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Probabilistic Localization of Robot in Outdoor Environment Using GNSS

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Abstract. This paper describes a method to determine the two-dimensional position of a mobile robot in known map in an outdoor environment from GNSS measurements. The map is composed of roads from Open Street Map. The algorithm is divided in three parts. First part is preprocessing of measured data by Kalman filter. Second part is localization in the known map – road identification, mobile robot is localized on one specific road. The last part is precise localization on this specific road by particle filter. Algorithm is working with different methods (Kalman filter, fuzzy logic, particle filter) together and obtains good results. The algorithm's performance is demonstrated by using GNSS receiver GTPA010. Verification tests are described at the end of this paper.

Introduction

In mobile robotics, localization is a problem that can be solved by many different approaches. The choice for a best localization method vastly depends on the type of the environment where the robot should move as well as on the task that it should solve [1-4]. For example, while the GNSS localization will give good results in outdoor environment it would be useless in localization of robot inspecting sewers [5]. Another parameter that affects the choice of localization method is whether the environment in which robot moves is known or unknown and whether the environment is static or dynamic [6-7]. For known or partially known environments many absolute localization methods exist [8]. The most widely used absolute localization methods in outdoor environment are methods based on GNSS [9-12]. This is mostly thanks to its simplicity for end-user and cost of the receivers [10]. For indoor environments, there exist GNSS-like systems, but these require additional cost and effort for transmitter installation [13]. Another approach for robot localization is landmark detection. These systems require either costly sensor (e.g. laser rangefinder) [14] or they are computationally demanding (visual systems) [15, 2]. In the current research, many of these methods are integrated into a SLAM system [16, 6]. Some of these methods require sensors capable of distance measurement or environmental feature detection [17]. Every approach has its advantages as well as disadvantages. Some of the disadvantages, such as multipath problem or sky coverage in GNSS systems, arise from the used sensor, or processing methods used for localization, for example local minimum in ICP algorithm. The aim of this paper is to propose a post processing method that can be used as good initial guess for SLAM algorithms as well as a basic stand-alone method for mobile robot localization on a road. For this purpose

series of existing algorithms were used. These algorithms were integrated into a complex platform. According to our results, using multiple types of processing eliminates some of the disadvantages of respective algorithms and yields to better results than the results from using these algorithms on their own.
For measurements GNSS receiver GTPA010 was used. This GNSS receiver is sending data in NMEA sentences. Due to low sampling resolution of the sensor, steps in measurements are occurring. These steps need to be eliminated e.g. by preprocessing. Preprocessing methods are described in the first part. Requirements for preprocessing methods are characterized as low pass filter structure, which eliminates false measurements and evaluates trend in robot's movement. In this part Kalman filter is applied.
The second part of this paper describes proposed algorithm. It is based on localization of the mobile robot in a map. The map consists of roads that are obtained from Open Street Map framework (OSM). Thus the first step of mobile robot localization is identification of the road where it is possible for the robot to be present. This type of localization does not solve exact robot position, only the possible road (or part of the road). Therefore, particle filter is applied on these results. Particle filter is creating possible positions - particles of the mobile robot on the road. Density of the particles shows where the mobile robot could be. Verification tests of the complex algorithm are in the section 4 in this paper.

2 Theoretical backgrounds

In the following section theory of all methods that were used in the paper is described. First step of the proposed algorithm is preprocessing of the GNSS data. Good preprocessing method is essential for the next parts of the algorithm. In our research Kalman filter was applied. Kalman filter is a recursive filter which means that all previous measurements are incorporated in the last filtered measurement. Kalman filter in general solves the problem of state **x** estimation.
Kalman filter theory, which was used in this paper, is based on [11, 14, 16, 18-19].
The mobile robot is usually moving with slow velocity. In [19] is described how to set initial value of the covariance matrix **Q** for slow movement, which will be applied later.

$$\begin{aligned} \operatorname{diag}(\mathbf{A}) &= \begin{pmatrix} 1 & 1 & 1 & 1 \end{pmatrix} \\ \operatorname{diag}(\mathbf{Q}) &= \begin{pmatrix} Q'_{dx}\Delta t & Q'_{dy}\Delta t & Q'_{dz}\Delta t & \sigma^2_{\delta t} \end{pmatrix} \end{aligned} \tag{1}$$

The Kalman filter output is minimum mean-square error estimate of the real state. Kalman filter covariance matrixes were set according to parameters of our sensor that were identified through experiment. State vector **x** and its covariance matrix **P** were initialized to zero values.

