# Identifying Landmark Cues with LIDAR Laser Scanner Data Taken from Multiple Viewpoints

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Keywords: Robot, Navigation, Localization, Cue Identification, Neural Networks, Support Vector Machines, Classification, Pattern Recognition.

Abstract: In this paper, we report on our ongoing efforts to build a cue identifier for mobile robot navigation using a simple one-plane LIDAR laser scanner and machine learning techniques. We used simulated scans of environmental cues to which we applied various levels of Gaussian distortion to test a number of models the effectiveness of training and the response to noise in input data. We concluded that in contrast to back propagation neural networks, SVM-based models are very well suited for classifying cues, even with substantial Gaussian noise, while still preserving efficiency of training even with relatively large data sets. Unfortunately, models trained with data representing just one stationary point of view of a cue are inaccurate when tested on data representing different points of view of the cue. Although the models are resilient to noisy data coming from the vicinity of the original point of view used in training, data that originates in a point of view shifted forward or backward (as would be the case with a mobile robot) proved much more difficult to classify correctly. In the research reported here, we used an expanded set of synthetic training data representing three view points corresponding to three positions in robot movement in relation to the location of the cues. We show that by using the expanded data the accuracy of cue classification is dramatically increased for test data coming from any of the points.

## 1 INTRODUCTION

Automated Intelligent Delivery Robot (AIDer; shown in Figure 1) is a mobile robot platform for exploring autonomous intramural office delivery (Hilde et al., 2009; Rodrigues et al., 2009). The research reported in this paper was part of the overall effort to explore ways to deliver such functionality. The robot was to navigate in a known environment (a map of the facility is one of the elements of AIDer's configuration) and carry out tasks that were requested by the users through a Web-based application. Each request included the location of a load that was to be moved to another place that was also specified in the request. The pairs of start and target locations were entered into a queue that was managed by a path planning module. When the next job from the queue was selected, the robot was directed first to the start location where it was to get loaded after announcing itself, and then to the destination where it was to get unloaded after announcing its arrival. That routine was to be repeated indefinitely — if there were other requests waiting in the queue and as long as there was power.

Figure 1: Robot with a laser scanner (between the front wheels).



Bieszczad A..
Identifying Landmark Cues with LIDAR Laser Scanner Data Taken from Multiple Viewpoints.
DOI: 10.5220/0005508000780085
In *Proceedings of the 12th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2015), pages 78-85
ISBN: 978-989-758-122-9

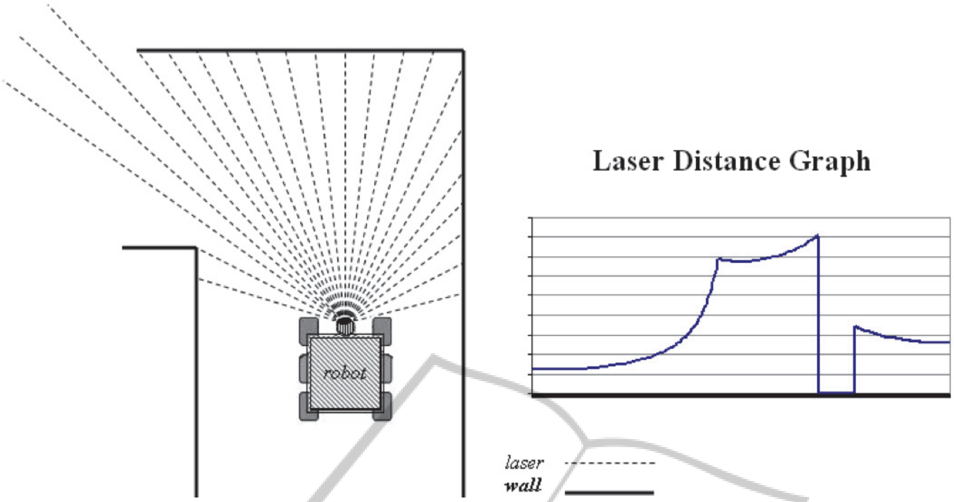


Figure 2: Robot LIDAR scan and the corresponding graph.



One of the major objectives was to provide the functionality at low cost. Therefore, AIDer has a very limited set of sensors for navigation: right side detectors of the distance from the wall, and a frontal 2D (one-plane) LIDAR laser scanner for detecting cues such as turns and intersections. The side sensors are used to provide a real-time feedback to a controller that corrects the position of the robot so it stays at a constant distance from the right wall (Hilde et al., 2007).

