Putting Mobile Robots into Industrial Warehouses

Dario Lodi Rizzini[1][0000−0002−3904−0638] and Stefano Caselli[1][0000−0003−0774−7871]

[1]RIMLab, University of Parma
Parco Area delle Scienze, 181A, Italy I-43124
www.rimlab.ce.unipr.it
{dario.lodirizzini, stefano.caselli}@unipr.it

Abstract. This paper illustrates the effort to transfer advanced results of mobile robot research into the practical operation of Automated Guided Vehicles (AGVs) in industrial warehouses. We focus on three contributions: automatic calibration of AGVs to achieve accurate positioning, AGV localization based on landmark extracted from laser scans, and detection of moving objects for safe navigation.

Keywords: Industrial applications · Mobile robots.

1 Introduction

The role of mobile robots in operation of industrial warehouses has constantly increased in the last three decades. In automation, they are commonly referred to as Automated Guided Vehicles (AGVs). Standard equipment of AGVs (Figure 1) includes laser scanners for localization and obstacle detection as well as forks or other grasping devices used in transportation of goods, that are often packed on pallets. AGVs must be able to localize in the environment, to plan their paths, to safely navigate without collision with people and obstacles, and to precisely reach with the forklift the desired operation points. The execution of these tasks is often guaranteed under rigid assumptions on the operating environment, like presence of artificial landmarks that must be carefully mapped, demanding manual calibration and configuration, strict safety regions.

Recently, the need for more flexibility has required to overcome these constraints and led to the investigation of novel algorithms and solutions for AGVs, often transferred from scientific research. The setup time of a new warehouse is a significant fraction of production and installation costs. Placement and mapping of special markers in large warehouses contribute to increase such setup time, and there may be areas where it is actually impossible to put stable markers. Moreover, the accurate positioning of each vehicle is affected by estimation of intrinsic and extrinsic parameters used respectively in odometry and sensor-based localization. If manually done, AGV calibration is prone to error and can cause large delays or downtimes in warehouse operation which should be avoided. Finally, key issues for human operators and AGVs co-existence in the warehouse

Fig. 1. Example of industrial AGV equipped with forklift as well as navigation and safety laser scanners (respectively, on the top and bottom part of the AGV). Also shown are reflective artificial landmarks used for localization and the outline of braking and halting safety areas (bottom-right).

must be addressed. Safety laser scanners are placed around the AGVs at ground level to monitor the presence of obstacles in given areas around the vehicle. The size of these areas must be carefully chosen as trade-off between safety and efficiency, since the vehicle slows down or stops whenever the area is occupied.

More advanced perception and estimation methods can increase the autonomy of industrial AGVs and the flexibility of plant setup. Localization or obstacle detection based on raw sensor data can address the previously discussed limitations. Solutions to quickly achieve high technology readiness level must take into account requirements and constraints of industrial systems. For example, industrial control architectures are often based on PLC-like embedded systems, which guarantee robustness, real-time execution as well as compliance with safety regulations, but are also subject to strong limitations on available programming libraries for advanced data structures and on computation capabilities.

In this paper, we present an overview of our works aimed at improving the capabilities of AGVs in actual industrial warehouses during our collaboration with AGV manufacturers. The first contribution is a set of algorithms for automatic calibration of intrinsic and extrinsic parameters. The intrinsic parameters are related to the model of the robot and are essential for computing its odometry.

Calibration algorithms have been developed for common AGV kinematic models with both three and four wheels, namely the tricycle [4], and the Ackermann and the Dual-Drive models [1]. The extrinsic parameters establish the relation between the sensors mounted on the AGV as well as their measurements and the robot reference frame. The working principle of calibration is the comparison of the expected paths given the input commands and of the real paths observed by one or more sensors.

The second contribution is the development of localization methods for AGV guidance in industrial plants without handcrafted landmarks. In spite of the extensive research on localization, there is a limited number of real industrial applications meeting with requirements in safety, robustness and technology readiness. We investigated several solutions designed for laser scanners including keypoint features like *FALKO* (Fast Adaptive Laser Keypoint Orientation-invariant) [3] and SKIP (SKeleton Interest Point) [8], as well as complete scan fingerprints like ARS (Angular Radon Spectrum) [6] or registration-based techniques. Both approaches have been integrated in the sensor models of the Extended Kalman Filter (EKF) localization previously implemented for artificial landmark localization.

The third contribution is the detection of moving objects like people and vehicles [8] or semi-static items [7] in the space around the AGV. The proposed algorithm exploits the laser scanners already mounted on AGVs for safety rules compliance. These sensors operate according to simple and rigid area-based policies that slow down or stop the AGV when an unexpected item is found. We extended their use to discriminate measurements belonging to dynamic parts of the scene in order to predict their motion and prevent collision.

