{array}\right]^T \\ \widehat{X}_{t+1|t+1}^a &= \left[\begin{array}{ccc} \widehat{X}_{t+1|t+1}^{\text{GPS}\,T} & 0_\Omega^T & 0_{\mathcal{V}^{\text{MAP}}}^T \end{array}\right]^T \\ \widetilde{P}_{t+1|t+1}^a &= \left[\begin{array}{ccc} \widetilde{P}_{t+1|t+1}^{\text{GPS}} & 0 & 0 \\ 0 & Q & 0 \\ 0 & 0 & R^{\text{MAP}} \end{array}\right] \end{aligned} \tag{22}$$

$0_{\mathcal{V}^{\text{MAP}}}$ is a null vector whose dimension is equal to the dimension $n_{\mathcal{V}^{\text{MAP}}}$ of $\mathcal{V}^{\text{MAP}}$. So, the new sigma points set is computed:

$$\chi^{a,\text{MAP}} = \left[\begin{array}{ccc} \chi^{\text{X}\,T} & \chi^{\Omega\,T} & \chi^{\nu^{\text{MAP}}\,T} \end{array}\right]^T \tag{23}$$

where $\chi^{\text{MAP},a}$ is a $n_a \times (2n_a+1)$ matrix. n_a is the dimension of the augmented state vector:

$$n_a = n + n_\Omega + n_{\mathcal{V}^{\text{MAP}}} \tag{24}$$

Through the unscented transform, we get the associated sigma points $\chi^{a,\text{MAP}}_{t+1|t+1}$:

$$\left[\begin{array}{c} \widehat{X}^a_{t+1|t+1} \\ \widehat{X}^a_{t+1|t+1} \pm \left(\sqrt{(n_a+\lambda)\,\widetilde{P}^a_{t+1|t+1}}\right)^k_{k=\{1,\ldots,n_a\}} \end{array} \right]^T \tag{25}$$

The unscented transform is then used to construct a prediction of the map measurement via Eq. 8:

$$\widehat{\mathcal{Z}}^{\text{MAP}}_{t+1|t+1} = \sum_{j=1}^{2n_a+1} w_j z^{j,\text{MAP}}_{t+1|t+1} \tag{26}$$

where $z^{j,\text{MAP}}_{t+1|t+1}$ is the j^{th} column of :

$$z^{\text{MAP}}_{t+1|t+1} = h^{\text{MAP}}(\chi^{\text{X}}_{t+1|t+1}, \chi^{\nu^{\text{MAP}}}_{t+1|t+1}) \tag{27}$$

The challenge now is to exploit this predicted measurement to match the state estimate with map data. Many methods have been proposed to refine the positioning with a map database [10]. Most are based on geometrical approaches. We propose to use a statistical approach of the map matching problem that relies on the Mahalanobis distance [11] between the predicted road map description (node position, orientation) and a map descriptor at time instant $t+1$.

In general, the map data are described by interconnected nodes. However, to get a more detailed description of the map, each road candidate to the matching procedure, is described by the orthogonal projection of the predicted map measurement onto each available arc of the database (in the vicinity of the vehicle) if possible, or by the nearest extremity to this projection. Let us note $\mathcal{Z}^{\text{MAP}}_m$ the set composed of these orthogonal projections:

$$\mathcal{Z}^{\text{MAP}}_m = \text{proj}_{\perp,m}(\widehat{\mathcal{Z}}^{\text{MAP}}_{t+1|t+1}) \tag{28}$$

$m = \{1, \ldots, m_{max}\}$ denotes all the possible projections onto the road network.

