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FAST SCAN MATCHING FOR MOBILE ROBOT LOCALIZATION

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Abstract

The paper is focused on fast method which uses subsequent proximity sensor scans of mobile robot environment to determine the robot position and orientation and to build a local map. The environment is supposed to be unknown. The method, based on Potential-Based Scan Matching which gives a measure of scan match is combined with gradient descent in order to find the proper match of two scans in reasonable time. Tests of robustness against the noise in sensor readings are included.

Key words: localization, scan matching, mobile robotics

Introduction

Localization task is determining robot position and orientation in the map. There is a number of methods solving the problem for know map. The problem becomes more challenging when map of environment is unknown and methods dealing with this issue are known as Simultaneous Localization and Mapping (SLAM). SLAM methods are often based on Kalman filters for update of expected robot position based on odometry error estimate and sensor scan matching. Presented paper introduces fast method for building the local map and localization of the robot by matching of two proximity sensor scans obtained from different locations (after robot moves) independent on odometry information.

Methods

The way the two proximity sensor scans are matched is based on Potential-Based Scan Matching (PSCM) method (Věchet 2007). For the two positions $P_0 = \left[x_0 \quad y_0 \quad j_0 \right]^T$ and $P_1 = \left[x_1 \quad y_1 \quad j_1 \right]^T$ the task is to determine the move $\Delta P = \left[\Delta x \quad \Delta y \quad \Delta j \right]^T$, using scans $S_0 = \left\{ d_1, d_2, .., d_n \right\}$ and $S_1 = \left\{ d_1, d_2, .., d_n \right\}$, where d_n is the distance to the closest obstacle. To do so, the set of possible locations M is generated and for each location 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 is the function of $m = f\left(\Delta x, \Delta y, \Delta j \right)$ and the resulting move corresponds to the minimum of the function:

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$$\Delta P = \arg\min_{M} f\left(\Delta x, \Delta y, \Delta j\right) \quad (1)$$

As the value of the match is calculated for the whole set *M*, we can use isosurfaces to visualize the match function. An example of such match function for the scans desribed in detail below is shown in Fig.1. Four isosurfaces for different percentage of match function value ranges are used. The range is given by minimum and maximum values of match function where minimum corresponds to the best match – correct combination of potential fields. Selected percentages (10, 25, 50, 70) gives a descriptive view of the overall match function shape. We can see that the function has clear single minimum. Therefore we can speed up the search for ΔP by applying the gradient method. As the set *M* is organized in fixed step length 3D grid, we can use discrete gradient and also check whether the true minimum was reached by the steepest descent. The initial selection of starting point depends on information available. If there is no odometry reading the method selects several points from the search space, finds the minimum and uses the extreme as a starting point. When odometry is available, its estimate serves as the starting point instead.

