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# AUTONOMOUS RECHARGING OF 4WD MECANUM WHEEL ROBOT VIA RGB-D SENSORY FUSION

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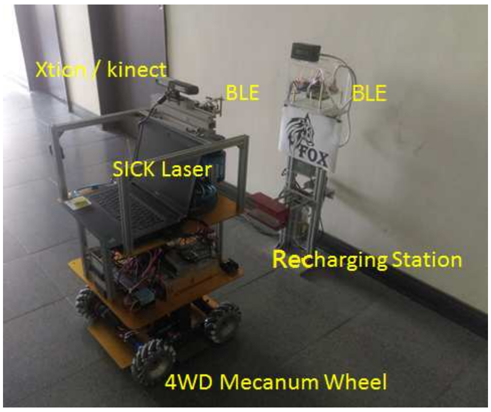
Abstract. *The recharging system for autonomous mobile robot is an important issue for keeping robot in long-time functionality. Recharging is necessary before the power has exhausted. In this paper, we propose a sensory fusion method to guide the 4WD mecanum wheel robot while performing the docking process for recharging. Firstly, an artificial pattern is employed as a visual cue on the charging station in order to be recognized and estimated from an RGB-D camera. At the same time, the 2D range data acquired by a laser ranger are modeled as line segments in the environment. Then the geometrical relationship between the robot and the docking station can be estimated by using sensory fusion methods from laser ranger and RGB-D camera. Finally, apply the kinematic model of 4WD mecanum wheel robot with a control rule, and a successful demonstration of mobile robot autonomous docking is shown in the experimental results.*
**Keywords:** Autonomous recharging, Sensory fusion

1. **Introduction.** Mobile robots will be widely employed in many applications, for example, factory automation, dangerous environments, office, hospitals, surgery, entertainment, space exploration, farmland, military, and security system. In addition, the robot must be capable of long-term autonomy. So how to guide the robot towards the recharging station and dock into the station is important issues for autonomous mobile development. The first work on robot recharging is made by Walter [1]. They developed the first autonomous recharging mobile robots and employed light to find a hut, which contains a light beacon and a battery recharger. Roufas et al. [2] used four IR LED emitters and one IR receiver to implement the docking.

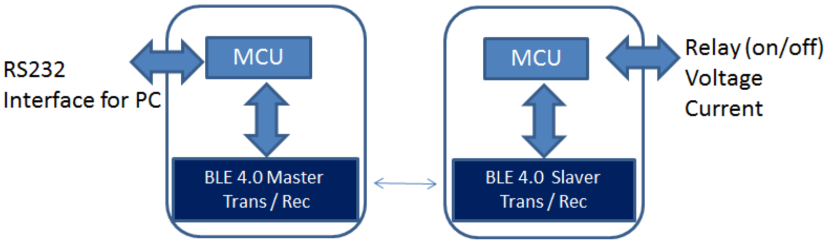
Nowadays, the laser ranger [3] is well for environment scanning/detection on mobile robot applications [10,11], but it is difficult to identify the recharging station from the 2D point cloud data. On the other side, the low cost RGB-D camera [4] will be useful in visual pattern recognition and the corresponding depth value will be good for reference. Some RGB-D camera applications are shown in [12,13]. In this work, we combine the laser ranger and RGB-D camera to locate the docking station in the environment. And the experimental results show the proposed fusion methods will achieve more accurate and consistent estimations for mobile robot docking process.

This paper is organized as follows. Section 2 shows the mobile robot system development, and describes the pattern extraction and sensory fusion methods. In Section 3, the kinematic model of robot and the control rule of docking are presented. Finally, Section 4 shows the experimental results and Section 5 presents a concluding comment.

2. **Robot System Development.** The 4WD mecanum wheel robot platform and charging station are shown in Figure 1(a). The robot is designed for autonomous patrol and delivery service in an office building. The robot is equipped with a 2D SICK laser ranger,

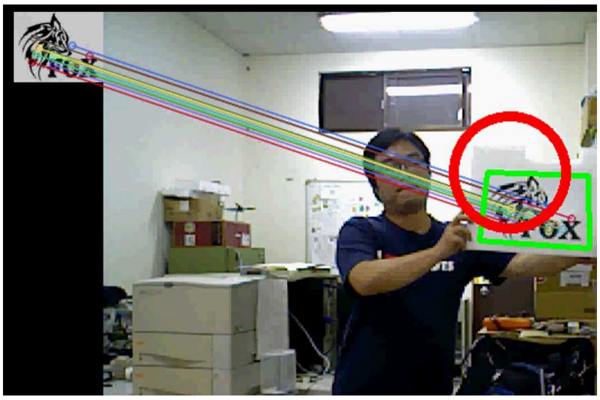



(a)

