2017 IEEE International Conference on Robotics and Automation (ICRA)
Singapore, May 29 - June 3, 2017

Duckietown: an Open, Inexpensive and Flexible Platform for Autonomy Education and Research

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***Abstract*— Duckietown is an *open*, *inexpensive* and *flexible* platform for autonomy education and research. The platform comprises small autonomous vehicles ("Duckiebots") built from off-the-shelf components, and cities ("Duckietowns") complete with roads, signage, traffic lights, obstacles, and citizens (duckies) in need of transportation. The Duckietown platform offers a wide range of functionalities at a low cost. Duckiebots sense the world with only one monocular camera and perform all processing onboard with a Raspberry Pi 2, yet are able to: follow lanes while avoiding obstacles, pedestrians (duckies) and other Duckiebots, localize within a global map, navigate a city, and coordinate with other Duckiebots to avoid collisions. Duckietown is a useful tool since educators and researchers can save money and time by not having to develop all of the necessary supporting infrastructure and capabilities. All materials are available as open source, and the hope is that others in the community will adopt the platform for education and research.**

Fig. 1. In Duckietown, inhabitants (duckies) are transported via an autonomous mobility service (Duckiebots). Duckietown is designed to be inexpensive and modular, yet still enable many of the research and educational opportunities of a full-scale self-driving car platform.

I. Introduction

Self-driving vehicles are poised to become one of the most pervasive and impactful applications of autonomy. However, difficult challenges still remain before their widespread deployment, many of which concern the system as a whole, rather than single components in isolation. Examples include the co-design of hardware components and algorithms, the coupled interactions between perception and control, the optimal allocation of finite computational resources to concurrent processes, and safe multi-agent behaviors.

A modern curriculum in autonomy should train students in the individual components and the system-level interactions alike. This poses several challenges. First, building a full-scale vehicle, let alone a fleet of vehicles, is very costly and also imposes significant logistical and safety-related problems. Second, the time required to develop all of the components and infrastructure is significant, and much of it is spent on tasks not directly related to the desired subject matter.

To address these issues, we propose Duckietown (Fig. 1), an open-source platform for autonomy education and research. It includes autonomous vehicles called "Duckiebots." The minimal configuration uses only a Raspberry Pi 2 for all computation and a single monocular camera for sensing, yet Duckiebots are capable of fairly complex single-robot and multi-robot behaviors. Duckiebots live in "Duckietowns," colorful miniature environments that are assembled from modular tiles. Duckietowns and Duckiebots are easily reproducible and inexpensive, costing approximately $\$150$ per vehicle and $\$2/\mathrm{m}^2$ for the environment.

Duckietowns are carefully designed to allow a sliding scale of difficulty in perception, inference and control tasks that makes the platform usable in a wide range of applications, from undergraduate-level education to research-level problems. For example, one solitary Duckiebot can successfully traverse the environment using only line detection and reactive control, while successful point-to-point navigation requires recognizing street signs. In turn, sign detections can be "simulated" either by using fiducials (AprilTags [1]) affixed to each sign, or it can be implemented using "real" object detection. Realizing more complex behaviors, such as vision-based decentralized multi-robot coordination, poses research-level challenges, especially considering resource constraints.

A major advantage of the Duckietown platform is derived from the complex software architecture provided, which contains components such as sensor calibration, configuration, low-level perception, object recognition, nonlinear relative estimation, global localization, high-level planning and decentralized coordination. Our goal was to provide a complete "textbook" architecture that is comparable in complexity with full-scale implementations (e.g. [2]), while still being understandable by beginners.

The main intended use of Duckietown is as support for

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TABLE I

MINIMAL AUTONOMY CONFIGURATION COMPONENTS

Subsystem	Item	OTS cost
Computation	Raspberry Pi 2 B + 8GB SD card	$40
Actuation	Chassis + 2DC motors	$15
Motor Controller	Adafruit DC motor hat	$20
Sensing	Camera with fish-eye lens	$25
Power	38.4Wh Battery	$15
Communication	Wireless dongle	$10
Misc.	Cables, Screws & Nuts	$10

Prices rounded to the closest $5. Exact items and links to vendors are available at the website http://duckietown.mit.edu.

an undergraduate or graduate-level class in autonomy. Duckietown is especially suited for *team-based learning*, where groups of students work on improving different subsystems that need to work together. This is how it was used at MIT in Spring 2016 [3]. Alternatively, Duckietown is suitable for classes focused on one specific field or subsystem (e.g., computer vision or nonlinear control). In that case, the benefit is that the effect of that particular subsystem on the full integrated system is immediately observable. This is how it has been used at National Chaio Tung University [4]. Duckietown becomes a research platform by relaxing the known prior assumptions about the environment (such as known dimensions, colors, positioning of signage, fiducials on signs, allowable network topologies, etc.). The authors are using Duckietown for research topics such as resource-constrained perception [5], co-design [6], and formal methods for safe vehicle coordination [7].

