Low Cost System: GPS/MEMS for Positioning

Alberto GUARNIERI, Andrea MENIN, Francesco PIROTTI, Antonio VETTORE

Key words – MMS, INS, MEMS, KF,

SUMMARY

This paper presents results of tests on a system which uses Micro-Electro-Mechanical-Systems (MEMS) and global positioning system (GPS) in place of more expensive Inertial Navigation Systems (INS). This is not an entirely new approach to sensor integration for positioning, as using a number of MEMS to replace INS has been studied since these components were put into the market. In our case we apply an algorithm for integrating data from GPS and MEMS in real time placed inside a van for mobile mapping. The Extended Kalman Filter (EKF) was used for this purpose. The method assumes movement on a plane, and analyses how EKF can reduce error thus decreasing the accuracy difference between INS and GPS/MEMS. It is taken into account that MEMS are not calibrated, therefore systematic errors which are not compensated by the EKF will occur. It is necessary to modify the EKF model putting new variables that represent error variables to account for bias and scale errors in the MEMS.

INTRODUCTION

Recent technological advance put into the market low cost GPS with a positioning accuracy of 2-5 meters and a frequency of 1 Hz. Many applications require a higher accuracy as well as the orientation of the frame. This information is available using INS, but these systems are quite expensive and therefore their use is limited. Recent studies have brought interest into the use of alternative components with lower costs, the MEMS, along with methods to bring accuracy close to the level of INS. The challenge behind these studies is to substitute INS with a series of MEMS and a GPS unit which, with a correct configuration, can give accurate and reliable information. Correct configuration means rigid-framework of MEMS, with an algorithm for integration of GPS information and data processing.

The development of accurate positioning and navigation systems has taken interest in low cost components since the improvement in the field of signal processing (multiresolution wavelet transforms) and estimation using a-priori probability (Kalman Filter). The idea of integrating positioning and navigation data has been studied for a while (El-Sheimy, 2006; Shin, 2007) and now improved technology can bring new applications and interesting results.

Trajectory reconstruction using MEMS is not an entirely new idea, but the methods used and the specific case of movement along a plane are of interest.

It is not easy to measure the acceleration information directly because the MEMS are placed in the moving inertial frame and it is not possible to determine their exact position and orientation relative to the inertial frame. To solve this it is necessary to use a calibration

