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FEATURE BASED LOCALIZATION IN AN INDOOR ENVIRONMENT FOR A MOBILE ROBOT BASED ON ODOMETRY, LASER, AND PANORAMIC VISION DATA

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Abstract. *This paper discusses mobile robot localization in a dynamic office-like environment for a multi sensor platform. Odometry, Panoramic vision, and laser range finder data were fused in order to obtain a more realistic estimation of the mobile robot orientation and position. The experimental setup consists of two encoders used for odometry, two 180º laser range finders, and an omni-directional camera assembled on a mobile robot (Biba). The experiments caried out shown that in contrast to the exclusive use of odometry or laser sensor data, the multi sensor setup contributes to an substancial uncertainty reduction in robot localization and orientation. Considerng the orientation estimation of robot and environment features, we also observed that the use of vision data increased the precision of their orientation.*

Keywords*: Mobile robots, laser range measurement data, omni-directional camera, feature extraction, sensor fusion***.**

1. INTRODUCTION

In order to execute any task in an environment it is essential for the mobile robot being able to answer the following three questions: "*Where am I? Where am I going? How can I go there?*" (Leonard and Durrant-Whyte, 1992). These three classic questions stimulated the mobile robotics research community last two decades. During this period researchers focused their attention on the development of localization, map building, and navigation procedures that could run in real time and on board the mobile robots. The tremendous evolution on embedded sensors, hardware, and computational and memory power since the middle of 1990s allowed the mobile robots to improve considerably their autonomy and application field ranges (from hospitals, offices, and industries, to the exploration of planet surfaces). Today there are numerous approaches in the literature for problems that were considered hard to deal with a decade ago. An excellent example is the 2-D Simultaneous Localization and Map Building problem (SLAM) that was usually described as a "chicken-egg" problem. The problematic of SLAM lies on the need of a robot pose accurate estimation (position and orientation) and the fusion of sensor data with a precise map. Both are correlated and essential to produce a reliable environment map and reduce the odometry errors (Vazquez-Martin et al., 2006). Unfortunately the solely use of odometry is not sufficient for position estimation, because encoders always provide unbounded position errors. These errors are produced by wheel slippage, shifting payloads, inaccurate turns, etc. and the system-accumulated error represents an increasing difference between the robot's estimated and actual positions. Due to this, today the use of multi-sensor platforms including exteroceptive sensors (e.g.: laser range finders, omni-directional cameras, ultra-sound sensors, etc.) is frequent. Nevertheless, one should observe that the efficiency and robustness of SLAM procedure is directly influenced by the map representation type selection. The literature presents typical choices such as occupancy grids (Elfes, 1989, Schultz and Adams, 1998, Ivanjko and Petrovic, 2004, Ivanjko et al, 2005, and others), topological maps (Bandera et al, 2001, Zhuang, 2006, Tarutoko et al, 2006, and others), feature maps (Leonard et al., 1992, Janet et al, 1997, Salomon et al, 2006), and others.

Our work focuses the use of multiple sensors to increase the robustness of feature-based localization in indoor environments. Modeling the environment structure as geometric features provided us with a concise environment description that is convenient for environment mapping via data association. In this context, robust feature extraction plays an essential role in precise sensor data registration. We implemented the data registration procedure by applying transformation matrices that turns the measurements gathered into the inertial reference frame. The transformation matrix elements and its covariance matrix were estimated using an Extended Kalman Filter (EKF). As we assumed that the robot surroundings could be well represented in a 2-D space, line segments and line segment middle points were used as environment features. They were extracted after several segmentation phases, each one considered the indoor environment own characteristics (in our case, typical features found in office-like environments).

Initially a brief review of the basics of feature extraction and matching is addressed and the algorithms are shortly described. Next, the sensor data registration and data fusion procedures are presented. Then, the multi-sensor platform and the results obtained while using real data are shown. Finally, the conclusion and outlook are presented in the final section.

2. FEATURE EXTRACTION AND MATCHING

A feature is basically a physical object in the environment, which is static, perceptible, locally unique, and reliably recognizable. During this research we emphasized the extraction of robust geometric features from the laser range finder measurements considering the dynamic characteristics of the environment and the matching model. The feature extraction procedure is explained more in detail as follows.

2.1. Feature Extraction

In a nutshell feature extraction is the transformation from the observation space to the feature space. It is a sensor and scenario type dependent problem. There is no generic algorithm applicable neither to all sensor types (e.g.: vision, laser, sonar, etc.) nor scenario complexities (structured and unstructured environments). In this context, the segmentation process plays an essential rule on feature extraction procedure because it determines simultaneously which data points are part of the selected model and how these data contribute to the feature model. Robust extraction of geometric environment features and obtaining the estimate and uncertainties related to the model parameters provide a compact partial description of the structured environments and a means to solve the feature based matching problem.

In office-like environments, line segment models are considered perfect features due to their frequent occurrence and their simplicity for the extraction process. More specifically, the problem of fitting a model to raw data in the least squares sense has closed form solutions if the model is a line even when geometrically meaningful errors are minimized (Arras and Tomatis, 1999). Unfortunately slightly more complex models, e.g. circles, ellipses, etc., do not have this property anymore.