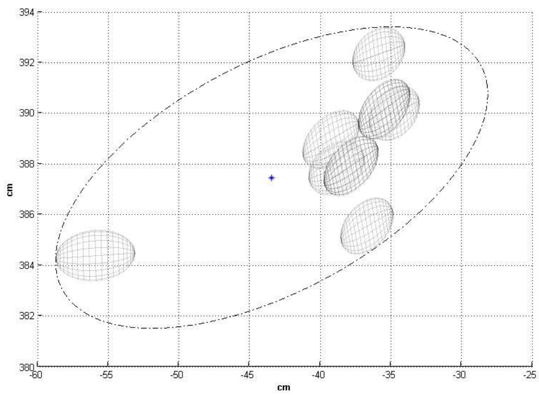



(b)

FIGURE 1. (a) 4WD mecanum wheel robot and charging station, (b) communication of robot and recharging station via BLE 4.0



(a)



(b)

FIGURE 2. (a) POI extraction via SIFT, (b) CU estimation for the POI's position

and a kinect RGB-D camera for environment perception. The radio communication between charging station and mobile robot is through the Bluetooth Low Energy (BLE) protocol which is shown in Figure 1(b).

2.1. **SIFT feature extraction for pattern of interesting.** In this work, the Scale Invariant Feature Transform (SIFT) [5,6] is applied for searching the pattern of interesting (POI) as shown in Figure 2(a). An important aspect of this approach is that it generates large numbers of features in the local region such as location, scale, rotation, magnitude, and orientation in order to record information of key points.

2.2. **CU estimation to locate the POI.** From the SIFT extraction of the image, the additional information of point depth from the RGB-D camera can also be used. The covariance union (CU) fusion method [7] will be applied under this situation. For example, given $n$ estimations represented by estimates $(P_{a_1}, a_1)$ $(P_{a_2}, a_2)$ $\ldots(P_{a_n}, a_n)$, CU produces an estimate $(P_u, u)$ that is guaranteed to be consistent as long as one of the estimates $(P_{a_i}, a_i)$ is consistent. This is achieved by guaranteeing that the estimate $(P_u, u)$ is consistent with respect to each of the estimates. The CU constraint is shown below:

$$\begin{aligned} P_u &\geq P_{a_1} + (u - a_1)(u - a_1)^T \\ P_u &\geq P_{a_2} + (u - a_2)(u - a_2)^T \\ P_u &\geq P_{a_3} + (u - a_3)(u - a_3)^T \\ &\vdots \\ P_u &\geq P_{a_n} + (u - a_n)(u - a_n)^T \end{aligned} \tag{1}$$

The CU optimization has simple linear constraints that are compatible with any generic constrained optimization package. Figure 2(b) shows the optimal ellipsoid fusion result of SIFT features in 3D point cloud which are projected in the $x$-$y$ plane.

2.3. **CI estimation fusion for recharging station.** The covariance intersection (CI) [8] is a data fusion algorithm which takes a convex combination of the means and covariance in the information space. Consider two different pieces of measurement $A$ and $B$ from different sources. If given the mean and variance: $E\{A\} = a$, $E\{B\} = b$, $\text{var}\{A, A\} = P_{aa}$, $\text{var}\{B, B\} = P_{bb}$, $\text{cov}\{A, B\} = P_{ab}$. Define the estimate $z$ as a linear combination of $A$ and $B$ which is presented in the previous estimate of the same target with certain measurement uncertainty. The CI approach is based on a geometric interpretation of the Kalman filter process. The general form of the Kalman filter can be written as:

$$\hat{z} = \omega_a a + \omega_b b \tag{2}$$

$$P_{zz} = \omega_a P_{aa} \omega_a^{\mathrm{T}} + \omega_a P_{ab} \omega_a^{\mathrm{T}} + \omega_b P_{ba} \omega_b^{\mathrm{T}} + \omega_b P_{bb} \omega_b^{\mathrm{T}} \tag{3}$$