Outline: Section II describes the Duckiebot platform, built from off-the-shelf components. The remainder of the paper describes the architecture developed. For each functionality, we will describe the baseline implementation, the topics that can be taught using that functionality, and the possible extensions by using fewer prior assumptions. We describe the architecture in order of behavioral complexity. Section III describes the pipeline for single-robot reactive lane following. Section IV describes the subsystems involved in single-robot localization, planning, and navigation. Section V describes the subsystems involved in multi-robot communication and coordination behaviors. Finally, we discuss the systems-level approach to resource management in Section VI and provide concluding remarks in Section VII.

II. THE DUCKIEBOT

Duckiebots are autonomous vehicles designed with the objectives of affordability, modularity and ease of construction. We present three configurations:

- The **minimal autonomy** configuration is sufficient to support all single-robot behaviors implemented.
- The **extended** configuration adds some "luxury" features that are convenient for development, such as a joystick and an on-board wireless access point.
- The **fleet** configuration includes light emitting diodes (LEDs) as a means of inter-Duckiebot communication and enables the multi-robot coordination behaviors.

1) Minimal Autonomy Configuration: The components of a Duckiebot in the minimal configuration are summarized in Table I. These are all off-the-shelf components that are easily replaceable. Each robot requires about 15 minutes of soldering work and 0.5-1.5 hours of assembly, depending on skill.

a) Computation: All computation is performed on a Raspberry Pi 2 (RasPi), which provides four 900MHz ARM cores and 1 GB RAM.

b) Actuation: The chassis of the Duckiebot can be any of the many available kits that can be found online that use two DC motors in a differential drive configuration. Since we do not use odometers, the chassis is the most fungible part of the design. The motors are controlled through an Adafruit DC Motor Hat that attaches as a "shield" on the RasPi.

c) Sensing: The only sensor used is a monocular camera with a fish-eye lens. The camera is connected to the RasPi through a dedicated parallel connection.

d) Communication: Access (for setup, debug and optional manual control through keyboard) is provided through a WiFi dongle or Ethernet port on the RasPi.

2) Extended Configuration: For teaching and research setups with large team deployments, the best solution to network saturation is to use an access point onboard each Duckiebot. These mobile hotspots create a dedicated 5GHz network for each robot and connect directly to the RasPi through Ethernet. Additionally, a wireless joystick with USB dongle enables more convenient manual control. Finally, a 32GB USB drive can be employed to store larger amounts of data logs. This configuration adds an additional $\approx$ $75.

3) Fleet Configuration: This version of the Duckiebot is equipped with five variable color LEDs, and an Adafruit pulse-width modulation (PWM) hat to drive them. The LEDs are employed for communicating with other vehicles by signaling the Duckiebot's status and intent. The introduction of these LEDs increases the platform cost by $\approx$ $30 over the base model.

We compare the base model Duckiebot with some other popular robots used for education and outreach in Table II.

TABLE II

A SAMPLE OF LOW COST PLATFORMS FOR EDUCATION AND RESEARCH

Product	Cost	Modular Hardware	Open Source Software	Line Following	Path Planning	Avoidance	Tracking	Decentralized Coordination	Visual Servoing
AERobot [8]	$20	✗	✓	✓	✗	✓	✗	✗	✗
Kilobot [9]	$50	✗	✓	✗	✓	✗	✓	✓	✗
3pi [10]	$100	★	✗	✓	✗	✓	✗	★	✗
Jasmine [11]	$120	✓	✓	✓	✓	✓	✗	✓	✗
LabRat [12]	$120	✓	✓	✗	✗	✓	✗	✓	★
Thymio II [13]	$130	✗	✓	✓	✗	✓	✗	✗	✗
Duckiebot	$150	✓	✓	✓	✓	✓	✓	★	✓
Scribbler-3 [14]	$180	✓	✓	✓	✓	✓	✗	✗	★
Boe-bot [15]	$180	✓	✓	★	★	✓	★	✗	✗
ActivityBot [16]	$200	✓	✗	★	★	✓	★	✗	✗
Create-2 [17]	$200	★	✗	★	★	✓	✗	✗	★
Bot‘n Roll [18]	$200	✓	✓	✓	✗	✓	✗	★	✗
R-one [19]	$250	✗	✓	✓	✗	✓	✓	✓	✗
Hemission [20]	$250	★	✗	✓	✗	✓	✗	✗	★
Pheeno [21]	$270	✓	✓	✓	✓	✓	✓	✗	✓

This list includes $\leq$$300 platforms with recent publications in the last 10 years (or available on the market). The prices listed are for the base model. Stars indicate available features for additional cost.

Of particularly note is how few low-priced available robots use vision as the primary sensor. The choice of a camera, as opposed to a proximity or infrared (IR) sensor makes our system a much more realistic representation of a full-sized platform.

III. Lane following

The most basic behavior of the Duckiebot is lane following. This behavior is implemented using a realistic computer vision pipeline (Fig. 2) that contains these steps:

- Illumination variability compensation.
- Detection of road markings.
- Re-projection from image space to world frame, based on extrinsic and intrinsic calibration.
- Lane localization with a nonparametric Bayes filter.
- Lane controller.