The map descriptor (see Eq. 8) also uses the road orientation. To complete the map matching, we construct the Mahalanobis distance $d_m = d(\mathcal{Z}^{\text{MAP}}_m, \widehat{\mathcal{Z}}^{\text{MAP}}_{t+1|t+1})$ in the case of a two-way road (θ_1, θ_2):

$$\left\{ \begin{array}{l} \mathcal{Z}^{\text{MAP},\,\theta_1}_m = (x^{\text{MAP}}_m,\ y^{\text{MAP}}_m,\ \theta^{\text{MAP}}_m)^T \\ \mathcal{Z}^{\text{MAP},\,\theta_2}_m = (x^{\text{MAP}}_m,\ y^{\text{MAP}}_m,\ \theta^{\text{MAP}}_m + \pi)^T \end{array} \right. \tag{29}$$

Depending on the road network configuration, there are some roads that can be traveled in one direction only. An OSM special attribute allows to detect them. The Mahalanobis distance can be written for θ_j:

$$(d^{\theta_j}_{m,t})^2 = (\mathcal{Z}^{\text{MAP},\,\theta_j}_m - \widehat{\mathcal{Z}}^{\text{MAP}}_{t+1|t+1})^T (\widetilde{P}^{\text{GPS}}_{t+1|t+1})^{-1} (\mathcal{Z}^{\text{MAP},\,\theta_j}_m - \widehat{\mathcal{Z}}^{\text{MAP}}_{t+1|t+1}) \tag{30}$$

The innovation process is supposed to have a Gaussian distribution. As a consequence, the squared Mahalanobis distances (see Eq. 30) are distributed according to a chi-square law with three degrees of freedom. Now, the state correction can only be done if a road segment candidate is identified. The statistical properties of the Mahalanobis distance allows to define a procedure for a map-based correction of the state, based on a threshold ε. The measurement $\mathcal{Z}^{\text{MAP},\theta^*}_{m^*}$ that minimizes the criterion $d^{\theta}_m(\mathcal{Z}^{\text{MAP}}_m, \widehat{\mathcal{Z}}^{\text{MAP}}_{t+1|t+1}) \leq \varepsilon$ is used to correct the GPS-based estimate:

$$\left\{ \begin{array}{l} K^{\text{MAP}}_{t+1} = \widetilde{P}_{X^{\text{GPS}}_{t+1}\mathcal{Z}^{\text{MAP}}_{t+1}} \widetilde{P}^{-1}_{\mathcal{Z}^{\text{MAP}}_{t+1}\mathcal{Z}^{\text{MAP}}_{t+1}} \\ \widetilde{P}^{\text{MAP}}_{t+1|t+1} = \widetilde{P}^{\text{GPS}}_{t+1|t+1} - K^{\text{MAP}}_{t+1} \widetilde{P}_{\mathcal{Z}^{\text{MAP}}_{t+1}\mathcal{Z}^{\text{MAP}}_{t+1}} K^{\text{MAP}\,T}_{t+1} \\ \widehat{X}^{\text{MAP}}_{t+1|t+1} = \widehat{X}^{\text{GPS}}_{t+1|t+1} + K^{\text{MAP}}_{t+1}(\mathcal{Z}^{\text{MAP}}_{t+1} - \widehat{\mathcal{Z}}^{\text{MAP}}_{t+1|t+1}) \end{array} \right. \tag{31}$$

where the error covariance $\widetilde{P}_{X^{\text{GPS}}_{t+1}\mathcal{Z}^{\text{MAP}}_{t+1}}$ is written as follows:

$$\widetilde{P}_{X^{\text{GPS}}_{t+1}\mathcal{Z}^{\text{MAP}}_{t+1}} = \sum_{j=1}^{2n_a+1} w_j (\chi^{j,\text{X}}_{t+1|t+1} - \widehat{X}^{\text{GPS}}_{t+1|t+1})(z^{j,\text{MAP}}_{t+1|t+1} - \widehat{\mathcal{Z}}^{\text{MAP}}_{t+1|t+1})^T \tag{32}$$

The global estimate is then:

$$\widehat{X}_{t+1|t+1} = \widehat{X}^{\text{MAP}}_{t+1|t+1} \tag{33}$$

C. Map updating

The goal now is to update the map database with on-line inclination estimation. In order to enhance the map description, for each line segment #s of the polylines, the projection of the state estimate (see Eq. 28) have been used to compute the inclination of the road segment.

