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# *Autonomous robotic system for picking up floor eggs in poultry houses*

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**ABSTRACT.**

***Current conveyor-type systems in broiler-breeder and cage-free layer houses automate transporting of the eggs from the nests to the sorting area. However, the problem of picking floor eggs remains mostly unsolved and requires a farm-hand to walk the house daily, leading to increased labor costs and greater risk of cross-contamination between the facilities. We have developed a robotic system for autonomous egg picking based on a ground rover. The system consists of two parts: the mobile robotic platform with Kinect v2 sensor and deep learning algorithms to detect the eggs on the floor and drive up to them, and a robotic arm combined with visual servoing algorithms to pick up the eggs and place them in a basket. Our approach is designed to be a cost-effective solution that is able to operate in commercial breeder/layer houses and robustly detect eggs in various lighting and environmental conditions. Robust testing of our egg picking algorithms yielded a success rate of 91.6% and we anticipate that the same approach can be used to achieve near-perfect success rate in picking non-damaged eggs.***

***Keywords.* *Agricultural robot, egg picking, poultry, machine learning, TensorFlow, ROS***

# Introduction

Modern poultry houses involve basic automation capabilities, such as feeding and controlling lighting and temperature. However, they still require daily monitoring by a farmer. To bring the automation to most poultry maintenance tasks we are developing a Grow-out House Robot (Gohbot), an autonomous ground rover equipped with sensors able to navigate the environment, including interacting with the chickens. This paper will focus on developing a crucial capability for the robot: picking up floor eggs.

Even though the houses have nests for the chickens, eggs are regularly found on the floor. It was observed that once there are floor eggs, other chickens are more likely to lay eggs around it, which can result in reduction of overall egg quality (Appleby, Hughes, Elson, & others, 1992). Thus, timely pick-up will keep the percentage of the nest eggs higher, increasing the robustness of transporting the eggs to the sorting area. Currently, there is no commercial solutions addressing this problem and research prototypes (Vroegindeweij, 2015) relied on costly components that would make it commercially not viable. Among the goals of the project was to use off-the-shelf and open-source robotic components, as well as utilize the recent advances in Computer Vision and Machine Learning to address the egg-picking problem.

# Platform Description

### Hardware description

Our robot is assembled using affordable and commercially available components. These include an NVIDIA Jetson TX1 board, Microsoft Kinect v2 RGB-D camera, uArm Metal — a 4DOF robotic arm with a payload of 500g, and a Raspberry Pi board used to interface with the arm. Figure 1 gives an overview of the current system architecture as well as the external view of the rover with the robotic arm mounted.

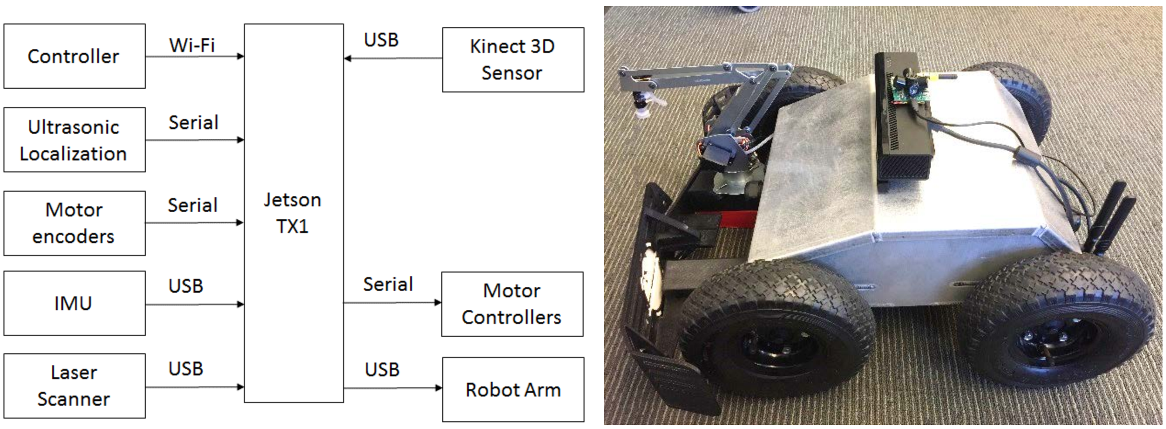


Figure 1 Gohbot system overview

### Software description

Gohbot runs Ubuntu arm64 on Jetson TX1. This board offers a high-performance power-effective solution with 256 cores and CUDA support. Our software platform is based on ROS and its Navigation Stack.