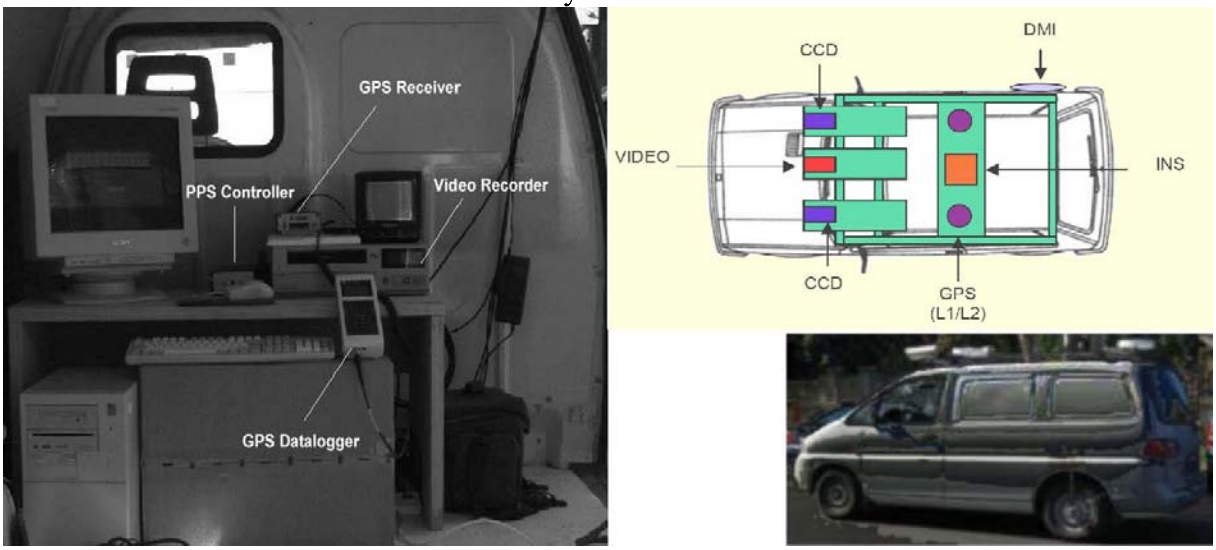


Fig. 1: Inside and outside view of the mobile mapping van and sensor arrangement

procedure which extracts position and orientation for each MEMS element. To this purpose an algorithm was implemented which outputs this information using a test trajectory. This procedure is applied after data collection, but it is feasable to apply it to real time data stream from MEMS and GPS.

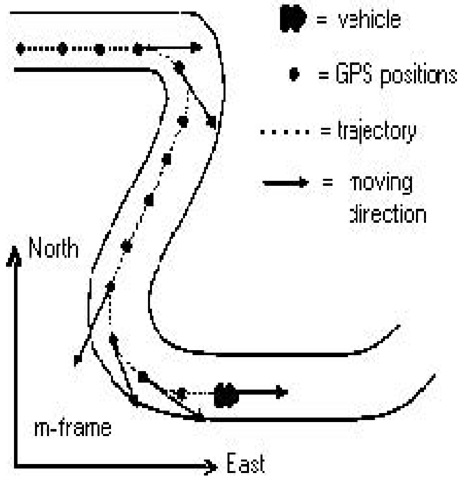
MATERIALS AND METHODS

The sensors are containted inside a van equipped with digital and analogic cameras as well as sensors for registration of geographic position of the vehicle. The positioning sensors are GPS/INS include a Novatel OFM3 and a Litton LN200. The MEMS accellerometers used were the LIS2L02AS by ST Microelectronics. These MEMS have a 4 kHz bandwith which was reduced with a low-pass filter at 120 Hz. Noise and vibration outliers were corrected for by using the average filter. The GPS antenna center is in-line with the rear wheel shaft and so is the center of the MEMS system.

A model representing frame dynamics has been implemented, and the EKF is applied to integrate accelleration in the three axes and orientation along with GPS positions to correct the drift of the MEMS (Fig. 2). The principal error components are considered; noise, bias and scale factor are taken into consideration applying the necessary modifications to the model.

Test trajectories were used to check how the process improves accuracy. The van was driven along these paths which included straight lines, soft curves, round-abouts and a tunnel as well, to test for different accelleration conditions along the two axes parallel to the plane along movement.

GPS was set at 1 Hz, while the MEMS were set at 120 Hz. The GPS data was post-processed with the IMU information. The application of the filtering on the model plans to improve the positioning accuracy of the uncorrected GPS data. A simulation was also made to assume a loss of GPS coverage to see the performance of the system in this kind of situation.



The first processing method deals with the MEMS position and orientation; to solve the problem of these unknown elements the six position static test was done (Titterton and West, 2004). In this procedure the elements are placed orthogonal to each other and they are tested along a known trajectory. The operation is done several times rotating the cube so that each face covers the six possible sides.

In order to estimate the orientation and position of the van between and at each collected GPS point, we employed the prediction-update strategy of the Extended *Kalman* filter (El-Sheimy et al., 2006).

MATHEMATICAL MODEL

The coordinate systems involved are the MEMS reference frame, the GPS antenna center which defines another reference frame, the moving van's frame (inertial frame) and the mapping frame. Since the components (MEMS, GPS and van) are together in a rigid frame, an univocal relationship can be established between them (Σ_c) and a unique reference frame called the inertial frame (Σ_i), whereas the world frame (Σ_w) is the coordinate system we want our data to be in. To obtain our final data in 3D data the following operations have to be done:

