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Robust Special Strategies Re sampling for Mobile Inertial Navigation Systems

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Abstract*: *The mobile navigation services in an obstructed area can be extremely challenging especially if the Global Positioning System (GPS) is blocked. In such conditions, users will find it difficult to navigate directly on-site. This needs to use inertial sensor in order to determine the location as standalone, low cost and ubiquity. However, the usage of accurate inertial sensor and fast localization module in the system would lead the phenomenon of sample impoverishment, which it is contribute computation burden to the system. There are different situation of the sample impoverishment, and the solution by using special strategies resampling algorithm cannot be used or fitted in different cases in altogether. Adaptations relating to particle filtering attribute need to be made to the algorithm in order to make resampling more intelligent, reliable and robust. In this paper, we are proposes a robust special strategy resampling algorithm by adapting particle filtering attribute such as; noise and particle measurement. This adaptation is used to counteract sample impoverishment in different cases in altogether. Finally, the paper presents the proposed solution can survive in three (3) types of sample impoverishment situation inside mobile computing platform.

Keywords* :*Resampling, Sample Impoverishment, Inertial Navigation Systems, Mobile Computing

I. INTRODUCTION

The rapid advancement in location technologies and tracking devices and the demand for flawless solutions to overcome the problems associated with current mobile location based techniques has led to widespread interest in mobile inertial navigation systems[1][2]. One of the major components of mobile inertial navigation systems is inertial-based positioning, which facilitates the tracing of individuals (or mobile nodes) within corridors or other enclosed structures by using an inertial sensor.

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The inertial sensor can be used to determine user location wherever the user may be without having to use extra building infrastructure as the sensor is already found in many types of smart phones used today [3]. Some examples of inertial-based mobile IPS include mobile asset navigation, mobile first-responder navigation and mobile emergency rescue and tracking [4][5][6][7]. One of the major issues of mobile inertial navigation systems is sample impoverishment during particle filtering. This phenomenon causes a computation burden on the overall systems [8] and is due to either a small noise measurement in accurate sensor or an insufficient number of particles [9]. In order to counter the phenomenon, a special strategies resampling algorithm can be used. However, such special strategies resampling algorithms can only be used in certain environments. As mobile inertial navigation systems need to work with different kinds of sensors and a varying number of particles, it would be beneficial if it could survive within different environments. This paper proposes a robust special strategies resampling algorithm by adapting noise and particle measurement. This adaptation is to determine the most suitable algorithm out of the special strategies resampling algorithms that could be used. The structure of this paper is as follows: Section 2 presents the basic concept related to mobile inertial navigation systems. Section 3 presents the problem formulation. Section 4 presents the objectives of this paper. Section 5 presents the proposed method. Section 6 presents the special strategies resampling algorithm that will be used and manipulated in the proposed method. Section 7 presents the experimental setup. Section 8 presents the experiment results and Section 9 concludes with a discussion and recommendations for further research.

II. FUNDAMENTAL OF INERTIAL NAVIGATION SYSTEMS IN MOBILE COMPUTING PLATFORM

This section discusses the basic concept of inertial-based indoor positioning on mobile sensing platforms. The concept regards positioning determination across all environments (see Figure 1 for fundamental system architecture) [10][11][12][13]. Usually, it requires a multi-sensor approach, augmenting the standalone positioning with other signals, motion sensors and environmental features [14][15][16]. This may be enhanced using three-dimensional (3D) mapping, context awareness and cooperation between users. As can be seen in Figure 1, the mobile inertial navigation systems generally consist of three 3 subsystems: the field subsystem, the interface subsystem, and the database subsystem.

In a normal situation, the inertial sensor will continuously send its signal to the central processing unit (which is located in the interface subsystem). The received signals are processed by a central processing unit (where the positioning algorithm is installed) before it is compared with the surveying data in the database server. Finally, the output of the system will display the mapping location on a mobile device screen. The following section will present the problem formulation of this paper.

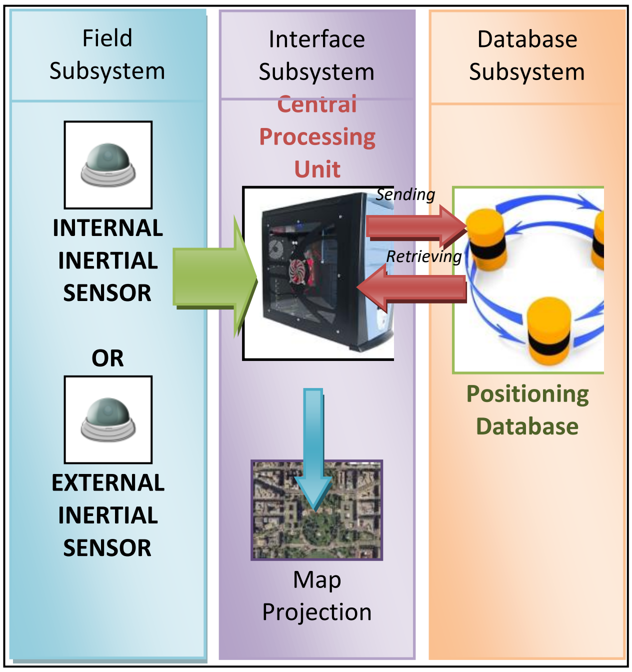


Fig. 1. Fundamental System Architecture of Inertial-based Indoor Positioning on Mobile Sensing Platform

III. PROBLEM FORMULATIONS

The sample impoverishment phenomenon is an issue in mobile inertial navigation systems caused when very few particles have significant weight, most having been abandoned during the resampling process due to their very small weight (see Figure 2 for an illustration of the sample impoverishment phenomenon). This situation occurs during particle filtering and contributes to the computation burden of the overall system.