Higher-level navigation in AIDer is based on following paths that consist of a series of intervals between landmarks (Rodrigues et al., 2009). A map of the facility is provided as an element of the configuration (using a custom notation), so the robot is not tasked with mapping the environment. The map configuration file includes locations of landmarks along with exact distances between the landmarks. Upon receiving the next task to carry out, the robot determines the path to travel in terms of the landmarks. The path is divided into a sequence of landmarks, and the robot is successively directed to move to the next landmark. After the current target landmark is identified, the robot receives the next target landmark to go to. To accommodate for error in mobility (like slippage of the wheels) that may skew the robot orientation based purely on traveling exact distances, the robot relies on identification of cues to verify reaching landmarks.

In an environment lacking GPS, identification of environmental cues is a critical low-level task necessary for recognizing landmarks (Thrun, 1998), since landmarks are defined in terms of cues. The frontal laser-scanner in AIDer serves that purpose. Each scan produces a sequence of measurements that differ depending on the shape of the surrounding walls. For example, Figure 2 shows a scan of a left turn. The scan results - a sequence of numbers representing the measured distance (e.g., in inches) - are graphed using angles on the x axis and the distances on the y axis. Due to the range limitations of the laser scanner, certain measurement may be read as zeros; that is visible as a sudden drop in the curve shown in the figure.

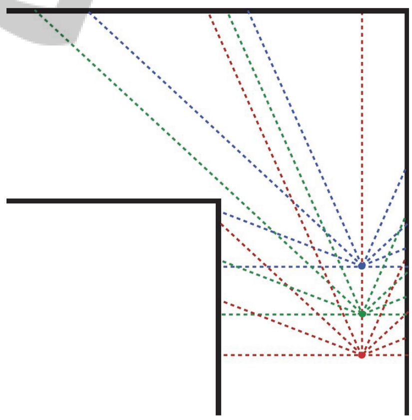

Figure 3: Multipoint view of a cue “left turn”. Only 9 measurements from each viewpoint shown here for clarity.

In (Hilde et al., 2007), an approach similar to (Hinkel et al, 1988) was taken with a selective subset of measurements used to define cues analytically with a limited success.

In this paper, the complete raw set is used for this purpose as will be shortly explained. Our earlier attempts to use raw data in such a way were not completely successful (Henderson, 2012), and the research reported here remedies that.