1) Compute the van dynamic data in inertial frame (Σ_i) by rototraslation from MEMS frame and GPS frame of respective data (Σ_c), $\mathbf{r}_i^r(t) = \mathbf{r}_c^r + \mathbf{R}_c^r \cdot \mathbf{r}_c^r(t)$ (1)
2) Compute the van's position in the mapping frame (Σ_w) by rototraslation from inertial frame (Σ_r), $\mathbf{r}_i^m(t) = \mathbf{r}_r^m(t) + \mathbf{R}_r^m(t) \cdot \mathbf{r}_i^r(t)$ (2) The whole georeferencing process can be summarized by following relationship:

mmmr rc

$$\mathbf{r}\,(t) = \mathbf{r}\,(t) + \mathbf{R}\,(t) \cdot \left[\mathbf{r}\,(t) + \mathbf{R} \cdot \mathbf{r}\,(t)\right] \quad (3)$$

ir rcci The adopted kinematic model describes the vehicle trajectory in terms of state vectors represented by time dependent positional vectors, as derived from discrete-time measurements:

$$\begin{bmatrix} \dot{\mathbf{r}} \\ \dot{\mathbf{v}} \\ \dot{\mathbf{a}} \end{bmatrix} = \begin{bmatrix} \mathbf{v} \\ \mathbf{a} \\ 0 \end{bmatrix} \qquad \mathbf{r}(t) = \left\{ x(t), y(t), z(t) \right\} \quad (4)$$

This model can be applied in different operating modes, employing as state vectors whether pseudo-range or carrier phase observables, as collected by only one receiver or with differential corrections. Note that (4) represents a constant acceleration model, in which vectors *v* and *a* incorporates the linear and angular components.

In order to take into account the error introduced by our unique positioning device (GPS) we use following formula:

$$\dot{\mathbf{s}}(t) = \mathbf{f}\left\{\mathbf{s}(t); t\right\} + \mathbf{w}(t) \quad (5)$$

where

- **s**(t) is the state vector;
- **f**(t) describes mathematically the nonlinear relationship between parameters in **s**(t) and the process;
- **w**(t) models sensor (rover receiver) systematic errors, which are considered as white Gaussian noise with covariance **Q**. In order to determine the components of **s**(t), kinematic measurements are employed according to the formula below:

$$\mathbf{z}_k = \mathbf{H} \cdot \mathbf{s}(t) + \mathbf{n}_k \quad (6)$$

where

- $\mathbf{z}_k$ measurements vector collected at discrete time t_k;
- **H** matrix of measuring states;
- $\mathbf{n}_k$ measurement Gaussian error with covariance **R**.

Since the Extended Kalman Filter (EKF) represents the optimal estimate procedure in case of uncorrelated measurements and Gaussian noise with null average, the employed algorithm can be summarized by following formulas:

• Prediction step,

$$\hat{\mathbf{s}}(k+1 \mid k) = \mathbf{f}_k^d(\hat{\mathbf{s}}(k \mid k)) \quad (7)$$

$\mathbf{P}(k+1|k) = \Phi(k|k) \cdot \mathbf{P}(k|k) \cdot \Phi(k|k)' + \mathbf{Q}(k)$ (8)

• Update step,

$\Lambda(k+1) = \mathbf{H} \cdot \mathbf{P}(k+1|k) \cdot \mathbf{H}' + \mathbf{R}$ (9)

$\mathbf{L}(k+1) = \mathbf{P}(k+1|k) \cdot \mathbf{H}' \cdot \Lambda(k+1)^{-1}$ (10)

$$\hat{\mathbf{s}}(k+1|k+1) = \hat{\mathbf{s}}(k+1|k) + \mathbf{L}(k+1) \cdot \ldots \cdot \left[\mathbf{z}(k+1) - \mathbf{H} \cdot \hat{\mathbf{s}}(k+1|k) \right] \quad (11)$$

$$\mathbf{P}(k+1|k+1) = \left[\mathbf{I} - \mathbf{L}(k+1) \cdot \mathbf{H} \right] \cdot \mathbf{P}(k+1|k) \cdot \ldots \cdot \left[\mathbf{I} - \mathbf{L}(k+1) \cdot \mathbf{H} \right]' + \mathbf{L}(k+1) \cdot \mathbf{R} \cdot \mathbf{L}(k+1)' \quad (12)$$