When the mobile robot is moving through crossroads it is hard to decide on which of the roads it is located. In this kind of situation the algorithm needs to work with a hypothesis that the robot is located on any of these roads. Fuzzy logic allows to work with a set of information where sum of the probabilities is bigger than 1. Truth of sentence is described by membership function, which evaluates the sentence by the value of probability. These sets are called fuzzy sets. Membership function are typically trapezoidal, triangular or in Z or S form [20, 18].
In this paper fuzzy logic is used for probability calculation, on which road in the map is mobile robot located on. Each of the roads can have probability between 0 and 1, with 0.5 being a threshold value where the algorithm presumes that the robot is located on that road.

Thus fuzzy logic application for the mobile robot localization allows the algorithm to work with more than one road with a probability higher than 0.5.

After this localization one or more roads have higher probability than 0.5 with no exact position on these roads. Due to this, it is necessary to apply next method for more precise localization. For this problem, particle filter is applied.

Particle filter is Bayes filter. In general, particle filter algorithm consists of 4 steps (figure 1). In the first step particles are created randomly. For best results particles should have uniform distribution. In the next step the state of each particle is changed according to a control signal. The third step occurs when a new measurement is obtained. According to this measurement, probability is calculated for each particle. The probability is higher for particles that are located near the measurement and lower for more distant particles. In the last step of the algorithm particles are resampled from previous particles according to their probability [8, 15, 18, 21].

Algorithm Particle_filter($\mathcal{X}_{t-1}, u_t, z_t$)**:**
  $\bar{\mathcal{X}}_t = \mathcal{X}_t = \emptyset$
  for $m = 1$ to M do
    sample $x_t^{[m]} \sim p(x_t \mid u_t, x_{t-1}^{[m]})$
    $w_t^{[m]} = p(z_t \mid x_t^{[m]})$
    $\bar{\mathcal{X}}_t = \bar{\mathcal{X}}_t + \langle x_t^{[m]}, w_t^{[m]} \rangle$
  endfor
  for $m = 1$ to M do
    draw i with probability $\propto w_t^{[i]}$
    add $x_t^{[i]}$ to $\mathcal{X}_t$
  endfor
  return $\mathcal{X}_t$

Fig. 1: Algorithm of Particle filter [23]

3 Algorithm

In the following text, the basic principles of proposed localization method are described. The map where the mobile robot is localized is based on roads obtained from Open Street Map. Probability for each road that is near the robot is determined. This value describes odds that the mobile robot is located on the road. The probability is determined as a fuzzy function of the distance between GNSS position and its projection on the road. The function is determined on the basis of experimental measurements in different conditions. Fuzzy membership function is based on:

- precision of the sensor,
- shortest distance between filtered position,
- and the road and HDOP information from GGA sentence.

For better clarity, the road probability in following figures is plotted in a color scale (fig. 2). Thanks to the fuzzy logic it is possible to set higher probability than 0.5 to more than one road (e.g. situation on a crossroad).

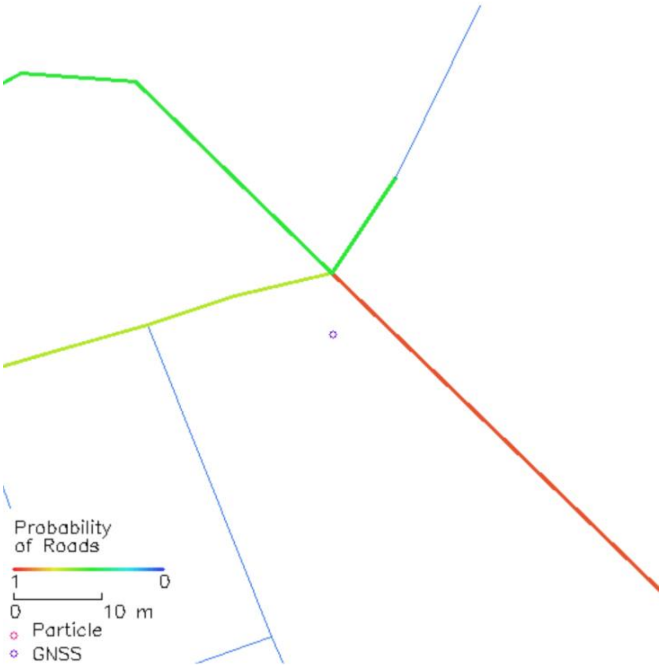

Fig. 2: Map of identified roads

This method of mobile robot localization does not calculate the exact robot position. The output of this algorithm is set of roads, with probability that is higher than 0.5 e.g. there is a chance that the robot is on one of these roads. To determine the robot position on the road particle filter is used. Particle filter generates 500 particles - positions, that are distributed on all roads with probability higher than 0.5. The count of the particles on a particular road is determined by its probability and sum of the probabilities of all roads with probability higher than 0.5.