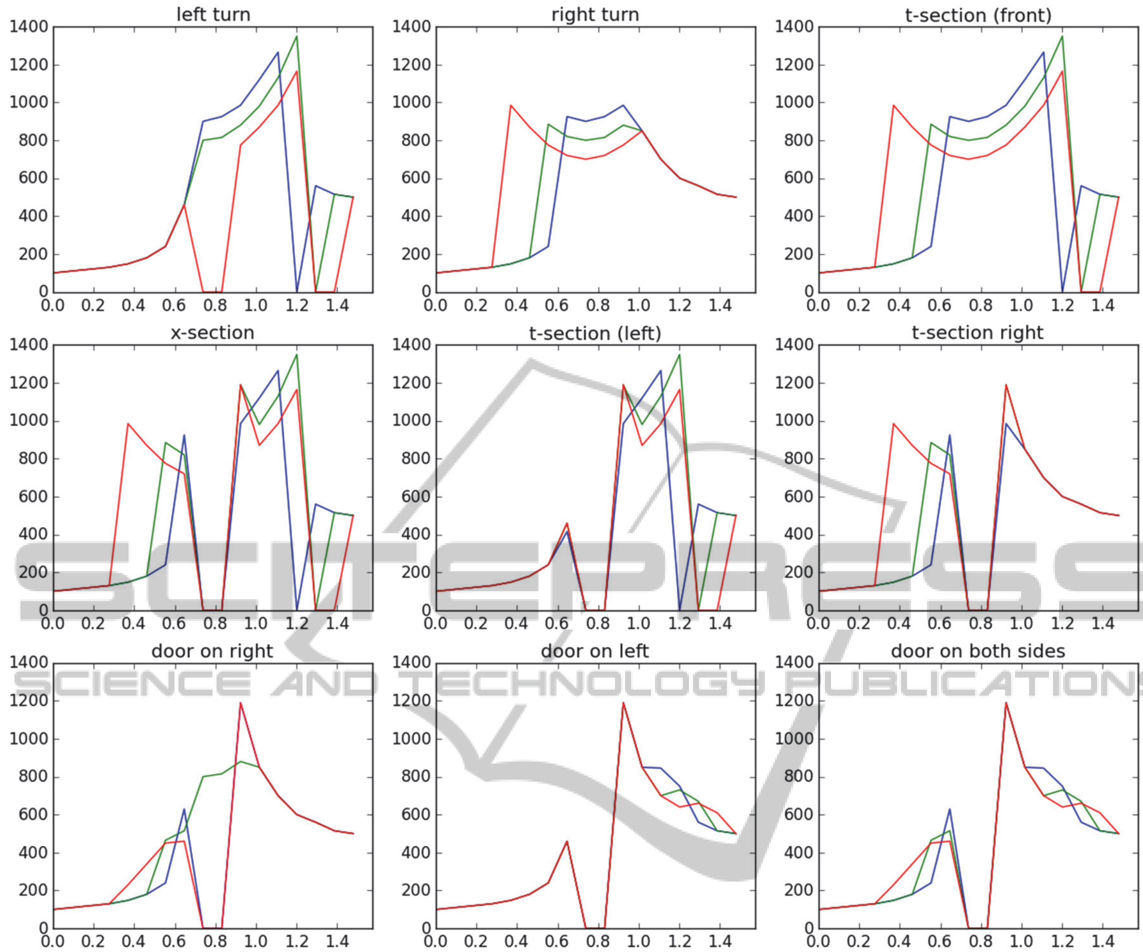


Figure 4: Three curves corresponding to three points of view for each of the nine cues. The y axis shows LIDAR measurements given in inches, and the x axis shows progression of the angle for each successive measurement.

## 2 RELATED WORK

Mapping and localization services are the foundation of autonomous navigation (Thrun, 1998). As we already stated, mapping is not a functional objective of the AIDer. Vast majority of the current localization work is based on utilization of very sophisticated equipment as seen in cars participating in R&D efforts in academia, auto industry, and government-sponsored contests (e.g., Leonard et al., 2008). Utilizing simple sensors with very limited capabilities started the field (Borenstein, 1997), but currently it's rare to depend on just such limited functionality. Yet, the use of inexpensive devices is important in environments lacking access to powerful computers or abundant power supplies (e.g., Roman et al., 2007), and when cost is a concern (e.g., Tan et al., 2010).

LIDAR-based identification was successfully solved by analytical methods in (Hinkel et al, 1988) in which histograms of laser measurements were used as the input data. There have been numerous attempts to use similar data using a variety of analytical approaches (e.g., Zhang et al., 2000; Shu et al., 2013; Kubota et al., 2007; Nunez et al., 2006).

(Vilasis-Cardona et al., 2002) used cellular neural networks to classify cues, but the localization was based on processing 2D images of vertical and horizontal lines placed on the floor rather then 1D LIDAR measurements. Just like in (Henderson, 2012), histogram data were used as inputs to backpropagation neural network in research reported in (Harb et al., 2010), but the authors did not specify the details of the back propagation algorithm that they used. In (Bieszczad, 2015), we follow that sub symbolic approach studying the capabilities of back propagation models and contrasting them with training based on support vector machines (SVM).

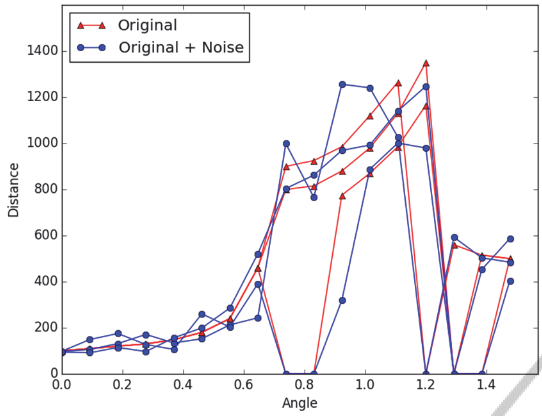


Figure 5: Three cue curves corresponding to three different points of view of the cue *lt* along with their distorted versions obtained by applying Gaussian noise $\sigma = 0.2$. All of these curves must classify as *lt*.