The notable components are:

- Skid-steer base controller
- Kalman filter fusing wheel odometry, IMU, and ultrasound indoor beacons
- Navigation and planning with move_base package
- Deep learning-based object detection framework
- Egg localization and arm controls for picking

# Egg detection and approach

The robot's regular behavior consists of navigating the house between a set of waypoints and involves nudging the chickens to clear the path. Egg detection is designed to run continuously during the navigation and trigger egg-picking behavior if an egg is identified. As a vision sensor we utilize Kinect v2, mounted on top of the robot, with open-source drivers (Wiedemeyer, 2014).

Our object detection package is based on an implementation of Faster-RCNN (Ren, He, Girshick, & Sun, 2015) approach using TensorFlow library. This approach integrates object proposals, classification, and bounding box regression into a single network, resulting in tight detection boxes around the objects (see Figure 2). One notable issue while working on mobile platforms is limited computational resources and memory. To address it, we use a small VGG-M network architecture that fits into Jetson memory during the runtime. The network is pre-trained on the large ImageNet dataset of generic objects before being fine-tuned to our small domain-specific dataset with about 100 instances.

Figure 2 Egg and chicken detections using Deep Learning framework

We perform detection only using RGB channels and lookup the object’s center location in the registered point cloud to get the position of the object with respect to the robot. Once the egg is detected then issue a new navigation goal such that the robot stops with the egg being within robotic arm’s workspace. To achieve that we apply a fixed offset to the egg position to get a new goal with respect to the robot end effector. To compute the goal orientation we use the direction vector between the goal position and the original egg location. The new 6D pose is then send to the planner and the robot drives up to the egg with the final orientation facing the object.

For the moment, our approach was tested in the lab using a dataset with the eggs laid on the carpet. The mAP of 81.8% was achieved for the testing set (using the evaluation methodology analogous to Pascal VOC), hinting that it should learn the egg features nicely when we transition into real grow-out houses. Current detection frame rate is on average 1.4 Hz, with the computational power being the bottleneck.

## Egg picking

The next stage of the process starts when the robot has approached the egg and has it within its robotic arm reach. To precisely localize the egg we use a Raspberry Pi camera attached to the tip of the arm. Our algorithm utilizes OpenCV blob detector to identify a white blob of elliptical shape and extract its center. We use this output to continuously adjust the position of the arm to gradually center on the egg. Current controls of the arm are implemented using uArm’s Python API. Once the distance (estimated in the image space) from the tip to the egg is within predefined threshold we begin to move the tip vertically towards the egg. We continue to descend until the tip’s pressure sensor is activated meaning it is pushing against the egg. At that point the suction cup is activated and the robot lifts the egg and places it in the basket using a predefined motion.