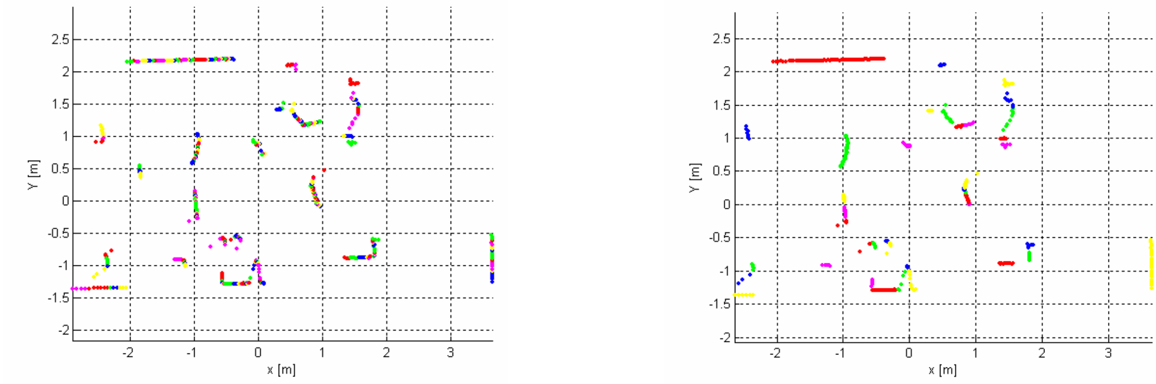
In this work, the laser range data is filtered before the segmentation phase in order to take into account the environment dynamic characteristics. The filtering process is carried out considering the line segment model compactness and lengthiness proprieties commonly found in office-like environments. It is applied to the laser scan data in order to filter mainly the dynamic objects found in the environment. As they are considered outliers to the environment features or landmarks, obviously they can be filtered. In every consecutive scan, the filtering process works in the following sequence:

1: **for** each new Laser Scan Frame **do**
2: Obtain current scan data;
3: Compute Subsequent Measurement Data Distances $\Rightarrow$ SMDD;
4: Smooth SMDD by applying a Smooth Filter to each data neighborhood $\Rightarrow$ SSMDD;
5: Segment the data according to the Element Model Threshold Values;
6: Filter the Segments based on the minimum quantity of Element Models;
7: Filter and Update the Scan Data, removing the outliner data $\Rightarrow$ FSD;
8: **end for**

The segmentation procedure is then applied to the filtered laser scan data. It consists of several steps; each one related to a specific line model aspect, for instance, data linearity and compactness. In the same manner, the segmentation algorithm is present as follows. The threshold values are represented as TV.

1: **for** each Filtered Scan Data **do**
2: Compute Subsequent Filtered Data Distances $\Rightarrow$ SFDD;
3: Smooth SFDD by applying a Smooth Filter to each data neighborhood $\Rightarrow$ SSFDD;
4: Compute the Laplacian Distance of SSFDD by applying a Laplacian Filter $\Rightarrow$ LD;
5: Apply a Transition Filter to LD;
6: Segment the Data based on a Distance TV;
7: Segment the segments obtained based on each Laplacian Distance TV;
8: Filter the segments based on the minimum model element quantity TV for segments;
9: Compute the segment lengths;
10: Filter the segments based on the minimum length for the line segment model $\Rightarrow$ FS;
11: Segment the FS based on the filter parameters (smoothed angles Laplacian) $\Rightarrow$ SubSeg;
12: Integrate the Sub Segments (SubSeg) into a Super Segment;
13: Compute the Segment Lengths;
14: Filter the Segments according to the minimum desired length and element quantity;
15: **end for**

It is possible to observe in this algorithm that after the eighth line, if the laser range measurements gathered in a specific time are classified as a range image, the range image is then partitioned into model outliers. These model outliners are not considered for further discussions neither into model outliers anymore. Figure 1-a presents a typical segmented range image that is still over segmented (sometimes a single segment is represented by more than 30 small segments). This is a consequence of ignoring the information from collinear (but distinct) segments which lie on the same physical object, e.g.: a wall that is a common office-like environment feature. The integration of such segments is carried out according to the Laplacian angle of the lines fitted to a neighbor of the middle points of the lines. Candidate segments for extraction of line models showing the same laser scan which is shown in Fig. 1-a are presented in Fig. 1-b.



(a) (b)

Figure 1. A scan image from two SICK LMS 200 laser range finders that is over segmented (a) and the same scan image after segment integration (b). Each segment is represented by a different color.

The fitting method applied for line segment model extraction has been previously described in Arras and Siegwart (1997). The method outputs are the line segment model parameters, which first order covariance is estimated using polar coordinates. The line model is:

$$\rho\cos(\theta-\alpha)-r=0 \tag{1}$$

Where α is the angle of the perpendicular to the line and r is its length. With (ρ_i, θ_i, ω_i) as the measurement at time i and α and r as line parameters. The uncertainty of line model parameters is defined as:

$$C=\begin{bmatrix}\sigma_{\alpha\sigma} & \sigma_{\alpha r}\\ \sigma_{r\alpha} & \sigma_{rr}\end{bmatrix} \tag{2}$$

Aiming the line fitting, the nonlinear regression equations have been explicitly derived for polar coordinates minimizing the weighted perpendicular error from the points to the line. Opposed to a Kalman filter, more general error scenarios of possibly correlated measurements can be taken into account in this manner (Arras et al., 2000). Figure 2 shows the result of applying the regression line fitting method to the same scan image shown in Fig. 1-a and 1-b.

