A Fuzzy Controller for GPS/INS/Odm Integrated Navigation System

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Abstract: Navigation technology has an important role in designing intelligent vehicles and advanced robots. To have a continuous navigation solution that does not suffer from interruption, GPS (Global Positioning System) data is merged with relative positioning techniques such as inertial navigation system (INS) or odometry (Odm). To accomplish the reliability and integrity desired, it is therefore necessary to take into account physical capabilities and limitations of each sensor during navigation. A fuzzy switcher controller (FSC) is well suited for this task. FSC is an Expert rule-based method for choosing the best fusion from multiple redundant integration methodologies (GPS/INS, GPS/Odometry, Odometry/INS or GPS/INS/Odometry) based on navigation conditions and accuracy of the navigation systems.

1 INTRODUCTION

Road navigation systems are one of the main field of interest in the intelligent transport domain such as advanced driver assistance, route guidance or traveller information which require a Road Side Equipment (RSE) able to provide an accurate position at low price (Boysen,2004). The commonly used sensors in these applications may be divided into two categories, external sensors and Dead Reckoning Sensors (DRS) such as Inertial Navigation System (INS) and Odometry.

The common external sensors for land vehicle positioning are satellite navigation systems such as Global Positioning Systems (GPS). However, in GPS-denied environments (tunnels, canyons urban) the GPS satellite signal is not often available. Hence the positioning information provided is not accurate. To achieve continuous navigation solution even during GPS outages, the GPS is augmented with dead reckoning sensors.

Inertial Navigation Systems and Odometry have always been presented as valuable sensors in many applications. Their advantages are well known: high update rates; position and heading accuracy in short time. However, Combining odometry with INS which is called in the literature "Reduced Inertial Sensor System –RISS- (North, 2012)" can enhance the positioning accuracy compared to INS or odometry alone. Indeed, odometry and INS have, to some degree, complementary characteristics: INS can provide the heading/attitude information (Xiaochuan, 2009), while odometry can remarkably limit the position error accumulation of INS with respect to time. To design more precise systems, external sensors are usually integrated with dead reckoning sensors taken on many forms, such as GPS/INS integration, GPS/Odm integration or integrating the three sensors together (GPS/RISS) (North, 2012). This latter gives the best solution when the three sensors are used in best conditions. In the case of failure of one of them the position accuracy decreases (North, 2012).

To accomplish the best reliability and integrity desired, it is therefore necessary to choose which sensors integration gives the best result. A Fuzzy Logic based on expert rules derived from careful observations of the physical functioning of each sensor is certainly required to process the available data. The algorithms must provide fault detection and data fusion capabilities to make the best use of the available information (Xiaochuan, 2009), (Singhala, 2014).

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To fuse information coming from sensors different approaches can be found in the literature. Many of them rely on the implementation of an Extended Kalman Filter (EKF) (Boysen, 2004), (Boucher, 2004), (Hay, 2005), (Sukkarieh, 2000). The performance of the EKF is reliable in many practical situations, but the non-linear state equations may lead to instability problems. Other filtering methods can be found in the literature, such as the Unscented Kalman Filter (St-Pierre, 2004) and particle based solution (Boucher, 2004).

This paper aims to develop an experimental approach of GPS/INS/Odometry data fusion that uses fuzzy rule-based system. It is divided into four (4) main sections. Section 2 presents different integration methodologies (GPS/INS, GPS/Odometry, GPS/INS/Odometry and Odometry/ INS integration) and a brief description of Fuzzy Switcher. Finally section 3 presents the results and discussion with a hardware implementation. A conclusion is given in Section 4.

2 INTEGRATION ALGORITHMS

The concept of integrating GPS and dead reckoning sensors (INS or Odometry) has been well discussed in the research community. Different integration strategies have been developed and tested with different grades of INS. Typically; three main strategies are used, namely loose integration, tight integration and ultra-tight (or deep) integration. We have chosen the loose coupling integration scheme with close-loop. This schema lets control the navigation accuracy and reduce the cost of design (Sakhi, 2014).

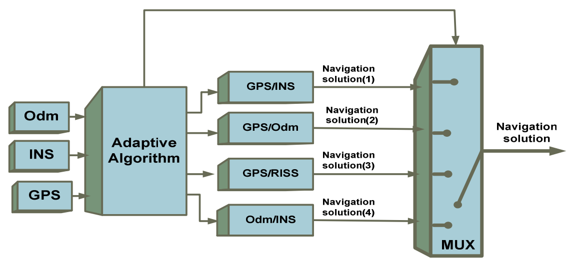

Figure 1: Architecture of proposed integrated GPS/INS/Odm system.