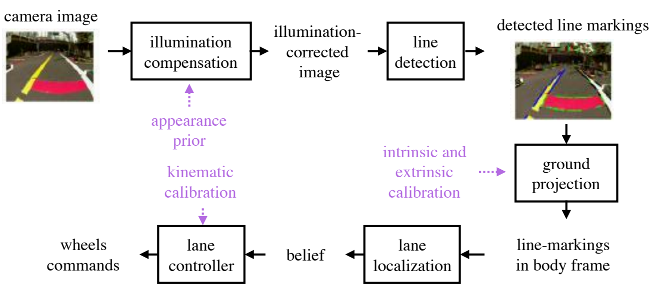


Fig. 2. The lane following pipeline runs on-board at 10Hz with a resolution of 320x240 and a latency of 110ms. The purple text indicates prior information.

A. Infrastructure - The Duckietown Road Layer

The design of Duckietowns are an easily-understandable example of a *formal specification*: if the environment satisfies the specification, then the Duckiebot is guaranteed to be able to navigate it.

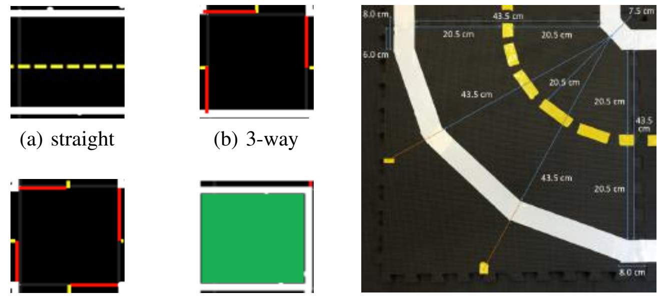
Duckietowns have two layers: one for the road and one for the signals. Lane following only depends on the road layer. The road layer is constructed by arranging the five types of interlocking tiles (Fig. 3). The precise color and positioning of the road markings are part of the specification and constitute a strong *prior* that can be used by perception.

B. Illumination Compensation

Illumination variability is one of the challenges of computer vision. We use this procedure to teach:

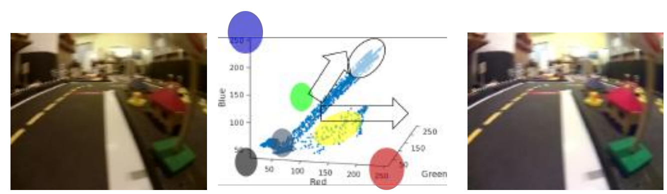
- How machine learning can be used “in the loop” for autonomous robots.
- The importance of using prior information; in this case, the prior on the colors is given by the Duckietowns road layer specification.

In the baseline implementation of this functionality, we use the k-means clustering algorithm over a subsample of the sensor pixels in order to detect the main clusters on the road, and we match them to the expected clusters of red, yellow, white, and gray, according to the prior. We then fit an affine transformation in RGB colorspace between the detected clusters and their color-balanced version. Regularization



(a) straight (b) 3-way (c) 4-way (d) empty (e) turn

Fig. 3. Duckietowns are modular assemblies of five different tile types: (a) straight road, (b) a three-way intersection, (c) a four-way intersection, (d) non-road, and (e) turn. These tiles can be arranged to obtain arbitrary topologies. The tapes on the right hand side of a lane are white and solid, the tapes on the left hand side of a lane are yellow and dashed, and the stop lines are red and solid.



(a) before (b) after

Fig. 4. Camera image before and after illumination compensation. Pixel distribution (blue dots), representative main colors (large colored blobs) and the transformation performed (white arrows) in RGB color space.

expresses our prior belief on illumination conditions and road marker colors. The transformations allowed are channel-separate:

$$I_{\text{obs}}^{(i)} = a_i I_{\text{orig}}^{(i)} + b_i + n, \quad i \in \{\text{R}, \text{G}, \text{B}\}, \tag{1}$$

where n is Gaussian measurement noise, and, for regularization, we assume a Gaussian prior for the parameters a_i, b_i. The resulting 6×6 linear system of equations is

$$\begin{pmatrix} A_{\text{data}} \\ A_{\text{reg}} \end{pmatrix} p_I = \begin{pmatrix} b_{\text{data}} \\ b_{\text{reg}} \end{pmatrix}, \tag{2}$$

where $A_{\text{data}}, b_{\text{data}}$ result from the observation model of (1), and $A_{\text{reg}}, b_{\text{reg}}$ result from the regularization. The vector p_I is the vector of illumination parameters. The squared residual error in (2) gives an estimation of fit quality and allows the system to detect failure.

C. Road Markings Detection

Duckiebots perform localization in a lane by extracting oriented line segments along the border of lane markings, and then running a nonparametric Bayesian filter (more details in Sec III-E). Due to the robustness of our lane filtering approach, we prioritize high recall at the expense of some false positive.

An overview of the oriented line segments detection pipeline is shown in Fig. 5. The image is first downsampled, then two filters act in parallel: a Canny filter to detect edges, and Hue-Saturation-Value colorspace thresholding to detect the given color. The results are fed through an “AND” gate. Individual line segments are extracted using a probabilistic Hough transform [22].