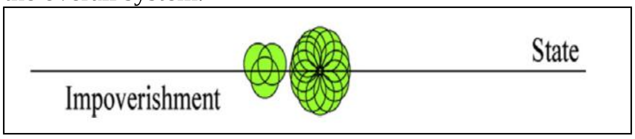


Fig. 2. Illustration of Sample Impoverishment Phenomenon in Mobile Inertial Navigation Systems. [17]

According to [9], the sample impoverishment is caused by small noise measurement and low particle number.The small noise measurement usually happens while the software is using the accurate sensor, while low particle numbers usually occur in real time applications. In order to counter this phenomenon, a special strategies resampling algorithm was used. There are three common types of resampling algorithms: modified resampling, variable resampling and roughening resampling algorithms. Modified resampling works by adjusting the weight of particles (that is, the size of the particles); variable resampling works by reducing the particle number and roughening resampling works by moving the particles that are grouped in one direction. All the resampling algorithms work by splitting the particle distribution grouped in one direction, so that the diversity of particle distribution is increased. As a general rule, these algorithms have their own purpose and capability (see algorithm capability in more detail in Table 1). Roughening resampling can be used to solve the problem of small noise measurement during particle filtering; variable resampling can be used to solve small particle numbers and modified resampling can be used to solve the problem of normal noise measurement and a large particle number. However, these algorithms are only suited to particular environments. If the environment changes, the algorithm cannot survive. Thus, it would be useful if the algorithm were robust enough to survive in different environments (normal and small noise measurement and small particle number). The following section describes the objectives of this paper.

Table- I: Comparison of Special Strategies Resampling

Categorizations	Modified Resampling	Variable Resampling	Roughening Resampling
Particle Size	Big [18][19][20]	Small [21]	Big [21]
Noise Measurement	Normal [18][10]	Normal [9]	Small or Normal [9]

IV. OBJECTIVE

This study aims to present a credible new special strategies resampling algorithm which adapts noise measurement and particle number. This algorithm can be used to overcome the problem of sample impoverishment in different environments and has the robustness to be used in different mobile inertial navigation systems[22][23]. The results of the study could also significantly contribute to modernising current location detection systems and provide useful findings for use in other inertial-based positioning systems studies [24][25][26][27]. The following section will discuss the proposed method of development of a special strategies resampling algorithm.

V. ROBUST NOISE AND PARTICLE BASED SPECIAL STRATEGIES RESAMPLING ALGORITHM

The aim of this paper is to propose a new special strategies resampling algorithm with an adaptation for noise measurement and particle number (see figure 2). This study focuses on three types of situations involving the use of mobile inertial navigation systems, namely, when using an internal inertial sensor; when using an external inertial sensor; and, in a real time application.

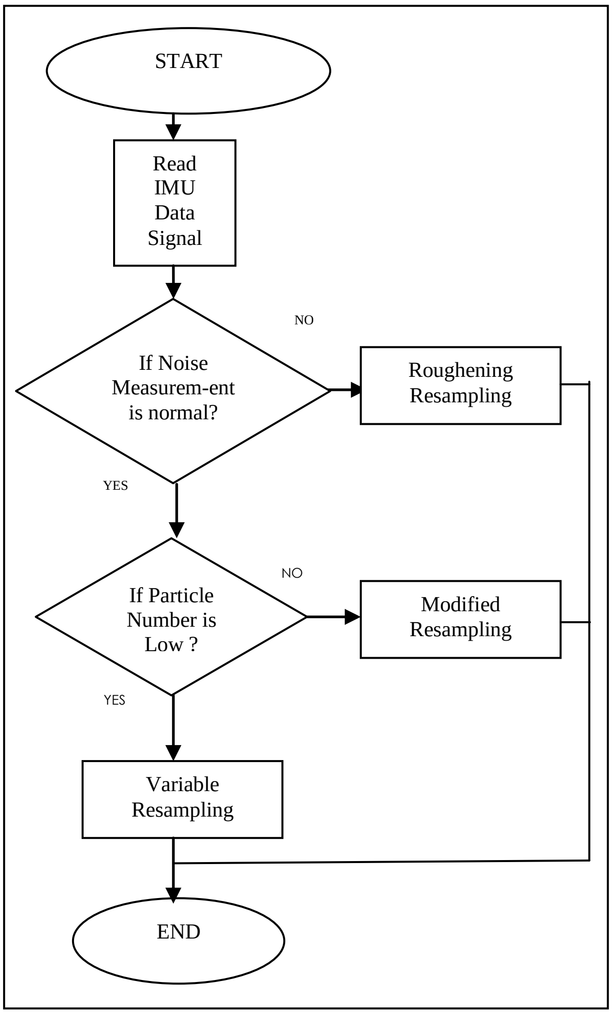


Fig 3. Block Diagram of Adaptive Noise and Particle based Special Strategies Resampling

These situations cause sample impoverishment for positioning determination. In figure 2 presents a block diagram showing the adaptive noise and particle based special strategies resampling algorithm. Initially, the system will receive the inertial data signal from the sensor. First, the noise measurement will be measured. If the noise measurement is high, the algorithm will switch to the roughening resampling algorithm. If the noise measurement is low, the particle number will be measured. Finally, the algorithm will carry out the resampling procedure based on modified resampling (if the particle is high) or variable resampling (if the particle is low). The following section will discuss the special strategies resampling algorithm that will be used and manipulated in the method used in this study.