Let us note:

$$\mathcal{Z}_{s,j} = a_s \rho_{s,j} + z_{s,0} \tag{34}$$

the relationship between the elevation $\mathcal{Z}$ and the radial distance $\rho_{s,j}$ of the projected estimation at time instant j onto the line segment #s to the extremity $(x_{s,0}, y_{s,0})$. $a_{s,0}$ denotes the slope of the selected line segment #s and $z_{s,0}$ its intercept.

Eq. 34 can be written in a matrix form:

$$\mathcal{Z}_s = \mathcal{H}u = \left(\begin{array}{cc} \rho_{s,1} & 1 \\ \vdots & \vdots \\ \rho_{s,n_s} & 1 \end{array} \right) \left(\begin{array}{c} a_s \\ z_{s,0} \end{array} \right) \tag{35}$$

where $\rho_{s,j}$ is the radial distance of the projection j to the origin of the line segment #s:

$$\rho_{s,j} = \sqrt{(x^{\text{MAP}}_{s,j} - x_{s,0})^2 + (y^{\text{MAP}}_{s,j} - y_{s,0})^2}\ , \quad \forall j \tag{36}$$

$\mathcal{H}$ is a $n_s \times 2$ matrix whose size n_s depends on the number of projected estimate onto the line segment #s. The parameters of the road segments are now computed using a global least square approach when the vehicle leaves the segment:

$$\left(\begin{array}{c} \hat{a}_s \\ \hat{z}_{s,0} \end{array} \right) = \left(\mathcal{H}^T\mathcal{H}\right)^{-1} \mathcal{H}^T \mathcal{Z}_s \tag{37}$$

This approach is applied on-line for each line segment that has been matched to the estimator $\widehat{X}$. Hence, the map database will be automatically enhanced by our approach, under statistical considerations.

IV. Experimental results

We have tested the proposed method in a real framework using OSM data. Map enhancements are presented here by focusing on road features estimation.

A. Framework description

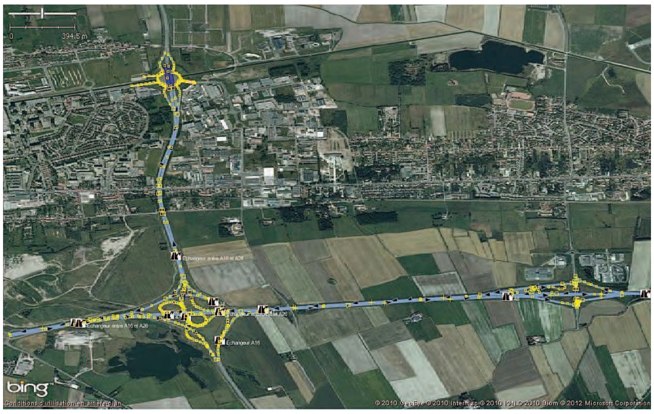

Fig. 1. Aerial view of the used OSM database

The objective is to estimate the road inclination in this routable map. To this end, we have driven a dual-GPS fitted vehicle along these roads to collect 3-D map-matched location data (see Fig. 1). The antennas of the two u-blox EVK-6T GPS receivers are positioned on the roof of the vehicle so as to be aligned with the driver side. The distance between the two antennas has been calibrated. This information is required in the GPS measurement equations. Navigation update rate of GPS receivers was set to 1Hz. This kind of low-cost receiver is also able to manage the SBAS - EGNOS positioning improvement.

Fig. 2 shows the set of ways and nodes that describe the used OSM database in which we try to estimate road inclinations.