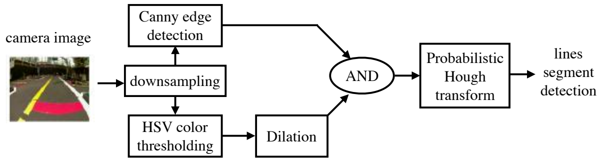


Fig. 5. Pipeline of the line segment detection algorithm.

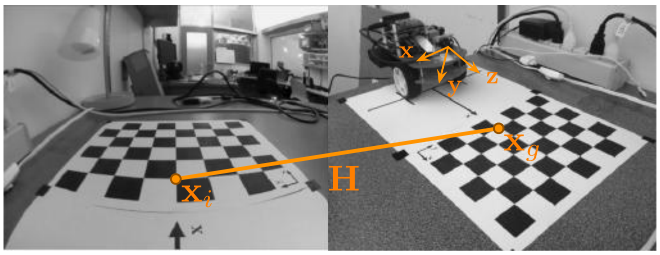


Fig. 6. Extrinsic camera calibration. The right image is the setup for the extrinsic camera calibration. The left image is an undistorted image captured via the camera on the Duckiebot. Once a homography $\mathbf{H}$ is estimated, it is possible to map from a point in image $\mathbf{x}_i$ to a corresponding point on the ground $\mathbf{x}_g$. The coordinate frame on the right image represents the camera coordinate frame of the Duckiebot.

D. Image Plane $\rightarrow$ Road Plane Homography

The next step consists in transforming the oriented line segments detections in image space to oriented points in 3D in body coordinates. Using the prior of a planar environment, it is possible to create a 1-to-1 map from image space to 3D space. First, the points are undistorted using the camera's intrinsic calibration. Then the map is represented by a homography, $\mathbf{x}_i \simeq \mathbf{H}\mathbf{x}_g$, where $\mathbf{x}_i$ and $\mathbf{x}_g$ are the points in the image and ground planes respectively, $\mathbf{H} \in \mathbb{R}^{3\times3}$ is the homography matrix, and $\simeq$ represents equivalence up to scale.

Duckietown includes a calibration tool that allows one to estimate the camera's intrinsics and extrinsics (Fig. 6).

E. Lane-Relative Estimation

To execute the lane following behavior, we must obtain an estimate of the Duckiebot's lateral position and orientation relative to the lane (d and ϕ as indicated in Fig. 7). However, we do not need to know the longitudinal coordinate. This is an example of a "minimal sufficient statistics" for performing a control task.

A standard parametric approach to the estimation problem (such as a Kalman filter which employs a Gaussian assumption) would likely fail due to the presence of such a potentially high percentage of outliers and the nonlinearity of the process model. As a result, in the baseline implementation we employ a nonlinear non-parametric histogram filter [23].

The state of the car in the lane at time t is represented by the reduced-dimension state: $x_t \triangleq \langle d_t, \phi_t \rangle$, where $d_t \in [d_{min}, d_{max}]$ is the lateral displacement in the lane (with the $d = 0$ line being defined as the center of the lane) and $\phi_t \in [\phi_{min}, \phi_{max}]$ is the angle relative to the center axis as shown in Fig. 7. From the specification, we know the width of the lane, w, and the widths of the right (white) and left (yellow), l_W and l_Y respectively, and we can use this information together to generate a unique hypothesis of the state from each segment detected by the road marking detector.

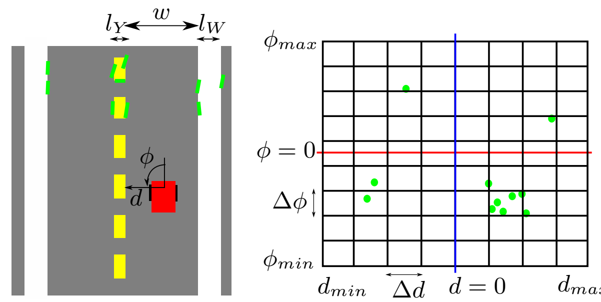


Fig. 7. Lane Filtering. **Left**: Coordinate system for the lane estimation and control with some line detections and the specified dimensions of the lane and lane markings indicated. **Right**: The measurement likelihood as a result of processing one list of segments, such as the ones shown on the left, which is used in the measurement update step of the filter. Each green dot corresponds to a vote generated by an individual segment detected in the image.

Each incoming list of segments constitutes a single measurement. We use each segment to produce a "vote". The votes are binned in a histogram and the entire histogram represents the measurement likelihood (Fig. 7).

Once all of the segments have been processed, the histogram is normalized and used to perform the measurement update in the Bayes filter.

F. Lane Controller

Once we have an estimate of the position and orientation of the Duckiebot in the lane, we use it to generate the control signals to drive down the lane. We have designed the curves explicitly such that the proportional error as the Duckiebot performs a turn (Fig. 3-(e)) is small enough such that it is still within the basin of convergence of a simple linear tracking controller. This alleviates the need to do any parameterization of the reference trajectory.

A proportional-derivative (PD) controller is employed, in which the control command takes the form $u(t) = k_d d(t) + k_\phi \phi(t)$ (the k_ϕ terms acts like a derivative).

