DEALING WITH SENSOR ERRORS IN SCAN MATCHING FOR SIMULTANEOUS LOCALIZATION AND MAPPING

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The paper presents Potential-Based Scan Matching (PSCM) method used for simultaneous localization and mapping of mobile robot in unknown environment. The method is based on matching two proximity sensor scans from different robot locations. The resistance of the method against errors in sensor readings is investigated using both general sensor error model and error model for LMS 200 laser scanner. The method proved to be highly resistant against the noise with respect to the localization issue, the mapping is consistent for the noise levels exceeding the commonly used instruments.

Key words: *localization, mobile robotics, SLAM*

1. Introduction

There are several problem areas in mobile robotics which obtained a great attention in past few years. Among those we can recognize the sensor data fusion issues (i.e. how to combine contradictory data from various sensors), localization (determining robot pose in given map), mapping (creating the map when moving in unknown environment), path planning (how to efficiently get from the initial position to the goal position), etc. Localization method together with mapping is the key feature in path planning (we can not plan the path if we do not know where we are and how does the environment look like).

When moving in partially or totally unknown environment the localization and mapping must be performed simultaneously, resulting in a map of environment and location in such a map. This approach is generally called SLAM (Simultaneous Localization And Mapping). In order to do so, several methods can be implied. This paper is focused on scan matching method, which combines the data from proximity sensors scans from two different locations to build a local map out of the scan data and determine the position and orientation of the robot in the map. When robot sequentially moves the updated position is calculated and global map of environment can be made by matching the local maps.

2. SLAM

Every SLAM method essentially depends on the proximity sensor data – the distance from the nearest obstacle in sensor range – from the complete 360° range. Such data can be obtained from a range of sensors. Nowadays the laser scanners are the most popular. The only disadvantages are the high cost of the sensor and bad readings in certain special conditions (glass surfaces, underwater readings). The weight of the sensor and its feeding requirements prohibit its use in small and light robots. The second possibility is the sonar,

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light and cheap compared to the laser, but with wide beam which degrades the readings. Computer vision is another possibility, possibly light and cheap, however the computational requirements are extremely high and the dependency on light conditions is also discouraging. For the further described method we do not take into account the way the distance scan is obtained, however reading errors are taken into account.

SLAM in general uses odometry data and the most general form is shown on Fig. 1. Whenever odometry update is recorded the position estimation is calculated. The proximity sensor scan is compared with the original location scan and data obtained from such comparison are used for update of position estimation. At the same time the scan data are used for creation of a local map which might be combined with the previously constructed local maps to build up the global map of the environment. Even though the general SLAM uses odometry data, the proximity sensor data might be sufficient for the localization itself.

There is a number of methods usable for each step in SLAM. When odometry data are used the EKF (Extended Kalman Filter) can be used for both odometry update and the uncertainty in landmarks extracted from the scans [2]. In this paper we investigate the Potential-Based Scan Matching (PSCM) method [1] with respect to the scan reading errors. The method is intended for 2D problems only, in contrast to general SLAM model. The below described method in principle does not require the odometry readings. However as further discussed the odometry information can be used to speed up the scan matching and also avoid the minimization procedure to be stuck in local extreme.