## 3 CUE DATA SETS

### 3.1 Single-point View

The laser mounted on AIDer is capable of scanning 180o with a granularity yielding 512 measurements per scan. Such a high-dimension space would be inconvenient for exploration of the techniques, so in (Bieszczad, 2015) we handcrafted a smaller, 17dimensional, synthetic data set for a miniaturized virtual model that otherwise preserved the geometry of the office environment and the nature of the problem. Our results reported in (Bieszczad, 2015) indicated that good models can be built with both back-propagation neural networks applying Broyden–Fletcher–Goldfarb–Shannon (BFGS) optimization augmented with regularization, and with Support Vector Machines (SVM) assuming that data shaping took place with a normalization followed by Principal Component Analysis (PCA). Neural networks using another optimization approaches were not as successful frequently failing to converge and yielding large errors.

Unfortunately, we also showed that expanding data dimension thirty-fold, from 17 back to the original 512-dimensional space was not handled well by the models built using neural network techniques. Training was failing or taking too long to converge on a relatively fast platform that we had available for the experiments (see TABLE 1 and 2).

In contrast to the models built with neural networks, SVM models overcame the challenges and scaled up very well preserving the effectiveness of training and the accuracy of classification.

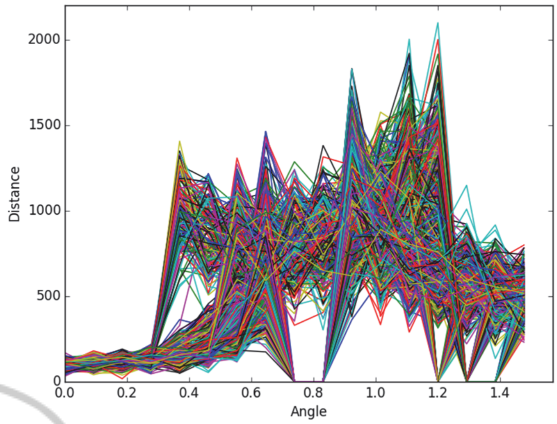


Figure 6: One thousand curves representing randomly generated cues with applied noise with $\sigma = 0.2$.

### 3.2 Multi-point View

In the research reported in this paper, we use the same approach, namely training an SVM (Bieszczad, 2015), but with the original problem expanded from identifying a cue from a single point of view to identifying cues from multiple, namely three, points of view.

Following the same illustrative approach shown in Figure 2, if we take LIDAR snapshots from three points as shown in Figure 3, then we obtain three model curves for each of the original nine cues: *lt* (left turn), *rt* (right turn), *ts* (t-section/front), *xs* (x-section), *tl* (left t-section), *tr* (right t-section), *dr* (door on right), *dl* (door on left), and *d2* (door on both sides). In this miniaturized model (rather than the original model with 512 dimensions) every (simulated) scan is a sequence of distance measurements made with the laser angle progressing in 17 steps in the interval $[0, \frac{\pi}{2}]$. All curves are shown in Figure 4.

As in the earlier experiments we apply Gaussian noise to all curves for training and for testing. Figure 5 illustrates the level of distortion of three curves corresponding to the cue *lt* caused by applying noise with a standard deviation $\sigma$=0.2. Both the normalization and the PCA transforms are built using only the training data, and then applied to test data.

The data present a very challenging task for classifiers as illustrated in Figure 6; the curves representing the cues are similar in many respects. The PCA analysis of the cue data shows that although the clusters are noticeable, they are overlapping as shown in Figure 7.

We attempted to apply dimension reduction using PCA, but that led to increased error rates; especially with larger noise. Indeed, even with the low dimensional cue data a closer examination of the principal components revealed that most of the dimensions were actually significant as shown by computing the variance ratios:

```
[  0.27065951  0.19814385 0.13178777
   0.05885712  0.04639313 0.03896735
   0.03728837  0.03559292 0.03151982
   0.02958179  0.02692341 0.0266508
   0.02205014  0.02059795 0.01286112
   0.00689689  0.00522805]
```

# 4 RESULTS

## 4.1 Testing One-viewpoint Model

Our first fundamental question was if the model trained with data generated from one point of view (the midpoint in Figure 3) can identify same cues as perceived from different points of view (backward and forward; shifted by a delta that is the same as the distance from the wall in our data set). We generated training samples just like we did in (Bieszczad, 2015): we applied Gaussian noise to distort the curves corresponding to cues taken from the midpoint to generate ten thousand samples. An SVM model built promptly on our computing platform, so we could test a number of variants. However, unlike in (Bieszczad, 2015) this time around we generated test sets from curves corresponding to measurements taken from all three (rather than just one) points.