We evaluated the performance of the lane following behavior on a square track with rounded corners with errors shown in Fig. 8. Under nominal lighting conditions, the reliability of the lane following behavior of the Duckiebot is very high, with a mean time to failure greater than 30 min and a cross track error within 0.15m at all times.

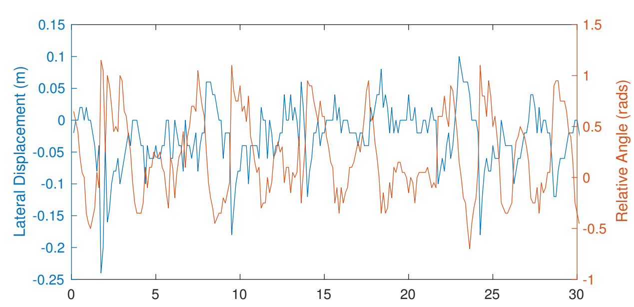


Fig. 8. Lane following performance: The lateral displacement and the relative angle of the vehicle in the lane during a loop traversal.

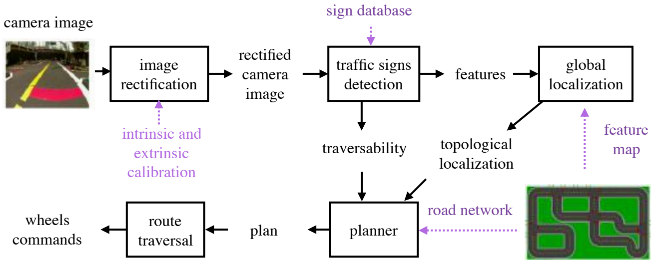


Fig. 9. Navigation with map-based localization and route planning. We use a higher resolution (640x480) image since we can tolerate much higher latency ($\approx 0.5s$) and lower throughput (runs at 2Hz).

IV. Navigation

The basic lane following pipeline acts as a nested inner loop to enable more complex and interesting behaviors. As an example, an overview of the navigation pipeline is shown in Fig. 9.

A. Infrastructure - Layer 2- The Signal Layer

The second layer of Duckietown is made of signals, such as signs and traffic lights. Signs are present in two varieties: (i) traffic signs; and (ii) street names. The traffic signs can indicate the traversability of an intersection, the type of an intersection (traffic light or stop sign), or some other important road information, as shown in Fig. 10. These signs alone contain all necessary information for localization and navigation. Each sign is additionally equipped with an AprilTag [1] to enable the parallel development of the algorithms that detect the signs from the components of the system that use these detections. We constrain the signs to be placed at one of eight fixed poses on a tile to: (a) guarantee that the signs are in the camera field of view of a Duckiebot at a stop line; and (b) enable the automatic generation of the metric feature map.

B. Map Representation

Since Duckietowns are composed of modular tiles, a map can be completely specified by a matrix of tile types (shown in Fig. 3). Additionally, we can specify the presence, type and position of any signs on these tiles. This matrix can be used to automatically generate two different map representations: a metric feature map used for localization, and a topological network graph used for planning. These two maps are shown in Fig. 11.

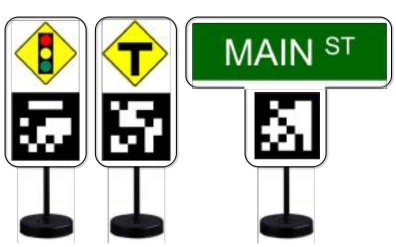


Fig. 10. Traffic and street signs. Traffic signs are used to distinguish among intersection types and indicate traversability. Road name signs are used primarily for localization. Each sign is outfitted with an AprilTag of fixed and known size for ground truth detection.

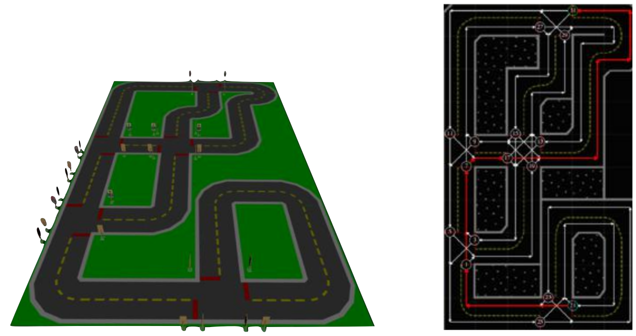


Fig. 11. A map is inputted as matrix of tile types. From this, two representations can be automatically generated. **Left:** The metric feature map, which uses the exact known locations the signs should be placed at on the tiles, and **Right:** A topological graph network that can be used to plan paths. An example path is shown in red.

Fig. 12. Global localization. **Left:** The real Duckiebot at an intersection in Duckietown, **Middle:** The Duckiebot having localized within the map, **Right:** The internal camera view with the sign detections highlighted.

C. Global Localization

Global localization consists of the estimation of the Duckiebot pose with respect to a global reference frame. The knowledge of the pose in a global frame is a key enabler for other functionalities, such as the planning of a path towards a desired destination. As is the case for humans, traffic signs and street names provide a useful tool for localization. In the baseline localization scheme we assume an accurate map is provided by the automated map generation scheme (Fig. 11). However, a natural extension would be to simultaneously discover the map and localize within it (SLAM). Using the known size of the tag we can obtain a full relative pose measurement of the camera with respect to the sign whenever one is detected. Since the pose of the tag is known, each detection provides a measurement of the absolute pose of the Duckiebot. In Fig. 12 the Duckiebot is at an intersection in Duckietown. From its internal camera it is able to localize itself on the map.

