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Pallet Pose Estimation with LIDAR and Vision for Autonomous Forklifts

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Abstract: This paper is focused on enhancing current AGV flexibility in non structured environments. It proposes a scheme to solve the problem of identifying a pallet, which pose is known with large uncertainty, from fused laser range and vision data and navigating to it by on line calculating and performing highly continuous paths for a precise target reaching. The novelty is in the combination of range and colorimetric measurements still not exploited, to our knowledge, for pallet recognition and localization.

Keywords: AGV, autonomous forklift, pallet, docking, LIDAR, vision, continuous curvature.

1. INTRODUCTION

This paper presents a work aimed at increasing the current industrial AGV (Autonomous Guided Vehicles) capabilities of automated material handling. Up to now AGV are able to work only in highly structured, and therefore more expensive, environment. They can not face the spatial uncertainty typical of human operations like unload of pallets in casual locations. Furthermore, faulty situations can occur also in highly repetitive and deterministic tasks when, for example, a pallet lies in unexpected position and a blind pick-up would probably cause damage.

Therefore the present work proposes a more robust industrial-compliant approach for making an AGV able to identify a pallet autonomously, to estimate its location, to reach it for loading and unloading in the proper locations. This enables the system to carry pallets and to cope with indoor and outdoor industrial environments, where the pallets are stored in not well defined positions. The proposed method is based on a combined laser range and vision sensing of the pallet. While laser is used to precisely localise the pallet, an associated structured camera is used to filter out useless and ambiguous range data. It is an upgrade of our previous work using only a laser rangefinder (Baglivo et al. 2008).

Other works on casual pallet localization are present in literature. The work of Lecking (Lecking, Wulf & Wagner. 2006) proposes a method based upon a laser rangefinder placed in front of the vehicle. Two alternatives are shown, one with the aid of reflective targets placed in the front part of the pallet, and one to cope with the standard natural pallet. This is not convenient as generic pallets cannot be used and, due to the harsh industrial environment and to the fact that the pallet itself is subjected to unavoidable impacts during its loading/unloading phases, the reflective targets can be damaged. Nygards, Hogson & Wernersson (2000) uses structured light and a CCD camera to estimate the position of the front structure of the pallet. Since range camera accuracy varies with distance, this method is shown to work within ranges of about 1 meter. This oblige the vehicle to get close to the pallet, than to recognize it, than to go back in order to achieve a feasible path to pick it. The pallet can only be in a limited range outside its nominal position. Furthermore, to add a sheet of light is not so convenient as far as laser rangefinders are always embedded in the modern vehicles. Pagès (Pagès et al. 2001) proposed a image segmentation method based on colour and the geometric characteristics of the pallet. For this approach a camera calibration algorithm and a good illumination system are required. The approach of (Seelinger & Yoder 2006) does not require to maintain a strict camera calibration but fiducials are used, which are artificial visual features placed on the pallets and on the forks. Both methods do not use the robust combination of range and colorimetric measurements. This in general means that some range points that comes from nearby objects can be accounted for the pallets thus leading to wrong estimation particularly when different pallets are one close to each other with the presence of structures in the neighbourhood.

The combination of range and colorimetric measurements, still not exploited for pallet recognition and localization, enables a more reliable estimates also in the presence of more than one pallet and nearby structures in a standard industrial situation.

Once a pallet is localized the AGV could be at any unforeseen position with a certain attitude and has to autonomously plan and perform a safe path to reach the pallet with a prescribed precision, that is to solve a path planning and control problem. It is well known that if the path is feasible for a mobile (mostly nonholonomic) robot its tracking will be accurate, otherwise there will be non negligible differences between the planned and the executed path and in this case AGV position uncertainty and tracking error could increase due to slippage and velocity has to be reduced.

Planning continuous curvature path can be a good choice in terms of compatibility with respect to kinematics and dynamics. This for a huge variety of robot motion models. Various methods have been employed to plan smooth trajectories (Labakhua et al. 2006, Rodrigues, Leite & Rosa 2003). To cope with more complex representation of curvature, Kelly (Kelly & Nagy 2002) proposed a method for trajectory planning based upon parametric trajectory representations. The method employs a polynomial representation of curvature. This is still a research field, obviously not for the geometric representations in itself, but for the definition of numerical algorithms and control strategies efficiently employable in Real Time and for the systematic investigation of their robustness to parameters changes and measurement uncertainties.