The implemented algorithms consist of four (4) filters. The first filter fuses the INS and GPS measures, the second filter fuses the odometry and GPS measures, and the third filter fuses odometry and inertial data, while the fourth filter fuses the three sensors data together. Then, an adaptive algorithm, based on signal degradation conditions of the different navigation systems, is used to choose the best combination that gives the best navigation solution. These algorithms are summarized in the following diagram (Figure 1).

Kalman filter is a suitable filter used to integrate sensors information. The prediction step, of the used filter, is based on a kinematics model of motion. Because of the non-linearity of the process model, we have used an EKF filter.

The Extended Kalman filter (EKF) proceeds by linearizing the model about the latest estimate to meet the Kalman Filter assumptions (Boucher, 2004). EKF is summarized by the flow chart showed in Figure 2.

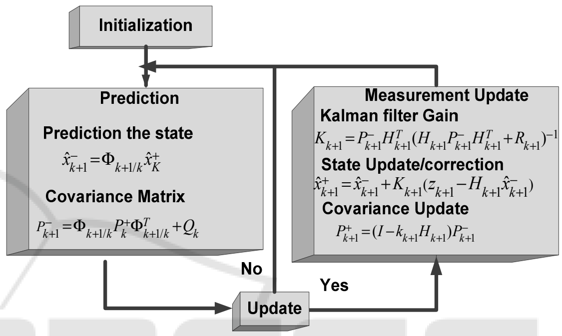

Figure 2: Kalman Filter Algorithm.

x_k : state vector of the process at epoch t_k,
z_{k+1} : actual observation,
$\Phi_{k+1/k}$: state transition matrix from time t_k to t_{k+1},
R_k, Q_k : measurement and process covariance matrix,
P_k : error covariance matrix,
K_{k+1} : Kalman gain matrix,
z_{k+1} : observation matrices,

Where $\hat{x}^+_k$, $\hat{x}^-_k$ represent a prior and a posterior estimated state vector.

The implemented algorithms consist of an Extended Kalman filter of 5-states including position, velocity, and angular velocity in two (2) dimensions for GPS/INS integration. However, for both INS/Odm and GPS/RISS integration we have used a Kalman filter of 3-state. The three integrated algorithms are summarized in the following.

2.1 INS/GPS Integration Algorithm

Several techniques are proposed in the literature for inertial and GPS fusion (Xiaochuan, 2009), (Quinchia, 2011), (North, 2009). We have chosen the loose coupling integration scheme with close-loop, as shown in Figure 3, in order to reduce inertial unit errors. This has implications for inertial units of low and medium precision (Sakhi, 2014).

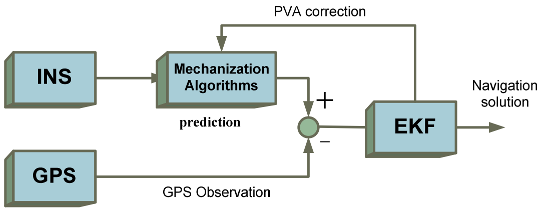

Figure 3: Loose coupling integration scheme (INS/GPS).

We have used the kinematics model which is defined by the following equations (Kubrak, 2007) instead of using dynamics model of a robot in order to reduce the complexity of calculations.

$$\begin{aligned}
x_m(k+1) &= x_m(k) + T_e \dot{x}_m(k) + 0.5T_e^2 a_{x.m}(k) \\
\dot{x}_m(k+1) &= \dot{x}_m(k) + T_e a_{x.m}(k) \\
y_m(k+1) &= y_m(k) + T_e \dot{y}_m(k) + 0.5T_e^2 a_{y.m}(k) \\
\dot{y}_m(k+1) &= \dot{y}_m(k) + T_e a_{y.m}(k) \\
\theta_m(k+1) &= \theta_m(k) + T_e \dot{\theta}_m(k)
\end{aligned} \quad (1)$$

2.2 Odometry/GPS Integration Algorithm

Many techniques are proposed for integrating Odometry with GPS (Lamon, 2004). We have chosen a loose coupling integration scheme with close-loop, where the state feedback PVA (Position, Velocity and Attitude) correction to the Odometry system, as shown in Figure 4 in order to reduce scale factor errors.

