Design of AI Ground Robots for Intelligent Combat in a Dynamic Arena

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ROBOMASTER

EQUIPE DE ROBOTIQUE AUTONOME

Introduction

In this poster, we describe our work towards the IEEE ICRA Robomaster AI challenge. The Ai challenge represents an amalgamation of the current problems in ground robotics, and is an excellent platform to develop and test solutions to problems varying from overhead perception, image segmentation, sim-to-real Reinforcement Learning, Localization in symmetric sparse arena etc. Our developed algorithms are codependent and are deployable on embedded compute, provide high frame rates and precise results

Robotic Platform

The platform used the the 2020 AI robot by DJI, and has been modified to house sensors to enable execution of algorithms

Modifications

- For sensing the robot surroundings, we endow the platform with an Intel RealSense D455 RGB-D camera, an RPLiDAR A1M8 and 4K ELP cameras.
- For onboard computing requirements, we use Intel NUC Enthusiast with parallel computing capabilities in order to deploy neural networks and other algorithmic components.

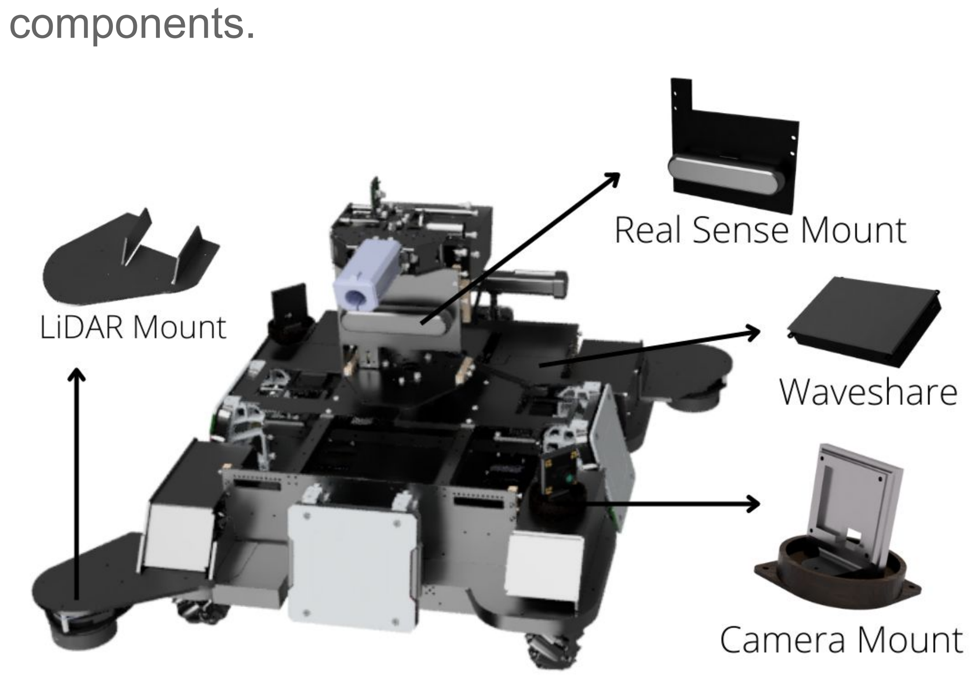

Fig.1: Mechanical Attachments for AI Robot.

Visual Perception

Determination of the enemy is achieved by classifying the 8 **classes** of armor plates of the enemy with a **mAP score of 85.68% @ 60fps**. This is done using a CNN based on the YOLO architecture that utilizes IoU technique to make faster and more accurate predictions.