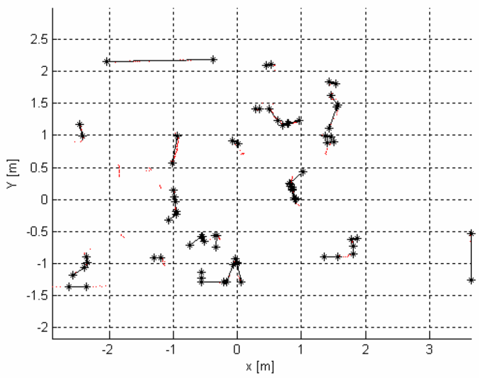


Figure 2. The result of applying regression line fitting method to the same scan image as in Fig 1-b.

Another feature model extracted from range data used in this work is the middle points of the line segments. A point feature g_P is a corner feature without orientation. It is defined as:

$$g_P=(x,y) \tag{3}$$

The uncertainty of corner model parameters which are its Cartesian coordinates is defined as:

$$C = \begin{bmatrix} \sigma_{xx} & \sigma_{xy} \\ \sigma_{yx} & \sigma_{yy} \end{bmatrix} \tag{4}$$

The uncertainty of line segment and line segment middle point model parameters is determined using the Eq. obtained in Smith et al (1990).

$$C(y) \approx F_x C(x) F_x^T \tag{5}$$

Where y is a nonlinear function of x as $y = f(x)$ and $C(x)$ is the covariance matrix of x and F is the Jacobian of the function f. The uncertainty of the features' parameters is found by first writing the equations defining each parameter of the feature model and then finding the Jacobian matrix used in the above equation using the uncertainty of the model parameters found so far.

2.2. Matching

In mobile robot map building literature, matching is often defined as the problem of deciding which feature in the current frame belongs to a physical object in the environment, from the global EKF localization point of view. In contrast to this description if we consider matching as an operation that takes into account only two consecutive observations made by a sensor, the matching problem would be simplified to extracting information problem that compares two consecutive observations acquired by a sensor in order to estimate the desired information. In our case, the desired information extracted is the system state vector.

2.2.1. Matching Line Segments and Line Segment Middle Points Extracted From Laser Scan Images

The criterion for the quality of line segment pairing was defined according to their segment characteristic. 'Best' for line segment pairing means pairing of the two line segments for which the maximum of the distance between their first and last points is the least one between the probable matches. Matched pairs are then filtered so that the quality of matching would be better than a certain threshold which is a measure of the distance of two line model segments. The center of the matched line segments in the current and last frame are then considered as matched landmarks of the two frames and used later for data registration purpose.

Matching two omni-directional camera images

The matching procedure of two consecutive omni-directional camera images was carried out considering that we did not have camera calibration parameters available. Due to this, the extraction of environment features is not possible and no matching is done between the features extracted from laser scan images and the features extracted from the images taken by the omni-directional camera. Then, the image integrality is conserved between consecutive acquisition of images and the whole images are compared with each other to extract the system state vector related information. This way, the uncertainty in the extraction of camera calibration parameters feature extraction from camera images does not contribute in system state vector estimation uncertainty.

In our case, consecutive images are not necessarily the images taken in consecutive time stamps. It means that there should be a mean for the selection of the images which will be compared. The reason for not comparing each two consecutive observations by the camera is the fact that the images need to be preprocessed before the matching step.

The image preprocessing is done taking into account that the images often need to be smoothed by a filter like the median filter to get rid of salt and pepper noise often present in the images taken by a camera without loosing edge information. The other reason for image preprocessing is that the center of the camera mirror is not necessarily the center of the taken image. This fact is observable by considering the chain of images and the fact that the support of the camera mirror can be observed at the center of the image by a high contrast and considering the outer circle in the image to be of the highest accuracy. Then, the center of the mirror should be extracted and the circle consisting camera image of the environment should be centered to the image center. This is done by first considering the camera mirror ray which was mentioned by the mirror producer to be of 238 pixels length and considering a square in the center of the image as the area in which the probability of moving circle center is not zero. After making a square with the center of each pixel in the square with the ray of 238 pixels in an image found by applying a Sobel Gradient finding filter to the gray level image and having a binary image after applying a threshold to the resulted Gradient values, the number of points on the circle which belong to an edge is counted and compared with the same number from other square pixels. The pixel having the highest value is most probable to be the center of the image mirror.

The fact that each image needs preprocessing before matching is not negligible especially if robot mapping and localization is done in real time. This is another reason not all the images are selected for matching. The criteria for image selection in this work are according to the idea of extracting the rotation angle of robot reference frame between two image acquisitions. This information later contributes to the state prediction of the system and also laser scan data registration in the initial frame of the robot or the world fixed frame. The selection is done according to the resolution of this angle.