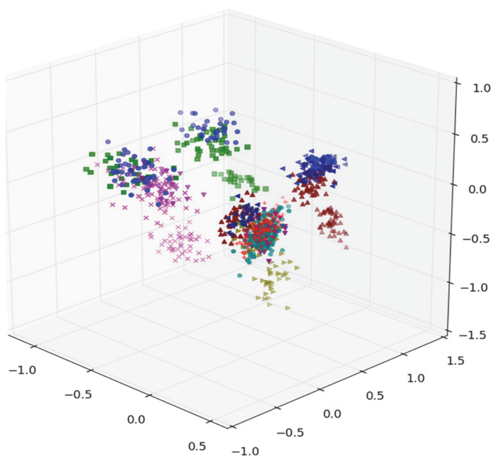

Figure 7: Clusters obtained with the principal component analysis applied to one thousand curves representing randomly generated cues with applied noise with σ = 0.2. Please note that for drawing in 3D only the first three principal components are used. Although the clusters are overlapping in 3D, they are much better separated in higher dimensions.

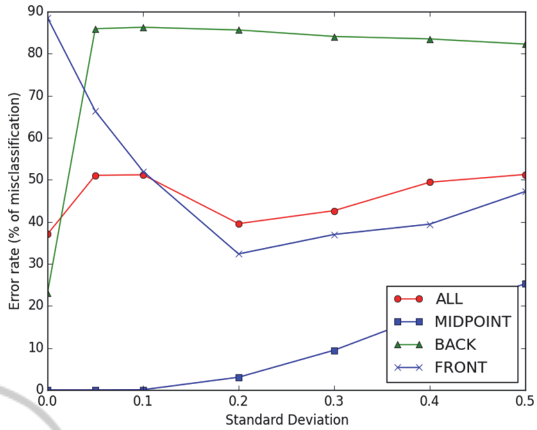


Figure 8: Performance of the SVM model created using a training set generated from cue curves taken from a single point of view, but test against test sets created from all and from each individual point of view.

We applied random noise to randomly selected ten thousand of test samples and then tested the set against a number of models built with different levels of distortion (i.e., noise). As shown in Figure 8, the model preserves the accuracy of the curves concentrated around the viewpoint used for generating training set, but fails badly for curves that represent cues from different point of views. It also performs poorly if the test set is constructed randomly using cue scans taken from all points of view.

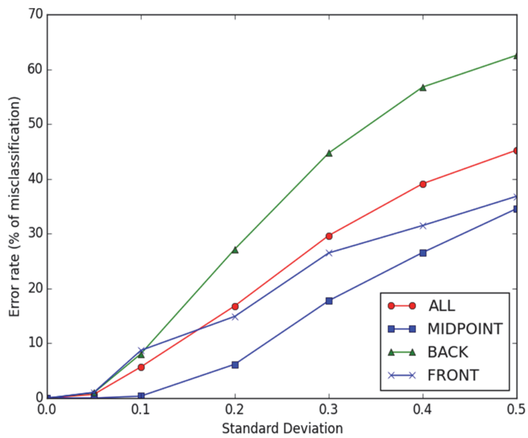


Figure 9: Performance of the SVM model created using a training set generated from cue curves taken from a multiple points of view, and tested against test sets created from all and from each individual point of view.

## 4.2 Testing Multi-view Model

In an attempt to find a remedy, we created a model using our extended data set generated as described earlier from three different points of view. We tested the model in the same way as the former.

The results can be seen in Figure 9. Comparing the graphs with the ones drawn in Figure 8 shows that the new model performs dramatically better on all test data sets although not as well as the single-point model performed with the test data taken from the same single point of view that was used for training. Still, the identification of cues scanned from the mid-point is very close to the one shown in Figure 8, although the impact of high-level of distortion on the error rate is stronger. As before, the scans from the back point of view are most difficult to identify, but evidently moving the robot forward is less of the problem in this particular environment.