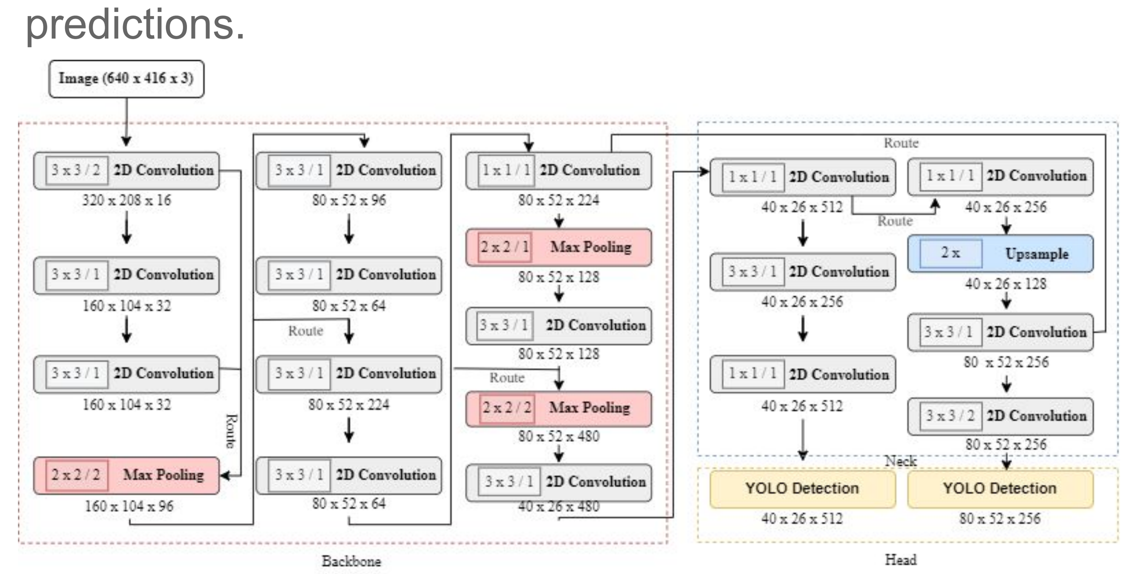

Fig. 2: Neural Network Architecture

Further, the predicted coordinates of each detected enemy armor plate along with perceived depth obtained from realsense 535 are utilized to estimate the pose of the enemy robot. At the sentry level, the robots are detected using the live feed from 2 HD cameras using YOLO architecture. The predicted coordinates obtained after detection are then fed into a perspective transforming matrix that returns real-world coordinates of the enemy robot.

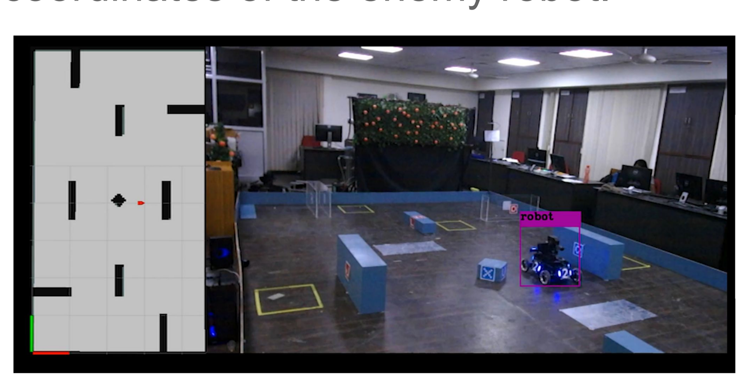

Fig 3: Sentry Level Camera Coordinate Transformation

Such high accuracy has been achieved in the detection using a custom dataset created using more than 2000 images of each class, which were further augmented to different brightnesses, contrasts, exposures, was rotated, and sheared at different angles and further combined to form mosaics.

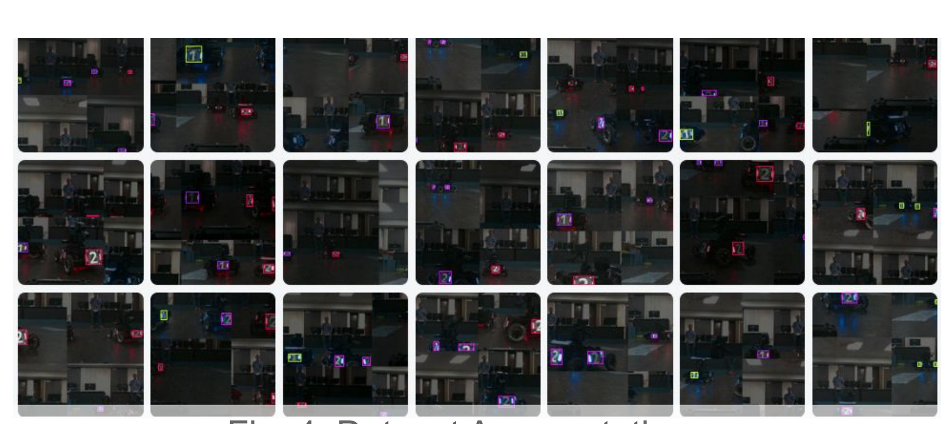

Fig. 4: Dataset Augmentation

Positioning

The robot uses two 2-Megapixel USB cameras with 2.1mm wide angle lens mounted on opposite ends to localize itself by detecting the visual tags fixed with respect to the arena by adaptive thresholding and contour recognition and then comparing it with the custom dictionary storing the bit values of the marker.

Fig. 5: Visual Marker Detection

Further the Lidars mounted on the robot obtain the odometry of the bot accurately when the markers are not detected accurately by the camera. RF2O scan based alignment package was used on the data obtained from the LiDARs for it.

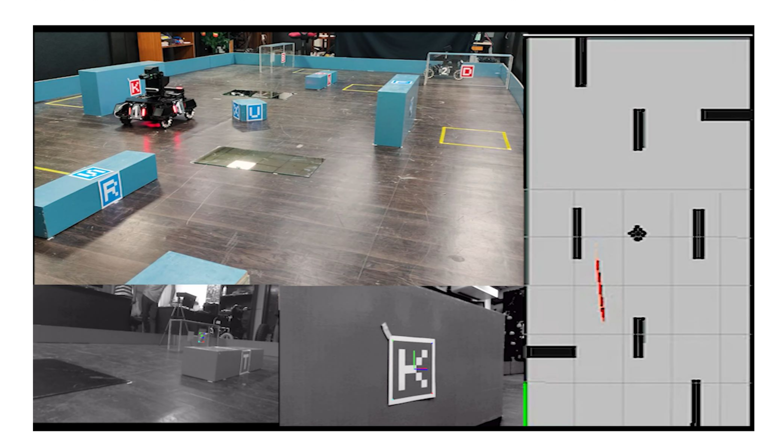

Fig 6: Ego Localization

The Kalman filter takes in the absolute pose of the visual marker detection strategy and the lidar based odometry and filters the noise by using the covariance matrices of the each component data and helps in increasing the accuracy of the prediction of the measurement of the pose of the bot.