This basic algorithm ensures accurate localization whenever tags can be detected. In our tests, the Duckiebot was able to estimate its position at 2Hz, with localization errors in the order of 0.1m when at least three tags were visible.

D. Planning

To navigate, the Duckiebot requires a mapping from the metric location, as determined by the global localization module, onto the topological road network graph which is searched over to find connected feasible routes (Fig. 11).

Once the graph is generated and a start and goal location are specified we apply the A* search algorithm to generate an optimal plan to traverse the map. An interesting extension

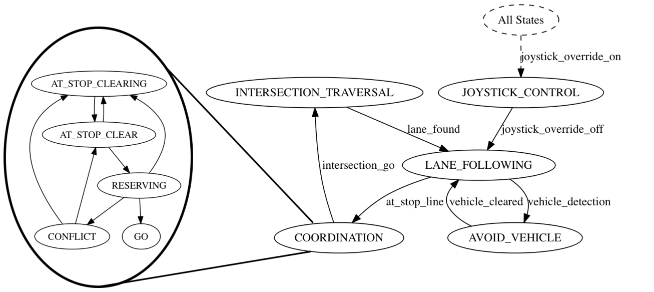


Fig. 13. A simplified version of the finite state machine used to control the vehicle. To see the full version, please visit our github repository.

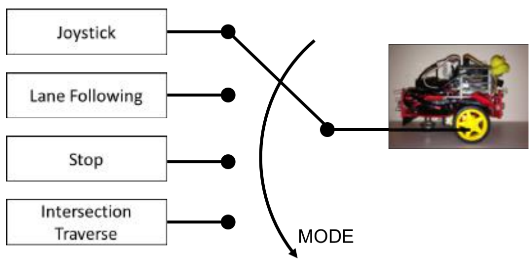


Fig. 14. The Duckiebot as a hybrid system. A bank of controllers are continuously active. The active motor controller at any instant is determined by the FSM mode.

would be to plan the paths of multiple Duckiebots simultaneously simulating a fleet management system.

E. Finite State Machine

The macro level operation of the Duckiebot is regulated through a finite state machine (FSM), a simplified version of which is shown in (Fig 13). The transitions in the FSM are generated by asynchronous perception-based events, such as detecting a stop line. The mode is used to control the Duckiebot in a hybrid (discrete-continuous) system configuration [24]. A bank of controllers are developed corresponding to the different desired actions, and the mode from the FSM in Fig. 13 is used to select which controller is active and connects that controller to the wheels driver (Fig. 14).

F. Route Traversal

Once a plan has been generated, following it requires executing the correct sequence of turns at each intersection. For the example shown in Fig. 11-(b) this sequence corresponds to $[s, f, s, f, r, f, s, f]$, where f, s, r, and l correspond to *follow lane*, *go straight*, *turn right*, and *turn left*, respectively.

The traversal of any individual intersection is achieved by executing the sequence states "LANE_FOLLOWING" $\rightarrow$ "INTERSECTION_TRAVERSAL" in a loop until the final destination is reached (assuming single-Duckiebot behavior at this stage we bypass the "COORDINATION" behavior and assume that the intersection is always free). The transition from LANE_FOLLOWING to INTERSECTION_TRAVERSAL is triggered by the arrival at the stop line. The transition from INTERSECTION_TRAVERSAL back to LANE_FOLLOWING is triggered by the lane estimate reporting convergence as measured by an entropy threshold.

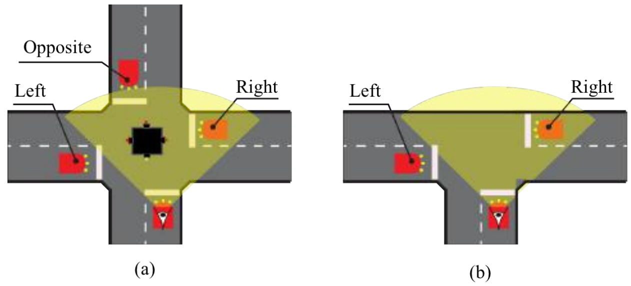


Fig. 15. Intersections. **(a)**: Traffic light intersection with four Duckiebots. **(b)**: A stop sign intersection. In both cases the yellow shaded area corresponds to the bottom vehicle's sensor field of view.

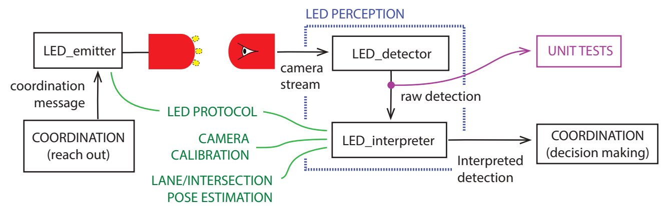


Fig. 16. Communication based on LED frequency detection.