Matching of two selected images is done by considering a range of rotation according to the resolution of the reference frame rotation angle. Then, the second image is rotated and compared to the first image according to the gray level of the corresponding pixels in two images. For this reason, the centered images should be cropped first to have the same size first. The image comparison is done by adding the abstract difference of the gray levels. The two images having the least difference show the rotation angle of the robot reference frame between the time stamps of the two images. This way, the angular velocity of the rotation of the robot reference frame according to the world reference frame is derived. This information later contributes in fusion step by EKF.

Sensor Data Registration

When the vehicle moves while scanning the movement imposes a distortion onto the raw data. The problem is also known as data registration or alignment (Bar-Shalom and Li, 1995). The important issue is that this effect has to be compensated on the raw data level and not at later levels of perception like the feature level because in this case, data analysis would operate with unmodeled, artificially modified raw data evidence.

We compensate for the robot displacement during a scan by transforming each range measurement ${}^{S'}P$ into the non stationary robot frame *R'* and then into the world frame followed by a re transform into the stationary robot frame *R* and finally into the desired reference frame of the scan *S*. For an on-the-fly scan compensation, *S* must be the sensor frame at the start position of the robot. Each time a new range scan arrives, it gets immediately transformed by the below expression.

$$ {}^{S}R = {}^{R}_{S}T^{-1}\ {}^{W}_{R}T^{-1}\ {}^{W}_{R'}T\ {}^{R'}_{S'}T\ {}^{S'}R \tag{6} $$

Where. ${}^{R}_{S}T = {}^{R'}_{S'}T$ The 4x4 matrices *T* are homogeneous transformation matrices including the translation and rotation of a transform. ${}^{R}_{S}T$ is the sensor to robot frame transform and ${}^{W}_{R}T$ is the world to robot transform given by the robot pose vector (Craig, 1989).

In this work, the Eq. (4) is written as:

$$ {}^{S}R = H\ {}^{S'}R \tag{7} $$

Where *H* is the transformation matrix directly transforming new range scans whenever they are available.

A Kalman Filter was used to estimate the transformation matrix mentioned above and its covariance matrix. Each two matched line segment center points from two consequent scan images contribute in finding a priori estimation of the state vector of the system *X* at time *t* which is defined as below.

$$ X^{t} = [\cos(\Delta\theta)\ \ \sin(\Delta\theta)\ \Delta x\ \Delta y] \tag{8} $$

Where $\delta\theta$ is the change in the robot orientation between two sensor readings. Δx and Δy are the changes in robot position in Cartesian coordinates. Registration of two line center models of the scan data measured at time *t* in the robot frame at time *t-1* is done via the equation below.

$$ \begin{bmatrix} x_1^{t-1} \\ y_1^{t-1} \\ x_2^{t-1} \\ y_2^{t-1} \end{bmatrix} = \begin{bmatrix} x_1^{t} & -y_1^{t} & 1 & 0 \\ y_1^{t} & x_1^{t} & 0 & 1 \\ x_2^{t} & -y_2^{t} & 1 & 0 \\ y_2^{t} & x_2^{t} & 0 & 1 \end{bmatrix} X \tag{9} $$

In this way, the state vector *X* can be obtained. The covariance matrix of the state can be obtained using the equations expressing the elements according to line segment center point model parameters and Eq. (5). The initial state vector is selected considering the fact that the best estimate for robot translation and rotation is zero giving the state vector below.

$$ X^{0} = [1\ \ 0\ 0\ 0] \tag{10} $$

By keeping the product of the state vectors obtained in the previous frames, the overall transformation matrix H at time t in Eq. (7) can be calculated as below.

$$H = \left(\prod_{i=1}^{t-1} X^i \right) X^t \tag{11}$$

When there are n matched line segment center points in the current range scan, a set consisting $\binom{n}{2} = \frac{n(n-1)}{2}$ state estimates and covariance matrices is obtained. A Kalman Filter is used here to get a single estimation of the state vector. Another Kalman Filter then estimates the state of the system which is likely defined as in Eq. (8) using the state estimate in the last frame as predictions. The state vector estimated using feature matching plays the role of the observations for this Kalman Filter. Attention should be paid to the fact that despite the absence of the constant robot translation and rotation speed, they are assumed to be constant between two consequent data acquisition.

Data Fusion

The main difference between step by step and on the fly navigation of a multi sensor platform lies in the fact that temporal relations of observations, predictions and estimations of all sensors have to be maintained and related to the present. As the robot used in the experiments has two SICK sensors back to back covering 360º, there are two time stamps which are manually estimated and averaged. When sensor A acquires new measurements, the observations receive a time stamp T_A. Odometry data are also time stamped and recorded to be used as the state prediction input of the Kalman Filter used to estimate the state of the system after feature extraction is completed. Feature extraction gives the observation used in the correction phase by the Kalman Filter (Arras et al., 2000).