VI. ROUGHENING, MODIFIED AND VARIABLE RESAMPLING

This section discusses the special strategies resampling algorithm that is used and manipulated in the method used in this study. The special strategies resampling algorithm is chosen on the basis of noise measurement and particle number criteria. Three types of special strategies resampling algorithms will be used to counter the particle impoverishment phenomenon, namely: roughening resampling, modified resampling and variable resampling [28][29][17][30] . Roughening will move the particle location by spreading the distribution. After initialisation at time $t = 1$, the algorithm proceeds with a rejuvenation at each subsequent integer of time. The rejuvenation comprises two steps: a resample step and a move step. At the start, the rejuvenation will carry out initialisation at time $t = 1$, and generate the initial set of particles S_1 by sampling independently for $j = 1, \ldots . n_1$,

$$\theta_1^{(j)} \sim \pi_1 \tag{1}$$

where $\sim$ denotes 'is sampled from'. Then, for $k = 1, 2, \ldots$, the rejuvenation step is carried out. After initialisation, the process of rejuvenation will take place. At each time $t = k + 1$, the algorithm will calculate weight $w_k^{(i)}$, for $i = 1, \ldots, n_k$ and then generate S_{k+1} by performing two steps independently for $j = 1 \ldots, n_{k+1}$. The steps are resampling and moving. The steps are followed by random selection of particles from S_k, (such that $\theta_k^{(i)}$ is selected with probability proportional to $w_k^{(i)}$, for $i = , \ldots, n_k$) and the selected particles are denoted by $\theta_k^{(ij)}$), and moved $\theta_k^{(ij)}$ to a new position $\theta_{k+1}^{(i)}$by sampling.

Secondly, in the modified resampling, all the particles are resampled based on their probability,$p_t^{[m]}$. The probabilities are generally equivalent to the weight of the particles, $w_t^{[m]}$. However, generally, the particles having probabilities as the function of their weights are drawn, for instance:

$$p_t^{(m)} \propto (w_t^{(m)})^{\alpha} \tag{2}$$

Where in $\alpha > 0$. If, $0 < \alpha < 1$, the low-weight particles are boosted further and the particles with large weights display suppressed probabilities, thus improving the diversity of the particles. Contrastingly, $\alpha > 1$ ensures that there is a higher preference for the high-weight particles. Also, using the auxillary weights, one can implement the knowledge with regard to the subsequent observation before carrying out the particle resampling. Thus, particles having better probabilities are more likely to survive. The step involving generation of the auxillary variables that represents the particle fitness is seen as being the resampling step which considers the instant future and the present state while selecting particles. The idea of fusing the data obtained from recent observations with the present weights while selecting the particles is very commendable.

Variable resampling helps to determine the required particle number depending on the KLD observed between the distribution of interests and the sample based maximum likelihood estimates. The needed, N, particle number, is determined to have a probability value of $1 - \rho$. It is seen that the KLD present between the distribution of interests and the sample based maximum likely estimates for the desired particle distribution is lower than the pre-specified error-bound threshold value of f. It is seen that;

$$\text{Where} \quad N = \frac{1}{2\varepsilon} q \tag{3}$$

$$q = F^{-1}(1 - \rho) \tag{4}$$

Where, $F^{-1}(.)$ represents the inverse of the cumulative chi-squared distribution having a $k-1$degree of freedom and k refers to the bin number [non-overlapping (multi)dimensional interval] that is used for particle sorting. The Nvalue in Equation 3 can be computed approximately. However, in practice, the particle number in resampling would be hard-pressed to exceed the minimal threshold value. Generally, the posterior of the state is ideally used as the desired distribution. This posterior can be calculated by using the method of predictive distribution. In theory, it is more difficult and more flexible to use Equation 3 while resampling instead of sampling, which then leads to the KLD-resampling technique. In the KLD technique, the particle resampling is conducted individually until the needed amount defined by Equation 3 is achieved. The following section will discuss the experimental setup of the method used in this study.

VII. EXPERIMENT SETUP

This section discusses the experiment setup of the proposed adaptive noise measurement and particle special strategies resampling algorithm. A number of simulations were conducted to study the performance of the proposed algorithm. The experiment was simulated with the parameters set as follows. The process and measurement noise covariance matrices were taken as being:

Table- II: Parameter Setting for Experiment Setup [9]

Situation	Measurement Noise	Process Noise	Particle Number	Performance Metric
Situation 1: Positioning using low cost inertial sensor devices	0.1	0.5	500	Estimated positioning and localisation error
Situation 2: Positioning using accurate inertial sensor devices	0.1 and 0.05	0.5	500	Estimated positioning and localisation error
Situation 3: Fast positioning using small particle quantity	0.1	0.5	50 and 10	Estimated positioning and localisation error

$$\sigma_w = 0.1 \tag{5}$$

$$\sigma_v = 0.5 \tag{6}$$

To allow for a fair comparison, a comprehensive quantitative comparison of the resampling methods was carried out using three tracking problem situations (see Table 2, parameter setting for experiment setup). The situations considered were: positioning using a low cost inertial sensor device, positioning using an accurate inertial sensor device and fast positioning using a small particle quantity. These situations were chosen to establish whether the proposed algorithm can survive in a different environment of sample impoverishment. For the first situation, the algorithm was simulated using 500 generated particles with the initial position being unknown. For the second situation, the algorithm was simulated in two different generated noise measurements, that is $\sigma_v = 0.1$ and $\sigma_v = 0.05$. In the third situation, the algorithm was simulated using small particle numbers, that is $N = 50$ and $N = 10$. The following section presents the conclusion and suggestions for further research.

