2017 17th International Conference on Control, Automation and Systems (ICCAS 2017)
Oct. 18–21, 2017, Ramada Plaza, Jeju, Korea

System Design for Autonomous Table Tennis Ball Collecting Robot

Seong Ho Yeon[1], Dayeon Kim[1,2], Gilhyun Ryou[1,3], and Youngwoo Sim[1,4]

[1]NAVER LABS, Gyeonggi-do, 13494, Korea (syeon@mit.edu)
[2]Department of Mechanical Engineering, POSTECH, Pohang, 37673, Korea (dayon95@postech.ac.kr)
[3]Department of Electrical and Computer Engineering,
Seoul National University, Seoul, 08826, Korea (brightgh@snu.ac.kr)
[4]Department of Mechanical and Aerospace Engineering,
Seoul National University, Seoul, 08826, Korea (ywsim@snu.ac.kr)

Abstract: This paper presents design methodologies and an implementation of autonomous table tennis ball collecting robot. The robot is designed with three major emphases to collect balls effectively in a real table tennis court: ball detection, navigation, and ball collection. For ball detection, a combination of blob detection and cascade classifier was utilized. The robot generates an optimal path toward detected balls using A* graph search algorithm and follows the path based on a mecanum-wheeled platform. The detected balls are collected using a suction motor and a 2-DOF active nozzle. The integrated system successfully demonstrates the given task in a real table tennis court.

Keywords: Autonomous mobile robot, ball recognition, navigation, ball collection

1. INTRODUCTION

Picking up table tennis balls spread over the court is like the torture of Sisyphus with its endless repetitions. While playing table tennis, players have to stop every few minutes to pick up the balls. To ease the burden of players, we developed an autonomous robot that collects balls in a real table tennis court.

In the past, several ball collecting robots were developed to use in diverse environments. Ball-Picking Robot developed by Y. Liu [1] and Ballbot developed by J. Wang [2] were presented for a tennis court navigating based on fixed lines on the court, but these architectures are not suitable for a table tennis court due to the lack of fixed lines. Blackhole developed by C. H. Yun [3] and Vision-guided golf-ball collecting mobile robot developed by S. W. Wu [4] were operated on a golf court, but they are not operable without additional court infrastructures including external cameras to detect distant balls.

The objective of this research is to design a stand-alone robot platform for ball collection in any real table tennis court. We simplified and targeted three major challenges in a real table tennis court:

- Distinguishing table tennis balls, a white sphere with a 40mm diameter, from other white confusing elements
- Avoiding obstacles such as a table, chairs, walls, people, and moving fences
- Collecting table tennis balls everywhere on the court even surrounded by objects and walls

To address these challenges, we propose an effective autonomous table tennis ball collecting robot, TT-bot, with three design approaches as shown in Fig. 1; to detect balls, vision processing with blob detection and cascade classifier were implemented; to navigate effectively, A* graph search algorithm and mecanum wheels were utilized; to collect balls, a suction method and a two-degree-of-freedom (2-DOF) active nozzle were used. The robot was integrated with a backseat/frontseat architecture with compact PC and a real time controller and utilized one LIDAR and camera.

The next section shows a brief overview of the system configuration of the proposed robot platform, TT-bot. Section 3 introduces our approach to detect table tennis balls, and section 4 suggests a practical methodology for the stand-alone robot navigation. In Section 5, we present a design approach to collect balls. Finally, section 6 discusses a performance of TT-bot and desired future works.

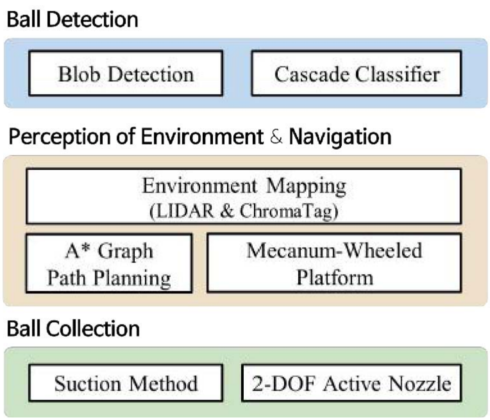

Fig. 1 Three design approaches for TT-bot.