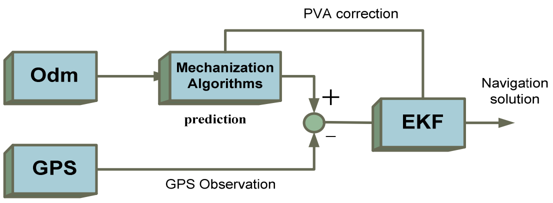

Figure 4: Loose coupling integration scheme (GPS/Odm).

The motion model equations that transform odometer measures in the navigation frame are equations expressing the predicted function:

$$\begin{aligned}
x(k+1) &= x(k) + T_e V(k)\cos(\theta(k)) \\
y(k+1) &= y(k) + T_e V(k)\sin(\theta(k)) \\
\theta(k+1) &= \theta(k) + T_e \frac{V(k)}{L}\tan(\phi(k))
\end{aligned} \quad (2)$$

Where this state is defined by the coordinates of its center M and the angle θ relative to x, the velocity V of the center based on the average wheel speeds and the steering angle of wheels ϕ.

2.3 RISS/GPS Integration Algorithm

The concept of RISS (Reduced Inertial Sensor System) was used in vehicle navigation in order to further higher the accuracy of the positioning solution. The RISS used in (North, 2009) involves a single-axis gyroscope and the vehicle odometer model to provide 2-D navigation solution , with the assumption that the vehicle mostly stays in the horizontal plane.

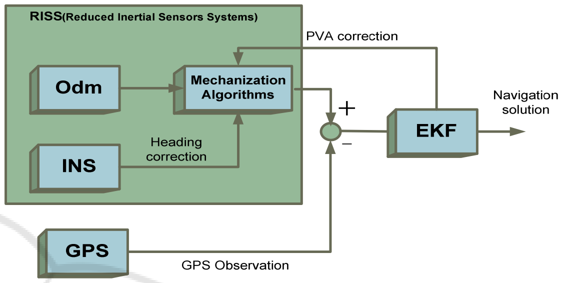

Figure 5: Schematic diagram of the RISS/GPS Integration.

The discrete form of Mechanization equations is:

$$\begin{aligned}
x(k+1) &= x(k) + T_e V(k)\cos(\theta(k)) \\
y(k+1) &= y(k) + T_e V(k)\sin(\theta(k)) \\
\theta(k+1) &= \theta(k) + T_e Wz
\end{aligned} \quad (3)$$

Where Wz is the gyroscope measurement (rate of turns) in radium/second.

2.4 Odometry/INS Integration Algorithm

Different configurations are proposed in the literature (North, 2012), (Rogers, 2012) for integrating Odometers and INS. In (North, 2012), N. Eric used an IMU and the information delivered by odometry as measurement update of the Kalman filter .

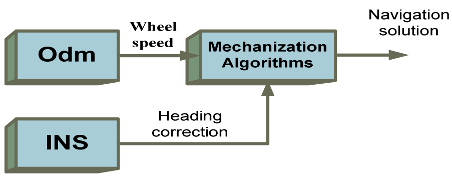

Figure 6: Schematic diagram of the Odm/INS Integration.

In our work, after testing several methods we have chosen the RISS configuration which gives a good positioning accuracy with simple integration strategies without the need of filter. The system model based on inertial and Odometry data is depicted in (Figure 6).

2.5 Fuzzy Switcher Controller (FSC)

When designing a fusion system, we must take into consideration the multi-rate sensor data collection, and implement the integration algorithm appropriately. Here, the term "fusion" refers generally to the process of combining three sets of measures to produce a consistent solution. That is, we need to fuse odometry, inertial and GPS data when all sensors perform well, but in the case of a sensor failure, which may lead to degradation of overall system performance, we have to eliminate its use.

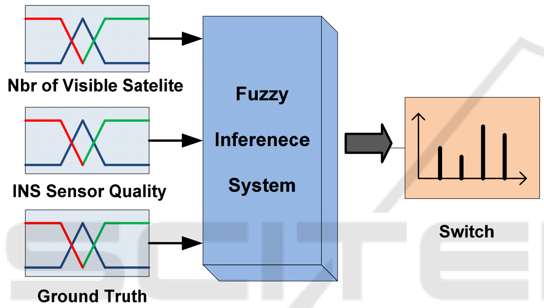

Figure 7: Architecture of the fuzzy logic data classification system.