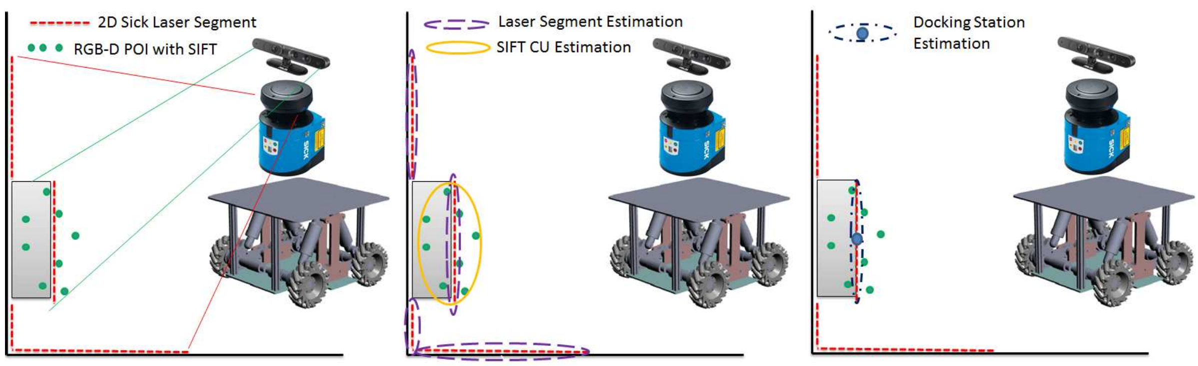
where the weights $\omega_a$ and $\omega_b$ are chosen to minimize $P_{zz}$. This form reduces the conventional Kalman filter if the estimates are independent ($P_{ab} = 0$). The covariance ellipsoid of CI will enclose the intersection region and the estimate is consistent. Given the upper bounds $P_{aa} - \bar{P}_{aa} \geq 0$ and $P_{bb} - \bar{P}_{bb} \geq 0$, the covariance intersection estimate outputs are defined as follows:

$$z = P_{zz}\left\{\omega_a P_{aa}^{-1} a + \omega_b P_{bb}^{-1} b\right\} \tag{4}$$

$$P_{zz}^{-1} = \omega_a P_{aa}^{-1} + \omega_b P_{bb}^{-1} \tag{5}$$

where $\omega_a + \omega_b = 1$, $0 \leq \omega_a, \omega_b \leq 1$.

The parameter $\omega$ modifies the relative weights assigned to $A$ and $B$. Different choices of $\omega$ can be used to optimize the covariance estimate with respect to different performance criteria such as minimizing the trace or the determinant of $P_{zz}$. The estimation fusion sequences are shown as below in Figure 3.




(a) (b) (c)

FIGURE 3. Sensory fusion for charging station estimation: (a) feature extraction, (b) covariance estimation, (c) covariance intersection result

## 3. Mecanum Wheel Robot Configuration.

**3.1. Kinematic model.** The mobile robot is combined with four Mecanum wheels, and each wheel is connected to a separate motor with independent control. Depending on each individual wheel direction and speed, the mobile platform can move forward, backward, sideways and any other desired directions or spin [9]. The kinematic formula is described as below:

$$\begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \\ \omega_4 \end{bmatrix} = \frac{1}{R} \begin{bmatrix} 1 & 1 & -(L_1+L_2) \\ 1 & -1 & (L_1+L_2) \\ 1 & -1 & -(L_1+L_2) \\ 1 & 1 & (L_1+L_2) \end{bmatrix} \begin{bmatrix} V_x \\ V_y \\ \omega \end{bmatrix} \tag{6}$$

where $V_x$, $V_y$ represent the velocity vectors of robot and $\omega$ represents the angular velocity of robot. $\omega_1 \sim \omega_4$ represent the angular velocity of the four mecanum wheels.

**3.2. Control rule of docking.** For the actual robot applications, the robot will navigate to nearby charging station for preparing self-recharging. Figure 4(a) shows the robot is searching the pattern of charging station by SIFT features. After identifying the pattern of charging station, the estimation fusion algorithm is applied to locating the target as shown in Figure 4(b). Figure 4(c) shows the robot will forward to the critical region as $R > R'$, and Figure 4(d) shows the robot will move to the center of critical region via the kinematic control of 4WD mecanum wheel. When robot aligns to the charging station as shown in Figure 4(e), then robot is forward for docking with the distance threshold $d$ as shown in Figure 4(f) for completing docking process.

