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DETERMINATION OF PROBABILISTIC MODEL OF ROBOT MOTION

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Summary: *This paper deals with the probabilistic model of wheel robot motion. Such probabilistic model is often used in navigation algorithms for prediction of the real position of the robot. We prepared a number of experiments with real robot called Bender and results were used for the verification of simulation model. The paper provides detail information about preparation and performing the experiments in real world environment.*

1. Introduction

The identification of true robot position is one of the standard tasks in mobile robotics. This task is called localization. The complexity of the localization methods depends on the robots operating environment and also on the type of a problem which has to be solved. The robot must be capable of solving a number of problems which can be divided approximately into the following categories: indoor, outdoor navigation, position tracking, local and global localization, mapping, etc. In these types of tasks the robot executes four main commands in never-ending loop: read sensors, localize itself, create/update map, move.

In spite of the fact that there are some methods for robot localization which do not require information about a traveled distance (odometry), measuring of traveled distance is still the most important input parameter for every category of navigation methods. Because of this importance of odometry, many navigation methods use robot odometry model for the prediction of robot position and orientation [2]. In this paper we describe the determination of probabilistic model of robot motion. The paper is organized as follows: chapter 2 deals with the simulation model of robot motion, chapter 3 describes the details on measuring necessary data on real robot called Bender and it also describes the parameters identification, the chapter 4 summarizes the whole process from measuring to the parameters identification.

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2. Simulation model

Wheeled robot Bender [1] is used in navigation tasks which are performed in our laboratory. The chassis is standard car alike (steerable front wheels, rear 2WD drive), as the main purpose of this robot is the movement in outdoor environment. Standard simulation model of such type of chassis is based on Ackerman steering principle, as you can see on figure 1.

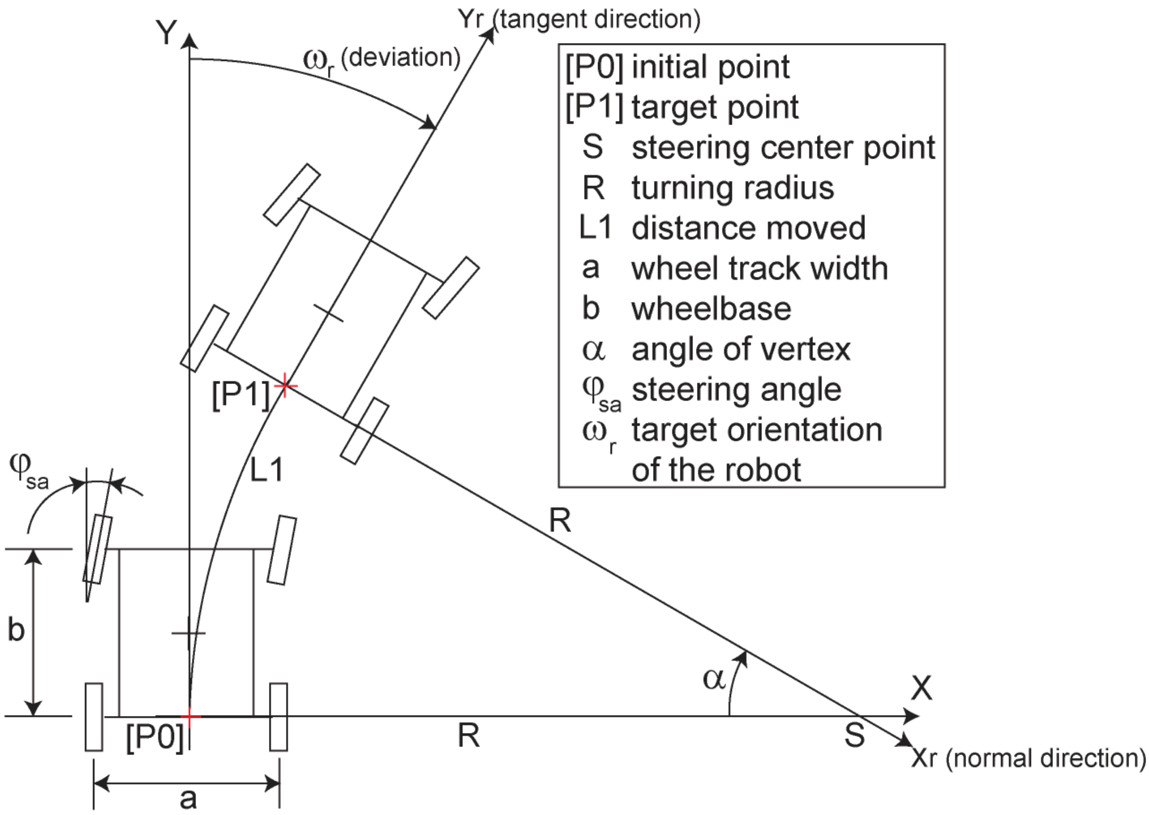

Figure 1: Ackerman steering principle

When the robot performs some kind of movement, the end position after this movement is a little bit different from the prediction calculated from ideal form (without disturbances) of equations resulting from Ackerman steering (1). When the robot's initial pose is $P_0 = \begin{bmatrix} x_0 & y_0 & \omega_{r0} \end{bmatrix}^T$ then the final pose computed from equations (1) is $P_1 = \begin{bmatrix} x_1 & y_1 & \omega_{r1} \end{bmatrix}^T$, but the true robot's pose is $P_1' = \begin{bmatrix} x_1' & y_1' & \omega_{r1}' \end{bmatrix}^T$.