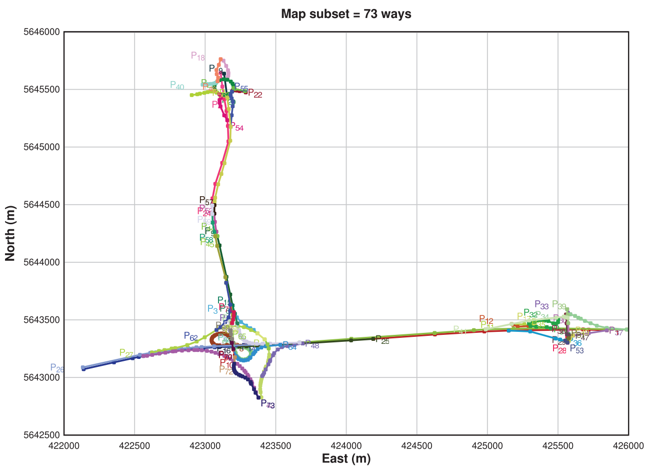

Fig. 2. OSM ways and nodes of the map subset

B. Map-matching procedure

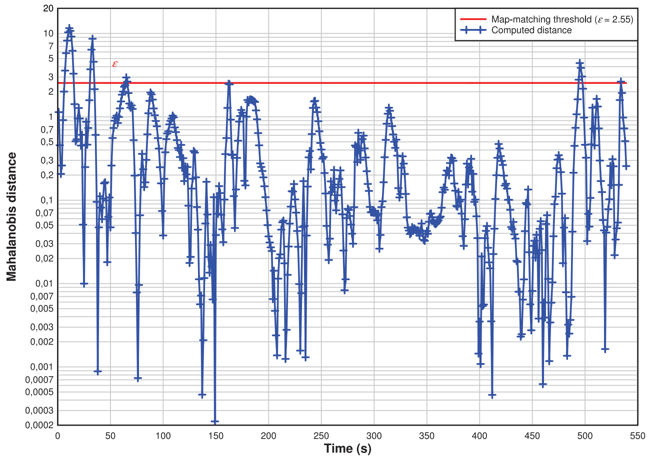

Fig. 3. Mahalanobis distance in the map-matching procedure

The matching procedure is a crucial step of the proposed method. This step allows to identify the road segment traveled by the vehicle for which 3-D location of two GPS receivers are collected. It relies on the computation of the Mahalanobis distance at each time instant (see Fig. 3). In addition, the map-matching threshold ε defines in which conditions the existing road map database can be used to improve the vehicle ground-location.

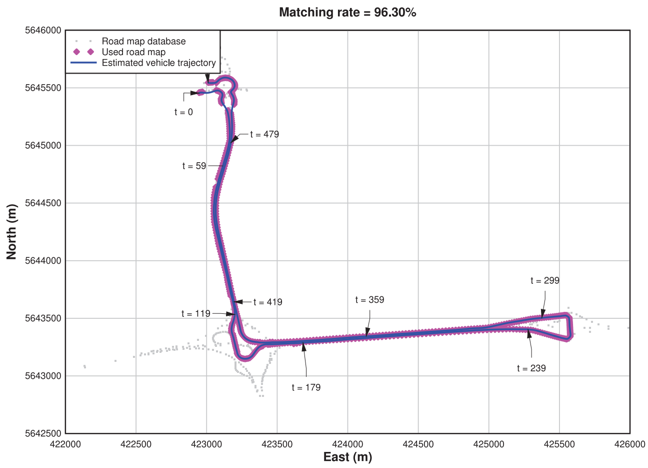

Fig. 4. UKF-based path estimation of the vehicle

Fig. 4 shows the used OSM data and the estimation of the 2-D path of the driven vehicle. Our map-matching procedure performs efficiently so that the matching rate reaches here 96.3%.