2. SYSTEM CONFIGURATION

The hardware of the proposed robot, TT-bot, is shown in Fig. 2. The robot was built on aluminum plate chassis with four mecanum wheels actuated by servo motors

Research was conducted as a part of NAVER LABS Research Internship Program. S. H. Yeon, D. Kim, G. Ryou, and Y. Sim contributed equally to this work.

(Dynamixel MX-28). Similar to a vacuum cleaner, the robot collects balls using a 160W suction motor, and a nozzle is actuated by two servo motors (Dynamixel MX-28). The collected balls are stored in a basket which can hold up to fifty balls. For navigation, a wide-view webcam (Genius 120 degree Ultra), a single channel LIDAR (Slamtec RPLidar A2), and six ultrasound distance sensors (HY-SRF05) were installed. The webcam is actuated with one servo motor (Dynamixel MX-64) to acquire side view images. The processors of the robot utilized a backseat/frontseat architecture consisting of a small PC (Intel NUC) and a real time processor (NI myRIO) with FPGA (Xilinx Z-7010). The PC interfaces with the LIDAR and the webcam for high level control of the robot and communicates with the real time processor to control the peripherals via TCP/IP communication. The real time processor controls a suction motor, seven servo motors, and six ultrasound sensors. Vision processing software was developed on ROS environment running on the PC.

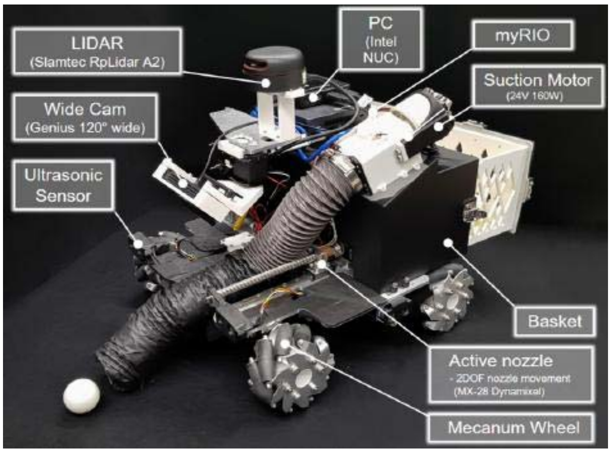

Fig. 2 TT-bot hardware overview.

3. BALL DETECTION

Detecting a table tennis ball in a real court is challenging due to several rationales as shown in Fig. 3: a) distant balls are presented in small size which is less than 10×10 px, and some table tennis balls are occluded by obstacles, b) several objects and lightings look similar to table tennis balls.

A common ball detection problem uses geometric model based detection algorithms, such as Circle Hough Transform [5] and Gradient Vectors based approaches [6]. However, they are vulnerable to detecting small balls which lack circular features. Also, those algorithms cannot distinguish a target ball from other visually similar objects. Due to these limitations of geometric model based detection algorithms, learning based detection algorithm was chosen and applied instead.

As described in Fig. 4, the learning based detection algorithm consists of two major steps: Region of Interest(ROI) extraction and classification. A blob detection

(a) (b)

Fig. 3 Challenging cases in ball detection. (a) Target balls, (b) Objects visually similar to a table tennis ball.

algorithm is used to extract ROI cut-outs from a raw camera image, and a Local Binary Pattern(LBP) feature [7] based cascade classifier [8] is applied as a classification process. The overall ball detection processes were implemented based on OpenCV.

3.1 ROI Extraction

In order to reduce the computational complexity in the ball detection algorithm, dimension reduction process is used as a primary step of the algorithm. The common strategy in dimension reduction is feature extraction. However, in some cases with a relatively large input image, even the feature extraction process would work as a computational bottleneck. To address this issue, several learning based detection algorithms use ROI cut-out as an input for feature extraction. ROI extraction method can vary depends on target problems, and LIDAR data [9] or blob detection results [10] are commonly used.

For table tennis ball detection problem, we used blob detection algorithm to extract ROI. Since the blob detection method can detect objects with a low resolution, it enables the robot to include distant balls in ROI set. Our ROI extraction method consists of three steps: color refinement, color masking, and blob detection. In the color refinement step, single erode morphological operation is applied to differentiate table tennis balls from reflected lights. As a following step, color filters are applied to create a masked image that only contains pixels of color similar to that of table tennis balls. The clusters on masked image implies the possible position of the table tennis balls as shown in Fig. 4 (b). Blob detection algorithm is applied to this color mask to calculate the center coordinates of each cluster. Considering that the size of the cluster is smaller at the top of the image, we divided the image into three sections (top, middle, bottom), and extracted ROI cut-outs respectively.