The proposed technological advancements have been developed by taking into account actual industrial mobile robotic platforms. We claim that gradual integration of state-of-the-art solutions is an effective approach to achieve high technology readiness levels and bring the full potential of mobile robotics into operational warehouses.

2 Calibration of AGVs

Calibration parameters are divided into intrinsic and extrinsic. The intrinsic parameters depend on the specific kinematic model whereas the extrinsic ones represent the pose of the navigation sensor (usually a laser scanner) w.r.t. the robot frame. Since mobile robots move on the ground plane, the kinematic models are planar.

The robot configurations typically used in warehouse logistics have three or four wheels, like those displayed in Figure 2. Intrinsic parameters are often related to the state of wheel. They include the *steering offset* of a wheel, which is the angle between the real wheel direction and the reference angle of steering encoder, and the *driving scale*, which is the length of the travelled path of a wheel by a single encoder tick. Steering offset and driving scale allow to relate

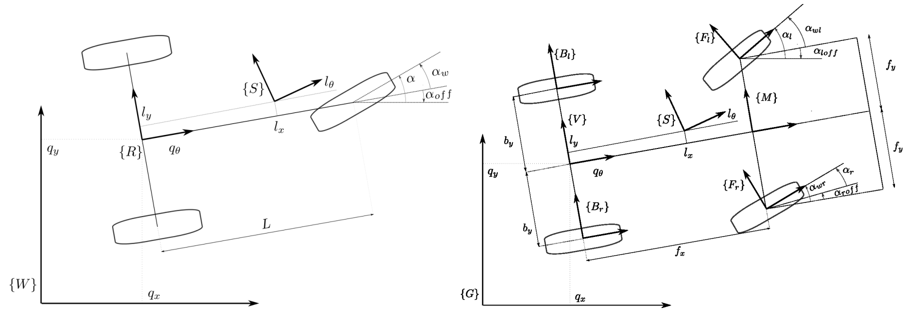

Fig. 2. Widespread AGV kinematics: the three-wheel model or *Tricycle* (left), and the four-wheel models, namely *Ackermann* and *Dual-Drive* (right).

the motion of each single wheel with the state of the mobile robot. In earlier work, we addressed the following models:

- *Tricycle.* It has a single front actuated and steering wheel with steering offset α_{off} and driving scale s_w and two passive back wheels.
- *Ackermann.* It has two front actuated steering wheels and two passive back wheels. Both the front left and front right wheels are described by steering offsets (respectively α_{loff} and α_{roff}) and driving scales (respectively s_{wl} and s_{wr}).
- *Dual-Drive.* It is similar to Ackermann, but the two front wheels are steering whereas the back wheels are non-steering and actuated. The front steering wheels are defined by steering offsets α_{loff} and α_{roff}, the back wheels are described by their driving scales s_{wl} and s_{wr}.

Extrinsic parameters are the pose of the sensor frame $\{S\}$ w.r.t. the robot frame $\{R\}$, i.e. $\mathbf{l} = [l_x, l_y, l_\theta]^\top$.

The principle adopted for estimation of calibration parameters is the comparison between the trajectory measured by the on-board sensor and the expected trajectory of the AGV. We assume that at every time instant each wheel is aligned with the Instantaneous Center of Rotation (ICR) of the AGV rigid body and that there is no wheel slipping. Under such assumption the calibration parameters are observable. The calibration procedure collects data while the AGV iteratively moves along several paths segments. We choose path segments to be circular arcs obtained with constant input commands because the kinematic equations have straightforward and reliable solutions, although other path geometries could be used.

For each path segment k, the robot collects the nominal steering angles α_* measured by steering encoders and the number of encoder ticks n_* measured by the motion encoders (symbol $*$ is a placeholder for any wheel label). The AGV is equipped with a sensor, usually a laser scanner, that can be used to estimate the egomotion $\boldsymbol{\zeta}_k$ over path segment k. The egomotion, i.e. the relative motion