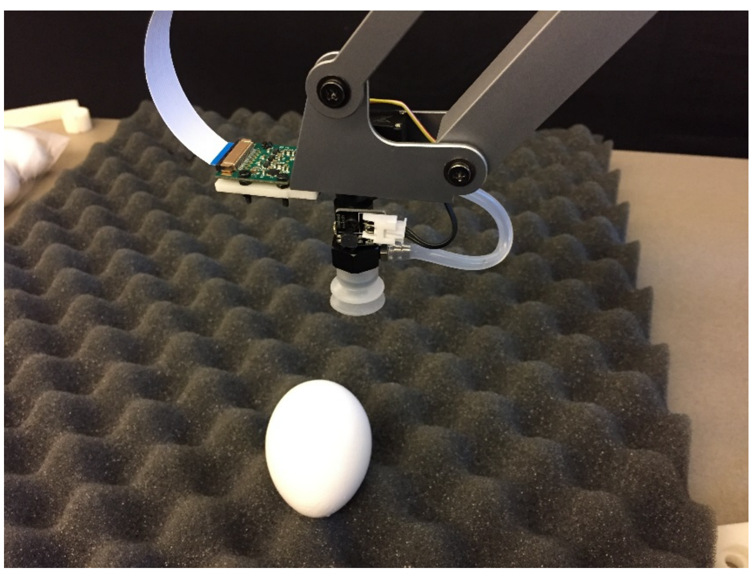

Figure 3 The robotic arm with a suction cup and a camera

# Experiments

We evaluated the final egg localization and picking parts of the task. To set up the experiment we placed an egg crate foam approximately 10x8 inches in size in front of the robotic arm. Each iteration an egg was moved to the next crate and the egg picking was run and its success evaluated. Only the cells that are within the arm's reach were included in the experiment. After a total of 83 trials, the measured success rate was 91.57%. It should be noted that the failures are clustered on the bottom of the workspace (see Figure 4) and are likely due to the accuracy issues that the arm has in that area. During the runtime this problem could be addressed by reducing the workspace and physically moving the robot, such that the egg's starting location is within the area known to work well for the arm. Among other issues we observed with the arm was its relatively low repeatability of 0.5cm. Although it didn't affect our experiment, such offset is enough for the tip to have a point of contact off the egg's center, thus pushing it to the side rather than downwards. It's likelier to be a problem on a hard surface, rather than woodchips commonly used in the grow-out houses.

| | Test 1 | Test 2 | Total |
|---|---|---|---|
| Trials: | 42 | 41 | 83 |
| Pass: | 38 | 38 | 76 |
| Fail: | 4 | 3 | 7 |
| Success rate: | 90.48% | 92.68% | 91.57% |

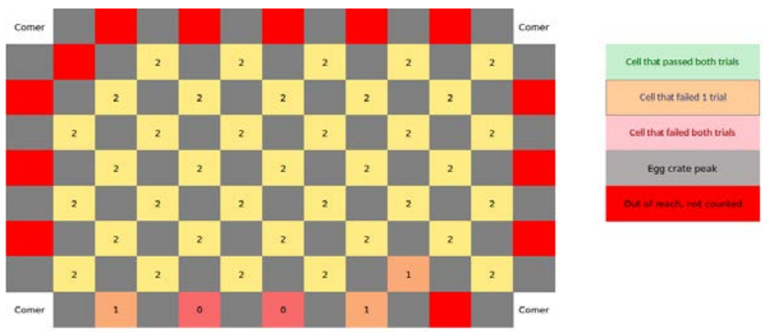


Figure 4 Results from the trials (top) and the visualization of the pass/failure distribution (bottom)

# Future Work

Our immediate improvements include several hardware updates. In particular, to address aforementioned precision issue we plan to replace the robotic arm with uArm Swift Pro. It offers repeatability of 0.2mm, along with more robust motors and encoders. Another planned hardware update is moving to a new Jetson TX2 board. It roughly doubles the maximum computational performance, as well as increases the available RAM to 8 GiB. This will reduce the detection time and allow more resources for the costly point cloud manipulation. The major improvement on the algorithmic side will be incorporation of Kinect's depth data into object detection pipeline. We believe addition of spatial information may be crucial for challenging environments and occluded eggs.

# Conclusion

Our robotic platform demonstrates feasibility of complex behaviors like egg picking in unstructured environments involving animals. While the navigational aspects of the system underwent considerable amount of field testing, egg picking still requires thorough evaluation and improvement to produce a robust solution suitable for commercial houses. However, the preliminary tests of the system in lab environment, show that the inexpensive commercially available components and contemporary computer vision and robotics algorithms can produce a reliable way to autonomously perform the whole egg-picking pipeline.

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