In this work, a separate Extended Kalman filter is used for each sensor type if applicable so that each sensor would have its own estimation of the system state each time it acquires new data. The system state which is estimated by each sensor type extended Kalman Filter is defined as below.

$$X^t = [\frac{\cos(\Delta\theta)}{\Delta t} \quad \frac{\sin(\Delta\theta)}{\Delta t} \quad \frac{\Delta x}{\Delta t} \quad \frac{\Delta y}{\Delta t}] \tag{12}$$

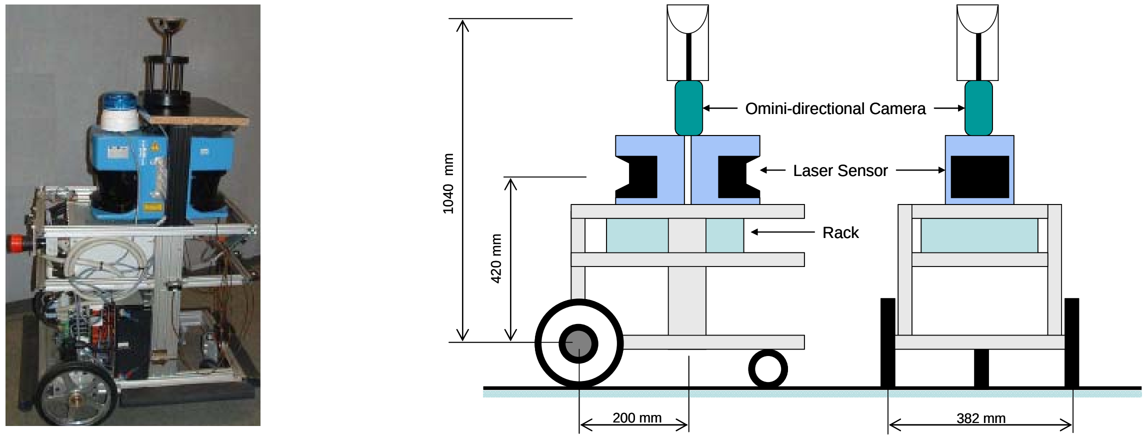
Where Δt is the time elapsed between two consecutive scan measurements.

The a priori state estimation is considered equal to the last scan a posteriori state estimation. This is done according to the assumption of having constant translation and angular rotation speed between consecutive data acquisitions. The overall system state which is defined in Eq. (12) is estimated by another Kalman Filter. The estimates from different sensor types are fused in the succession of their respective observations. The succession is determined considering the time stamps of the observations. In this way, both the complementary and the redundancy characteristics of different sensor types can be taken into account and the estimations done by different sensors at different times can be integrated to get a better first and second order estimations of the system state.

The final EKF is used to fuse the first two elements of the system state vector obtained from the images taken by the omni-directional camera and the scan images acquired by the laser range finder sensors. The multi sensor setup performance is compared to the case in which only one type of sensor is used comparing the localization accuracy.

3. BIBA ROBOT

The BIBA robot, shown in Fig. 3 was designed for indoor use. It is a non-holonomic differential drive robot and can move up to 1.0 m/s. It runs a real-time operating system handling data acquisition and actuator control. BIBA is equipped with two SICK LMS 200 laser range finders measuring a horizontal plane at 0.55m above the ground. For the indoor experiments the lasers are running in a high-precision mode (8.0m, 0.5º resolution and an accuracy of 1mm). The horizontal laser scanners provide the robot with a 360º view of its environment. Scans are available at 37 Hz and are read over a 500 kBaud serial line, which allows autonomous navigation and obstacle avoidance in real-time. Additionally an omni-directional vision system was assembled on BIBA. It consists of a firewire Sony DFWVL500 camera and a panoramic mirror type Kaidan 360 One VR with a field of view of 360º x 100º. The maximal resolution of the camera is 640 x 480 pixels at a frame rate of 30 frames per second. The panoramic mirror is equiangular, thus every pixel spans an equal angle irrespective of its distance from the center of the image, which simplifies the unwrapping and finding corresponding points in the horizontal scan.

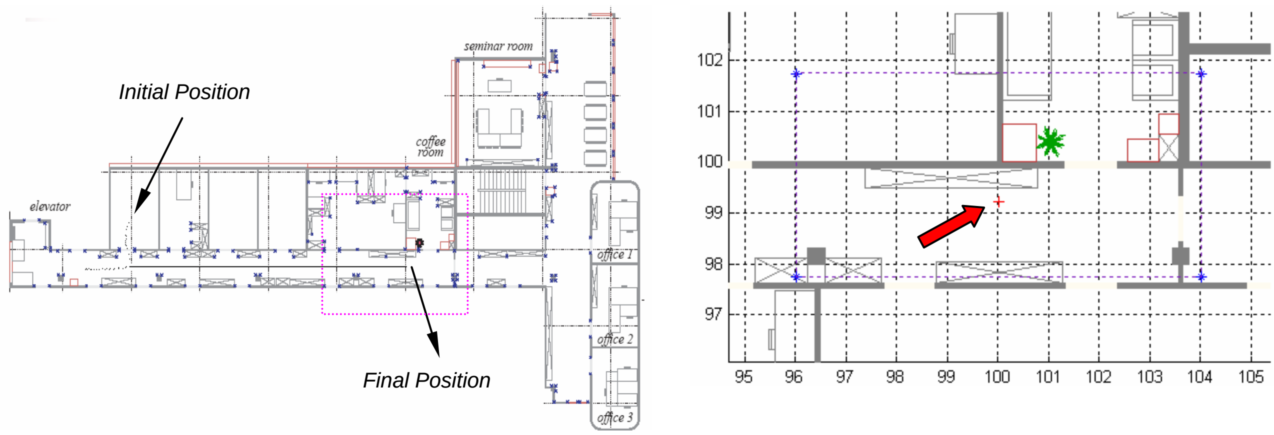


(a) (b)

Figure 3. The BIBA robot.