Starting from the method of Kelly, we optimized the search strategy in order to extend the converging solutions and we also added a control algorithm that is perfectly integrated with the planning method resulting in a technique called Polynomial Curvature Sliding control, PC-Sliding (De Cecco et al. 2007). The proposed pallet localization method by means of combined camera and 2D laser scans, and the PC-Sliding method together constitute a complete scheme for the robust achievement of flexible pallet engagement.

2. PALLET LOCALIZATION

2.1 Localization Algorithm using LIDAR Data

The system utilized for object localization is a Sick OEM-1000 laser rangefinder with a viewing angle of 360° and an angular step of 0.125° that provides planar range scans of the immediate surroundings in a fixed height parallel to the floor.

The aim is to find, if it exists, a best fit between the actual current scan data and an object model made up of line segments of the supporting blocks (Fig. 2).

The sensory data are collected from a standing robot position and are preprocessed by averaging (20 scans) for random noise reduction.

The best object position is assumed to minimize an energy function over a set of object model trial positions:

$$P_0 = (x_0, y_0, \delta_0) = \arg\min\left\{-\sum_{i=1}^{n}\left[(1/k\sigma)\cdot\exp(-d_i/\sigma)\right]\right\} \quad (1)$$

Where n is the number of scan points after preprocessing, d_i is the distance of the i-th point from the nearest line segment of the object model in the current trial position and attitude, k and σ are tuned constant depending respectively on energy decaying rate and sensor uncertainty.

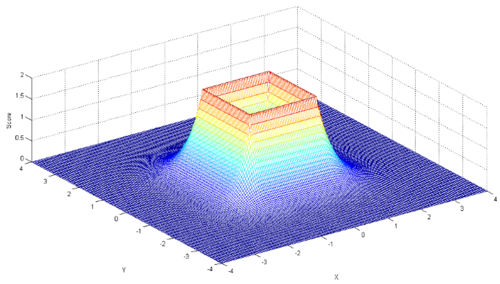

Fig. 1. Energy function value (opposite sign) near a pallet foot.

Tests were made using both squared and normal argument of the exponential kind of functions proved that the latter choice improves convergence. A resulting example of energy function is in Fig. 1.

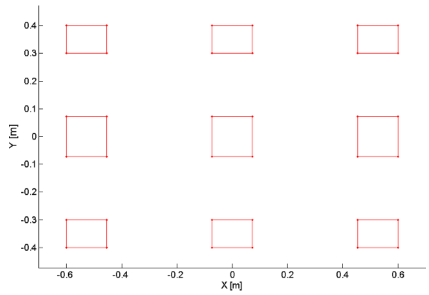

Fig. 2. Pallet model

A genetic optimization algorithm was used for the function minimization, using real value variables (Ballester & Carter 2003) instead of binary coding: both methods have been tested, and the choice is given by the poor speed of binary coding, for the great number of genes (number of bits, 16 to 18 used) per chromosome (variables, 3 used) needed to achieve the adequate resolution and accuracy.

It has been chosen a genetic algorithm because of the presence of many local minima, as explained in §2.2.

To improve the solution, it is performed a local search on the best children of every population: Nelder & Mead simplex method (Nelder and Mead 1965, Wright 1996) has been chosen, so that there is no need for gradient evaluation. Computation times vary according to the number of iterations and used points. A C implementation on a Centrino 2 GHz processor gives times from 0.068 s to 0.44 s over about one hundred of runs with different pallet layouts.

Furthermore, the convergence of the algorithm is guided by a matching criterion (ICP-like) based on a laser sensor beam ray-casting simulation: once the search has finished and an object position is found, a virtual scan of the pallet in that position is simulated and the points so obtained are coupled with the nearest ones from the real data as in Fig. 3. Object position is accepted if maximum percentage of distances between coupled points is inside a threshold based on LIDAR uncertainty (ex. 3 cm and 80% with OEM-1000), otherwise a new search starts till convergence or localization failure occur. Extended simulations showed a 0.5% of false positives using this convergence criterion.