Probability of the particles that is used in 5th step of the algorithm is defined as fuzzy function which is based on distance. Control signal was obtained from mobile robot. Particle filter algorithm is shown in figure 4. New particles have uniform probability within a limited distance from crossroad location. When the road is identified again the new particles are generated from the previous ones that were associated with this road with respect to their probability - resampling. Result of this algorithm is possible mobile robot location on the road.

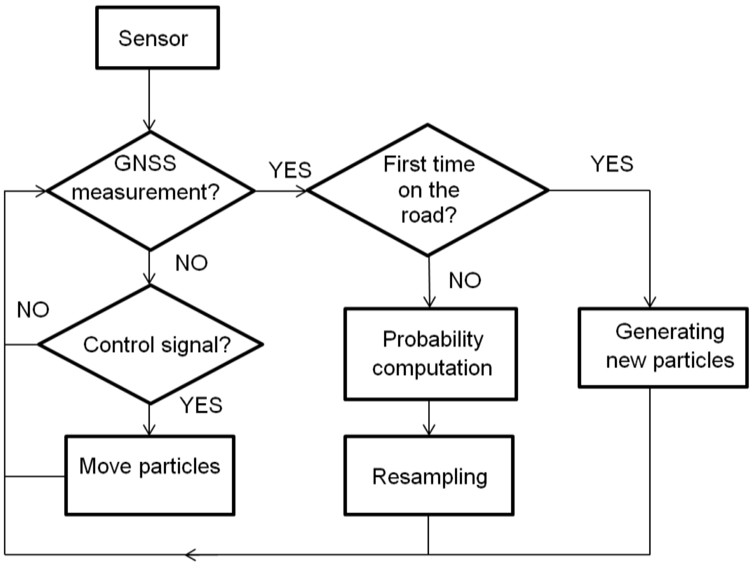

Fig. 3: Algorithm of particle filter

4 Verification

Following section deals with verification of proposed algorithm in real life experiments. The aim of these experiments is to determine whether the algorithm works correctly. Four measurements were made in park with huge road net for verification of the proposed algorithm. Every measurement contains more than 3 000 samples. Information about the roads from OSM was used as reference. All movements passed through crossroads and part of the movement was under trees or close to buildings. Measurements were made in varied time periods with different satellite constellations. Situation in measurement 3 is shown in figure 4 and detail is in figure 5.

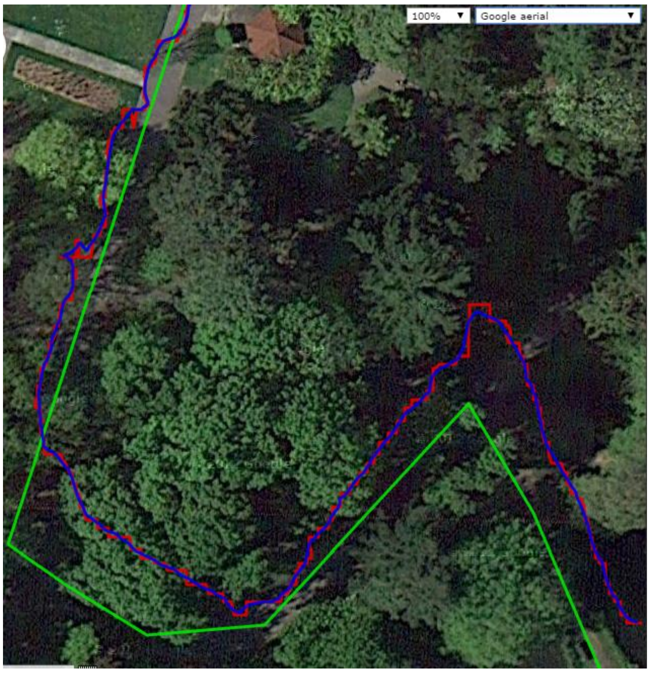

Fig. 4: Measurement 3 in Google Map. Red - measured data, blue - filtered data, green – road OSM data