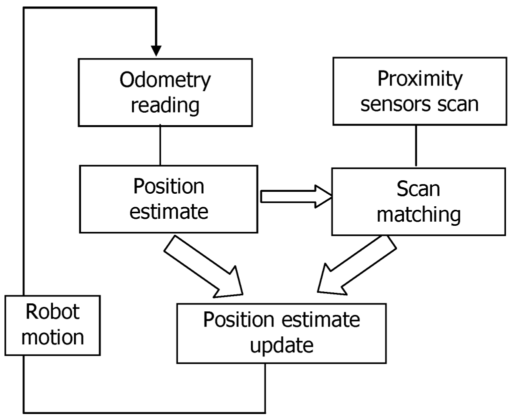


Fig.1: SLAM – general version block diagram

3. Potential based scan matching method

Let's denote the initial position of the robot $P_0 = [x_0\ y_0\ \varphi_0]^{\mathrm{T}}$ and $P_1 = [x_1\ y_1\ \varphi_1]^{\mathrm{T}}$ the position after performing the move. This new position is unknown (odometry data are unused at this point) and the task is to determine the move $\Delta P = [\Delta x\ \Delta y\ \Delta\varphi]^{\mathrm{T}}$, where $\Delta x = x_1 - x_0$, $\Delta y = y_1 - y_0$ and $\Delta\varphi = \varphi_1 - \varphi_0$. To do so the proximity sensor scans $S_0 = \{d_1, d_2, \dots, d_n\}$ and $S_1 = \{d_1, d_2, \dots, d_n\}$ are used, where d_i is the distance to the closest obstacle obtained from the sensor. The pool M of possible locations is generated based on the initial position and motion limits (representing $\pm\Delta_{\max}$ for each variable). For each location from the pool the scan is recomputed, potential field is calculated for the initial and recomputed scan and scans are matched together to create final potential field. The match can be therefore denoted as the function of $m = f(\Delta x, \Delta y, \Delta\varphi)$ and the resulting move corresponds to the minimum of the function:

$$\Delta P = \arg\min_{M} f(\Delta x, \Delta y, \Delta\varphi) \tag{1}$$

There are several ways how both the potential field and the match can be calculated. Each d_i represents the end point of the beam. As the distances measurements are disrupted by a noise, the natural way to express the observed obstacle is to use the Gaussian generated around the end point. The combination of all the Gaussians then creates the potential field for given scan. To match the scans and to obtain the match value m we simply combine both potential fields and calculate the occupied space on resulting field.

$$m = \sum_{i_\mathrm{x}=0}^{i_{\mathrm{x}\max}} \sum_{i_\mathrm{y}=0}^{i_{\mathrm{y}\max}} o(i_\mathrm{x}, i_\mathrm{y}) \;, \quad \text{where} \quad o(i_\mathrm{x}, i_\mathrm{y}) = \begin{cases} 1 & \text{if} \quad \mathrm{pfield}(x, y) > 0 \;, \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where pfield is the value of potential field in given coordinates, i_x is the index for x coordinate running from 1 to number of discrete steps in given axis, i_y the same for y coordinate. One can notice that only the occupancy logical value is used instead of the actual value of potential field.

When no odometry data are used, the pool M generation requires the discrete grid of possible locations around the initial position. If there is additional information available (e.g. the odometry update, initial state of the robot and statistical model of its motion, etc.) we can still use the discrete approach with the pool center in expected position, or we can omit the pool generation completely and use minimization of the match function.

The local map is created from resulting potential field of found ΔP scans. Simple occupancy transformation can be used (as with the o calculation), the whole potential field can be taken into account, or certain layer of potential field. The layer approach should be advantageous when dealing with the dynamic obstacles whose position changes in time.