4. EXPERIMENTAL TESTS

The environment is presented in Fig. 4-a where the desired robot path is shown. Figure 4-b shows a zoom view of the environment where one can observe the robot final position (red cross).



(a) (b)

Figure 4. The robot assumed trajectory in the ASL environment map (a) and detail of the final position of the robot according to the planned trajectory path (b) – red cross.

4.1. Localization Results only based on Odometry Data

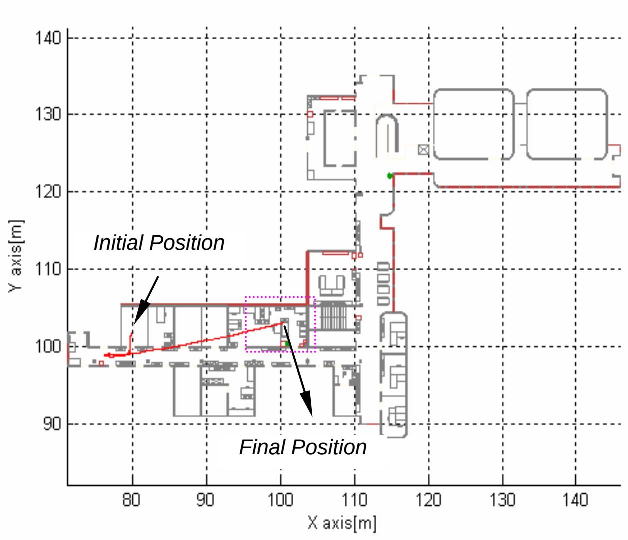
The odometry data used is composed of the robot abstract position and orientation in robot initial reference frame and the time stamps. The system state is obtained by applying Eq. (8). Unfortunately there were no synchronization between laser and odometry data. Due to this, we used the time difference between the observations and the robot translational and the angular velocities to infer the odometry and laser data at the same time step.

The whole trajectory resulted when applying the localization algorithm to the odometry data can be observed in Fig. 5-a. The accumulative nature of the odometry error is easily noticed (this error can induce the robot to collide with mapped obstacles). Figure 5-b shows a zoom view of the environment where one may observe the robot final position according to the state prediction based only on the odometry data.

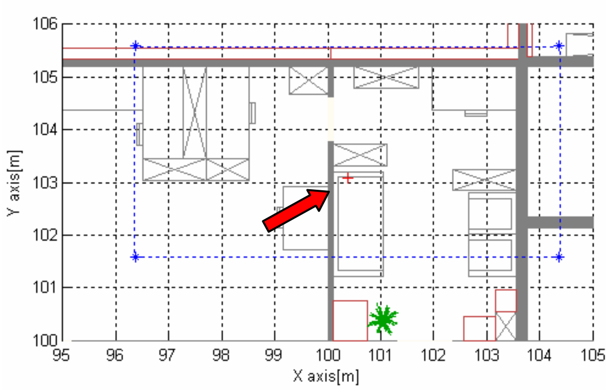
4.2. Localization results only based on Laser Sensor Data

The laser range scans are composed of the position and orientation of the obstacles the laser beam collides with in robot initial reference frame and the scan time stamp. The system state can be obtained by Eq. (8) and the laser scan points are moved to the initial reference frame of the robot applying data alignment process (or data registration) described in Eq. (7).

The whole trajectory estimated by applying the localization algorithm to the laser scan data is presented in Fig. 6-a. One may compare the trajectories predicted using only odometry (red line) and only the laser data (blue line). The final position estimated for the robot is shown in Fig. 6-b. It is obvious that the laser data produced more accurate localization predictions. To predict the system state firstly each scan image was filtered and then the segmentation and feature extraction process was carried out. A system state estimate was approximated by matching each pair of line segment middle points that matched in two consecutive laser scan images. Due to this, the features were kept between the scans. A phenomenon called "miss frame" might happen if there is no matching between two consecutive laser scans. In this case, the state posterior estimate is assumed to be equal to the last frame state estimate. In the end, an EKF fuses the state estimates of several feature matching and another EKF fuses consecutive laser scan state estimates. Similarly to odometry data based localization, the accumulative nature of the lased data based localization error can be easily observed in Fig. 6.

