Simultaneous Mapping and Navigation for Skid Steered Mobile Robot

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Abstract: - This paper presents extended kalman filter based algorithm for simultaneous localisation and mapping. This algorithm was designed for use with skid steer mobile robot platform. Also models of laser proximity sensor and mobile platform are presented and their properties are specified.

Key-words: - Skid steer mobile robot, extended Kalman filter, Radon transform, laser proximity sensor

1 Introduction
In the area of the autonomous mobile robotics there is the high emphasis put on autonomous work of mobile robot. Autonomy in the robotics is taken as a capability to pursue activity without human intervention in an unstructured area. The mobile robot has to fulfill following conditions in order to be autonomous:

- The ability to work for a long time without human intervention
- The ability to maneuver through working area
- The ability to avoid situations that could lead to destruction of the robot or the injury
- The ability to collect information about its working area

2 Mobile robot and equipment
To fulfill all of the above mentioned conditions it is necessary to know the precise position of the mobile robot. It is possible to obtain the information about robot’s position in several ways. The most important method is to get the measurement without intervention to the measured area. This condition assumes impossibility to make artificial landmarks. For this purpose the robot is equipped with laser proximity sensor SICK LMS100. This laser scanner is not primarily meant for use in mobile robotics. But its price, performance and robustness allow using it for the localisation purpose. For the navigation purpose robot is equipped only with this device.

Robot U.T.A.R is skid steered mobile platform that is designated to work in both of kinds of terrain, either indoor or outdoor. This advantage is counterbalanced with impossibility to make an easy kinematic model the position estimation is complicated due the fact, that the turning is accomplished via skid that is unmeasurable with optical encoders fastened on the driving motors.

Fig. 1 – Skid steered robot U.T.A.R.

3 Extended Kalman Filter
The extended Kalman filter (EKF) algorithm was selected as the algorithm for the Simultaneous Mapping and Localisation (SLAM) as the popular approximation of the Bayes filter method.
The system (mobile robot platform) is described as:

\[ x_{(k+1)} = f[x_{(k)}, u_{(k)}, v_{(k)}] \]

\[ y_{(k)} = h[x_{(k)}, w_{(k)}] \]  

where \( f \) is the nonlinear function describing the system, \( v_{(k)} \) is zero mean process noise, with covariance \( Q \). The \( h \) is function describing the observation and \( w_{(k)} \) is measurement noise with the same properties as \( v_{(k)} \) and covariance \( R \). The EKF algorithm allows computing the best estimate of the robot state (position) based on the difference between value measured by the sensor and value predicted by mathematical model.

Prediction of the robot state and its covariance:

\[ \tilde{x}(k+1|k) = f[x_{(k)}, u_{(k)}, 0] \]

\[ P(k+1|k) = \nabla f_k P_{(k|k)} \nabla f_k^T + \nabla f_k Q_k \nabla f_k^T \]  

New state of the robot and its covariance (update) is then computed from:

\[ \tilde{x}(k+1|k+1) = \tilde{x}(k+1|k) + W(k+1)u(k+1) \]

\[ P(k+1|k+1) = P(k+1|k) - W(k+1)S_{\tilde{x}u}(k+1)W^T(k+1) \]

where: \( u(k+1) = y(k+1) - h[x_{(k)}, 0] \)

is called innovation vector its covariance:

\[ S_{\tilde{x}u} = \nabla h_k P_{(k|k)} \nabla h_k^T + \nabla h_k R_{(k+1)} \nabla h_k^T \]

and Kalman weighting matrix:

\[ W(k+1) = P(k+1|k) \nabla h_k^T S_{\tilde{x}u}^{-1}(k+1) \]

The detailed description of the algorithm is introduced in [1,2]. The mathematical models of the robotic platform and sensor are proposed in the next sections. Also the foundation of the feature extraction algorithm is presented.

4 Robot model

For the purpose of the position estimation algorithm the verification of conditions for use of easy kinematic model was done. The idea is to use the kinematic model of the differential driven robot. Such a substitution is possible due the fact that centre of gravity is in the geometric centre of the robot.