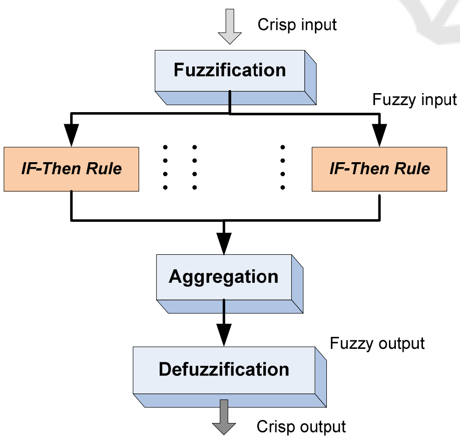

Figure 8: Block diagram of the fuzzy inference system (Wang, 2006).

A fusion algorithm that takes into accounts the physical capabilities and limitations of each sensor is therefore necessary. A Fuzzy Logic is well suited for this task. The down-mentioned expert rule-based method for choosing best fusion result from multiple redundant algorithms can help in selecting the most accurate fusion algorithm. Our fuzzy algorithm uses three fuzzy membership function inputs and one output, as shown in Figure 7.

In a typical fuzzy system (Figure 8) the crisp inputs are first converted to the input fuzzy sets using the membership functions. Then, the input fuzzy sets are mapped into a consequent fuzzy set based on the adopted fuzzy logic operators, if-then rules and aggregation strategy. Finally, the consequent fuzzy set is converted into a scalar quantity as the system output using a defuzzification method.

2.5.1 Fuzzification Interface

It transforms crisp data (GPS data, Ground Truth, and sensor's data quality) into fuzzy sets. The assignment of membership values to fuzzy variables are based on experimental testing and logical operations. For a computational simplicity, the triangle membership function (equation 4) , shown in Figure 9, is used.

$$f(x)=\begin{cases} \dfrac{x-a}{b-a}, a<x\leq b \\ \dfrac{c-x}{c-b}, b<x\leq c \\ 0, otherwise \end{cases} \tag{4}$$

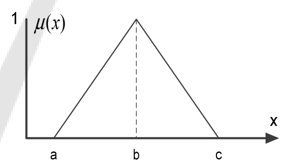

Figure 9: Trapezoidal fuzzy membership function.

<u>Path Condition Fuzzification:</u> It is beneficial to know if a robot (or vehicle) is crossing sandy surfaces in order to eliminate the use of odometers and reduce positioning errors. For the detection of sandy surfaces, the robot literally bounces on the ground when the rear bogie wheels go through rough terrain. Shocks occurring during the experiment are easily identified when looking at the roll angel variation. The equations used to calculate roll from accelerometers are based on the idea presented in (Kubrak, 2007).

$$\phi=\tan^{-1}\left(\frac{a_y}{a_z}\right) \tag{5}$$

$where:\ a_y, a_z$ are the accelerometer readings.

An effective method for estimating the ground truth is to calculate the current roll angle of the land vehicle displacements. The Variation of this angle is beings used to select the appropriate fuzzy decision to the navigated terrain.

In our case the roll angle is the mean computed for a period of 1 second (which corresponding to 40 samples of odometer's data). After experiments test we have assigned our membership function of path condition as shown in Figure 10.

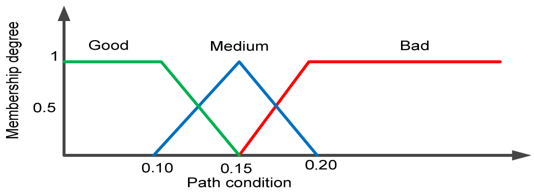

Figure 10 : The first input variable (Path Condition).

Number of Satellite Fuzzification: The second input (Figure 11) represents the number of satellites. As we have seen in experiments, RISS outperforms all the other compared solutions when the number of visible satellites is less than tree (3). Furthermore, the RISS solution provides very good results, compared to IMU or Odometer alone. So it is very important to detect degradations of GPS signal to use RISS for position estimation.

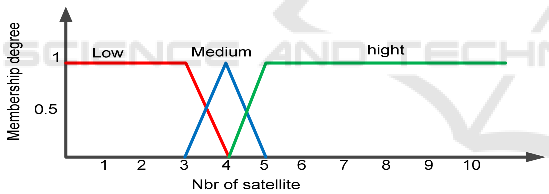

Figure 11: The second input variable (number of satilites).