3.2 Classification

Cascade classification [8] is a general methodology to extract an object from a given image by stacking a network of weak classifiers. To train each weak classifier, appropriate features have to be chosen. We used the LBP feature [7] because of its short training time and robustness over disturbances such as illumination change.

ROI cut-outs, which represent ball candidates, are used as input images. The ROI cut-outs extracted from

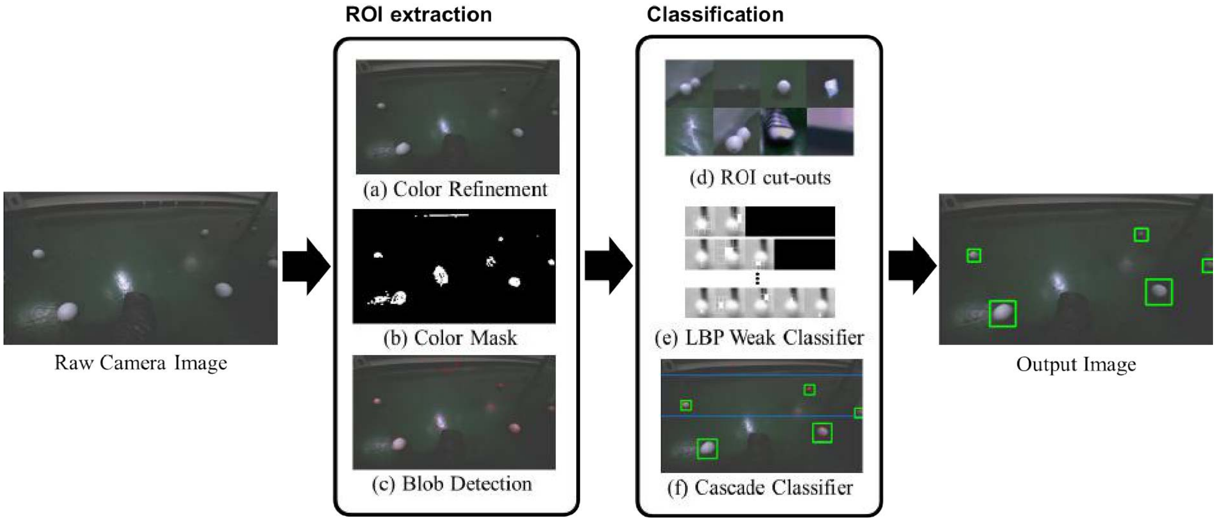

Fig. 4 The conceptual process of ball detection: (a) color refinement with erode operation, (b) color mask for blob detection, (c) calculating center position of each blob, (d) cropping out rectangular area around each blob as a ROI, (e) classification process of LBP feature based cascade classifier, (f) segmentation of screen to differentiate the size of ROI cut-outs, classifiers are also differentiated for each segment.

the three different sections of the input image contain different types of false ball candidates, which is shown in Fig. 4 (f). Thus, classifiers corresponding to each section of the input images are created and trained separately to distinguish a table tennis ball more accurately. As a result, we achieved ball detection accuracies of 80% (top section), 82% (middle section), and 92% (bottom section), and overall ball detection performance is shown in Fig. 5.

Fig. 5 A capture from processed image stream; Bouncing balls are recognized in green boxes.

4. PERCEPTION OF AMBIENT ENVIRONMENT AND NAVIGATION

For practical usage of the robot in a real table tennis court, it is required to collect scattered balls effectively while avoiding various obstacles and physical disturbances. Thus, in this section, we present strategic approaches for practical stand-alone robot navigation in a real table tennis court: mapping environments and targets using a camera and a LIDAR, path-planning using A* graph search algorithm, and holonomic mobile platform using mecanum Wheels.

4.1 Mapping of Environmental Information

Autonomous robot navigation requires path-planning based on information of obstacles and detected targets. Several sensors such as LIDAR were utilized for recognizing obstacles. In order to fuse information of several sensors' data on the same reference frame, we abstracted and projected each sensor data to a virtual map. As shown in the Fig. 6 (c), the map consists of 100×100 pixels with a size of 5×5 cm^2. The size was chosen to mitigate the computational complexity of the path search algorithm.