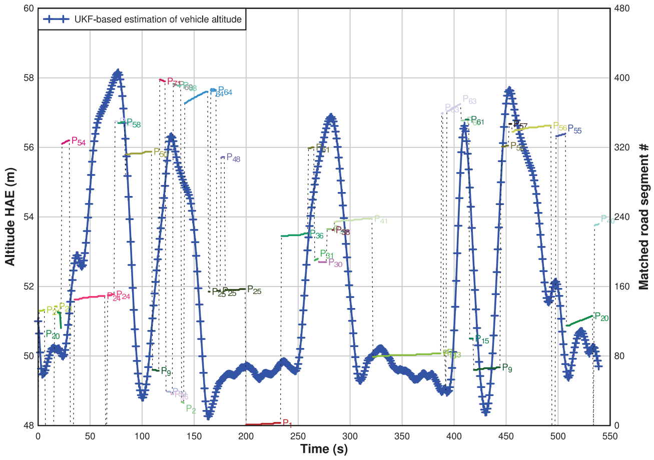

Fig. 5. UKF-based altitude estimation of the vehicle

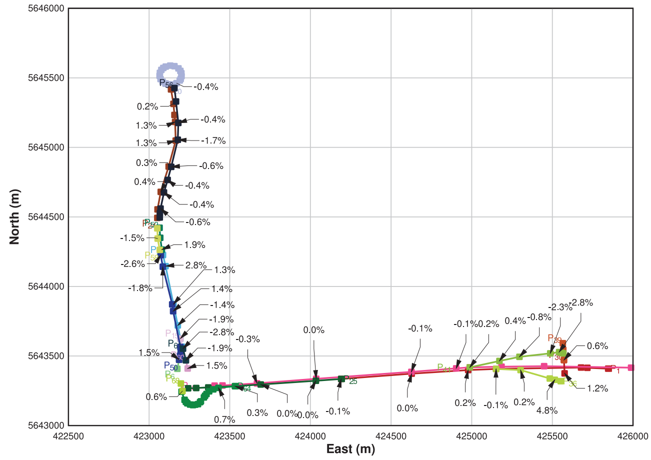

Fig. 7. Map view of estimated inclinations

C. Road inclination estimation

The altitudes of the two used GPS receivers are fused in our approach. Fig. 5 shows the estimated altitudes of the driven vehicle at each time instant. We also added the road segments that are matched in the previous step. These map data are linked to the estimated altitudes that are the basic components of our least squares method to estimate the inclination of the road segment.

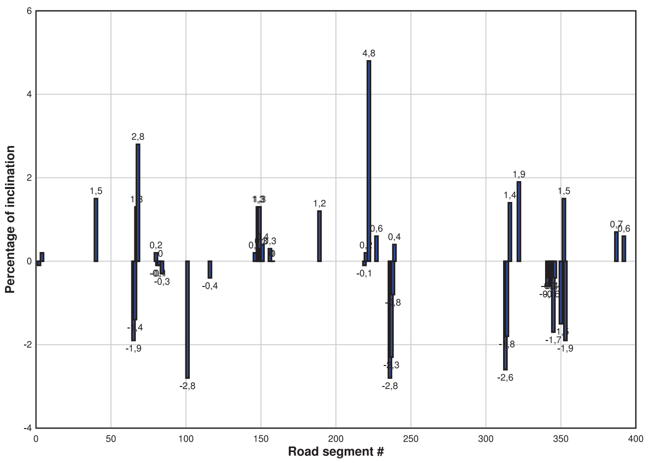

Fig. 6. Inclination estimation of road segments

Fig. 6 shows the estimated inclination (in %) of road segments that have been traveled by the instrumented vehicle. Note that this estimation depends on available altitudes. This minimal number is dynamically set depending on the road segment length, the vehicle speed and the navigation update rate.

Finally, we plotted in Fig. 7 the ways that have been automatically updated. Node labels indicate the estimated percentage of inclination at the entry of the road segment.

V. Conclusion

We propose in this paper a general method of roadmap database enhancement based on a dual-GPS system. In general, this procedure is done off-line and in a supervised manner. The approach developed here aims at realizing this step on-line and automatically. This is made possible by a statistical modeling of the map matching problem which allows the coupling with the estimation of the road segments inclination. Finally, we define a general theoretical framework based on a multi-GPS system that can be easily extended to additional proprioceptive sensors such that odometers, inertial navigation systems, etc.

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