where in (11) $\hat{\mathbf{s}}(k+1|k)$ is the new estimate at step (k+1), as derived by update $\hat{\mathbf{s}}(k|k)$ at time step k and discretized function $\hat{\mathbf{f}}^{d}_{k}(\cdot)$ (see 4.1), obtained from nonlinear relationship (6) without error $\mathbf{w}$(t); in (12) $\mathbf{P}(k+1|k)$ is the covariance matrix of *a priori* prediction error, Φ(k|k) is the fundamental matrix related to linear system $\dot{\xi} = \mathbf{F}(\mathbf{s}(t)) \cdot \xi$ and $\mathbf{Q}$(t) is the covariance matrix of discretized error $\mathbf{w}$(t), both reported in subsection 4.2; in (10) $\mathbf{L}$(k+1) is the gain matrix of the filter; in (11) $\hat{\mathbf{s}}(k+1|k+1)$ is the new update at time step (k+1); finally in

(16) $\mathbf{P}(k+1|k+1)$ is the *a posteriori* estimate error covariance.

In the prediction step, unlike the EKF theory, which states to solve the differential equation

$\dot{\mathbf{s}}(t) = \mathbf{f}(\mathbf{s}(t))$ $\mathbf{s}(t_k) = \hat{\mathbf{s}}(k|k)$ (13)

to compute the predictor

$\hat{\mathbf{s}}(k+1|k) = \hat{\mathbf{s}}(t_{k+1})$ (14)

we employ the discrete scheme below, which yields the discretized form in (7) of the predictor itself:

$$\mathbf{s}(k+1) = \mathbf{f}_d^{\,k}(\mathbf{s}(k)) = \mathbf{s}(k) + (t_{k+1} - t_k) \cdot \ldots \frac{(t_{k+1} - t_k)^2}{2} \qquad (15)$$

$$\cdot\, \mathbf{f}\,(\mathbf{s}(k)) + \cdot\, \mathbf{f}\,(\mathbf{s}(k))$$

RESULTS AND ANALYSIS

The application of the various rototranslation matrices on the MEMS data gave a singular vector matrix for the acceleration information. The acceleration in the three directions is easily de-noised with a low-pass filter (Fig. 3).

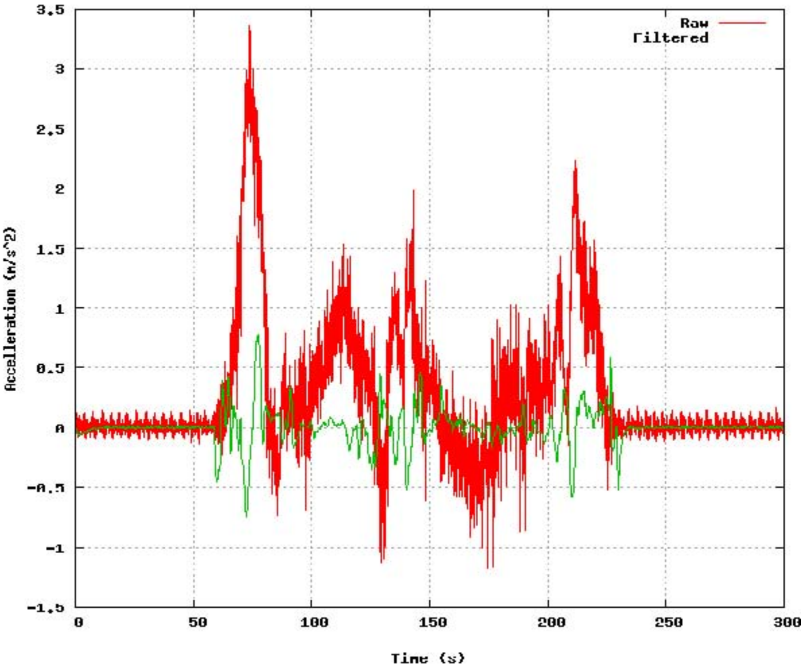


Fig. 3: Accelleration in the X direction before and after low pass filter

Different test schemas have been carried out, and more are planned on the future. For space sake only important results are analyzed. The schemas are the following:

- Straight line (150 m)
- Straight line (150 m) with GPS signal loss error
- Straight trajectory with roundabout
- Soft curve trajectory
- Soft curve trajectory with GPS signal loss error
- Complex trajectory with straight line + roundabout + soft and narrow curve

– Complex trajectory with straight line + roundabout + soft and narrow curve with GPS signal loss.