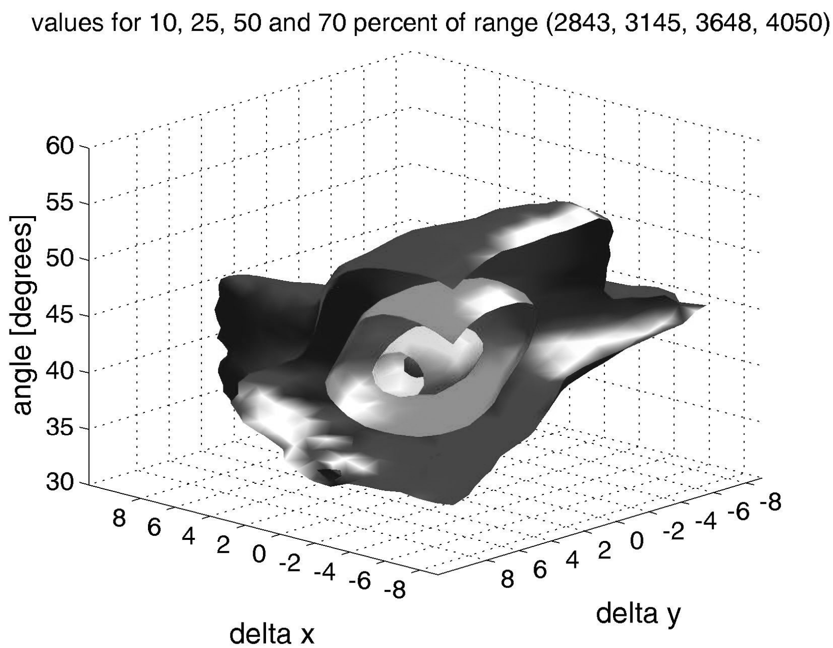

Fig. 1. Example of match function

Results and discussion

A number of simulation experiments was performed to verify the usability of the method. The map of the lab shown on Fig. 2. was used to generate the scans readings for two different positions of the robot. As the results are likely to be affected by the noise in sensor readings, the calculation was performed for various levels of Gaussian noise with normal distribution $N\left(0, s\right)$. Such noise model represent general sensor error model when the reading error depends on the measured distance. In the case of laser scanners, often used in mobile robotics the noise is distance independent and s is way below the levels used in our experiments (see e.g. Ye, 2002).

The positions of the robot in the map were chosen randomly. The potential field was calculated for grid of 400x400 covering the complete map. For all robot positions the potential field was first calculated completely in order to compare the results found by gradient method with the correct ones. An example of summed potential field (which represents the local map build from the scans) for found minimum of match function is shown in Fig. 3.

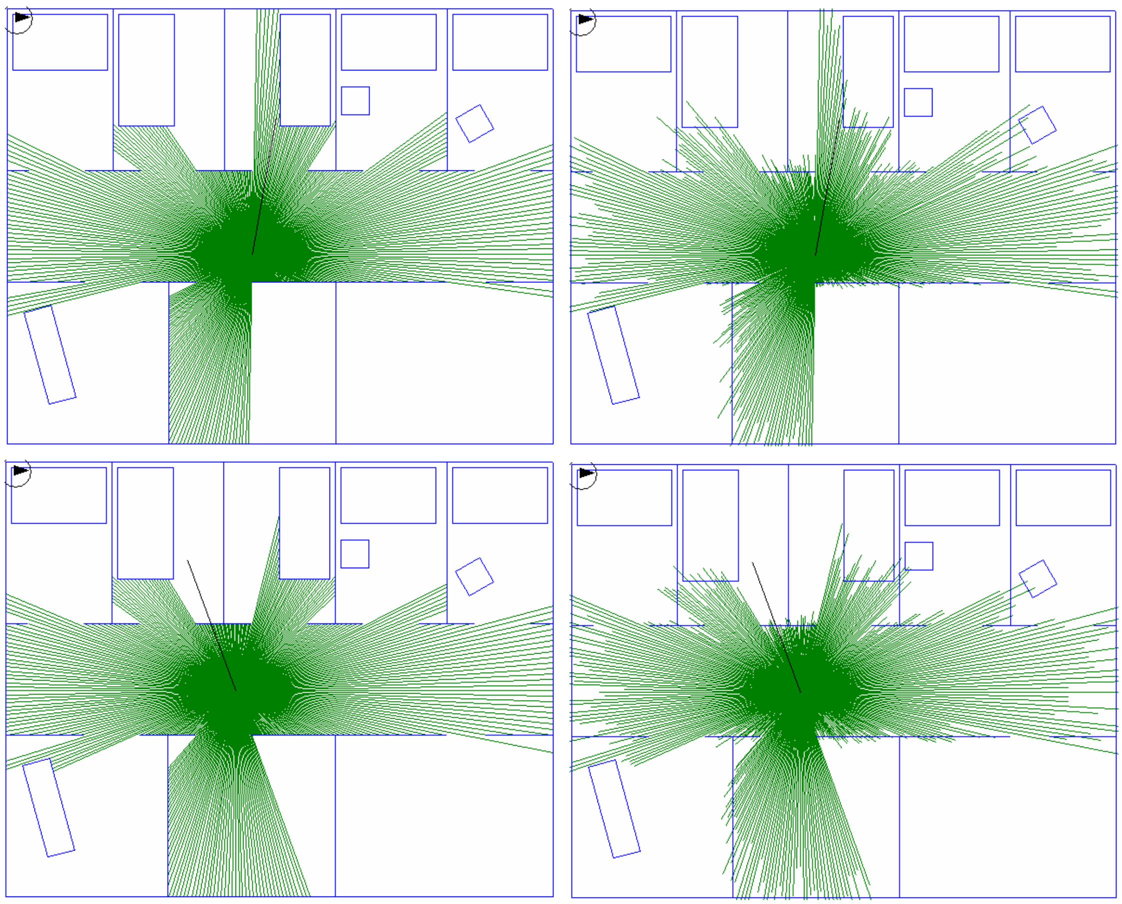

Fig. 2. Example of used map with both reference and new sensor scan for clear and noisy data (noise levels: $s = 0$ and 100 mm/m)

