Development of task-oriented ROS-based Autonomous UGV with 3D Object Detection

Rajesh Raveendran^{1*}, Siva Ariram^{1*}, Antti Tikanmäki¹ and Juha Röning¹

Abstract—In a scenario where fire accidents takes place the priority is always human safety and acting swiftly to contain the fire from further spreading. The modern autonomous systems can promise both human safety and can perform actions rapidly. One such scenario which is motivated by urban firefighting was designed in challenge 3 of MBZIRC 2020 competition. In this challenge the UAV's and UGV collaborate autonomously to detect the fire and quench the flames with water. So, in this project we have developed Robot Operating System (ROS)-based autonomous system to solve the challenge for UGV criteria by detecting targeted objects in real-time, in our case its simulated fire and red colored softballs. Then finally localize those targets as markers in the map and navigate autonomously to all those targets. This work has two sections, in the first section mapping and localizing the fire and softballs in highly cluttered environment and then reaching those targets autonomously. Robustly mapping the area with adequate sensors and detection of targets with optimally trained CNN based network is the key to localizing of the targeted objects in a highly cluttered environments.

Keywords: ROS, architecture, mapping, autonomous navigation, object detection, CNN, dataset

I. INTRODUCTION

Autonomous mobile systems have received more attention in recent days and slowly is integrating into daily activities of human life. Especially in disaster prone situation these systems can be deployed rapidly and contain the disaster. Recently in China, autonomous mobile robots were used to provide medicines to COVID-19 affected patients. Autonomous drones were used to monitor the people crowd and announcing awareness regarding COVID-19 in densely populated countries such as India and China, also in UAE. The unprecedented situation can be further contained if we have online shopping where last mile robots can deliver daily needs to our door steps, this can avoid further human contacts. In order to deploy autonomous systems in these scenarios we need very robust autonomous systems which can navigate in any cluttered environments safely and robustly. In robotics world there are many competitions that are conducted around the world to enhance the overall system robustness and accuracy of autonomous systems and they have to collaborate with each other. One such event is MBZIRC 2020 Challenge[5] which contains three challenges, collaborative UAVs to grab softballs with 11cm in diameter in highly dynamic environment, collaborative UAVs and UGV

for construction and finally urban firefighting scenario. In this work we have focused on the UGV's criteria for third scenario to localize simulated fire and navigate autonomously in a highly cluttered environment. The designed autonomous navigation system includes real-time path planning, mapping, obstacle avoidance and default recovery phase. We trained a Convolution Neural Network with training data-set using Darknet detection algorithm. Achieving the accuracy in object detection with data-set from different scenarios and training the network for highly optimized weights was one of the most challenging part.

II. BACKGROUND

In the development of any Simultaneous Localization and Mapping (SLAM) based autonomously navigating mobile systems, deciding the choice of representation of the environment is a critical design decision. Fundamentally, the environment can be represented in two ways based on features in the environment and dense representation such as occupancy grid map. And based on the choices SLAM's can be classified into two approaches, namely grid-based and feature-based approaches. In the feature-based approach, the features contain both semantic and metric information. It provides semantic features such as point, line and plane and metric features such as range and orientation [6]. And based on these features, a feature map is incrementally built and using this feature map the mobile system is simultaneously localized in the environment. Feature based maps are highly preferred in structured environment with open space with predefined landmarks [6] [7] and this also depends on what type of features some line based feature extractors provide optimum results in indoor with concrete wall and pillars. And feature-based approach is computationally less expensive compared to dense grid-based approach. Typical indoor environment using Rao-Blackwellized particle filters (RBPFs) are a high-performance solution, and has been integrated into open source software such as Gmapping [7] [8]. The data association step can fail if there are uncertainties arising from the scan data which in turn can lead to incorrect feature extraction [9] [10]. Hence, accuracy of scan data plays a vital role in feature extraction and grid mapping. Also, any type of sensor uncertainties has a probability to propagate into mapping and navigation stack. In this work we have chosen Hector Map [11] and OctoMap [12] which is chosen based on the base controller mode of operation. Most of the localization algorithms utilizes the extended Kalman filter (EKF), unscented Kalman filter (UKF) or Adaptive Monte-Carlo Localization (AMCL) par-

¹Biomimetics and Intelligent Systems Group(BISG), University of Oulu, 90570 Oulu, Finland. rajesh.raveendran@oulu.fi siva.ariram@oulu.fi

*Rajesh Raveendran and Siva Ariram have equally contributed to this work as first authors

FSB Dataset - <https://github.com/sivaariram/Fire-and-Ball-Dataset>

ticle filters. The Kalman Filter is based on Bayesian method and it computes recursively the optimal parameter estimation from its posterior density. The object dynamic function and posterior density are Gaussian distribution in Kalman filter and the process and measurement functions are linear. In EKF, the process function linearization is performed with Taylor series approximation and in UKF the approximation is based on sigma point sampling. In this project cascading EKF with different modalities has been implemented using *robot_localization* [14] package.

In order to achieve the high accuracy in object detection at different scales, the recent studies applied multiple layer architecture. At the same time the low-level feature in superficial layers may not perform the detection with high accuracy [4]. Most of the object detection algorithm is totally depend on training data-set and training parameters which helps to prevent the network over trained or under trained. Hence, we decided to collect enough data-sets under different scenarios and depends on number of classes we configured the training parameters. The other important factor is that the detection should not affect the system performance since most of the detection network occupies the GPU memory[1], so we implemented the network based on system performance.

III. SYSTEM DESCRIPTION

The UGV platform, Mörrri, is an evolutionary version of the high-performance platform that was first used ten years ago in Elrob 2008. Since then, the platform has undergone several development cycles, especially on sensors and computers, but the core features of powerful 5 kW motors, narrow body and large footprint relative to weight has remained the same. Figure 1 shows the sensors and cameras attached to the Mörrri.