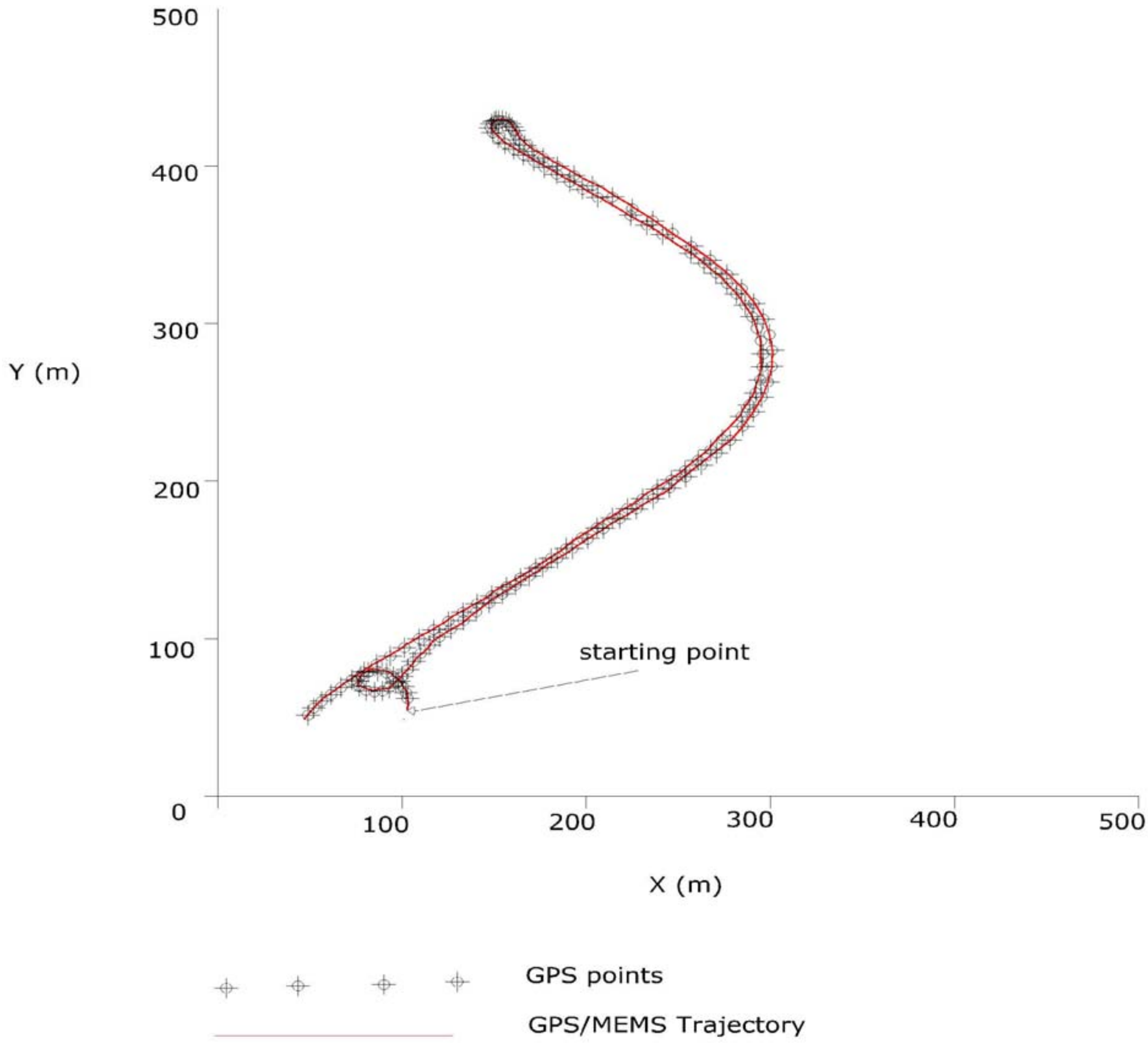


Fig. 4: TTrajectories with GPS/MEMS as opposed to GPS/INS without loss of GPS

The tests shown below are the last two listed above: with and without GPS signal loss (fig. 4 and fig. 5). It is evident that GPS data can correct efficiently the drift from the MEMS if there is significant coverage over time (at least 1 Hz). A loss of position data for more than one second has a significant effect on the correction of the MEMS. Sensor redundancy helps to have robust trajectory data by compensating the systematic error. Loss of GPS signal for 30 seconds (fig. 5) worsens considerably the trajectory calculation of the algorithms. The drift compensation is lost, but there is a significant path reconstruction even if accuracy is quite low. As is mentioned in the conclusion statement further work is to be done on position reconstruction and error compensation.