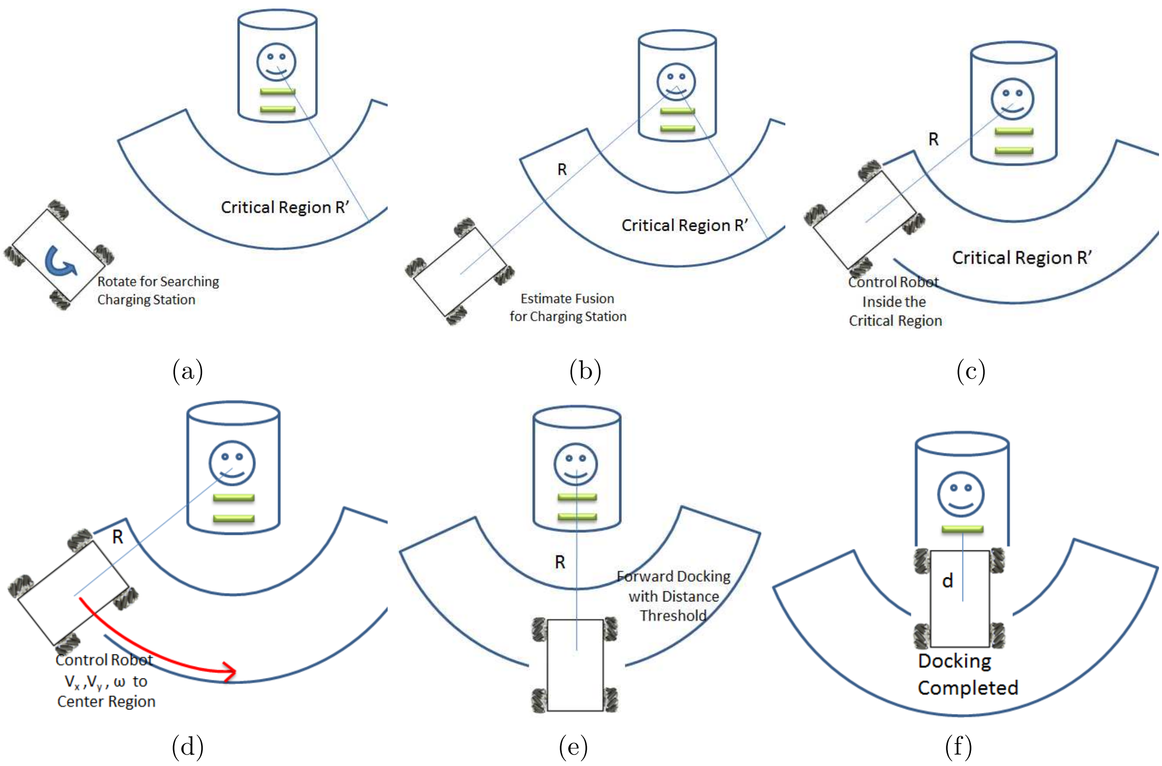



FIGURE 4. Docking sequences of 4WD mechanum wheel robot

## 4. Experiment Results.

The actual demonstration is shown in Figure 5. In time stamp 1, the pattern of charging station was identified. In time stamp 2, robot is forward to the critical region as in time stamp 4. In time stamps 5~7, the robot aligns to the center of charging station. In time stamp 8, robot is forward for docking and time stamp 9 shows the docking completed.