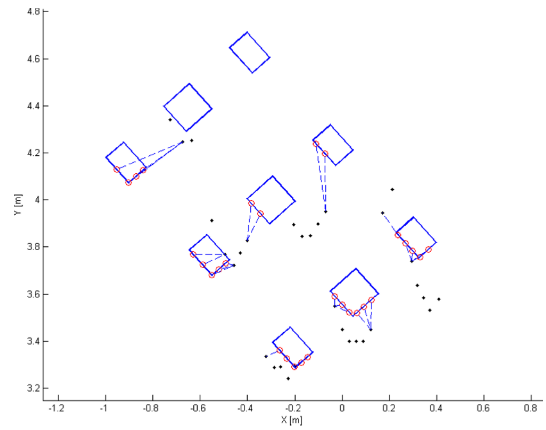

Fig. 3. Coupling between real and simulated data for stating convergence.

Genetic algorithms do not need a start point, and a common practice is to choose random points inside boundaries. If there is a priori knowledge of the pose of the pallet, instead of reducing boundaries one can build the initial population using a Gaussian distribution with mean on that information.

2.2 Localization Failures

The optimization algorithm is based on a combination of genetic and direct search algorithms. This choice is due to the presence of many local minima, as it is shown in Fig. 4, in which the cost function reduced to only the *x,y* position over the three variables expressing the pallet position and attitude is plotted in a range containing the true simulated solution, with the true attitude fixed (78°). The combination of genetic and direct search methods has shown to be more efficient, in particular using the local search (Nelder Mead Simplex method) every iteration of the genetic algorithm on best fitting population.

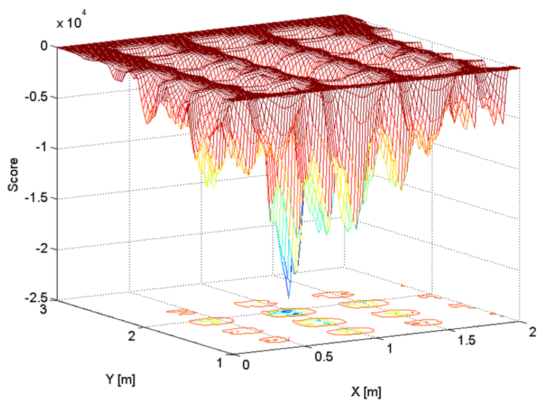

Fig. 4. Cost function near the solution

The most frequent cases that give rise to solution ambiguities:

A. other pallets are nearby the searched one;
B. there are obstacles (other objects) beside the pallet;
C. the pallet is symmetrically displaced over the LIDAR main axis

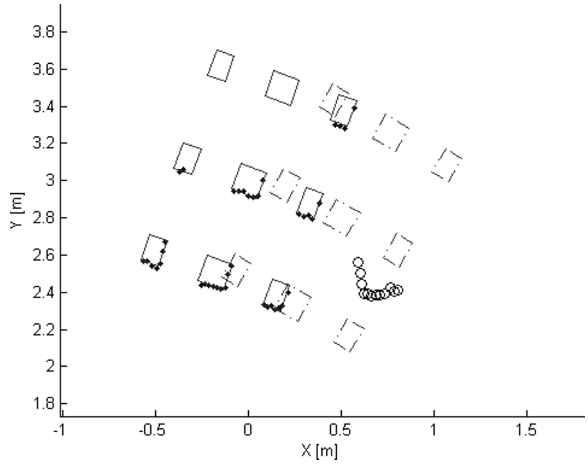

Fig. 5. Case B – objects nearby

For instance, case B is shown in Fig. 5: the points represent the simulated LIDAR scan of the pallet, while an object (a rectangular box) is plotted with circles; the continuous line is the pose of the pallet in the true position, while the dash-dotted line is the result (a wrong solution) of the optimum search. The failure occurs because the disturbing object has shape and dimension similar to that of the pallet slats and it cannot be filtered out. Besides, the disturbing object points have a major weigh in the cost function. Numerical simulations proved that the algorithm reaches a convergence of 99.5% when there are no obstacles beside the pallet or there are no problems of ambiguity (pallet in the proximities), in a field of search of -90°÷90° for attitude and ±1 m for position.