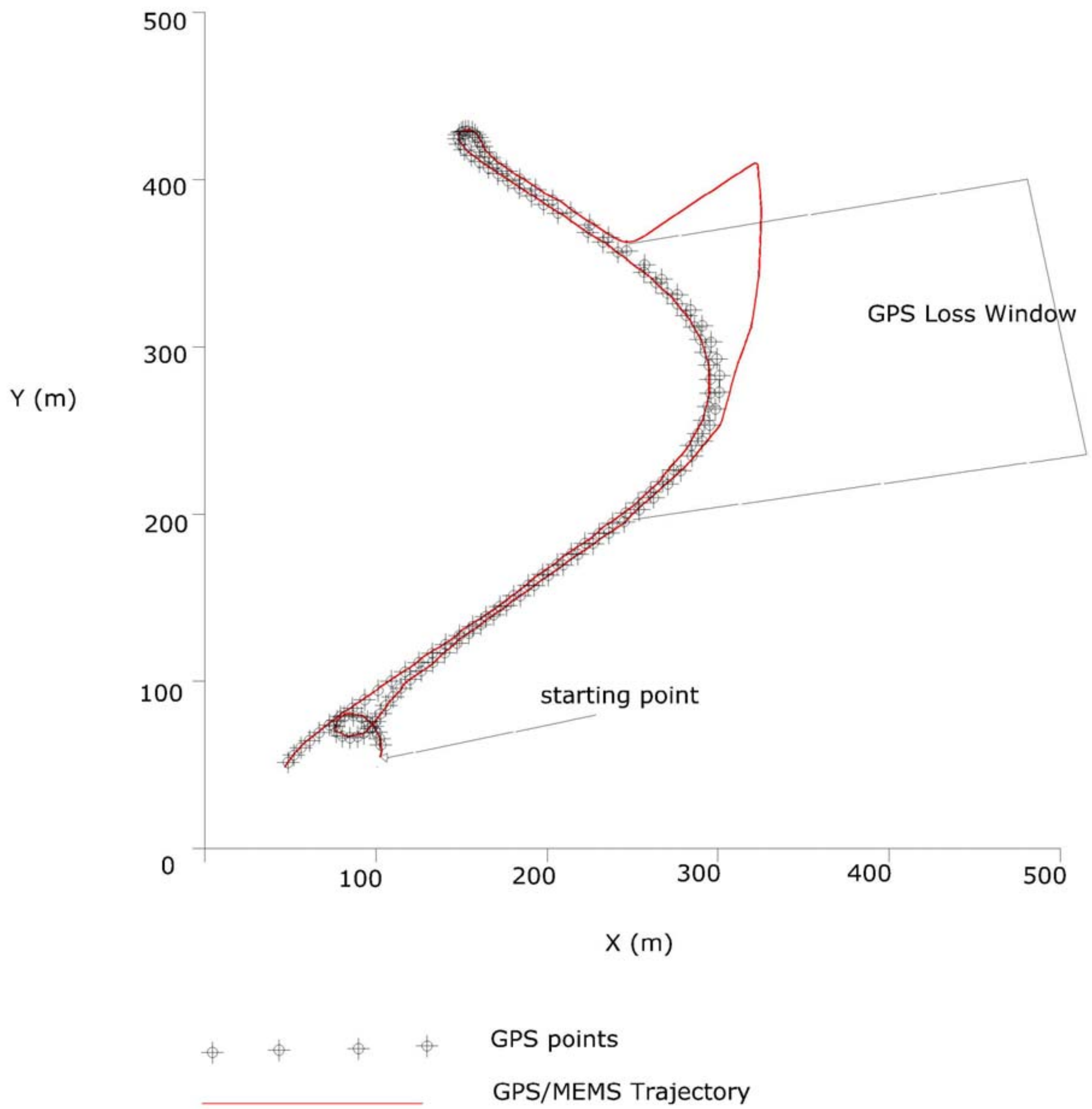


Fig. 5: Trajectories with GPS/MEMS as opposed to GPS/INS with loss of GPS

CONCLUSIONS

The algorithm implemented for the trajectory recontruction had a positive test result. The outcome of results confirms that a set of MEMS with adeguate data-fusion of GPS data can be considered an interesting alternative to traditional GPS/INS systems. The data which was collected proves a significant increase in accuracy of position and orientation information when there is a constant input of GPS signal. When signal is lost for about 10 seconds, the precedure keeps a trajectory with correct shape, but for longer time spans its results show go off course significantly. It is still interesting to assess behavior of low cost systems compared to more expensive equipment. Introducing low cost sensors which give direction and accelleration permit algorithm to decrease trajectory recoststruction error. The algorithm for position detection and sensor orientation of MEMS is robust when confronted with the MEMS errors. Future research consists of:

- removing the restrictive hypothesis on the analysis of error compensation algorithms for roll and pitch measurements extracted from MEMS,
- usage of adaptive techniques such as the Unscented Kalman Filter, Wavelet and Bayesian Filters (Shin and Naser, 2007) to increase position accuracy,
- integration of a positional variable in the algorithm.

Doing all of the above will give significant input to the algorithm providing an autocalibration procedure which increases accuracy.

REFERENCES

El-Sheimy, Nasser, Shin, S., Niu, X., 2006, Analysis of Varius Kalman Filter Algorithms with Different Inertial Systems for INS/GPS Integrated Systems, CASJ The Canadian Aeronautics and Space Journal, V. 52 n. 2, pp. 59-67.