IMU's Data Quality Fuzzification: Our fusion algorithm takes into account the physical capabilities and limitations of each sensor.

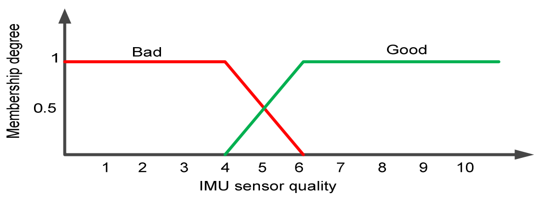

Figure 12: The third input variable (number of satellites).

Therefore, it is necessary to determine the quality of IMU data during experiments. Since we are looking to produce a simple and flexible algorithm suitable for any IMU quality, we took into account this point by giving users the possibility to predefine the quality of the IMU before starting experiments. Users can a score from 0 (very bad) to 10 (good), as shown in Figure 12, based on the bias and scale factor of the used inertial navigation sensor.

2.5.2 Inference System

To describe the relationship between the input and the output, a set of rules is applied as shown in Table 1. The fuzzy rules are derived directly from the three basic rules defined at the beginning of this section and they cover all possible combinations of input variables.

Table 1: If-then rules used in the fuzzy inference system for data classification.

	Inputs			Output
N.	NVS	PAC	SQ	SW
1	Low	Low	Bad	**INS/Odm**
2	Low	Low	Good	**INS/Odm**
3	Low	Med	Bad	**INS/Odm**
4	Low	Med	Good	**INS/Odm**
5	Low	High	Bad	**INS/Odm**
6	Low	High	Good	**INS/Odm**
7	Med	Low	Bad	**GPS/INS**
8	Med	Low	Good	**GPS/INS**
9	Med	Med	Bad	**GPS/INS**
10	Med	Med	Good	**GPS/INS**
11	Med	High	Bad	**GPS/Odm**
12	Med	High	Good	**RISS**
13	Med	Low	Bad	**GPS/INS**
14	High	Low	Good	**GPS/INS**
15	High	Med	Bad	**GPS/Odm**
16	High	Med	Good	**GPS/INS**
17	High	High	Bad	**GPS/Odm**
18	High	High	Good	**RISS**

NVS*:** Nbr of visible satellites, ***PAC: path condition
SQ: sensor quality, ***SW:*** *S*witch data fusions.

2.5.3 Defuzzification Interface

Several popular methods exist for defuzzification such as max-membership principle, centroid method, weighted average method, centre of sums (Singhala, 2014). In our algorithm, the result of the defuzzification has to be a single value that determines which sensors integration is used to give the best results, as shown in Figure 13.

In our case, outputs of the fuzzy fusion system, SW (switch) are dimensionless weighting factors that emphasize either the 1st (GPS/INS), 2nd (GPS/Odm), 3rd (GPS/RISS) or 4th (RISS) solution is the best in terms of accuracy. The weighted average defuzzification technique is the most prevalent and widely adopted defuzzification method. The centroid method is given by the following algebraic expression:

$$Defuz = \frac{\sum_{i=1}^{18} P[i] \times W[i]}{\sum_{i=1}^{18} W[i]} \quad (6)$$

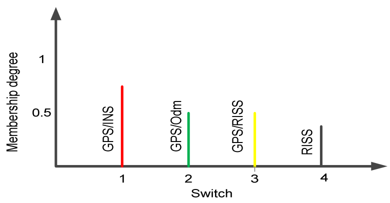

Figure 13: The output variable (Switch).

3 RESULTS AND DISCUSSION

In order to evaluate the FSC performances, several driving were performed using data of a driving simulator framework called Virtual Robot Experimentation Platform (V-REP). The V-REP is a very versatile and ideal for multi-robot applications. This software is an open source for use in research or academic environments which can model dynamics of several robots (Tharin, 2012).

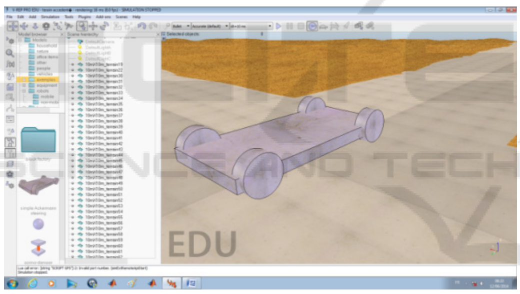

Figure 14: Screen shot of V-REP's application main window.