$$\begin{bmatrix} x_1 \\ y_1 \\ \omega_{r1} \end{bmatrix} = \begin{bmatrix} x_0 \\ y_0 \\ \omega_{r0} \end{bmatrix} + \begin{bmatrix} \dfrac{b}{\tan\varphi_{SA}}\left(1-\cos\omega\right) \\ \dfrac{b}{\tan\varphi_{SA}}\sin\omega \\ \dfrac{L_1\tan\varphi_{SA}}{b} \end{bmatrix} \tag{1}$$

This inaccuracy causes problem with correct identification of robots pose and is going to be larger with longer movements of the robot. To deal with this inaccuracy we use the probabilistic model of robot motion which is based on modeling the effect of noise to the final pose. Most of standard approaches use Gaussian noise model for the motion.

The final position of the robot is affected by three sources of errors (see figure 1). The first error is formed by the inaccuracy in position in tangent direction to the line of travel (e.g. due to the inaccuracy the traveled distance measurement), the second one is formed by small translation in normal direction relative to the line of travel (e.g. due to the unevenly distributed wheel loading) and the last one is caused by the deviation from desired direction (e.g. due to the inaccuracy in steering control).

When the robot performs the movement to the final position, the supposed position can be modeled statistically by random variables drawn from three Gausians with mean M_{tng}, M_{nrm}, M_{dvt} and standard deviations σ_{tng}, σ_{nrm}, σ_{dvt} which are found experimentally (see chapter 3).

Input: number *n* of samples in set of particles *S*, distance *d*

Output: set of particles *S*

```
for j in range n: //for each sample
    Etng=random.gaus(Mtng,σtng)
    Enrm=random.gaus(Mnrm,σnrm)
    ω=d*tg(φ)/b
    X=(b/tg(φ))*(1-cos(φ))+Etng
    Y=(b/tg(φ))*sin(φ)+Etng
    S[j]=[ ω X Y]^T
    return S
```

Table 1: Pseudo algorithm of samples generator

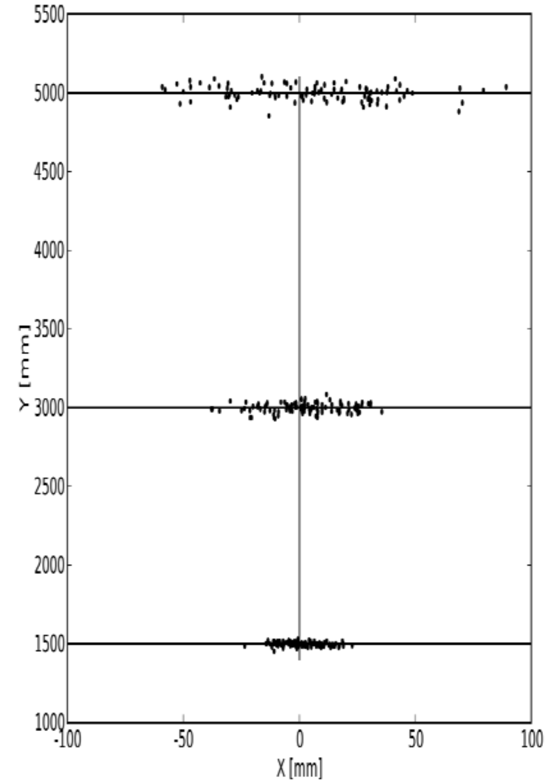

Figure 2: Generated samples for zero mean a and σ_{tng}=9.2mm/m and *σ_{nrm}=6mm/m*

Following pseudo code of the algorithm (see table 1) provides formal description of the generator of a set of particles *S*, which represents the expected positions of the robot for a forward movement by distance *d*.

On figure 2 you can see the graphical representation of the effect of the two Gausians (in tangent and normal directions) in the simulation model. Each set of samples is generated after the robot makes a single forward motion of 1.5m, 3m and 5m. Zero mean is used in these cases and figure 2 shows the results with standard deviation σ_{tng}=*9.2mm/m* and σ_{nrm}=*6mm/m*.