4.1.1 Physical Obstacles

Physical obstacles are detected by a single channel LIDAR into a form of point-cloud data, and these data are mapped directly on the virtual map to generate walls for path-finding and obstacle avoidance.

4.1.2 Virtual Obstacles

In a real tennis court, it is important to limit and specify the scope of activity for the robot, even without physical obstacles. In order to achieve this requirement, we introduced ChromaTag [11] as shown in Fig. 7 (a). The robot recognizes the ChromaTag as a virtual obstacle, and it abstracts barriers on the virtual map (for path-search). Fig. 7 (b) shows an abstracted virtual obstacle. With this feature, the user can easily control the robot's scope of activity.

4.1.3 Detected Balls

In order to chase and collect detected balls, it is required to project and map the absolute positions of the detected balls on the virtual map. Through homography matrix of the camera, positions of the detected balls on the camera view are translated into 2D positions on the floor and projected on the virtual map. In the virtual map shown in the Fig. 6 (c), the green dots represent the detected balls and the yellow dot represents the target ball currently being tracked.

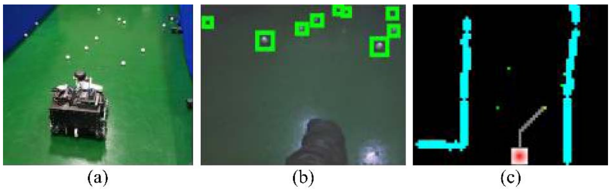

Fig. 6 (a) A robot in a test court, (b) Camera view detection, (c) Abstracted map.

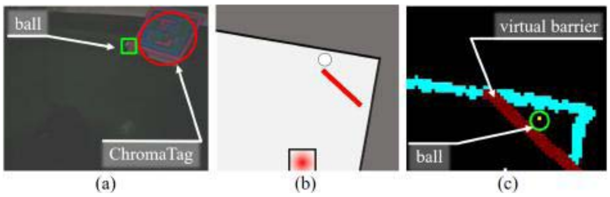

Fig. 7 (a) Installation of ChromaTag, (b) Graphic schematic illustration, (c) An abstracted map with extended virtual barrier.

4.2 Path Planning

As mentioned above, the ambient environment of the robot is simplified and abstracted to the robot-centered spatially relative virtual map for navigational purpose. The map provides an effective basis for path-planning and driving to collect ball while avoiding obstacles. For path searching and planning on the map, A* algorithm [12] is utilized. The purpose of running A* algorithm is to follow the path, but without SLAM (simultaneous localization and mapping) capability, it is impossible to monitor whether the robot is correctly following the generated path on the same reference frame; the next-updated map would have shifted ambient information based on robot movement, and it is impossible to reflect past frames generated plan. As an alternative to monitor the robots trajectory, for every update of the map, A* algorithm is utilized to evaluate a temporary optimal path on the updated map, and the robot drives toward the direction of the point about 25cm from the origin of temporarily generated path until the map is updated to the next frame. The gray line shown in the Fig. 6 (c) shows the generated path for the robot.

4.3 Mecanum Platform

Paths generated by the graph search algorithm are mostly cranky due to environmental hindrance in a real table tennis court. In the case of using a conventional differential drive system, two problems appear; complicated motion and intermittent stops are required to follow cranky paths; frequent z-axis rotation affects the camera's view, and this increases the possibility of vision based detection failure. To negate these problems, mecanum-wheeled holonomic platform is introduced.

5. DESIGN PRINCIPLE FOR BALL COLLECTION

A suction motor is widely implemented as a robotic end-effector [13–15]. Despite its large power consumption, it allows a compact mechanical setup for an end-effector. In a narrow space, where bulky rigid grippers are hard to reach, a suction type end-effector can approach a target with its compact configuration.

Several mechanisms have been in use for ball collection: rotating disks [2], a net of elastic wire [16], and a gripper [17]. These are mostly bulky, and they consist of rigid components. For these mechanisms to function soundly, open space around a ball is required. In the case of pneumatic soft grippers [18, 19] with a small form factor, they require physical contact with an object to generate pulling force. These apparatus, however, are not suitable for a table tennis ball in a tight area. The existing mechanisms focus on securing a tight capture, abandoning targets in the corner or under furniture; they have a high probability of collision with surroundings as illustrated in Fig. 8.