For differential driven robotic platform following equations could be applied:

\[ \omega = \frac{V_{ld} - V_{Pl}}{wh. spacing} \]  

and position is then expressed as:

\[ x_{(i)} = \int v \cos(\phi_{(i)}) dt \]

\[ y_{(i)} = \int v \sin(\phi_{(i)}) dt \]

\[ \phi_{(i)} = \int \omega_{(i)} dt \]

The precondition for use of such a simple model is that the terrain where the robot moves is homogenous and the skid and slip forces are equivalent for all the four wheels. It is possible to satisfy these conditions for indoor use of robot.

\[ \omega \]

\[ v \]

\[ \frac{V_{ld} - V_{Pl}}{wh. spacing} \]  

\[ \int v \cos(\phi_{(i)}) dt \]

\[ \int v \sin(\phi_{(i)}) dt \]

\[ \int \omega_{(i)} dt \]  

This idea was verified with experiment, where the position of the centre of gravity and all four wheels was measured with the camera. Measurement of the position of the centre of gravity was then compared with position calculated from the model in Matlab Simulink.
Figure 4 shows comparison between measured position and position computed from kinematic model. The blue points represent measured position. The cluster of points in the upper right corner is caused by imperfection of detection algorithm that is primarily determined for position detection in robotic soccer game. Red points correspond to the position computed from kinematic model.

From these experiments it is obvious, that the kinematic model of the differential driven platform can substitute the model (dynamic) of the skid steering robot in indoor areas, where the flooring is homogenous and with no slope.

5 Sensor Model

The second important part of the EKF localisation algorithm is the model of the sensor. The mobile robotic platform is equipped with the SICK LMS 200 laser scanner that measures distance via the time of flight of the reflected laser beam.

Also for verification of the sensor model the experiments were done. These experiments were focused on the dispersion on measured value.

In order to validate the influence of an obstacle’s reflectivity on the measurement reliability, it was necessary to manipulate the reflectivity of certain material. Since a diffuse material was used and the laser scanner’s wavelength is constant, the reflectivity could only be changed by the change of material properties. This was done by using a matte paper and printing different shades of gray, controlling the percentage of the black in coverage. To limit the number of measurements to be taken at different distances, the number of shades was set to 5, where 5 corresponds to white paper and thus highest reflectivity and 1 corresponds to 100% coverage by black ink.

Although the measurement of the reflectivity was not available in the time of the experiment, the reflectivity of the shade No. 3 is set to 18%. This value is well known in digital photography as a 18% middle grey. It lies in the middle of the black-white gamut. Its composition in [R,G,B] space is defined as [127, 127, 127].

Another issue was to estimate whether the reliability of the measurements changes over the distance differently for objects of different colors. The fact that objects seem to have different colors in human perception is due to the sensitivity of the object’s reflectivity to the incidental radiation wavelength, meaning that certain objects have higher reflectivity for certain wavelengths (colors). To perform such experiment, a set of colored papers was created. Unfortunately this part of the experiment lacks important validation of the sample objects because a device to measure spectral intensities was not available at the time of experiment.

Therefore the results are only illustrative and they cannot be used for modeling of the sensor taking color sensitivity into account.
In figure 6 the dependency of the standard deviation on distance measurement is presented. Values of std. deviation are average values through all grey levels respective all colors. Based on these results, model of the sensor was created.

\[
\begin{bmatrix}
    r_i \\
    \gamma_i
\end{bmatrix} = \begin{bmatrix}
    x_i^2 + y_i^2 \\
    \tan \left( \frac{y_i}{x_i} \right)
\end{bmatrix} + \begin{bmatrix}
    w_r \\
    w_{\phi}
\end{bmatrix} \quad (9)
\]

This simple model is taken with respect of the sensor coordinates. In case of use this model for mapping or localisation it is necessary to transfer it into global coordinate frame \([X_G, Y_G]\).

From our experiment we are able to determine the component of measurement noise \(w\) as:

\[
w_r = 1.12x + 9.24 \quad (10)
\]

The other component \(w_{\phi}\) was determined on the basis of the product datasheet [6] as:

\[
w_{\phi} = 1^\circ \quad (11)
\]

6 Measured data processing

For the robotic mapping and localisation via the EKF algorithm it is necessary to compare predicted position of the obstacle with measured distance. In our case the comparison of the positions of the features was selected.