# 5 CONCLUSIONS

We showed that the cue identification model first presented in (Henderson, 2012) and (Bieszczad, 2015) can be improved by extending the training set to data collected from multiple points of view. Such a model will be more accurate for the robot in motion. Therefore, the need to pinpoint exactly the location most appropriate to take a scan for identification is somewhat relaxed. Instead of a single point of opportunity, now the robot has a window of opportunity to identify cues.

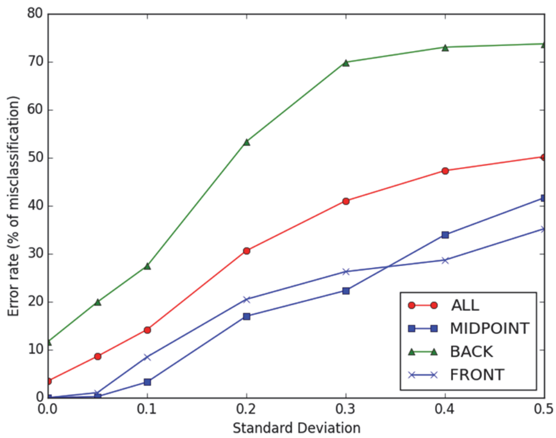


Figure 10: Performance of the SVM model created using data with dimension reduced to three principal components.

We tried to reduce the dimension of the data used in our experiments by trimming them down to just three principal components. Unfortunately, as in our earlier experiments we did end up with models that were performing substantially worse than the models preserving the original dimensionality of data as illustrated by the results shown in Figure 10.

These results indicate that a machine learning approach is a viable alternative to analytical methods originating in (Hinkel et al., 1998), although more experiments are needed that will test the method with a higher granularity of robot movements (e.g., continuous movement) and well as robot orientation.

# 6 FUTURE DIRECTIONS

Using a physical machine for numerous experiments is inconvenient and inefficient, so we are planning to build a simulator with which it would be easier to test our models. Such a simulator will also help us in using a better granularity for multiple view points. Instead of just three points, we will be able to select a range of robot displacements (up to continuous) and work with scans from within that range. The capability to generate such improved data sets will be useful in both testing our current models and in building potentially improved models.

One important problem set aside in this paper is the fact that cues often are present together at the same time, so scans may include data for multiple cues. In the current approach, such a complex super-cue is just another cue. However, decomposing complex cues may be a viable alternative; especially in a more diversified environment and if a 360° scanner is used — as we plan. We plan to use data sets that mix cues to some degree to test the identification capabilities of the models trained under such circumstances. One idea to deal with this problem — if it arises — is to extract individual cues from curves. Such attempts have been made by some researchers in the papers listed in the references (e.g., Vilasis-Cardona, 2002), and in more complex approaches to the localization problem (e.g., through feature extraction using image processing techniques).

A difficult problem to overcome is the issue of accuracy of laser scans when dealing with light conditions and various materials from which obstacles are made. These issues are of paramount importance in outdoor navigation in an unknown terrain as described in (Roman et al., 2007) and elsewhere. To explore possible solutions — and in general to test in in the physical world the ideas explored with the simulator — we are in a process of building a smaller robot similar to AIDer that is both more convenient to use, and substantially less expensive.

Another venue that we are planning to explore is acquiring goal-oriented behavior based on our earlier work on Neurosolver (Bieszczad, 1996).

Table 1: Software Environment.

| Software | Version |
|---|---|
| Python | 3.4.2 64bit [GCC 4.2.1 Compatible Apple LLVM 6.0 (clang-600.0.54)] |
| IPython | 2.3.1 |
| OS | Darwin 14.1.0 x86_64 i386 64bit |
| numpy | 1.9.1 |
| scipy | 0.15.1 |
| matplotlib | 1.4.2 |
| sklearn | 0.15.2 |
| neurolab | 0.3.5 |

Table 2: Hardware Environment.

| | |
|---|---|
| System | iMac Retina 5K, 27-inch, Late 2014 |
| Processor | 4 GHz Intel Core 7 (4 cores) |
| Memory | 32 GB 1600 MHz DDR3 |

# ACKNOWLEDGEMENTS

We would like to thank Advanced Motion Control (AMC), a Camarillo, CA, company that generously made their AIDer robot available to us.

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