El-Sheimy, N., Sameh Na., Ahoelmagd N., 2004, Wavelet Denoising for IMU Alignment, IEEE A&E Systems Magazine, October 2004 pp. 32-39.

El-Sheimy, N., 2003, Inertial Techniques and INS/DGPS Integration, Calgary.

Shin, E-H.,El-Sheimy Naser, 2007, Unscented Kalman Filter and Large Attitude Errors in Inertial Navigation Systems, Navigation, Journal of the US Institute of Navigation (ION), Vol. 54 No. 1, pp. 1-9.

Shin, Eun-Hwan, 2001, Accuracy Improvement of Low-Cost INS/GPS for Land Applications, Department of Geomatics Engineering University of Calgary, PhD Thesis.

Tan C.W., ParkS., Mostov K., Varaya Pl, 2001, Design of Gyroscope-Free Navigation Systems, Proceedings of IEEE Intelligent Transoportation Systems Conference, Oakland (CA), USA, August 2001.

Titterton, D.H., Weston J.L., 2004, Strapdown Inertial Navigation Technology. Second edition. American Institute of Aeronautics and Astronautics IEE.

Wan, E. A. and var der Merwe, R., 2000, The unscented Kalman filter for nonlinear estimation, Proceedings of Symposium on adaptive Systesms for signal processing, communications and control, Lake Louise, Alberta, Canada.

CONTACTS

Antonio Vettore and Alberto Guarnieri work at CIRGEO – Interdepartmental Research Center of Geomatics at the University of Padua, Italy. Viale dell'Università 16 – 35020 Legnaro (PD) – Italy. Phone +39 – 049 -8272522, fax. +39 – 049 -8272686, email cirgeo@unipd.it – antonio.vettore@unipd.it.

Francesco Pirotti works at TESAF, Department of Land Management at the University of Padua. Viale dell'Università 16 – 35020 Legnaro (PD) – Italy. Phone +39 – 049 -8272710 email francesco.pirotti@unipd.it.

Andrea Menin works at DAUR, the Department of Architecture and Urbanistics and Surveying at the faculty of Engineering of the University of Padua. Via Marzolo 9 – 30100 Padova – Italy. Phone +39-049-8275581.