3. Data measurement

To estimate the required model parameters (see chapter 2) we prepared an experimental area with landmarks placed on the ground. These landmarks represent a global coordinates system for the robot. We used a robot called Bender with Ackerman steering (see figure 3).

Figure 3: experimental robot Bender

The experiments were organized as follows: the robot was set to the initial position P_0 in global position system $P_0 = \begin{bmatrix} x_0 & y_0 & \omega_{r0} \end{bmatrix}^T = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}$, then the robot moved forward by a distance *d* over the experimental area and the final pose $P_1^{'} = \begin{bmatrix} x_1^{'} & y_1^{'} & \omega_{r1}^{'} \end{bmatrix}^T$ was measured, finally the pose of the robot was set to the origin P_0.

Figure 4 shows the error for 3m traveled distance, the robot moved straight-ahead 100 times over the experimental area. The first three subplots present a histogram of the error along the *X* and *Y* axis and for the orientation ω_r. The fourth subplot presents the spatial distribution of the robot poses for all the movements. All measured data is presented in coordinates system relative to the ideal final position of the robot. The *X* and *Y* axis represent normal or tangent directions along the line of travel and represent the same coordinate system if robot moves straight-ahead only (in presented experiments this condition is satisfied).

Table 2: Mean error and standard deviation along X,Y-axis (mm) and orientation φ (degrees)

Traveled distance	1.5m (50 samples)		3m (100samples)		1.5m (50 samples)	
	M	σ	M	σ	M	σ
X	0.5	10.3	4.5	17.8	-56.5	51.3
Y	139.2	22.6	107.7	27.6	10.1	20.3
φ	-1.4	0.9	-2.9	0.9	-0.7	1.1

Table 2 shows the Gausians parameters obtained from performed experiments. You can also see the results for traveled distance 1.5m or 5m, but for those cases the robot was moved only 50 times.

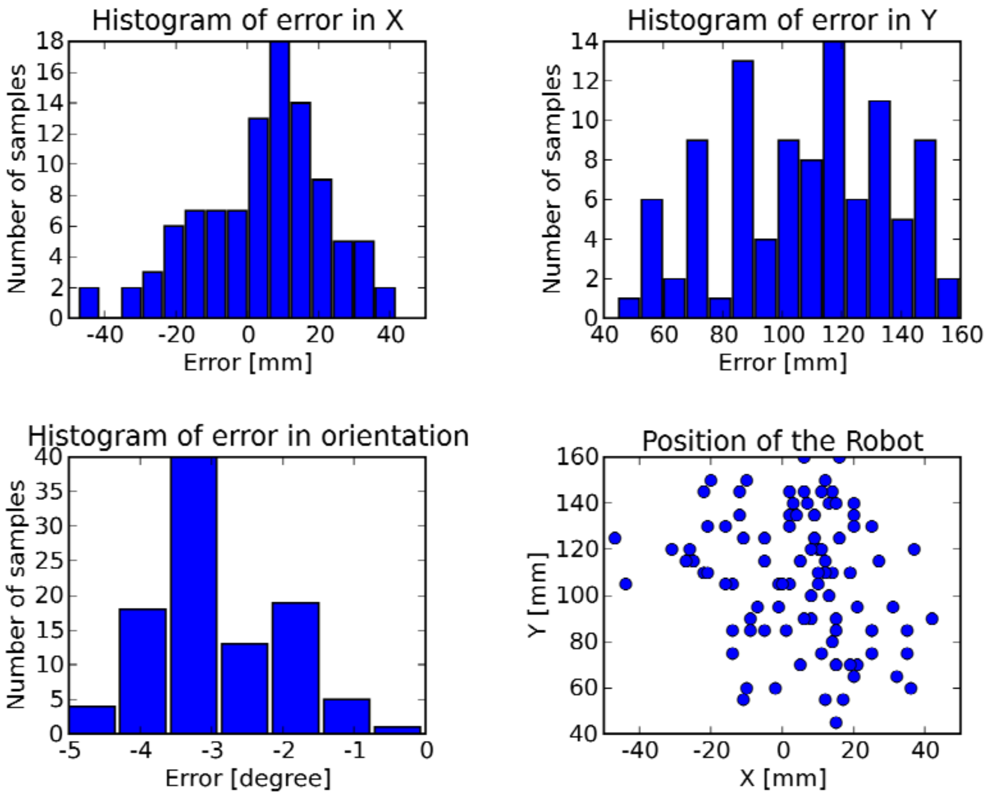

Figure 4: Error distribution after straight motion of 3m, 100 samples.

4. Conclusions

This paper summarizes our approach to creation of a probabilistic motion model for wheeled robot. In presented results you can see substantial influence of components which are used for the design of the robot. The robot’s deviation from line of travel is asymmetric, because of unevenly distributed wheel loading and the properties of used tires (see table 2). Future work will be focused on adding a probabilistic steering model to the proposed model.

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