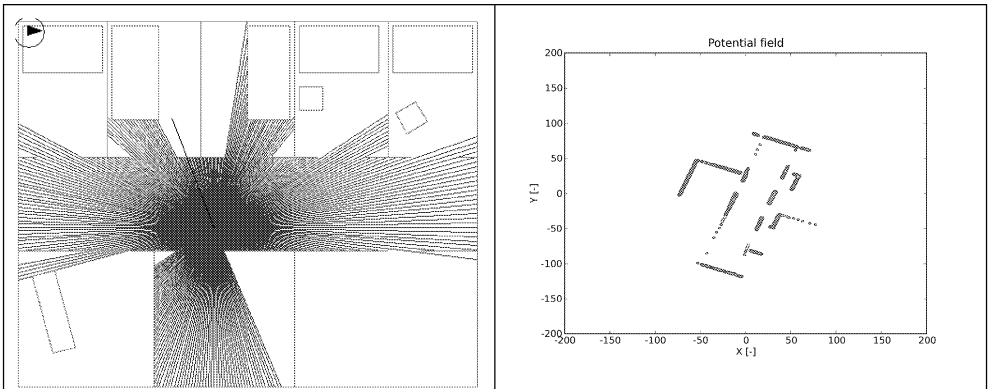
4. Simulations

Simulation experiments were performed to determine the influence of proximity sensor errors to the shape of f function and more importantly the error in ΔP determination. For the experiments further described the discrete approach was used. For given map and random initial position the scans were computed with various levels of error. Error modeling depends on expected type of proximity sensor. Two sets of experiments were carried out. The first one uses the general model of the sensor error using the Gaussian noise with normal distribution $N(0, \sigma)$, where dependency of σ on measured value is linear (longer distances = larger error). Therefore the value of each beam d_i is calculated as:

$$\bar{d_i} = d_i \pm \mathrm{gausian}(0, \sigma_\mathrm{d}) \;, \tag{3}$$

where $\sigma_\mathrm{d} = d_i/\mathrm{nl}$, where nl is a constant determining the level of noise.

The second set of experiments was carried with currently the most common type of sensor used in mobile robotics – laser rangefinder. In our case we used the error model published literature [3], where the huge number of experiments was performed for LMS 200 laser scanner by Sick. The scanner is based on the measurement of time-of-flight (TOF). The most important observation regarding the error modeling is that the error is essentially independent on the measured distance. The target surface properties also do not affect the mean, only the distribution of measured ranges. The effect of the incidence angle and also the effect of drift were omitted in our experiments, and the measurement error consisted of the systematic error of the instrument (three cases for negative, zero and positive error of 15 mm were performed) and Gaussian noise with normal distribution $N(0, \sigma)$.



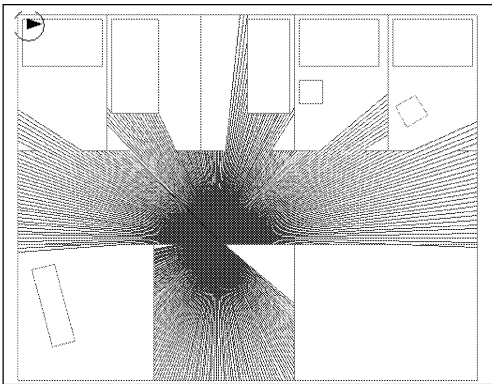
a) Initial scan with zero level noise | b) Initial potential field with zero level noise

Fig.2: Initial scan and its potential field

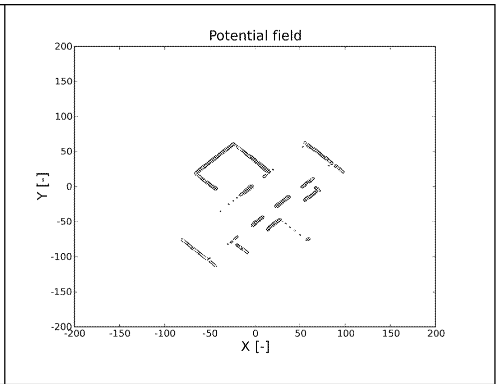
The robot motion was restricted to limits in both planar coordinates to $\langle -0.5, 0.5\rangle$ m and in angular change to $\langle -45, 45\rangle$ deg. Angular resolution for the pool M was one degree, x and y resolution was 25 mm, thus giving the pool size of $M_{\text{size}} = 40{\times}40{\times}91 = 145600$. An example of the results for single particular position change is shown in Figs. 2–4. Figure 2 shows the initial scan and resulting potential field with no noise. Figure 3 shows the scans and their corresponding fields after the move (52 mm, −367 mm, 24°) for three levels of noise $\sigma = \{0, 50, 100\}$ mm/m. Combined potential fields and corresponding match functions expressed as isosurface of certain values of the match function are shown for the same noise levels on Fig. 4. In order to get easy to read noise level, the value of σ/m in mm is given.

The course of determined position changes errors (the difference between the position change for which the scans were generated and the position change determined by PSCM) depending on the noise level are shown in Fig. 5 together with the course of minimum and maximum values of match function. Position change error is given separately for angle (in degrees) and for xy change as $err_{\text{xy}} = \sqrt{(\Delta x_{\text{given}} - \Delta x_{\text{obtained}})^2 + (\Delta y_{\text{given}} - \Delta y_{\text{obtained}})^2}$. The data are averages of 10 different random positions of the robot (with random robot motion).