As the method can generally operate without the odometry readings (no estimate of ΔP) the initial point determination is essential. As the angle dependency is the most important, the initial estimates are calculated for 2x2x3 positions symmetrical around the center with distances controlled by parameter d, e.g. first estimate coordinates are given as $x = x_{center} - x_{range} / d$. The best estimate is selected as starting point for the discrete gradient descent.

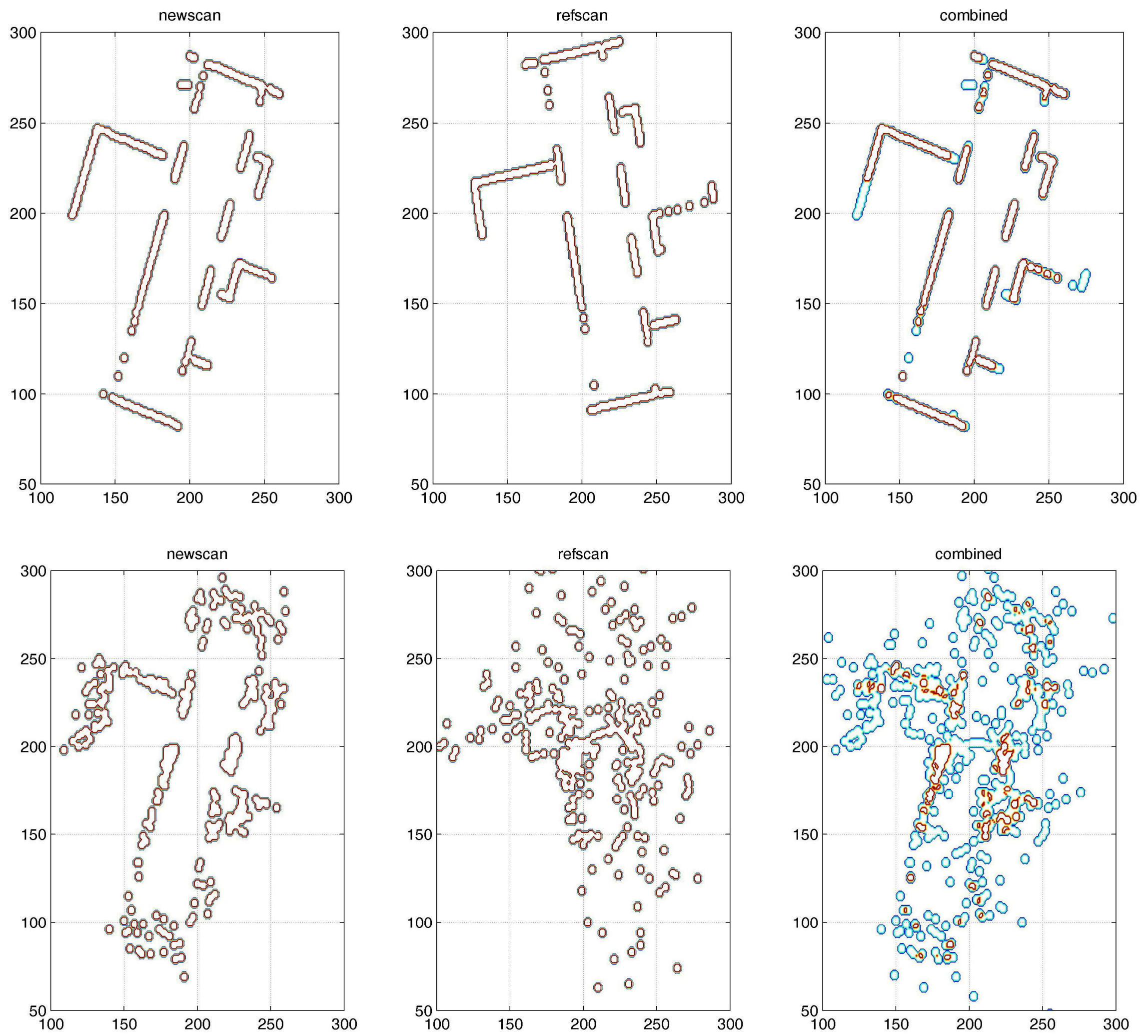

Fig. 3. Example of potential fields for new scan (after robot moves), reference scan (from original location) and combination (for the minimum of match function) for zero noise level (top) and noisy data (bottom)

The number of function evaluations depending on noise level and initial parameter d including the failure rate is shown in Fig 4. We can see that up to the noise level of $s = 130$mm/m the failure percentage is very low. Regarding the initial estimate parameter the optimum seems to be in range of 2-3, higher values result in higher failure rate.

The reduction of number of match function evaluations for higher noise levels is caused by the increased number of failures as the gradient method is quickly trapped in local minimum. As for the actual times of evaluations, the complete match function takes about 220 seconds on Pentium IV computer. If we take 150 evaluations when gradient method is used we get about 0.95 sec for single localization computation. As the calculation can be performed during the robot motion the speed achieved is satisfactory.