We have used a Simple Ackermann steering mobile robot. It has four-wheel drive and a steered locomotion system. The sensor part includes two encoders measuring rear wheels rotation at 20Hz. The system provide also GPS (1HZ) data and inertial (acceleration and gyroscope) at 40Hz.

3.1 Evaluation of Algorithms during GPS Outages

This section aims to evaluate the "standalone" performances of the different integrations by simulating a long GPS outage in sensor's data acquisition. During a period without GPS signal, no updates are performed. The resulting trajectory is built using only the prediction. Therefore, difference in terms of positions is well highlighted.

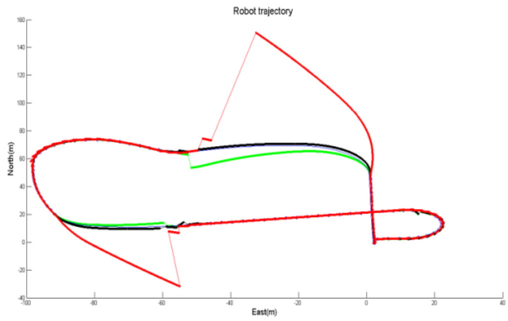

Figure 15: Estimated and reference trajectories: bleu for reference, Red for GPS/INS, Green for GPS/Odm, black for the GPS/RISS integration.

Table 2 presents difference in terms of position, resulting from a comparison of trajectories computed with the various GPS outages. These divergences are expressed using Root Mean Square (RMS). The maximum differences is also listed. Note that these different integrations are computed using only the trajectory differences during the outages.

Table 2: Comparison of trajectories computed with GPS outages of various duration. (5 s and 10 s).

		First GPS outage for 10s			Second GPS outage for 5s		
		GPS/INS	**GPS/Odm**	**GPS/RISS**	**GPS/INS**	**GPS/Odm**	**GPS/RISS**
East errors (m)	***Max***	16.25	1.21	3.42	4.11	1.50	2.11
	RMS	10.85	0.64	3.64	1.12	0.16	0.85
North errors (m)	***Max***	70.23	11.26	2.05	43.29	2.41	1.55
	RMS	24.28	6.04	1.32	11.72	1.48	0.69

Outages of short duration (5 seconds) are well bridged by the Odometry navigation system. Indeed, the maximum position deference ranges from 1.5 m to 11 m. But the range of errors proportionally increases with the GPS outages duration due to accumulation of errors which appears clearly in the first case when the outages is 10s. Moreover, the position accuracy of a GPS/RISS trajectory ranges from 1 m to 3 m. These results show that the reduced inertial navigation system (RISS) is able to bridge GPS outages of long duration or short duration with best position accuracy.

3.2 Evaluation of Fuzzy Switcher Controller

Several experiments with GPS outages and rough terrain condition, using good and bad quality of

IMU, were processed to evaluate FSC performances. We did a comprehensive set of tests in V-REP using different speeds varying between 5-25 m/s. The deferent characteristics, i.e. the RMS, and the max are well presented.

The trajectory used for this evaluation is similar to the applied in section A. Here, we introduced a variation in the number of satellites (on view) to see the functionality of the FSC during GPS signal degradation. However, we have simulated four GPS outages as shown in Figure 17.

The potential parameter used to detect the surface condition is computed from the variance of the roll angle using 40 last samples of the acceleration corresponding to 1s which is the frequency of GPS, as mentioned before. The rough terrain is easily detected as show in the Figure 16.

In the down-mentioned simulation results we have presented only the case of a medium Quality of inertial navigation system. However, we have given a mark of “6”. Figure 18 shows the output of Fuzzy switcher controller. Hence we are using an IMU with a good quality, the FSC switches to GPS/RISS during good surface and good GPS signal, but when the vehicle go by a rough surface the FSC eliminates the use of odometers measures by switching to GPS/INS. The same case is produced during GPS signals degradation. The FSC eliminate the use of GPS by switching to RISS.

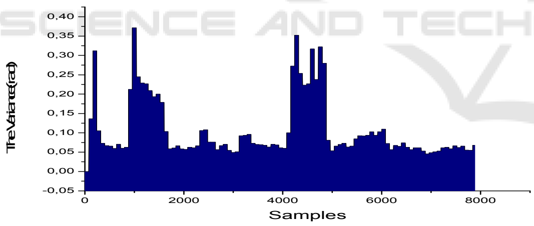

Figure 16: Variance of the roll angle during trajectory.