An improved mechanism is newly designed to collect balls. This mechanism is comprised of a suction motor with a nozzle, and two actuators to extend the work space of the end-effector. In this way, we can collect balls without physical contact, and at a distance of a few centimeters. Moreover, with the aid of the 2-DOF active nozzle, the robot can collect balls situated in a dead zone, where the robot itself is inaccessible.

5.1 Suction for Ball Collection

TT-bot inhales balls that are stuck in tight space or enclosed by walls. A suction motor forms air flow that pulls the ball with drag force. A 200 W suction motor is able to gather balls located up to 4 cm. Within the inhalation region, a ball can be collected without precise motion control.

After the ball enters the inside, as described in Fig. 9 (a), it is separated from the main passage to fall in a ball storage. For the separation, a reflector is used and designed to minimize air friction loss and ensure the separation. Thus, it has maximized area of openings and installed with suitable angle and height.

5.2 2-DOF Active Nozzle

When the robot is blocked by obstacles, the 2-DOF active nozzle enables the collection by its linear and rotational movement, as shown in Fig. 9 (b). The nozzle can move up to 15 cm frontward and rotate from -90 ° to 90°. A flexible tarpaulin nozzle is utilized, which can smoothly follow the movement of actuators.

Actuators are controlled based on the positions of recognized target balls and surrounding obstacles. Whenever the robot recognizes a target ball, the rotational actuator aligns the nozzle toward the ball. If the robot is blocked by obstacles, which can be recognized from ultrasound sensor, a linear actuator lengthens the nozzle to reach the ball.

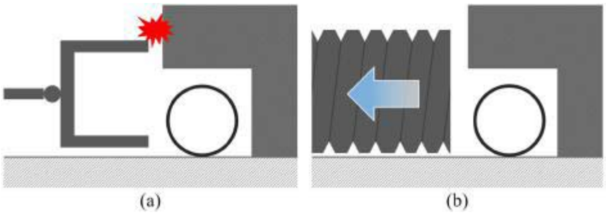

Fig. 8 (a) Earlier equipment is likely to collide with the surrounding environment, (b) Suction nozzle free of collision; target can be collected from afar.

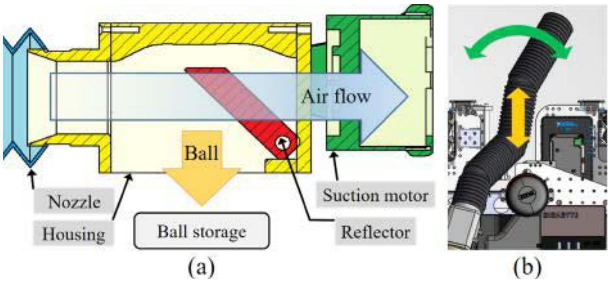

Fig. 9 (a) A cross-sectional view of the suction motor housing. A ball collides with the reflector, changing its direction to the ball storage, (b) 2-DOF active nozzle movement.

6. EXPERIMENTAL RESULT AND DISCUSSION

In this paper, we presented a stand-alone table tennis ball collecting robot, the TT-bot, with three design approaches. The performance of the robot is presented in a video which is available at https://youtu.be/fncadmZEQCk.

The robot detects small-sized balls and distinguishes them from other similar objects, using learning-based algorithms. Also, while avoiding obstacles, the robot moves toward a target object with the A* graph search algorithm. We maximized the efficacy of the search algorithm by using a holonomic movement platform with mecanum wheels. Additionally, the robot can collect balls located in narrow spaces or corners, using a suction method and a 2-DOF active nozzle.

Further development could be achieved by higher accuracy of ball detection. In order to overcome the limited performance of the feature-based object detection algorithm, an algorithm with a more complicated structure is required. One feasible solution is to utilize a Deep Neural Network based object detector such as Fast r-cnn [20].

Also, the navigation can be improved by introducing ball trackers. If a table tennis ball disappears from the screen, our navigation algorithm ignores the missing ball during the path planning process. Kalman Filter based tracker can address this limitation caused by the camera's field of view, as suggested in vehicle tracking [10].