VIII. EXPERIMENTAL RESULTS

The previous section discussed the experiment setup of proposed approach. Basically, the experiment will be done in three (3) kind of situation, which are; positioning using low cost inertial sensor, positioning using accurate sensor, and fast positioning using small particle quantity. This section discusses the experiment result of the proposed approach or known as robust special strategies resampling. Currently, a number of simulations have been conducted to study the performance of the proposed algorithm. For details of these algorithms, readers are referred to the pseudocodes given in the tutorial (the MATLAB codes for these resampling algorithms can be found at [15]). Figure 4, 5 and 6 is refer experiment in situation 1, Figure 7,8 and 9 is refer to the experiment in situation 2. Figure 10, 11, 12, 13, 14 and 15 is refer to the experiment in situation 3. In situation 1, the experiment has been done by using low cost inertial sensor. (see Figure 4, 5 and 6). It show that most of the particle that resampled is far away from true trajectory. Seems it is like the modified resampling and the proposed method is the most near with true trajectory. It is also can be seen that in Figure 6 is modified resampling and proposed method is the most of lowest mean error but at the end (during time 60), the mean error of roughening resampling become the lowest. For variable resampling, the mean error become worst. The reason is the roughening and variable resampling can survive in normal noise measurement. However, the variable resampling suffured because of the particle number is high. For the mean particle number (see Figure 5), the roughening, modified resampling and proposed method shows it continuously choose five hundred (500) number of particle and, the proposed method and the particle number of variable resampling continuously increase from twenty (20) hundred until one thousand (1000). In situation 2, the experiment has been done by using accurate inertial sensor. (see Figure 7, 8 and 9). It shows that most of the particle that resampled is near to true trajectory. Seems it is like the roughening and the proposed method is the most near with true trajectory. It is also can be seen that in Figure 9 is roughening and proposed method is the most of lowest mean error starting on time cycle 20.

For variable and modified resampling, the mean error become worst. The reason is the roughening and proposed method can survive in high noise measurement, meanwhile the modified resampling cannot. However, the variable resampling suffured because of the particle number is high. For the mean particle number (see Figure 8), the roughening, modified resampling and proposed method shows it continuously choose five hundred (500) number of particle and, the proposed method and the particle number of variable resampling continuously increase from two hundred (200) hundred until nine hundred (900). In situation 3, the experiment has been done by using accurate inertial sensor. (see Figure 10, 11, 12, 13, 14 and 15). In the experiment, it can be divided into two (2) of task. The first the experiment will be simulated by using one hundred (100) of particle number. The second (2nd) task, the experiment will be simulated by using ten (10) of particle number. During particle number was reduced in one hundred (100),it show that most of the particle that resampled is far away from true trajectory. Seems it is like the variable resampling and the proposed method is the most near with true trajectory (see Figure 10). It is also can be seen that in Figure 12 is variable resampling and proposed method is the most of lowest mean error. For modified and roughening resampling, the mean error become worst. The reason is the variable resampling and the proposed method can survive in low particle number, meanwhile, the modified and roughening resampling cannot. For the mean particle number (see Figure 11), the roughening and modified resampling shows it continuously choose one hundred (100) number of particle and, the proposed method and variable resampling continuously choose two hundred (200) number of particle. For the second (2nd) task, in situation 3, the experiment has been done by using accurate inertial sensor and ten (10) particle number (see Figure 13, 14 and 15). It's show that most of the particle that resampled is far away from true trajectory. Seems it is like the variable resampling and the proposed method is the most near with true trajectory (see Figure 13). It is also can be seen that in Figure 15 is variable resampling and proposed method is the most of lowest mean error.