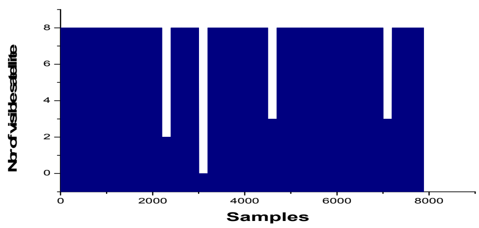

Figure 17: Variation of number of satellites.

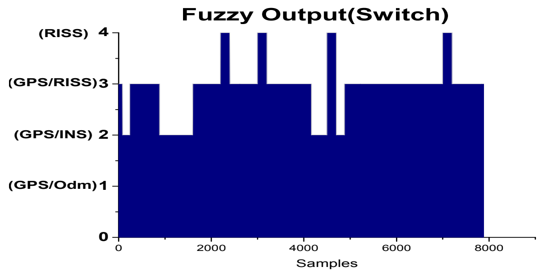

Figure 18: Outputs of the FSC during trajecory.

Figure 19 shows the estimated trajectory of the robot and the ground truth during the simulation. The trajectory is portion-colored to easily see the different integrations used during the trajectory.

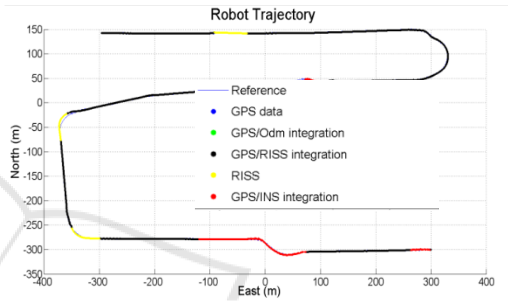

Figure 19: Trajectory plot using FSC.

Simulation results (Figure 20 and Figure 21) clearly show the advantage of FSC over GPS/RISS, GPS/Odm and GPS/IMU. However there is a big difference in 2-D positional errors when we compare GPS/INS and GPS/Odometry with results of FSC integration during GPS outages. This later has an average of the maximum positional error off 3m as shown in Table 4.

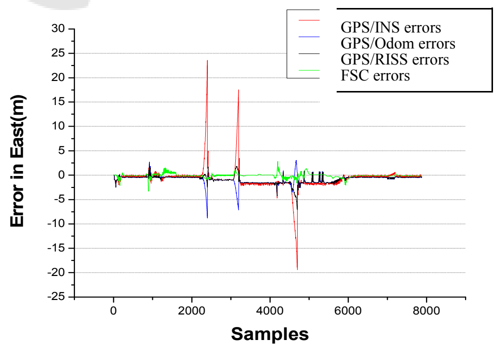

Figure 20: East position Error computed by different integrations.

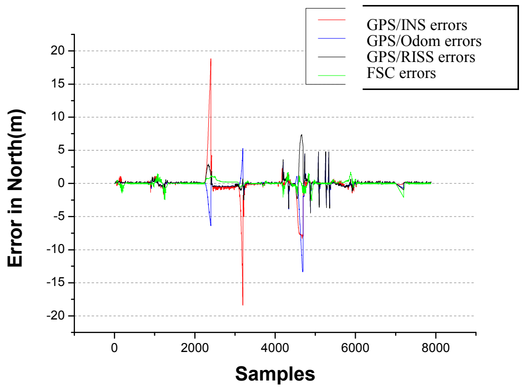

Figure 21: North position error computed by different integrations.

Table 3: Simulation measurements.

		Errors during GPS outages			
Outage .N°		**1**	**2**	**3**	**4**
Duration (s)		**10**	**10**	**10**	**10**
East errors (m)	***Max***	2.709	2.801	4.617	1.565
	RMS	1.969	1.778	2.042	0.547
North errors (m)	***Max***	3.070	3.299	3.188	1.011
	RMS	2.159	1.188	1.588	0.996

4 CONCLUSIONS

In this paper we introduced a Fuzzy Switcher Controller (FSC) for navigation systems. Several methodologies of integrating inertial sensors, Odometry and GPS data using a loosely coupled integration techniques are also presented. Results show that the Fuzzy switcher controller has a powerful adaptability to physical capabilities and limitations of navigation systems which improves the navigation positioning accuracy. Compared to others integration methods, the new position errors are controlled within ± 3m even during a GPS outages or a rough terrain condition.

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