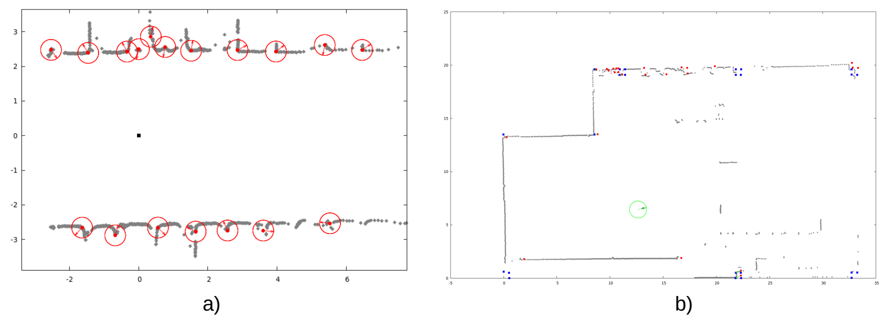

Fig. 3. Examples of keypoint features for robot localization: a) FALKO (red circles), b) SKIP (blue squares).

of the sensor over the time, is estimated through registration or alignment of consecutive laser scans. The specific kinematic equations of the AGV constrain the relative motion of the robot $\boldsymbol{\delta}_k$ on the path segment with α_*, n_* and the intrinsic parameters to be estimated. The egomotions $\boldsymbol{\zeta}_k$ and the relative motion $\boldsymbol{\delta}_k$ are constrained by extrinsic parameters as $\mathbf{l} \oplus \boldsymbol{\delta}_k = \boldsymbol{\zeta}_k \oplus \mathbf{l}$ where $\oplus$ is the pose composition operator. The solutions for these constraints have been derived for each kinematic model [1,4].

Automatic calibration has many advantages over the manual procedures previously used to assess the values of parameters. First, the precision of the estimated AGV parameters in repeated calibration trials is at most 0.1 deg for angular parameters and typically less than 5 mm for position parameters. More importantly, the positioning error on operation points is about $10 \div 15$ mm. Second, a standard automatic calibration procedure leads to more uniform positioning of a fleet of AGVs than the one achieved by the manual expertise of human operators. Finally, calibration requires about 15 minutes for each AGV with limited human intervention and no special expertise of the operator, instead of about one hour per AGV which must be manually calibrated by an expert operator. Indeed, expert operators with the ability to perform such calibrations are a scarce resource, whose unavailability leads to delays in warehouse setup or extended AGV downtimes. In plants with tens of AGVs, automatic calibration significantly reduces the setup time and potentially allows frequent re-calibration.

3 AGV Localization without Artificial Landmarks

The standard commercial solution for AGV localization is based on artificial markers made of reflective material observable by a laser scanner. The robot position and orientation are computed using EKF and landmark maps. Feature detection from raw laser scans avoids the reliance upon special landmarks for AGV localization.

The detection of stable and distinguishable interest points from laser measurements is a not trivial task. Scientific literature includes few keypoint features with descriptors like FLIRT [9]. In an effort to devise effective features suitable for industrial environments, we have developed two different algorithms: FALKO [2, 3] and SKIP [8], illustrated in Figure 3. Both FALKO and SKIP points are detected by associating to each point a saliency score. Such score is related to geometric parameters like the curvature of underlying obstacle surfaces. In the case of FALKO, features are extracted where there is a distinctive local distribution of neighbor points. The *cornerness* of a point $\mathbf{p}_i$ is computed by comparing the local points belonging to its neighborhood after a careful selection of valid points, e.g. avoiding those close to gaps due to occlusion. FALKO points allow the identification reasonably stable references for navigation and local mapping of AGVs. Experiments on AGVs have shown the effectiveness of FALKO keypoints as temporary landmarks for navigation in block storages, i.e. passages between lines of pallets (see 3(a)). Hence, a temporary map of FALKO features allows short-term navigation of AGVs. The main drawback of such interest points is that they do not faithfully describe the global shape of the free space in a laser scan, since the scoring depends only on a local neighborhood.

The novel feature SKIP [8] extracts interest points through simplification of the global contour defined by scan points. The general idea is brought from curve simplification techniques like Discrete Contour Evolution [5]. Instead of directly connecting the laser points adjacent according to their radial order, the scan is split into intervals in correspondence to gaps caused by occlusion. Gaps are pairs of consecutive points whose distance is above a given threshold and are strong discontinuities in the range values. Gaps are not included in the following assessment. A cornerness score is computed for each of the remaining points $\mathbf{p}_i$ based on its previous and next points, respectively $\mathbf{p}_{i-1}$ and $\mathbf{p}_{i+1}$. The chosen score is equal to $score(\mathbf{p}_i) = |\overline{\mathbf{p}_i\mathbf{p}_{i-1}} + \overline{\mathbf{p}_i \mathrm{i}+1} - \overline{\mathbf{p}_{i+1}\mathbf{p}_{i-1}}|$ where $\overline{\mathbf{ab}}$ is the length of the segment connecting points a and b. Then, the points are ordered according to their score and those with score value below a given threshold are iteratively removed. When a point is removed, the score of its adjacent points is updated according to their new neighbors. An example of the outcome of SKIP algorithm is illustrated in Figure 3(b). SKIP points are the blue squares identified at the corners. Gaps and other discarded points are marked in red. The algorithm has been tested on datasets acquired in an industrial warehouse and has shown to detect meaningful environmental features.