Other example (C) that often leads to meaningless values of solution is when the pallet is in perpendicular position with the laser rays, as in Fig. 6. In this case the problem is given by the poor view of all the pallet slats: the rear ones doesn't contribute enough in the cost function, mainly because of their limited number (only three acquired points on two slats) and of the kind of the optimum search. It has to be noticed that this case is the least frequent one, thanks to the ICP-like method (described in §2.1) that address the algorithm toward the optimum. If the solution is not accepted, a translation of the wrong solution could be done, moving the centroid of simulated pallet model scan toward the centroid of its ICP-coupled real points. This new point could be used as starting point for a new iteration. The most difficult situation is when two pallets are one beside the other, like in Fig. 7.

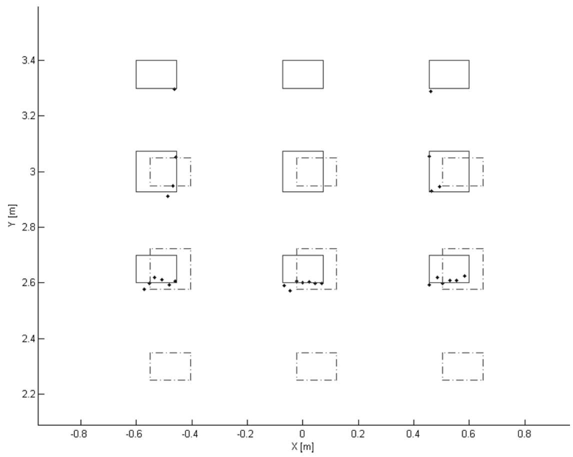

Fig. 6. Case C - pallet perpendicular to the laser

It is the mathematical definition of the cost function that brings to ambiguity, because its values in different poses (fig. 7) are similar, and the solution depends strongly on the laser noise, on the field of search and on the distance between the two objects.

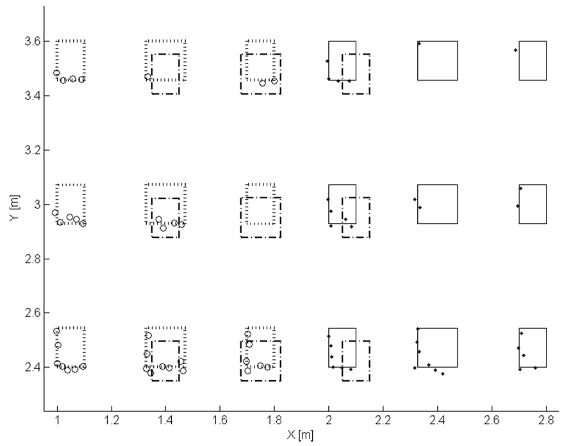

Fig. 7. Case A – close pallets. In this case the continuous thin line and the dotted one show two pallets in ideal position, with points and circles for the respective scans. Dash-dotted line is a (wrong) solution.

2.3 Camera and LIDAR Calibration

A fusion system between the LIDAR and a color camera, both mounted on the AGV, has been chosen to solve the ambiguity problems. The camera is mounted so that its field of view projects mainly in the laser measurement range of interest.

The first step is the determination of the reciprocal position and attitude between the two instruments, using a slightly modified algorithm presented in (Zhang & Pless 2004), which needs as input a checkerboard and the extrinsic and intrinsic camera parameters. These calibration parameters are obtained by an available software from Caltech (Bouget). An example of the experimental procedure is illustrated in Fig. 8.

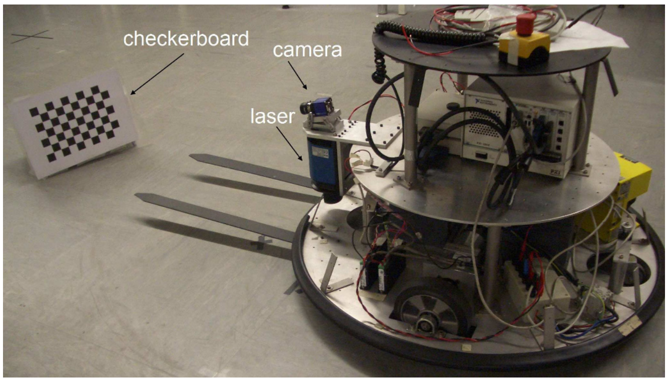

Fig. 8. Camera and LIDAR calibration experimental setup.

Next step is the fusion of information between the two instruments. It is achieved by expressing the laser points coordinates in the camera CCD reference frame and associating to them a chromatic information retrieved by meaning over the pixels nearby each laser point transform.

In this way it is possible to realize a statistical filter for the laser points that do not belong to the pallet, by taking into account the LIDAR-camera measurement uncertainty and a chromatic model of the pallet.

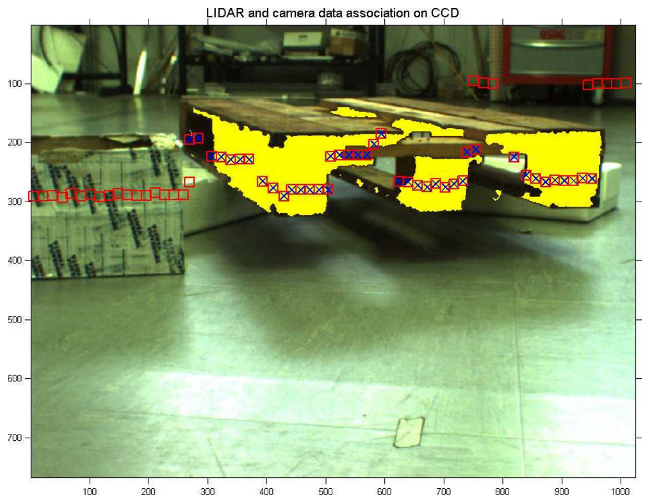

Fig. 9. Scan point and camera image association. Crossed squares are the laser measurement associated with pallet by the vision filter.

The image is locally filtered, in a region of interest where it's supposed to be the laser scan after the extrinsic parameter calibration between LIDAR and camera. The filtering is based on color properties of the pallet: pixels with certain RGB characteristic are selected. With morphological image processing, it is possible to obtain some regions which contain cluster of points with color properties similar to the pallet: then, a number of pixels are eliminated with a Chauvenet criterion based on distances between every pixel and the centroid of all pixels. The remaining pixels are supposed to be in the pallet region, and the LIDAR data are filtered with a criterion based on distance to the remaining pixels, thus obtaining only the points that are supposed to belong to the pallet.

2.4 Uncertainty Evaluation

The object localization procedure described above, allows to find out three values associated to the position and orientation of the object on a plane, starting from the data acquired from the LIDAR. This procedure can be considered as an indirect measurement of the object position and orientation, which are the output quantities of a virtual instrument, having the Laser Range Finder (LRF) measurements and own pose, and a pallet model as input quantities.

According to the GUM (BIPM 1995) , uncertainty can be expressed by a confidence interval which encompasses all possible values attributable to the measurand with a predetermined level of confidence. These values have been estimated experimentally. The LRF was mounted on a slide as in measured rotations and displacement in the Y direction along the slide. Instead of the object, the LRF was moved and these displacements were calculated from the object position estimated by the localization algorithm.

Nominal displacements were of 100 mm and 300 mm with respect to its initial position. Nominal rotation of 30° and 50° clockwise and counterclockwise for each displacement. The measurements were done for two initial distances of the LRF from the object of 2 m and 4 m and for two different object angle of 0° and 45°.

These measurements have been made both with the pallet alone or with disturbance beside: vertical pipes simulating surroundings have been placed among it.

In the case of 0° angle of the object and with other neighboring objects, the localization process was not robust due to bad incidence angle (see §2.2) and too few scan points on the object.

From a covariance analysis of the whole set of measurements obtained as described above, it resulted 0.3° mean error on object attitude estimation, 8 mm and 1 mm respectively on X and Y displacements; the standard uncertainties of these values are respectively 0.4°, 5 mm and 1 mm. No systematic effect was observed.

This work results are comparable with that of Lecking (Leking 2006) but the former have been obtained with a fewer a priori knowledge about the object position. Also, here it should be noted that the environment surrounding the pallet was cleared of other pallets or objects that might have confused the algorithm outside a circle of 3 m in diameter centered in the pallet supposed position: in this way it has been possible to reduce the computational cost proportional to the number of scan points, but not to exclude imposed disturbance (vertical pipes).

Euro-pallet pose measurements have been made in a industrial environment with a Sick S3000 LRF, 0.25° angular step, mounted on a AGV together with a Sick NAV200 as a reference sensor. The pallet was about 2.5 m and 3.5 m from the laser source and for each case the AGV moved 3 steps of 0.1 m. After checking that there was no bias in the pallet localization algorithm, the evaluated uncertainty of the integrated measuring system was computed considering that the pallet pose had to be fixed in the NAV200 world frame over the different AGV steps. The uncertainty in this case resulted comparable with that evaluated on the slide.