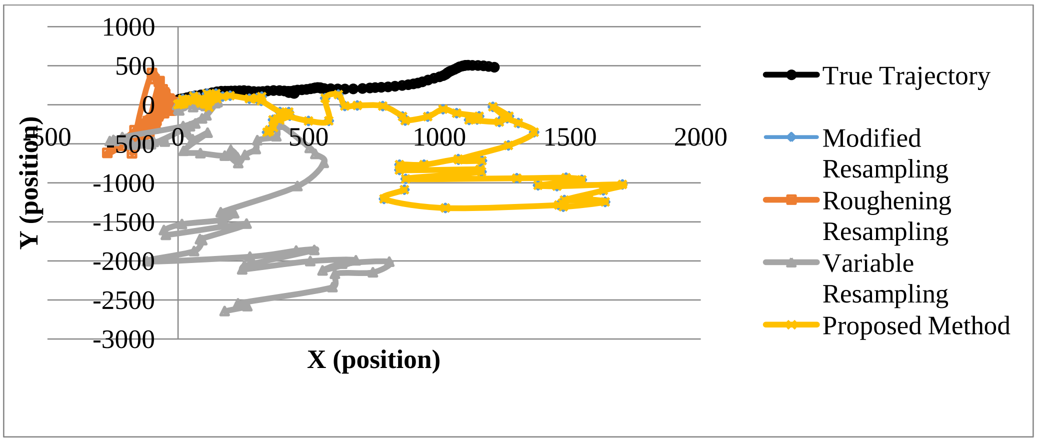
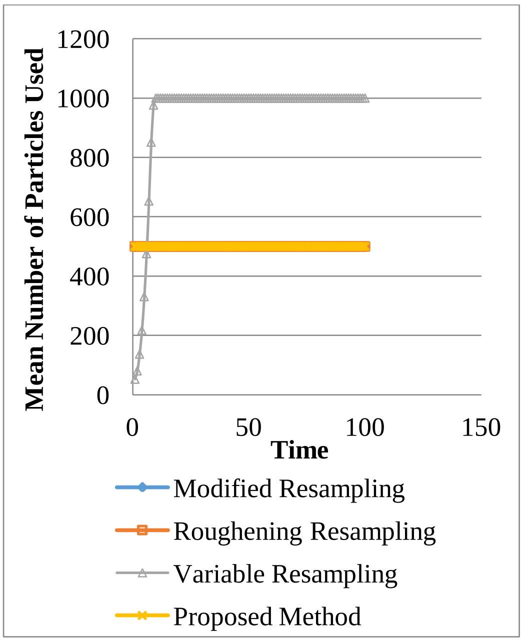


Fig. 4. Simulation of Particle Position Using Low Cost Inertial Sensor in Situation 1.



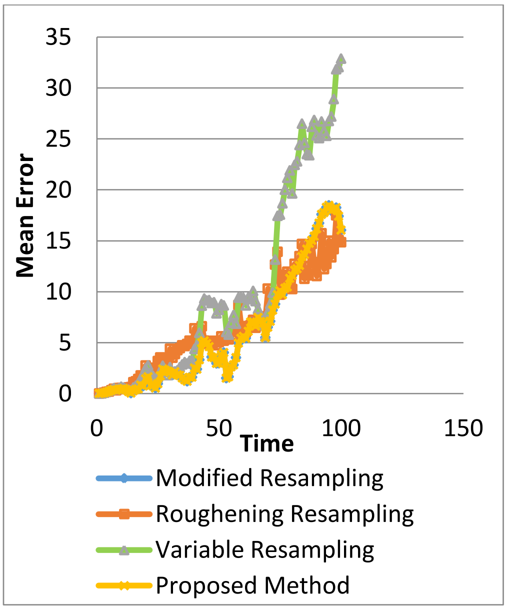


Fig. 5. Simulation of Mean Number of Particle Used Using Low Cost Inertial Sensor in Situation 1.

Fig. 6. Simulation of Mean Particle Error Using Lost Inertial Sensor in Situation 1..

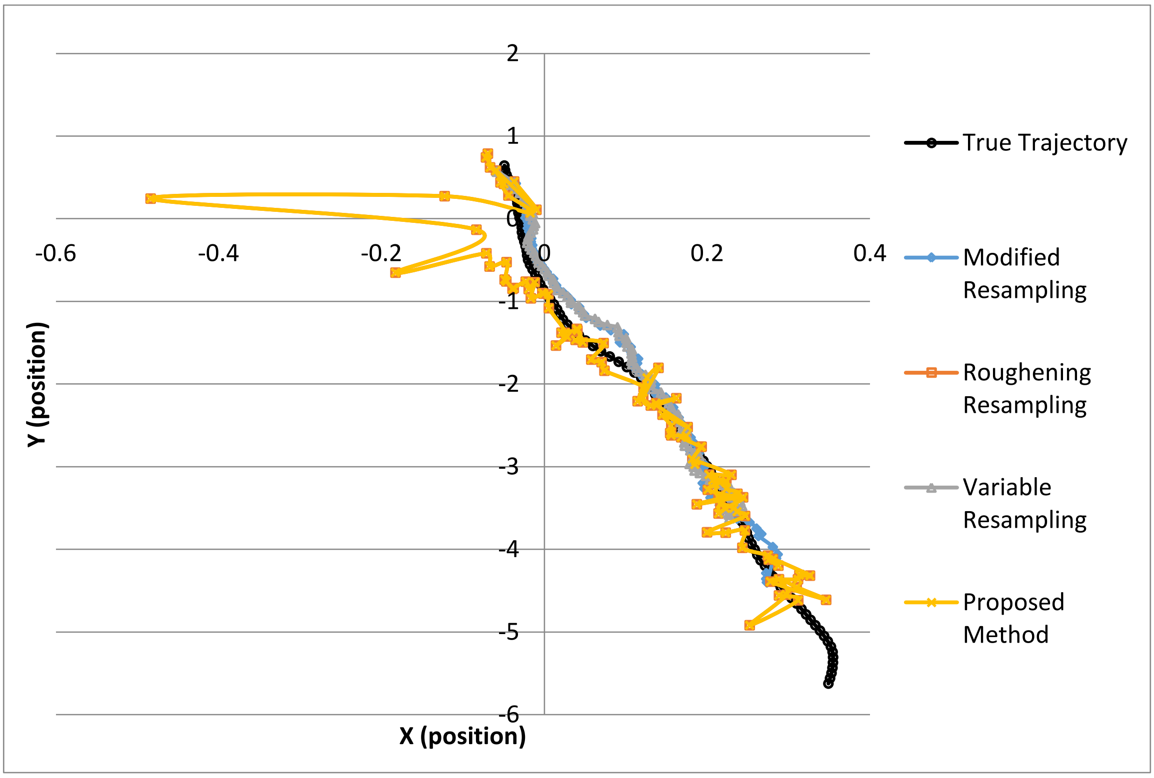


Fig. 7. Simulation of Particle Position Using Low Cost Inertial Sensor in Situation 2