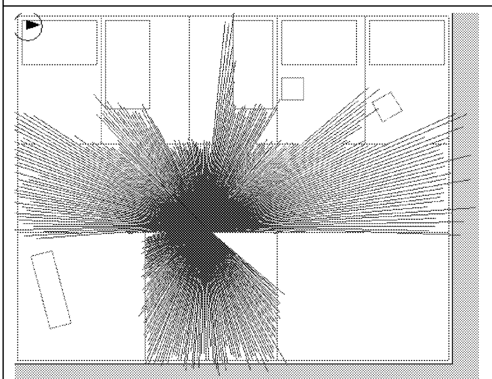
The second set of experiments taken for the LMS 200 laser scanner errors model was performed for double of systematic error given by instrument producer and triple of σ found in the literature [3]. The reason for this increment is the discrete grid which works as the filter of slightly modified beam values. The true observed imperfections of laser scanner would vanish due to the filtering. The experiment was performed for the same locations as with the general type of sensor. An example of resulting match function for the corresponding location is shown in Fig. 6. One can see that the difference with respect to the zero noise is



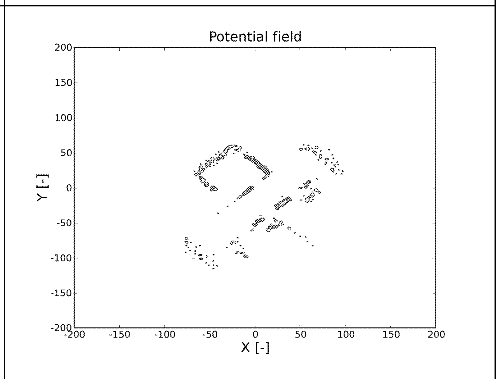
Scan – zero noise level



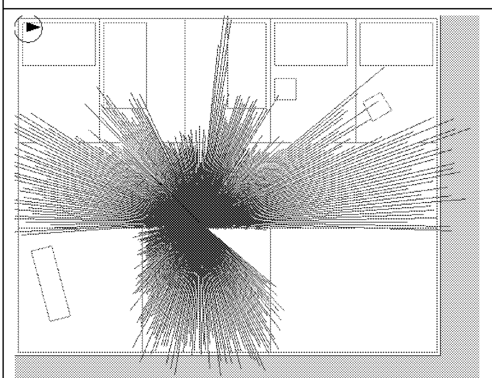
Potential field – zero noise level



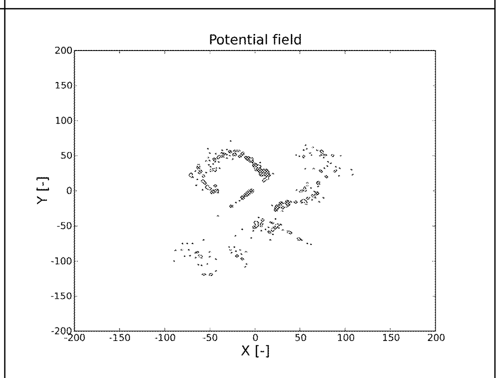
Scan – noise level $\sigma = 50$mm/m



Potential field – noise level $\sigma = 50$mm/m



Scan – noise level $\sigma = 100$mm/m



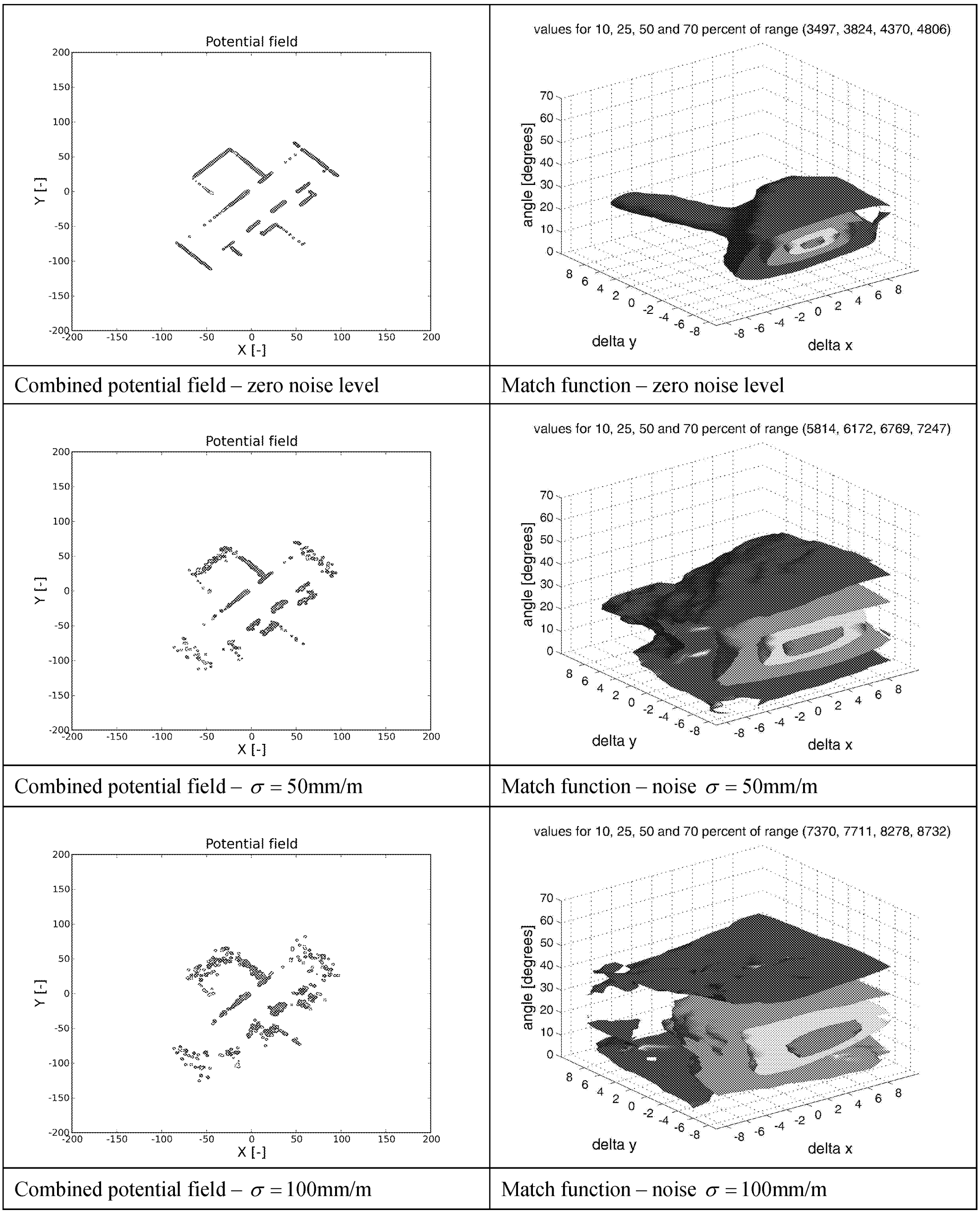
Potential field – noise level $\sigma = 100$mm/m

Fig.3: Scans and potential fields for increasing noise level

minimal (also note the small difference in the percentage values of the function) and thus the found minimum of match function is the same.