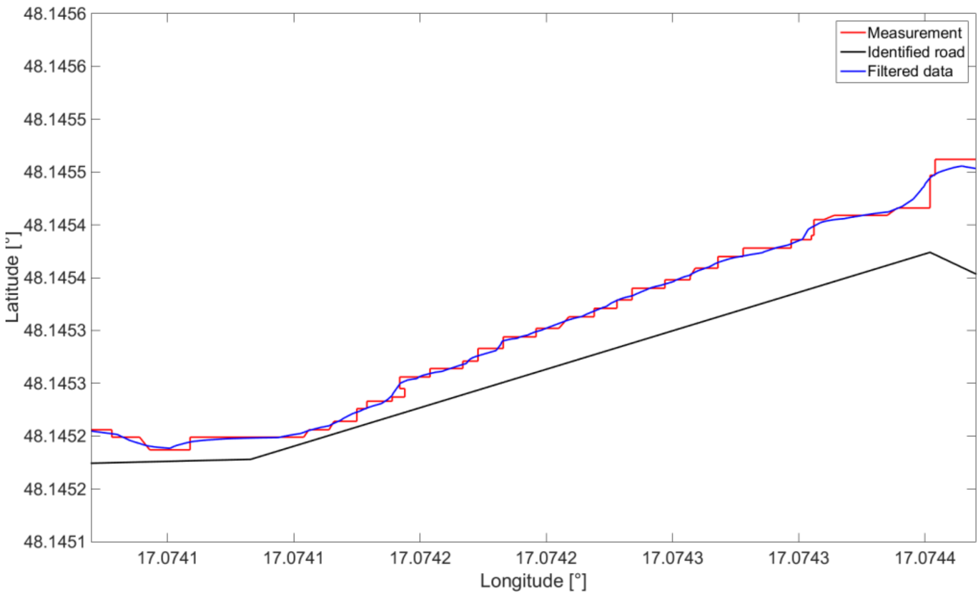

Fig. 5: Measurement 3 detail: Red - measured data, blue - filtered data, black - identified road in OSM

First test was performed on measured and filtered data. The aim of it was to validate Kalman filter application. Table 1 contains data from this test and describes RMS of filtered and measured data. The first column contains RMS for filtered data; the second column contains RMS for measured data. RMS is used to describe which data is numerically closer to the road.

Table 1 RMS of filtered and measured data

	RMS Filtered data [m]	RMS Measured data [m]
Measurement 1	2.90	2.85
Measurement 2	3.57	3.71
Measurement 3	2.49	2.56
Measurement 4	3.09	5.68

In this part of the first test filtered data had better results. Measurement 2 has better results for measured data. This may be caused due to different reasons. E.g. OSM allows to edit road information by users, that is why it is not known how was the road measured (wide road may have been measured in the middle or on the right or left side of the road). Other measurements are filtered closer to reference road. Generally filtered data are better than measured data.

Mobile robot movements are linear and continuous. Measured data are stepped and that is not similar to real robot movement. Kalman filter application suppresses these steps and therefore filtered movement looks more like a real robot motion. In this respect filtered data exceeds the measured data significantly. Choice of Kalman filter and its setting may be considered as sufficient (figure 5).

The second test was based on the same measurements as the previous one. The aim of this test is to verify the capability of the algorithm to correctly determine on which road the mobile robot is moving. This test is divided into two parts. First part consists of the mobile robot movement on a single road. Table 2 shows data from this first part and it is split into three columns. The first column (F - false) describes when no road was identified, the second column (FP – false positive) describes when a road was identified, but the mobile robot was moving on another road, the third column (P-positive) describes when a road was identified and the mobile robot was moving on this road.

Table 2 Identification on single road. F - false, FP - false positive and P - positive identification

Type of movement	Single road		
Identification	F [%]	FP [%]	P [%]
Measurement 1	11.9	13.1	75.0
Measurement 2	4.2	0.0	95.8
Measurement 3	5.5	0.0	94.6
Measurement 4	0.0	0.0	100.0

When mobile robot was moving on one road, this road was correctly identified in more than 75% of all measurements. Only in one measurement the road was not correctly identified and robot had identified its movement on other road. This could be caused by real road width, which is in contrast with map representation in OSM, which is represented as a line without width. Shift between the real position and GNSS position can be caused by bad visibility e.g. due to trees. The wrong identification happened in less than 5% in our experiments.