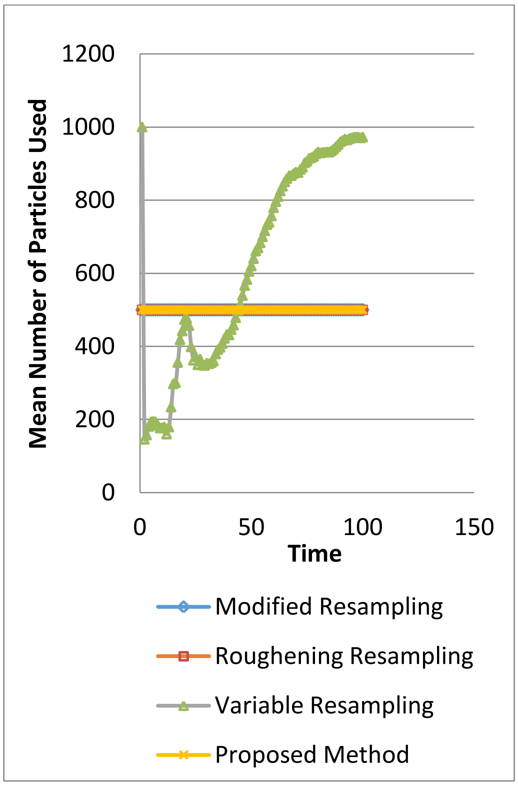


Fig. 8. Simulation of Mean Number of Particle Used Using Low Cost Inertial Sensor in Situation 2

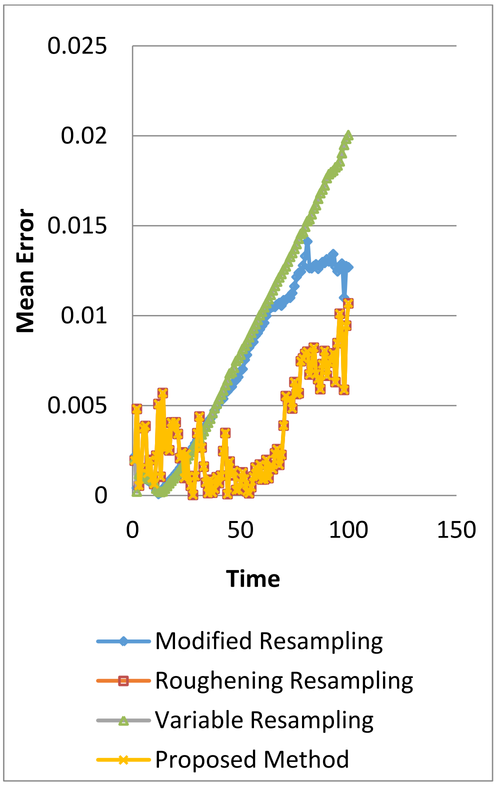


Fig. 9. Simulation of Mean Particle Error Using Lost Inertial Sensor in Situation 2