5. Discussion, conclusions and future work

As one can see from the figures, the PSCM method is very resistant against the noise in sensors. For $\sigma \leq 100\,\mathrm{mm/m}$ the error for robot position change is less than 100 mm, while error in orientation determination is less than 0.5 degree. Even with noise exceeding the

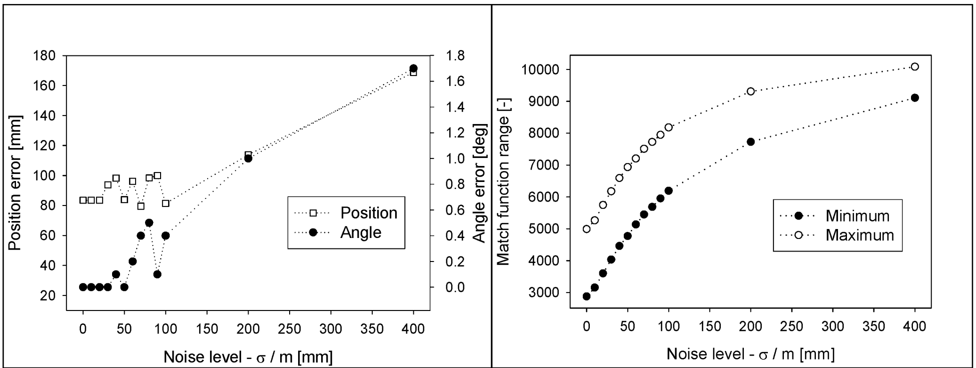


Combined potential field – zero noise level	Match function – zero noise level
Combined potential field – $\sigma = 50$mm/m	Match function – noise $\sigma = 50$mm/m
Combined potential field – $\sigma = 100$mm/m	Match function – noise $\sigma = 100$mm/m

Fig.4: Combined potential fields and match functions for increasing noise level

values of commonly used commercial sensors in order of magnitude, the localization error is acceptable. However, the local map obtained from such a scan would be unusable.

When we take a look at the match function range course, we can see that while the function minimum expectedly increases (as the potential field of noised scan is more blurred), the difference between minimum and maximum match is kept roughly the same. When looking at the visualization of match function itself (see Fig. 4), it is clear that with increasing noise the shape of isosurfaces is less consistent, however, the function still contains single clear global minimum.



PSCM error versus noise level	Match function course

Fig.5: PSCM error and match function limit values

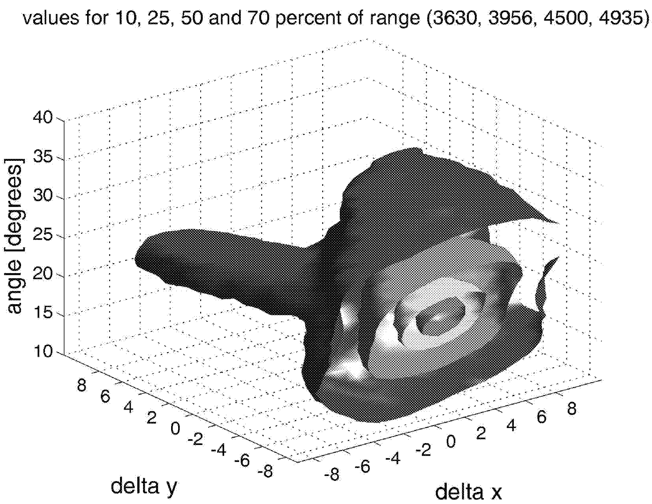


Fig.6: Resulting match function obtained for LMS 200 error model data

When using the LMS 200 laser scanner data with triplicate of errors the method is perfectly capable of localization and resulting local map is consistent. Match function shape change compared with zero level noise is hardly observable.

Therefore we can conclude that presented PSCM method is fully capable of successful determination of robot position and creation of local map from two consecutive proximity sensor scans, regardless the odometry measurement, and with great resistance again measurement noise. However, usually some knowledge of robot motion is available. It could be the direct odometry measurement (e.g. IRC sensors on wheels for wheeled robot), motion estimate on walking robot based on the leg control actions performed or estimate of the new position based on probabilistic model of the robot. Such information can be easily incorporated into the PSCM method as the center of pool M, thus reducing the number of potential fields to be generated and consequently reducing the computational time.

The method was preliminary verified by real experiments using LMS 200 laser scanner and experimental results fully correspond with the simulations.

Regarding the future work there are many possible areas. Among others we can mention the influence of limited beam range, the dealing with dynamic obstacles, the minimization of the match function using gradient descent or similar method.

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