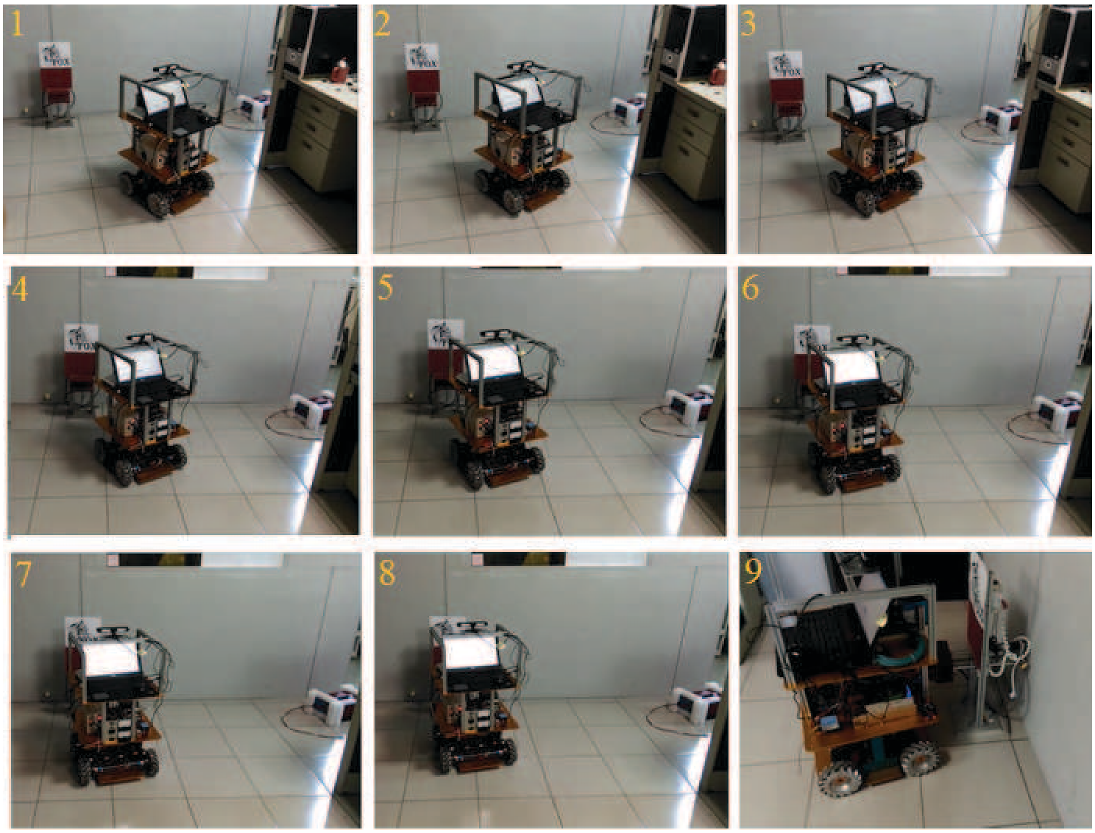



Figure 5. Autonomous docking of 4WD mechanum wheel robot

5. **Conclusions.** From the SIFT pattern comparison, we can get reliable orientation information from the RGB-D camera, and we also apply the covariance union method to estimating visual features with depth information. However, depth information of the RGB-D camera is not precision for docking. On the other hand, laser ranger is easy to get the accurate distance of an extracted object, but it is difficult to recognize the pattern in the environment. In this work, we applied the covariance union and covariance intersection methods to combining the advantages of these two sensors and improved the estimation performance for target (recharging station) estimation. The actual demonstration shows the approaches are well for mobile robot autonomous recharging.

## REFERENCES

[1] W. G. Walter, *The Living Brain*, W. W. Norton & Company, New York, 1963.
[2] K. Roufas, Y. Zhang, D. Duff and M. Yim, Six degree of freedom sensing for docking using IR LED emitters and receivers, *Experimental Robotics VI*, pp.91-100, 2000.
[3] C. Ye and J. Borenstein, Characterization of a 2-D laser scanner for mobile robot obstacle negotiation, *IEEE International Conference on Robotics and Automation*, 2002.
[4] Z. Zhang, Microsoft kinect sensor and its effect, *IEEE MultiMedia*, vol.19, pp.4-10, 2012.
[5] P. Scovanner, S. Ali and M. Shah, A 3-dimensional sift descriptor and its application to action recognition, *International conference on Multimedia*, pp.357-360, 2007.
[6] X. R. Gao, Y. Y. Wu, Y. Kai and J. L. Li, Vehicle bottom anomaly detection algorithm based on sift, *Optik-International Journal for Light and Electron Optics*, 2015.
[7] O. Bochardt et al., Generalized information representation and compression using covariance union, *International Conference on IEEE Information Fusion*, 2006.
[8] R. C. Luo and C. C. Lai, Enriched indoor map construction based on multi-sensor fusion approach for intelligent service robot, *IEEE Trans. Industrial Electronics*, vol.59, pp.3135-3145, 2012.
[9] *http://www.seeedstudio.com/wiki/4WD_Mecanum_Wheel_Robot_Kit_Series.*
[10] Z. Li and B. K. Ghosh, Line segment based map building and localization using 2D laser rangefinder, *IEEE International Conference on Robotics and Automation*, 2000.

[11] H. Baltzakis, A. Argyros and P. Trahanias, Fusion of laser and visual data for robot motion planning and collision avoidance, *Machine Vision and Applications*, vol.15, pp.92-100, 2003.
[12] E. Machida, M. Cao, T. Murao and H. Hashimoto, Human motion tracking of mobile robot with Kinect 3D sensor, *IEEE SICE Annual Conference*, pp.2207-2211, 2012.
[13] M. Cao and H. Hashimoto, Specific person recognition and tracking of mobile robot with kinect 3D sensor, *IEEE IECON Annual Conference*, 2013.