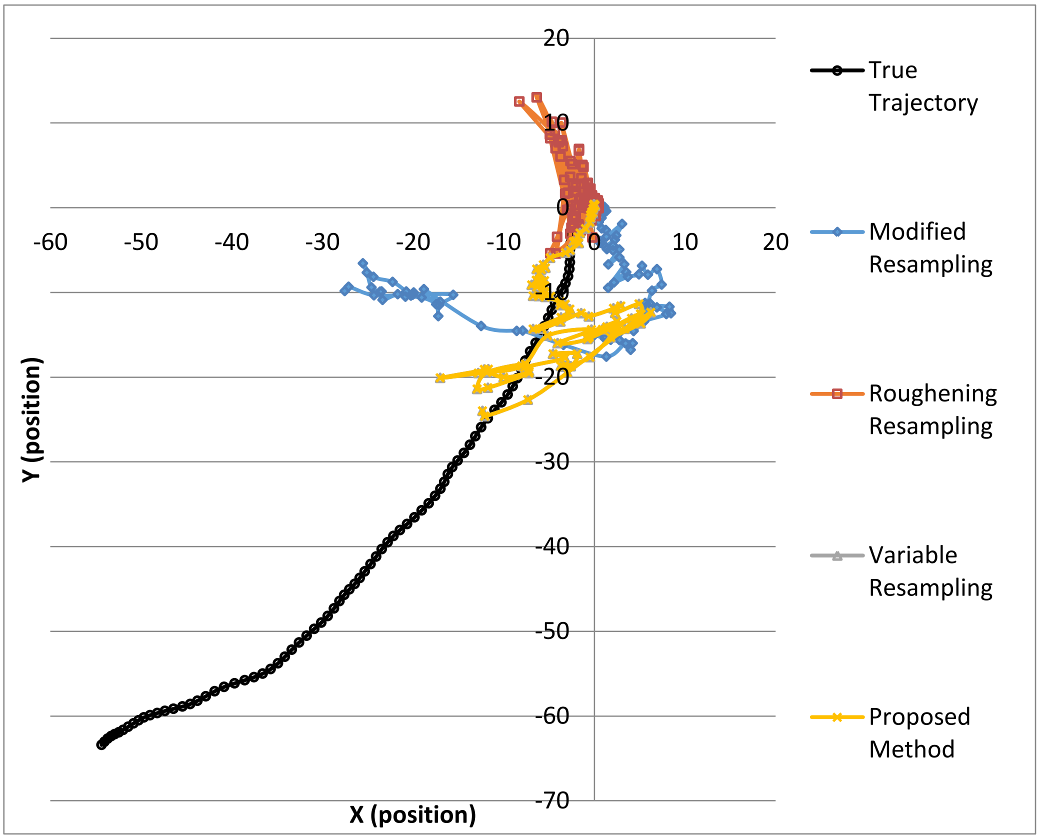
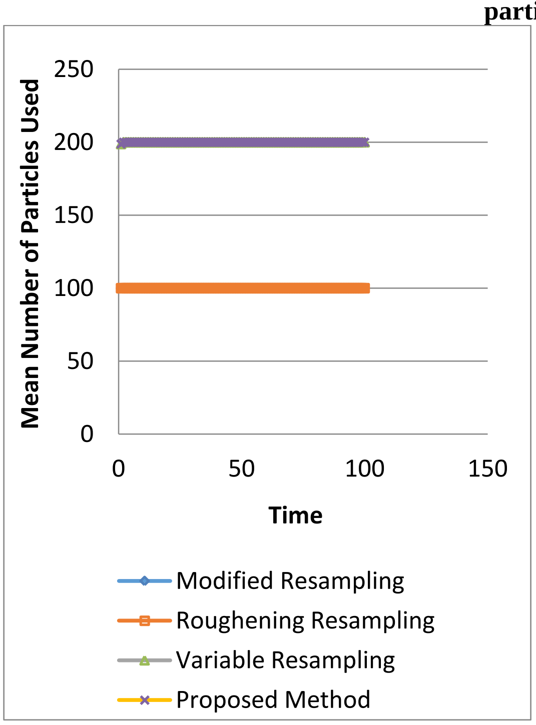


Fig. 10. Simulation of Particle Position Using Low Cost Inertial Sensor in Situation 3 (using 100 particle)



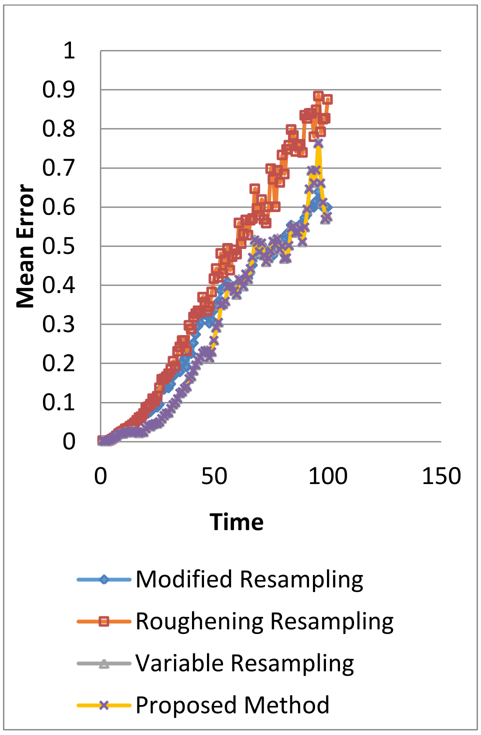


Fig. 11. Simulation of Mean Number of Particle Used Using Low Cost Inertial Sensor in Situation 3 (using 100 particle).

Fig. 12. Simulation of Mean Particle Error Using Lost Inertial Sensor in Situation 3 (using 100 particle)