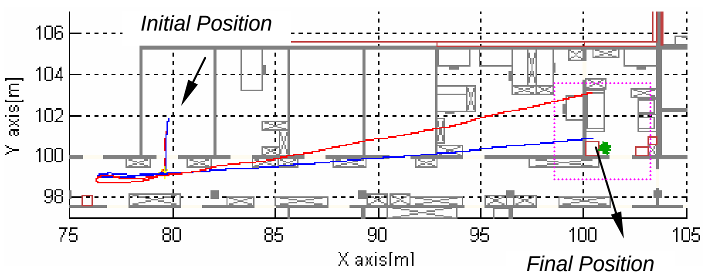


(a)

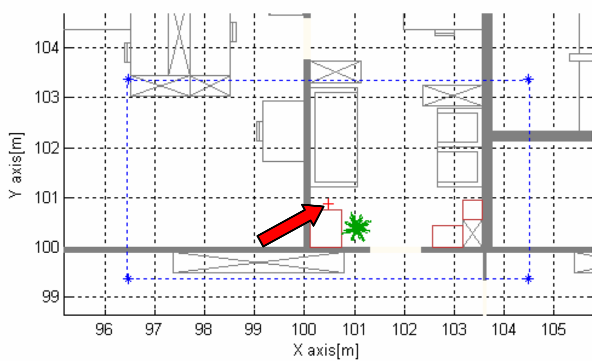


(b)

Figure 5. The mobile robot odometry-based resulted path (a) and detail of its final position according to odometry-based localization estimation (b) – red cross.



(a)

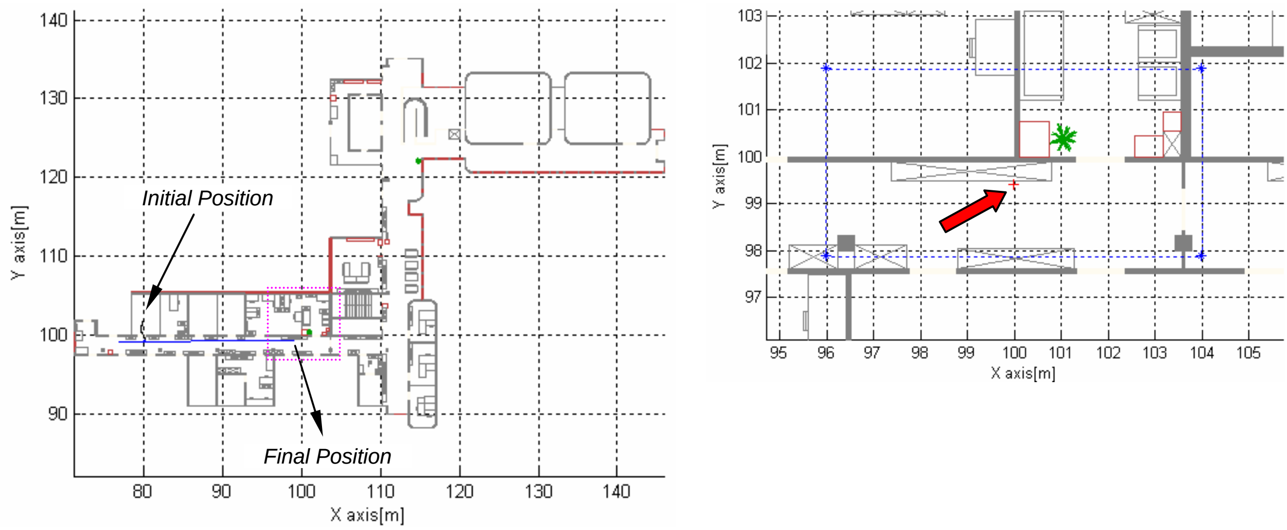


(b)

Figure 6. Trajectory generated by localization with odometry data, red line, in comparison with the trajectory resulted from laser data, blue line (a) and detail of laser data localization final position estimation (b).

4.2.3. Localization Results based on Laser Sensor and Omni-Camera State Prediction

After selecting the resolution of the transition of the robot reference frame by considering the first two elements of the state predictions obtained from the laser scan image matching process, omni-directional images are selected and pre processed to get centered to the image center and cropped to a fixed size. The matching step can derive the rotation estimate between two images. This way, the angular velocity of the rotation of the robot reference frame can be obtained and the rotation is predicted for laser scan timestamps. An EKF can be used then to fuse state predictions. The whole robot trajectory resulted from applying the algorithm mentioned above is presented in Fig. 7. One may observe that it was possible to increase the localization accuracy by the system state prediction comparing the path with that shown in Fig. 4. The error was also reduced and no collision with mapped environment obstacles was observed



(a) (b)

Figure 7. Trajectory estimation obtained from fusion of system state predictions by laser scan data and omni-directional camera images (a) and final robot position found.

6. CONCLUSIONS

In this paper we focused on mobile robot localization in a dynamic office-like environment for a multi sensor platform. The setup consists of two encoders, two 180º laser range finders, and an omni-directional camera. Robust extraction of line segment and point features from laser range finder scans was carried out by scan filtering and model integration phases considering dynamic environment properties. Feature model parameters uncertainties were propagated through the state estimation phase.

We defined the state vector in a non usual way what resulted in more accurate frame transformation of scan points. Due to this, the robot pose was indirectly estimated. The state estimates were passed to a sensor exclusive Extended Kalman Filter and then to another one to fuse robot frame rotation angular velocity estimation using laser and image data. The state vector was then used for data registration of the laser data.

Experiments were carried out using a real, differential drive mobile robot BIBA. They showed that in contrast to the use of the laser data only, the multi sensor setup contributed to a notable reduction of robot localization uncertainty. The used of vision data undoubtedly increased the state prediction precision, especially the orientation related elements.