The lines corresponding to the walls and sides of the obstacles and intersection of these lines were chosen as the features describing the area. From this choice follows the need of the algorithm for determining the equations of lines.

Because of the nature of the measured data (the distance between points corresponding to observed wall is increasing with increasing distance of obstacle) the method of the Hough transform in the form of the Radon transform was chosen.

Amongst the biggest advantages of this method falls the fact, that it is not sensitive for the data corrupted with the noise and growing distance between points.

6.1 Radon transform

Radon transform is an integral transform used in processing of tomography scans in medical sector. The radon transform itself is defined as:

\[
Rf(r, \phi) = \int f(x, y) \delta(r - x \cos(\phi) + y \sin(\phi)) dx dy
\]

where \(f(x, y)\) is an image function that is transferred into the value corresponding to the integral over the line defined as: \(r = x \cos(\phi) + y \sin(\phi)\) \((13)\)

The problem of finding the proper equations of line is then converted into the searching of the local maximums in the \(Rf(r, \phi)\) space, where \(r \in R\) and \(\phi \in [0, \pi]\).

The image received form the laser scanner is sharp edged. The value of the \(f(x, y)\) space are either 1 that represents detected obstacle or 0 for free space.

The Radon transform computes integral of intensity over all the lines \(r\). In the case of the distance image, it computes the number of points lying on the line \(r\). Because of the measurement noise and other influences the points are not in the exact line, there is necessary to determine which points belong to the line and which does not. This is done by cluster analysis [5].

The data assumed representing one line equation are joined into the cluster in \(Rf(r, \phi)\) space. From each of these cluster is then picked out the line where the number of the points of the original image \(f(x, y)\) is maximal.

The basic principle of clustering method is to find the dissimilarity between every pair of objects (points) in the data set. Each object is described by the \(m\) characteristic parameters:

\[
o_h = (x_{k1}, ..., x_{km})
\]

\[
x_{ki} = x_i
\]

\[
x_{k2} = \phi
\]

Then the dissimilarity function has following properties:

\[
d (o_h, o_s) = 0 \iff o_h = o_s
\]

\[
d (o_h, o_s) \geq 0
\]

\[
d (o_h, o_s) = d (o_s, o_h)
\]

(16)
Fig 8 – Objects separated into clusters

The most frequently used method for determining the dissimilarity is Euclidean metric:

\[ d(o_h, o_s) = d_E(o_h, o_s) = \sqrt{\sum_{j=1}^{m} (x_{kj} - x_{sj})^2} \]  

(17)

Clusters are created in the moment we have all the values of dissimilarities between all the objects. Then data are separated into the clusters by:

\[ d(o_i, o_{i+1}) \leq T \]

Where the \( T \) is threshold value for separating the clusters. This value in fact allows to set the sensitivity of the method. The smaller value of \( T \) the tinier lines are found.

In the moment all the accumulator is classified into clusters, it is necessary to find the lines with the maximum value. These found objects represent the straight lines \( l_1 \ldots l_N \) with parameters \( r_1, \varphi_1 \ldots r_N, \varphi_N \).

The radon transform allows finding of straight lines in the distance image. This fact limits the use of this method for structured environment.

Fig 9 – Distance image of the observed space with found lines, intersections (red circles) and begins of lines (blue circles)

8 SLAM

All the above described parts of algorithms are united together to form an SLAM algorithm, that is in the test stage in these days. The functionality of the proposed SLAM algorithm was verified in the well structured area, where all above described conditions (floor homogeneity, etc.) were fulfilled.

The sensitivity test for Radon transform algorithm has to be done. Also tests of the sensitivity of the proposed kinematic model of the mobile robot for the change of the floor material and other possible influences have to be tested.
Fig 10 – Map of the area assembled from the single measurements based on the position estimate.

8 Conclusion:
This article describes the EKF - SLAM algorithm that has been proposed for indoor mapping with the use of skid steering mobile robot and laser proximity scanner. Constituent elements of the algorithm.

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References: