TECHNICAL PROOF

Mobile Robot Positional Accuracy & Repeatability

In this case study, we describe a fleet of autonomous mobile robots (AMR) that move non-conveyable products/items in the courier industry using detachable carts. The main purpose of this case study is to find the positional accuracy and repeatability of LiDAR-driven AMRs for the design of docking applications.

We conducted several trials for collecting the positional data using a docking test bed at different speeds and times. The process uses a Kalman filter and Six-Sigma methods to define the docking constraints. Using these min and max positional constraints, we designed the detachable cart that can be used to move “non-conveyable” (NC) products. The current product has completed a trial deployment of a system that automates the transportation of NC or “irregular” (IRR) parcels at courier facilities at scale. This system is a first step toward our research goal of developing an architecture for robust robot planning, control, adaptation, error monitoring, error recovery, and interaction with users. We describe the current system, lessons learned from our earlier failures, organizing principles employed in the current system, and limits to the current approach.

Currently, NC products are manually pre-sorted and placed on carts that are assigned to a designated outbound location. Once the cart is full, a tug operator manually moves the full cart to outbound destination. The tug allows up to 4 carts to be transported from the NC load station to the outbound unload station. The large batch operation comes at the expense of having to wait for 4 carts be become available, loaded and ready for transport. The proposed robot system is a drop-in replacement to the current carts in operation.

While current carts may also be detachable, they are manually attached to the train of carts and rely on a tug operator for transportation in the facility. In the proposed system, the robots facilitate the operation of a LEAN Pull System. When a cart is loaded, it is immediately positioned for delivery to the appropriate outbound sorter, resulting in a reduction of time that the full carts sit idle thus improving workflow and decreasing congestion points.

NC sorting and loading to detachable carts in the robotic fleet is depicted in figure 1. The components are described according to the order of operations / flow.

Figure 1 NC Cart Loading Station

CART LOAD STATION

Team members manually sort NC product to designated sort area. Team members place products designated to a specific destination on the assigned detachable cart. The cart is then dispatched for transport to the outbound location via the robot system.

MIR500 MOBILE ROBOT

The MiR500 is a collaborative, autonomous mobile robot that uses forward and rear facing LiDAR sensors to map and localize to the surrounding environment. In addition to mapping and localization, these sensors provide the ability to dock to carts, stands, and equipment via the LiDAR signature of the structure's geometry for each case.

DETACHABLE CART

This cart is transported by the MiR500 mobile robot from the cart load area to the head of the IRR conveyor where it is positioned and released. It requires that the robot is capable of routinely docking-to and undocking-from a cart. Consequently, the robot must transport carts securely without need for manual intervention and hence the material subject of the current case study.

MIR500 MOBILE ROBOT DOCKING PERFORMANCE

The first step in attempting to improve the accuracy and repeatability of AMR is to examine the current state of the robotics technology and other related technologies. It is important to understand that robot manufacturers whose precision claims cannot stand up to the world's most sophisticated and available measurement systems have no place in the industry.

Assume we have taken measurements using four precise laser range sensors at time k, k+1, k+2, and k+3. Based on each measurement we estimate the robot's position. Such an estimate derived from the first sensor measurements is q1, the estimate of position based on the second measurement is q2, the estimate of position based on the third measurement is q3, and the estimate of position based on the fourth measurement is q4. Since we know that each measurement can be inaccurate, we wish to modulate these position estimates based on the measurement error expected from each sensor. Suppose that we use two variances to predict the error associated with each measurement. We will, of course, assume a unimodal error distribution throughout the remainder of the Kalman filter approach, yielding the two robot position estimates:

$q^{\wedge 1} = q^1$ with variance δ_1 $\quad$ $q^{\wedge 3} = q^3$ with variance δ_3

$q^{\wedge 2} = q^2$ with variance δ_2 $\quad$ $q^{\wedge 4} = q^4$ with variance δ_4

So, we have four measurements available to estimate robot position. The question is, how do we fuse (combine) these data to get the best estimate for the robot position?

We are assuming that there is no robot motion whenever sensors are performing the measurement, and therefore we can directly apply the least square technique. Thus, we write:

$$S = \sum_{i=1}^{n} \left(w_i * \left(q^{\wedge} - q_i \right)^2 \right)$$

with w_i being the weight measurement of i. To find the minimum error we set the derivative of S equal to zero.

If we take as the weight w_i,

$w_i = 1/\delta_i^2$

then the value of $\hat{q}$ in terms of four sensors measurements can be defined as follows:

$$= \left(2 * \hat{q} * \sum_{i=1}^{n} w_i - 2 * q_i * \sum_{i=1}^{n} w_i\right) = 0$$

From the above equation we can see that the resulting variance in positional data is less than the variance on the individual sensor measurement.

In this analysis, differential transformation theory is employed to obtain an estimate of the linear differential change from the theoretical position of the robot. The measurements are used to calculate the docking performance of the MiR500 and assumedly any similar LiDAR guided AMR available on the market where precise positioning of the robot needs to be understood. Our performance metric is derived from of the Six Sigma Process Capability Index, Cpk.

$$Cpl = (\mu\text{-}LSL)/(3\delta), \quad Cpu = (USL\text{-}\mu)/(3\delta)$$
$$Cpk = Min[Cpl, Cpu]$$

In our method, we set Cpk values to 2.0 for Six Sigma level output and calculated upper and lower statistical limits (ie. USL & LSL) as a result of the mean (μ) and standard deviation (δ). USL & LSL values empower users in understanding design constraints as a function of the robot's positioning capability. The results were found to be non-symmetric relative to the mean and most notably in the robot y-axis. The cause is LiDAR sensor placement on the vehicle.

On a MiR500, the LiDAR sensors are placed in opposing corners of the vehicle to remove sensor blind spots and thus minimize safety concerns while consequences of non-symmetric probability density functions are easily addressed via design. Table 1 shows the result of the docking analysis for an AMR.

	X-Axis (in.)	Y-Axis (in.)	θ-Axis (degree)
Max	0.253	0.060	0.236
Min	-0.220	-0.135	-0.213
Avg	0.036	-0.001	-0.010
StdDev	0.070	0.031	0.061
USL	0.390	0.087	0.318
LSL	-0.397	-0.290	-0.332
Cpk	2.000	2.000	2.000

Table 1 Measured Positional Accuracy

To ensure statistical robustness, the dataset was compiled several times with each time comprising 500+ docking exercises with associated measurement.

The repeatability of a robot indicates the robot's ability to return to the same position. Therefore, any variations in the dynamic parameters such obstacle in path, environmental effect, etc., do not affect the repeatability. The robot is already constructed no matter what the variations are, and nominal values are assigned to the static variables. When a position is added into the map, the robot only needs to remember the current state of the static variables, position data, and is not concerned with the values of the dynamic variables.

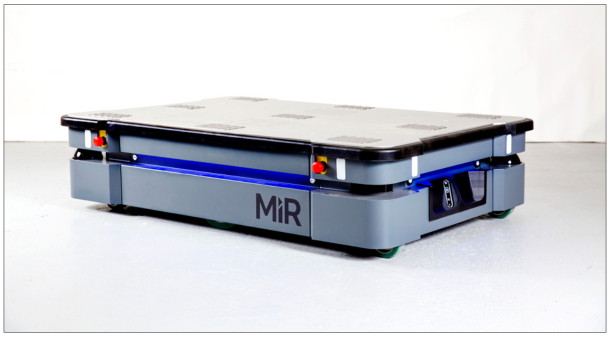

Figure 2 MiR500 Robot

The only information that the robot uses to return to the position is the x, y, and orientation angle (angle θ) variable values. The test bed used for measuring the mobile robot position accuracy and repeatability using four sensors is shown in Figure 3.

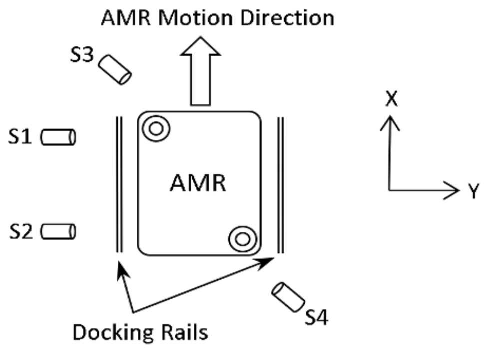

Figure 3 Test bed for accuracy and repeatability

Sensor S1 and S2 are used to measure the Y position and θ orientation while sensor S3 and S4 are used to measure the mobile robot X position. Figure 4 shows the docking repeatability measurement data for different number of trials.

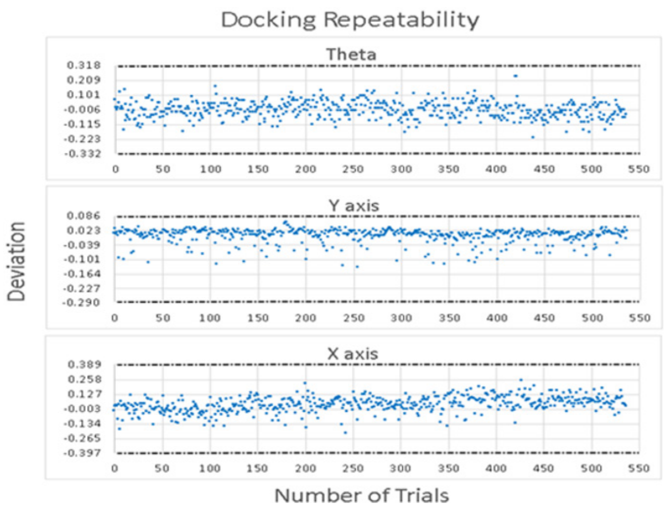

Figure 4 Docking Repeatability Measurement

CONCLUSIONS

The MiR500 has capability to dock to any set of similar features embedded into the cart/stand requiring accuracy of ±0.397" in x, ±0.290" in y, and ±0.332° in θ to a six-sigma level of certainty. The design constraints inclusive of this case study are:

[1] Docking to carts

[2] Docking to pallet racks

[3] Either case above with lock mechanism

[4] Positioning relative to equipment

In every case, the equipment interfacing accuracy becomes a process capability driver. For example, in the scenario of a conveyor-to-conveyor handshake between mobile robots or to fixed infrastructure will require understanding robot accuracy and repeatability.

For additional information related to this product and integration opportunities please contact the MHS Product Management team.

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