Navigation

We have deployed deterministic planning using A* search algorithm along with Timed Elastic Band optimization for planning the robot's trajectory with respect to trajectory execution time. A* provides the global plan using weighted graphs then the local TEB planner deals with obstacles continuously detected in the arena using the LiDAR sensor. The graph is finally optimized by the general (hyper)graph optimization "g2o" algorithm,I yielding the ultimate optimized local path that the robot will follow.

Post-Lurking Behaviour

In the lurking phase the enemy robot is detected using the health bar and elimination of ego coordinates using bot level localization data. On comparing the coordinates we can identify the enemy robots.

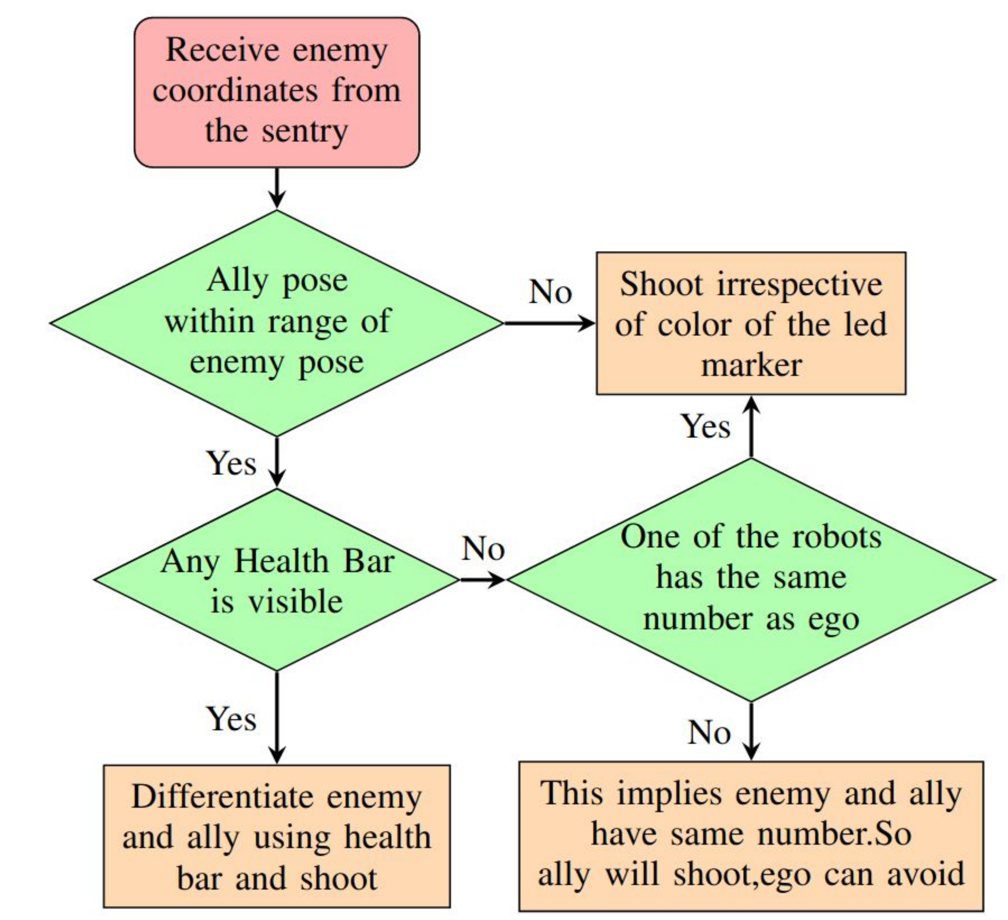

Fig. 7: Post-Learning Engage Pipeline

The pose is also estimated at this point, using the armor plate patterns. The images detected will be passed through the pre-trained Neural Network and the resulting output provides the orientation of the robot. Thus the pose and location of an enemy robot as reduced to a set of 2 points in order.

Technical Report Video

Scan this code for the Technical Report Video of the Team.

References

[1] Ashok Kumar Chaudhary, Suraj Hanchinal, Suryansh Agarwal, and Laxmidhar Behera. Chasing and aiming of a moving target.

[2] Ashish Kumar, Mohit Vohra, Ravi Prakash, and Laxmidhar Behera. Towards deep learning assisted autonomous uavs for manipulation tasks in gps-denied environments. *In 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 1613–1620. IEEE, 2020.*

Technical Report Video Link :: https://youtu.be/U3kv0PN-7x0

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