4 Detection of Semi-static and Dynamic Objects

AGVs are usually equipped with laser scanners at ground level to detect potentially colliding objects like obstacles, people and other vehicles. Decisions on the robot behavior, e.g. to slow down or halt its motion, are taken according to simple area-based policies. While required by safety regulations, this approach may prove rigid. Safety laser scanner could be used to predict the motion and to replan the robot trajectory.

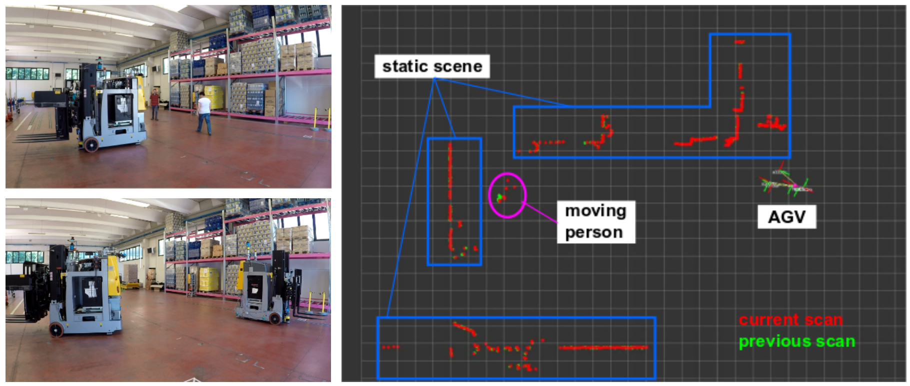

Fig. 4. An AGV coping with a moving person (top-left) and another AGV (bottom-left). Detection of dynamic objects and static scene is achieved by comparison of consecutive scans (right).

Parts of the scene can be classified into three categories: *dynamic*, *semi-static* and *static*. The classification depends on the frequency of location changes for the objects in the scene. For dynamic objects such change occurs while the AVG collects sensor data with the laser scans. When the AGV moves in a static or semi-static scene, the points acquired at two consecutive time instants are aligned by the same rigid motion that is the inverse of the robot motion. On the other hand, dynamically moving objects are aligned by a different transformation w.r.t. the background. The approach is illustrated in Figure 4.

In [8] an algorithm is proposed for dynamic object detection based on registration and difference between scans. First, the relative pose between two consecutive AGV poses is estimated via scan matching. Hough spectrum correlation [6] allows robust estimation of robot rotation. Once rotation is estimated, clustering is performed only on translation. *Motion clustering* is achieved by iteratively performing k-means clustering on groups of points with coherent translation motion. In particular, the points of the current scan are associated to their nearest neighbors in the previous scan and the respective difference vectors are computed. The difference vectors are then assigned to a cluster using k-means algorithm. The number of clusters k should be equal to the number of moving objects, which is unknown. Thus, the algorithm initially overestimates $k = 15$ clusters and, when the centroids of two clusters are very close, the two corresponding clusters are merged. The achieved classification is improved under the hypothesis that points belonging to the same object are more likely neighbors. Spatial clustering is performed and the initial point labels are corrected by adopting the same classification for the points in the same spatial cluster. Errors in cluster identification are further avoided through their tracking.

The identification of semi-static objects is more complex, since their location does not change during the transit of the AGV. Examples of semi-static objects in warehouses include pallets deposited for hours or days in a given location where they stay until their transportation to the buyer. Semi-static objects usually do not represent risks for safety, but they may unnecessarily slow down the AGV. We proposed a semi-static detection algorithm [7] that compares maps of the same region visited at different time instants. The environment is represented in the form of polyline maps that have limited footprint. Polylines are extracted from laser scans, simplified and compared with proper procedures. Experiments have shown the potential of the approach to detect semi-static objects, although the procedure has not been validated yet in an operational warehouse.

5 Conclusion

This paper has presented several works for improving mobile robot (aka AGV) operation and navigation in industrial warehouses through fast and accurate calibration of vehicles, localization and tracking of moving objects. The leading criterion in our work has been gradual integration on the existing industrial platforms. The first two contributions have achieved high technology readiness level and have been successfully applied in real plants.

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