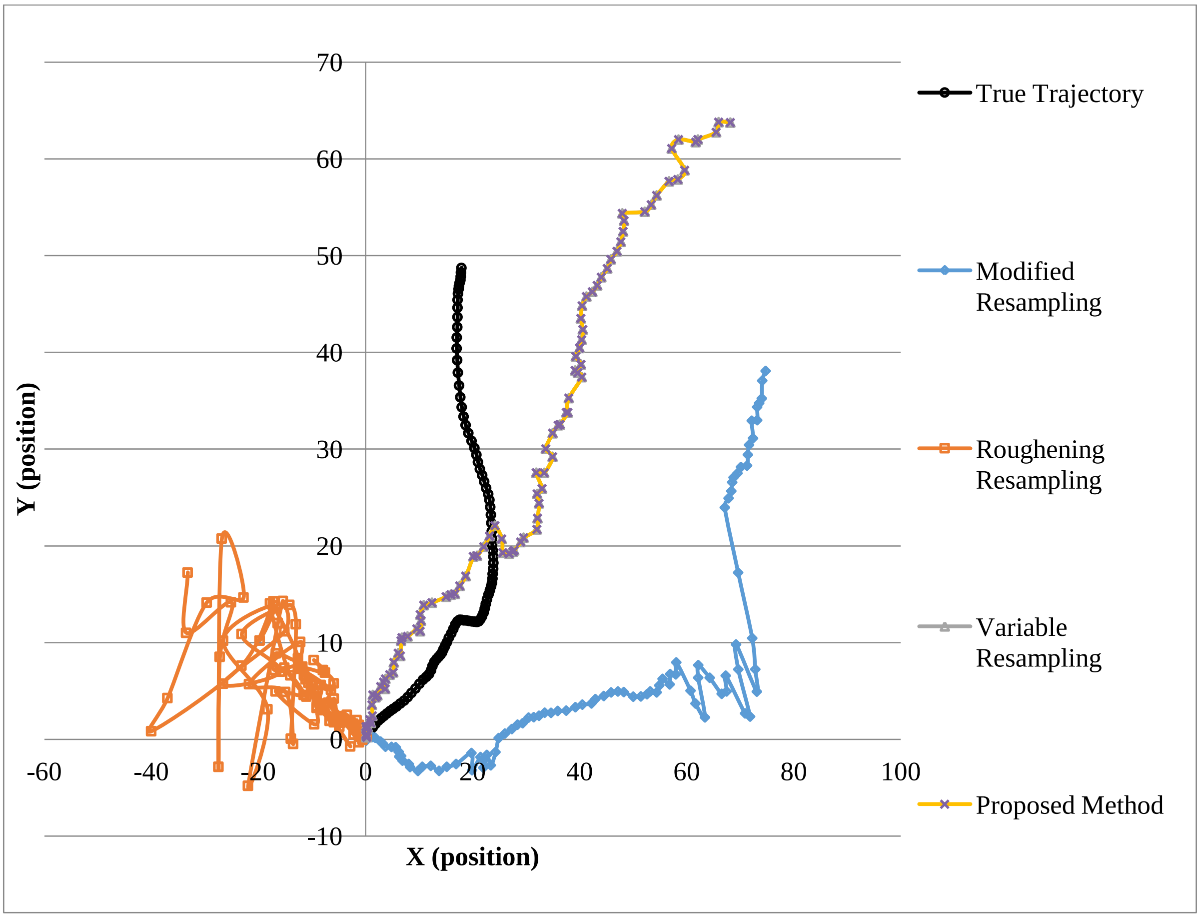


Fig. 13. Simulation of Particle Position Using Low Cost Inertial Sensor in Situation 3 (using 10 particle)

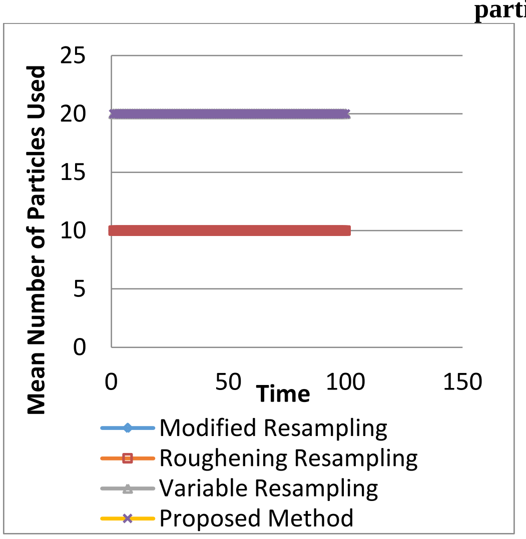


Fig. 14. Simulation of Mean Number of Particle Used Using Low Cost Inertial Sensor in Situation 3 (using 10 particle)

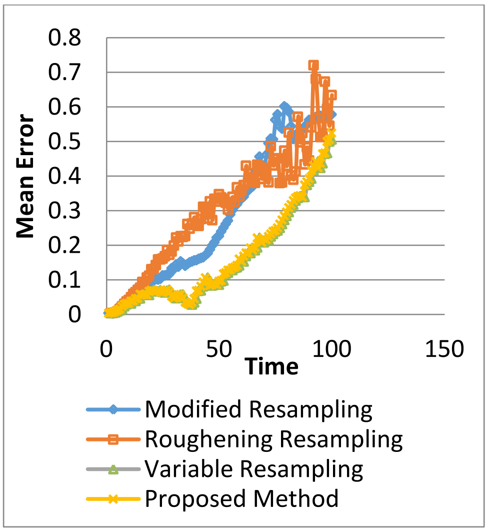


Fig. 15. Simulation of Mean Particle Error Using Low Cost Inertial Sensor in Situation 3 (using 10 particle)

IX. CONCLUSION AND SUGGESTIONS FOR FUTURE RESEARCH

This study considered ways to counteract the sample impoverishment phenomenon during particle filtering in mobile inertial navigation systems within different environments of noise measurement and particle numbers. The solution involved creating a algorithm that adapted noise measurement and number of particles for resampling that was more intelligent, reliable and robust. Thus, an robust special strategies resampling algorithm was created by adapting noise and particle measurement. These adaptations were chosen to determine the most suitable special strategies resampling algorithm that can be used to counter this phenomenon. The result shows, that our proposed method can be switched in term on resampling functionality according to given situation. It is also show can survive in different sample impoverishment environment. Finally, the proposed solution was used in an indoor environment setup. The researchers propose to continue experimenting using the results obtained to obtain more valuable findings.

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