3. PC-SLIDING PATH PLANNING AND CONTROL

PC-Sliding is a novel RT procedure for planning and control that can be summarized as follows. The steering command is directly related to the path curvature and as a natural consequence one of the two robot controls (the second could be the linear velocity) is chosen to be the curvature as a polynomial function of the path length. The function parameters are computed from a two-point boundary value problem driven by the differential posture (pose plus curvature). The control strategy works by re-planning (Fig. 10). While following the original main path the vehicle re-plans iteratively the path with a repetition rate that must not necessarily be deterministic. To the actual curvilinear coordinate it is added a piece forward, than computed the corresponding posture in the original planned path, finally re-planned the differential path steering the vehicle from the actual posture to the one just computed. The result is to force the vehicle to correct for deviations while sliding over the desired path. Those little pieces of correcting path have the property of fast convergence, thanks also to an optimized mathematical formulation, allowing a real time implementation of the strategy.

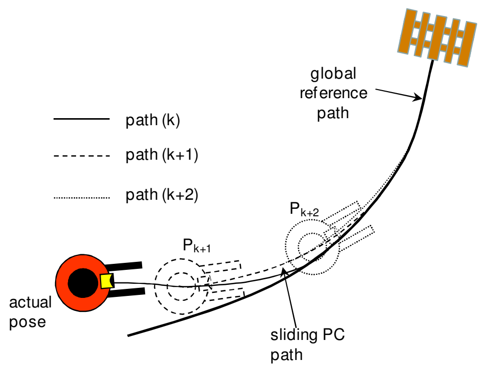

Fig. 10. The control algorithm as an iterative re-planning of Polynomial Curvature paths (k,k+1,k+2...) to lock to the reference original PC path to the object.

Advantages of the proposed method is its the use of the same strategy both for planning and control and the capability of imposing the final curvature of the path for precise approaching to the object. Controlling vehicles in curvature assures compatibility with respect to kinematics and partially to dynamics if the maximum rate of curvature variation is taken into consideration. Polynomial curvature trajectories are convenient to manipulate and execute in vehicle controllers.

Disadvantages could be the low degrees of freedom to plan obstacle-free path, but the method can readily be integrated with Reactive Simulation methods, or the degree of the polynomial representing curvature can be increased to cope with those situations.

Fig. 11 and Fig. 12 show, in the same order, a case of two executed PC-paths and the relative following error. A mock-up of differential drive robot 1.1 m diameter was used.

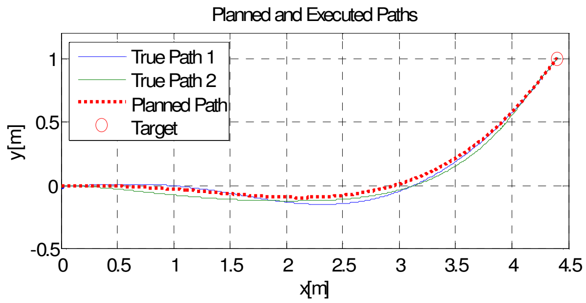

Fig. 11. A case of planned and performed paths for a desired final posture in [x,y,δ,κ] = [4.41 m,0.98 m, 48.7°, 0.1 m-1].

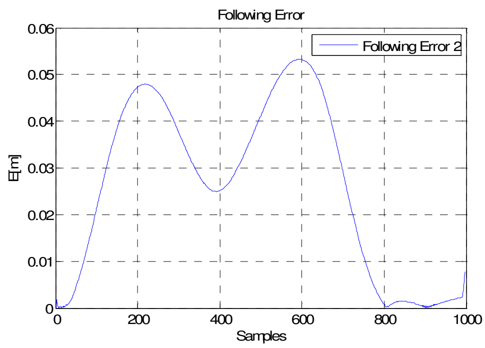

Fig. 12. Following error of path control in the case of Fig. 11.

4. FUTURE WORK

Extensive tests on the complete task of finding and docking industrial pallets will be done in order to fully exploit vision for robust pallet disambiguation and data filtering. The effects of different and changing light on system calibration will be investigated.

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