V. Multirobot Behaviors

The most advanced behaviors involve the interaction of many Duckiebots navigating in the same Duckietown. In this scenario, the Duckiebots must coordinate to share the roads and intersections.

We consider two types of intersections: traffic lights, and stop signs, as shown in Fig. 15. Traffic light intersections are a simpler and centralized solution to intersection negotiation. Stop signs require inter-Duckiebot communication. Communication is decentralized and perception-based, employing LEDs to signal intentions. The situation is complicated by the fact that the Duckiebot "to the left" is outside of the camera field of view when the Duckiebot is at the stop line, as shown in Fig. 15.

A. Infrastructure - Traffic Lights and LEDs

The traffic lights are equipped with LEDs facing each incoming road, and are constructed in the same way as the Duckiebots, but without a chassis.

B. Blinking LED Detection and Interpretation

The communication system based on LEDs has two decoupled components: the *detector*, which captures a camera stream and determines positions and frequencies of all LEDs present in the scene; and the *interpreter*, which receives this information and labels each detection with a physical object (e.g. vehicle or traffic light) and a coordination message.

An overview of the LED communication scheme is shown in Fig. 16. The details of the LED detector and interpreter are shown in Fig 17.

The interpreter leverages the assumption that the LEDs detected above the horizon belong to traffic lights, and those below correspond to Duckiebot communication LEDs.

C. Coordination Behaviors - Traffic Lights

Traffic lights at intersections sequentially communicate a "go" signal to one of the incoming roads while signalling

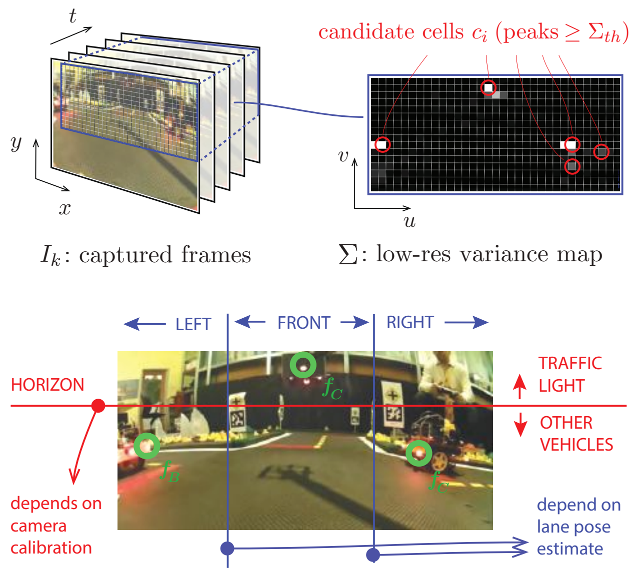


Fig. 17. LED communication algorithm. **Top**: The detector sequence of images I_k is captured from the camera (top left) and a relevant area (blue) is cropped and downsampled according to a low-resolution grid. The time-variance of the brightness is computed in each cell, producing a variance map (top right) whose peaks define candidate cells. FFT peak frequencies of the brightness on candidate cells are compared the known frequencies of the signals for matching, producing raw detections. **Bottom**: The interpreter takes the raw detections (green) and applies image-coordinate thresholds to determine the messages coming from the traffic light, the left, the opposing and the right vehicles in a scene.

a ”stop” in the other directions. Signals are encoded in the blinking frequency of LEDs. As Duckiebots interpret these signals they avoid ”jamming” the center of the intersection ensuring smooth traffic flow. When a Duckiebot arrives at a stop line, it starts detecting the frequency of the LEDs in its field of view and once it detects the frequency corresponding to the “go” signal, it starts maneuvering through the intersection.

D. Coordination Behaviors - Stop Sign Intersections

Stop sign intersections do not have any centralized infrastructure, so the Duckiebots communicate with one another to coordinate their turns through the intersection using LEDs mounted on each Duckiebot. As shown in Fig. 15, a Duckiebot at an intersection is not visible to a Duckiebot on its left due to the finite sensor field of view. The detection of the signal emitted by the other Duckiebots takes approximately 2s and the detection phases of individual Duckiebots are not synchronized. Intuitively, the decentralized negotiation protocol observes the following rules: (a) A Duckiebot yields to a Duckiebot on its right (since it sits outside of the field of view of the sensor of the Duckiebot to the right), (b) when two mutually opposing Duckiebots arrive at an intersection, the one that arrived earlier goes first, and (c) when the two opposing Duckiebots arrive simultaneously with respect to the detection precision, the Duckiebots resolve the ambiguity by waiting for a random amount of time before their next attempt to negotiate with the other Duckiebots.