7. ACKNOWLEDGEMENTS

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8. REFERENCES

Arras, K.O. and Siegwart, R., 1997, “Feature Extraction and Scene Interpretation for Map-Based Navigation and Map Building”, Proc. of SPIE, Mobile Robotics XII, Vol. 3210, p. 42-53.

Arras, K.O., Tomatis, N., 1999, “Improving Robustness and Precision in Mobile Robot Localization by Using Laser Range Finding and Monocular Vision”, 3rd European Workshop on Advanced Mobile Robots (Eurobot’99), Zurich, Switzerland.

Arras, K.O., Tomatis, N. and Siegwart, R., 2000, “Multisensor On-the-Fly Localization Using Laser and Vision”, Proceedings of the 2000 IEEE/RSJ International Conference on Intelligent Robots and Systems.

Arras, K.O. and Vestli, S.J., 1998, “Hybrid, High-Precision Localization for the Mail Distributing Mobile Robot System MoPS”, Proc. of the 1998 IEEE Int. Conf. on Robotics and Automation, p. 3134-3129, Leuven, Belgium.

Bandera, A., Urdiales, C., and Sandoval, F., 2001, **“**An hierarchical approach to grid-based and topological maps integration for autonomous indoor navigation”, in Proc. 2001 of IEEE/RSJ International Conference on Intelligent Robots and Systems, Volume 2, 29 Oct.-3 Nov., pp. 883 – 888.

Bar-Shalom, Y. and Li, X.-R., 1995, “Multi target Multi sensor Tracking: Principles and Techniques”, 1995.

Castellanos, J.A. and Tardós, J.D., 1996, “Laser-Based Segmentation and Localization for a Mobile Robot”, Proc. of the Sixth Int. Symposium on Robotics and Manufacturing (ISRAM’96), Montpellier, France.

Craig, J.J., 1989, “Introduction to Robotics: Mechanics and Control”, 2nd ed., Addison-Wesley.

Crowley, J.L., 1989, “World Modeling and Position Estimation for a Mobile Robot Using Ultrasonic Ranging”, Proc. of the 1989 IEEE Int. Conference on Robotics and Automation, p. 674-80.

Elfes, A., 1989, “Using occupancy grids for mobile robot perception and navigation”, in Computer, Volume 22, Issue 6, June 1989, pp.46 – 57.

Ivanjko, E. and Petrovic, I., 2004, “Extended Kalman filter based mobile robot pose tracking using occupancy grid maps” in Proceedings of the 12th IEEE Mediterranean Electrotechnical Conference - MELECON 2004, Volume 1, 12-15 May 2004, pp. 311 – 314.

Ivanjko, E., Vasak, M. and Petrovic, I., 2005, “Kalman filter theory based mobile robot pose tracking using occupancy grid maps” in Proc. of 2005 International Conference on Control and Automation - ICCA '05, Volume 2, 26-29 June 2005, pp. 869 – 874.

Iyengar, S. and Elfes, A., 1991, “Autonomous Mobile Robots”, volume 1 and 2. IEEE Computer Society Press.

Janet, J.A., Scoggins, S.M., White, M.W., Sutton, J.C., III, Grant, E., and Snyder, W.E., 1997, “Self-organizing geometric certainty maps: a compact and multifunctional approach to map building, place recognition and motion planning” in Proceedings of 1997 IEEE International Conference on Robotics and Automation, Volume 4, 20-25 April 1997, pp. 3421 – 3426.

Leonard, J.J. and Durrant-Whyte, H.F., 1992, “Directed Sonar Sensing for Mobile Robot Navigation”, Kluwer Academic Publishers, 1992.

Salomon, R., Burchardt, H., and Schulz, T. “Using self-organizing maps to control physical robots with omnidirectional drives”; in Proceedings of 2006 IEEE International Symposium on Circuits and Systems - ISCAS 2006, 21-24 May 2006, 4 pp.

Schultz, A.C. and Adams, W., 1998, “Continuous localization using evidence grids”, in Proceedings 1998 IEEE International Conference on Robotics and Automation, Volume 4, 16-20 May 1998, pp. 2833 – 2839.

Smith, R., Self, M., and Cheeseman, P., 1990, “Estimating Uncertain Spatial Relationships in Robotics”, in Autonomous Robot Vehicles, I. J. Cox and G. T. Wilfong, Eds.: Springer-Verlag, 1990, pp.167-193.

Tarutoko, Y., Kobayashi, K., and Watanabe, K., 2006, “Topological Map Generation based on Delaunay Triangulation for Mobile Robot”, in Proc. of International Joint Conference SICE-ICASE, Oct. 2006, pp. 492 – 496.

Vazquez-Martin, R., Núñez, P., del Toro, J.C., Bandeira, A., and Sandoval, F., 2006, “Adaptative Observation Covariance for EKF-SLAM in Indoor Environments using Laser Data”, in IEEE MELECON 2006, May 16-19, Spain, pp. 445-448.

Zhuang, Y., 2006, “Hybrid Mobile Robot Indoor Localization Using Large-Scale Metric-Topological Map”, in Proc. of The Sixth World Congress on Intelligent Control and Automation, Volume 2, 21-23 June 2006, pp. 9057 – 9062.

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