The second part is devoted to a situation where the robot is moving through crossroads of two or three roads. The crossroad is defined as a small area around a point where two or more roads are merging. These line segments are approximately 4-8 meters long. Table 3 describes data from second part of this test and it is split into two main columns. First main column is for two roads crossroads, second column is for three and more roads crossroads. Each of main columns is split to three subcolumns (F, FP, P). The column F describes when at least one of the roads from the crossroad had smaller probability than 0.5, the column FP describes when all roads in crossroad are identified but the mobile robot is moving through another crossroad or outside the crossroad area, the column P describes when all roads in crossroad are identified and the mobile robot is moving through this crossroad. In the fourth measurement robot was moving only on one road. For this reason the fourth measurement is not listed in the table 3.

Table 3 Identification on crossroad. F - false, FP - false positive and P - positive identification

Type of movement	Crossroads 2 roads			Crossroads 3 roads		
Identification	F [%]	FP [%]	P [%]	F [%]	FP [%]	P [%]
Measurement 1	0.0	0.0	21.0	0.0	0.0	79.0
Measurement 2	0.0	0.0	100.0	0.0	0.0	0.0
Measurement 3	0.0	0.0	23.9	0.0	0.0	76.1

When robot was moving through a crossroad all roads were identified correctly. The algorithm was working correctly and it also performed well when robot was moving close to the trees.

The output from the previous part of the algorithm is particular road or crossroad. To determine exact position on the road particle filter is applied for each identified road. The test for verification of the particle filter was based on real mobile robot position and the position gained from particle filter. The output of the particle filter is not only one possible position, but set of possible positions with its probability. Thus for this verification test one particle position had to be chosen from this set. The position was generated for each road that had particles as a center of gravity (CoG) of these particles. Results of this test are shown in table 4. Some results of particle filter are shown in figure 6.

Table 4 RMS of distance between CoG of particles and real position of the mobile robot

	RMS of distance - CoG and real: Single road [m]	RMS of distance - CoG and real: Crossroad [m]
Measurement 1	1.68	1.41
Measurement 2	1.89	1.93
Measurement 3	1.23	1.15
Measurement 4	1.10	-

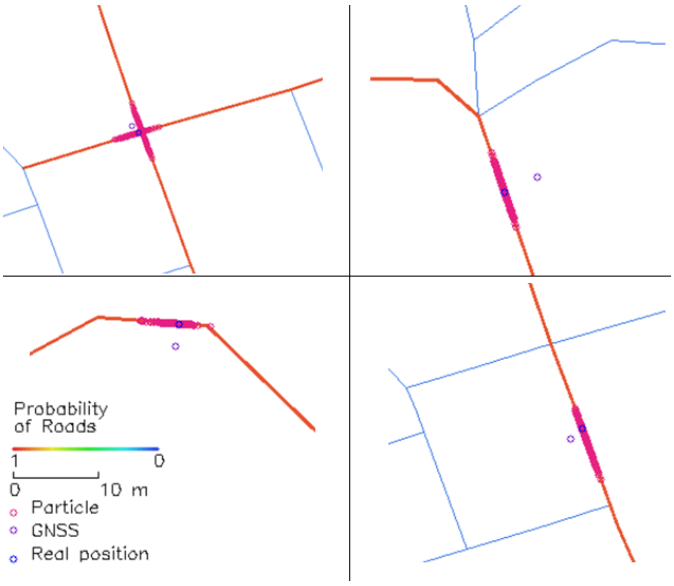

Fig. 6: Results of algorithm with particle filter

Average distance between CoG of particles and real position was between 1 and 2 meters. Accuracy of used GNSS receiver is 3 meters. Thus our algorithm can improve GNSS measured position by 33%.

7 Conclusion

In this paper results of GNSS positioning with filtering and road identification algorithms have been presented. In the introduction GNSS parameters and methods was described. Afterwards, the basics and parametrization of the filters were explained. Next section described the whole algorithm, which also uses particle filter for exact position identification. Results of several experiments, which support proposed algorithm, are also presented. Verification was made in several different environments and it shows that the algorithm is well designed. Every method improves results in some part. Kalman filter eliminates Gaussian noise. Implementation of fuzzy logic in road identification allows working with crossroads and not only with one road, and particle filter localizes robot on these roads. Combination of the methods used in our algorithms leads to better results than using these methods separately. Accuracy was improved to approximately 2 meters compared to 3 meters accuracy of GNSS receiver. Algorithm is proposed so that system can be expanded or changed. It can be expanded to by new sensor, which can improve data preprocessing or localization on the road. Moreover, proposed algorithm is able to work in real time. This is necessary condition for usage in mobile robot localization. The future work is to expand the system by INS sensor and implement data fusion of INS and GNSS, which will improve the algorithm. Other improvement of the algorithm is self-learning. Its aim is to make fuzzy function and covariance matrixes to learn from previous measurements.

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