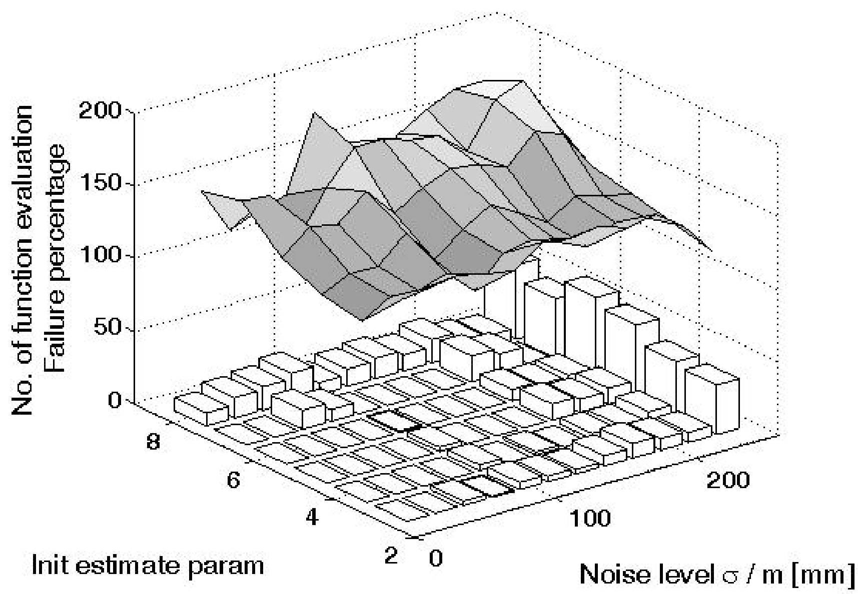

Fig. 4. Number of match function evaluations (surface graph) and failure rate percentage (column graph)

Conclusions

Using discrete gradient descent for match function minimum search proved to be an easy to implement but sufficient way how to reduce the search time. The method is resistant to the proximity sensor noise up to the levels exceeding the commonly used sensors errors. Odometry reading which would give us an estimate of starting point can further speed up the search, however the method can be successfully used in cases when such reading is unavailable (odometry sensors failure). The computational requirements are sufficiently low for the method to be used in real time task.

High resistance against the noise in proximity sensors in order of magnitude compared to commonly used sensors suggest the future work to be focused on the resistance against dynamic obstacles.

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References

Věchet S., Krejsa J.: Potential–Based Scan Matching in Mobile Robot Localization, *Modelling and Optimization of Physical Systems 6*, pp. 185-188, Gliwice 2007

Ye C., Borenstein J.: Characterization of a 2-D Laser Scanner for Mobile Robot Obstacle Negotiation, *in Proceedings of the 2002 IEEE International Conference on Robotics and Automation*, pp. 2512-2518, Washington DC, USA, 2002,