The coordination scheme progresses through a series of

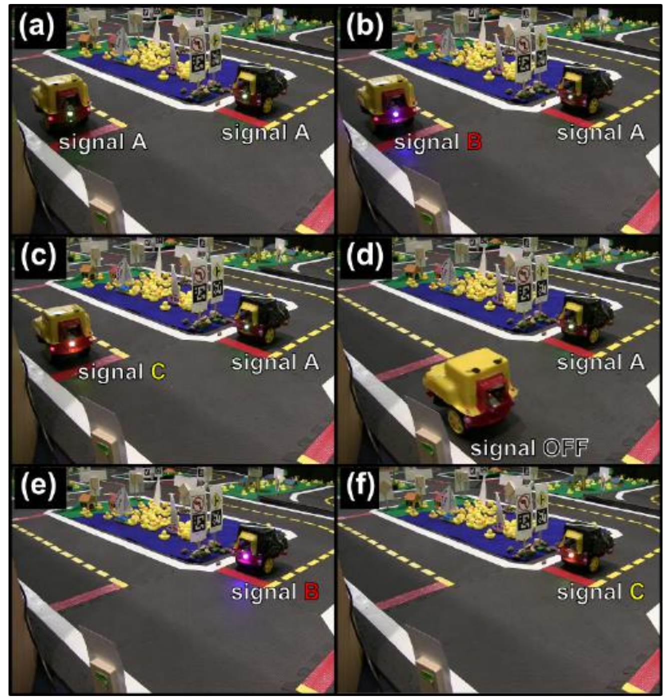


Fig. 18. Coordination at a stop sign intersection. **(a)** Two Duckiebots are waiting at a stop line. **(b)** The Duckiebot on the left is reserving the intersection and then in **(c)** is allowed to cross the intersection. **(d)** This Duckiebot turns off its LED and transitions to the LANE_FOLLOWING state. **(e)** The other Duckiebot reserves the intersection and in **(f)** is allowed to enter the intersection.

states as shown in Fig. 13. In AT_STOP_CLEARING, the Duckiebot is waiting a predetermined time to guarantee that the intersection is free, in AT_STOP_CLEAR a Duckiebot is waiting with no other Duckiebots in the intersection to guarantee that it is clear to go, in RESERVING the Duckiebot is signaling (through its LED) that it will attempt to traverse, in CONFLICT two Duckiebots have attempted to reserve the intersection simultaneously, and finally in GO the Duckiebot starts to navigate the intersection.

E. Evaluation

We tested the coordination behavior on both types of intersections and demonstrated the performance for several hours. Whe the vehicles stopped at the stop line oriented along the lane, the coordination behavior was able to reliably schedule the vehicles to pass through the intersection and avoid collisions. The result of the coordination behavior at a stop sign intersection is shown in Figure 18.

VI. Resource Management

Our objective as stated was to build an inexpensive yet capable platform for autonomy education and research. However, when the cost is reduced, available resources, such as sensing, computation, memory, power, and communications bandwidth are necessarily reduced. We have employed two fundamental strategies in our software architecture to reduce resource usage: event-based computation and mode-driven perception.

1) Event-based Computation: In our implementation we leverage the robot operating system (ROS), which predominantly employs a *publish-subscribe* model for data transport.

TABLE III

MODE-BASED RESOURCE ALLOCATION

Mode	Line Detector	Lane Filter	Stop Line Filter	Vehicle Detector	Sign Detector	LED Detector	LED Decoder
	Active Perception Modules						
JOYSTICK_CONTROL							
LOCALIZE					✓		
LANE_FOLLOWING	✓	✓	✓	✓			
COORDINATION						✓	✓
INTERSECTION_TRAV.	✓	✓					
AVOID_VEHICLE				✓			

Due to the limited computation resource of the platform, applications (nodes) utilize an event-based and rate-limited processing and publication scheme: a node only publishes when the output is significantly different from the last published output and when the limit on publication rate is preserved.

2) Mode-Driven Perception: The most computationally intensive tasks tend to be those related to perception, particularly since we are using vision as the only sensing modality. The most complex multi-robot behaviors require the robot to perform a number of perceptual tasks (line detection, lane filtering, stop line filtering, sign detection, LED detection, LED decoding, vehicle detection) but not simultaneously. Therefore, we impose a template whereby upon mode transitions a set of switches are published. These switches are used by all nodes and allow them determine the necessary input (images) at a given time. An overview of which perceptual modules are active in each of the FSM modes is given in Table III. We also control the resolution of the camera imagery based on the requirements of the given task, in a similar way.

VII. CONCLUSION

We have presented "Duckietown," a flexible platform for autonomy education and research. We have leveraged precise specification and resource management in developing the system to enable a sliding scale of realism. We have targeted an autonomous driving application here, however we believe this model, with augmented capabilities, can be extended to autonomy in other less structured domains, such as air, sea, and perhaps space robotics.

All materials are available under open source/free software licenses; pointers to the materials can be found at the website duckietown.mit.edu. Our hope is that others in the robotics community will adopt the platform and contribute to its growth.

ACKNOWLEDGMENTS

This work was supported by the National Science Foundation, with National Robotics Initiative award IIS-1405259, and with Robust Intelligence award IIS-1318392. Additional support was given by the Toyota Research Institute ("TRI") and the Ford Motor Company. However, note that this article solely reflects the opinions and conclusions of its authors and not TRI or any other Toyota entity. We would also like to acknowledge the contributions made by the students during the Spring 2016 semester of the MIT 2.166 class. Finally, we would like to thank Kirsten Bowser, the Duckietown Engineering Co. human resources coordinator.

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