ACKNOWLEDGMENT

The authors would like to thank all members of the Robotics Group at NAVER LABS for contributing greatly in every aspect of the project from ideation to realization.

REFERENCES

[1] Y. Liu, S. Li, and Z. Xia, "Path Planning Efficiency Maximization for Ball-Picking Robot Using Machine Learning Algorithm," *Int. Conf. Intelligent Transportation. Big Data, Smart City, no.*, ICITBS, pp. 551-555, 2015.

[2] J. Wang, "Ballbot a low-cost robot for tennis ball retrieval," *Masters thesis, EECS Department, University of California, Berkeley*, 2012.

[3] C. H. Yun, Y. S. Moon, and N. Y. Ko, "Vision based navigation for golf ball collecting mobile robot," *Int. Conf. Control. Autom. Syst., no.*, ICCAS, pp. 201-203, 2013.

[4] S. L. Wu, M. Y. Cheng, and W. C. Hsu, "Design and implementation of a prototype vision-guided golf-ball," *Mechatronics, 2005. ICM'05. IEEE International Conference on.* , IEEE, 2005.

[5] J. Borovicka, "Circle Detection Using Hough Transforms Documentation," *COMS30121 - Image Processing and Computer Vision*, 2003.

[6] A. A. Rad, K. Faez, and N. Qaragozlou, "Fast Circle Detection Using Gradient Pair Vectors," *Dicta*, pp. 879-888, 2003.

[7] S. Liao, X. Zhu, Z. Lei, L. Zhang and S. Z. Li, "Learning Multi-scale Block Local Binary Patterns for Face Recognition," *Advances in biometrics*, pp. 828-837, 2007.

[8] P. Viola, and M. Jones, "Rapid object detection using a boosted cascade of simple features," *In Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*, Vol. 1, pp. I-I, IEEE, 2001.

[9] C. Premebida, O. Ludwig, M. Silva, and U. Nunes, "A cascade classifier applied in pedestrian detection using laser and image-based features," *In Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*, pp. 1153-1159, IEEE, 2010.

[10] J. Melo, A. Naftel, A. Bernardino, and J. Santos-Victor, "Detection and classification of highway lanes using vehicle motion trajectories" *IEEE Transactions on intelligent transportation systems*, 7(2), 188-200, 2006.

[11] A. Walters, and B. Manja, "ChromaTag-A Colored Fiducial Marker," Internet: https://github.com/lettergram/chromatag, May 16, 2015, [May 15, 2017].

[12] P. Hart, N. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost

paths," *IEEE transactions on Systems Science and Cybernetics*, 4(2), 100-107, 1968.

[13] W. Zesch, M. Brunner, and A. Weber, " Vacuum tool for handling microobjects with a nanorobot," *In Robotics and Automation, 1997. Proceedings., 1997 IEEE International Conference on*, Vol. 2, pp. 1761-1766, IEEE, 1997.

[14] N. C. Tsourveloudis, R. Kolluru, K. P. Valavanis, and D. Gracanin, "Suction control of a robotic gripper: A neuro-fuzzy approach," *Journal of Intelligent & Robotic Systems,* 27(3), 215-235, 2000.

[15] T. Katsuma, "Vacuum manipulator for semiconductor manufacturing equipment," *Industrial Robot: An International Journal,* 29(4), 324-328. 2002

[16] Kurt. G. Beranek, "Tennis ball retriever," U.S. Patent 5 407 242, Apr. 18, 1995.

[17] K. Nicolaus, J. Hooper, R. Wood, and C. Ham, "Development of an Autonomous Ball-Picking Robot," *In Collaboration Technologies and Systems (CTS) 2016 International Conference on,* pp. 373-378, IEEE, October, 2016.

[18] Brown, Eric, et al."Universal robotic gripper based on the jamming of granular material," *Proceedings of the National Academy of Sciences* 107.44, 18809-18814, 2010.

[19] B. S.Homberg, R.K. Katzschmann, M. R. Dogar, and D. Rus, "Haptic identification of objects using a modular soft robotic gripper," *In Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on,* pp. 1698-1705, IEEE, September, 2015.

[20] R. Girshick, "Fast r-cnn," *In Proceedings of the IEEE International Conference on Computer Vision*, pp. 1440-1448, 2015.