Mörrri is equipped with custom made battery modules. Each module has 5Ah 24V capacity with integrated monitor and charger. Robust CAN bus is used to control each battery module (on/off, charging, etc.) and to read its status (how much charge left, temperature etc.). Operation time of Mörrri per one battery module is highly depending on the mass of payload, demanded speeds and accelerations, and environmental factors such as ground softness and slope. As a rough approximation, with one battery module Mörrri can travel 2km on hard surface. The number of batteries can be tuned according to each scenario's parameters so that "enough" batteries are attached to Mörrri. Currently, Mörrri has space for up to 12 battery modules. Mörrri has internal onboard computer Zotac with NVIDIA Geforce 1070 GPU enabling high performance CUDA processing. The complete navigation stack with obstacle avoidance and 3D model reconstruction are performed using this on-board computer so Mörrri can operate independently without external connection. Two different options for inter-process communication are available, the commonly used ROS interfaces and a proprietary high performance binary protocol tailored for real time control. Each ROS node utilizes messages from common_msgs stack in-order to avoid circular dependencies

Fig. 1: Mörrri UGV

with multiple stack. The system network is configured to use multiple machine with single ROS master. The Operator PC can be used to monitor the heartbeat of all the sensors and receive the messages.

IV. SYSTEM ARCHITECTURE

Mörrri runs in meta-operating system called ROS. The main reasons for opting ROS is easy construction of distributed computing systems, extensive tool-sets for debugging, visualization, logging, introspecting and saving the data in a bag format, has capability to provides libraries from low level system integration to control and perception of mobile systems and manipulators, it is supported by large ecosystem and improved constantly. Figure 2 depicts the software architecture developed based on ROS middleware.

The Mörrri's software architecture was developed with several open-sourced packages in Kinetic distro and packages that aid the integration of the available packages were developed. Also, some of the packages source codes were modified according to the system's specifics and computational efficiency. Most of the salient packages are built from source to improve the performance. Table I lists the packages used to construct the software architecture of Mörrri.

TABLE I: ROS packages for specific components

Components	Packages
Emlid Reach	<i>reach_rs_ros_driver</i>
Intel D435i	Intel RealSense SDK 2.0, <i>realsense-ros</i>
Hokuyo UTM 30LX (2D)	<i>hokuyo_node</i>
VLP-16 Puck LITE	<i>velodyne</i>
Xsens MTi-G	<i>xsens_driver</i>
Pixfalcon PX4	<i>mavros</i>
Hector Map	<i>hector_slam</i>
OctoMap	<i>octomap</i>
Localization	<i>robot_localization</i>
Navigation Stack	<i>ros_planning/navigation</i> , <i>teb_local_planner</i>
F710 Joystick	<i>joy_stick_drivers</i>
Visualization	<i>rviz</i> , <i>MapViz</i>
Darknet	<i>darknet_ros_3d</i>

V. DATA-SET COLLECTION & PREPARATION

The most important fundamental of object detection is collecting data-set, the different scenarios is the key attribute

Fig. 2: ROS-based software architecture

of data-set which provides multi angle view of the target. This improves the accuracy of detection under any circumstances. The data-set's original images were captured in the University of Oulu warehouse in summer 2019, it has variety of viewpoints. To support in the reproducibility of image classification and target recognition we have collected, labelled, generated the images in the Fire simulator and ball(FSB) data-set. Considering the results we achieved when training Darknet using FSB data-set, we note that it provides high quality and various images that are shown to be sufficient to train. For the data collection two different aerial robot vehicle and one ground robot vehicle were used.

Fig. 3: Example images of indoor and outdoor data-set from both UGV & UAV

In this compilation, the outdoor data-set of 67276 images and indoor data-set of 33600 images were collected. Im-

ages were captured using Realsense D435i Stereo camera, DJI Inspire Camera and Zed Stereo Camera. The sensors mounted in UAV and UGV vehicle's and yield high dynamic-range(HDR) images with 16bits linear color depth. We also included some of low dynamic-range(LDR) images with 8bit RGB images for comparability and compatibility of the data-set[3]. The labelling annotation was done for randomly chosen 1496 frames in a video snippet of different sensors. Figure 3 shows the randomly chosen images from the data-set and it also shows that data-set has variety of viewpoints under different scenarios. The following components of the training/validation sets have to be the images with annotated objects and the text file corresponding to each image which includes the following parameters,

- Label_ID - Numeric ID which has to be starting from 0, determines different classes.
- X.CENTER - Centre of the object lies on X coordinate
- Y.CENTER - Centre of the object lies on Y coordinate
- WIDTH - Width of the object
- HEIGHT - Height of the object

YOLO Mark is the tool which is used for producing such labels and text files.

VI. METHODOLOGY

In this section the fundamental components of the software architecture are explained in detail along with the training of Mörr network.

A. Base Controller System

The base controller is Pixfalcon PX4 with latest Rover firmware version stable-3.6. The Mörr platform can be op-

erated in three different modes *manual*, *manual with collision avoidance* and *autonomous with obstacle avoidance*, the corresponding modes in PX4 are MANUAL which allows RC, MANUAL with RC override which allows joystick drive and GUIDED. The PX4 controller uses vision based position and orientation rather than its internal filtered IMU which is not suitable in indoor as heading has sporadic errors. The PX4 uses odometry from the 2D LiDAR scan match when RC messages are overridden by joy stick during manual with collision avoidance. And in the case of GUIDED mode the odometry is similar to the odometry used in local planner or SLAM which is either based on OctoMap or Hector map selection. In upcoming Mapping section this is explained with further details.

B. Localization

One of the essential methods for position estimation of an autonomous system is odometry/dead reckoning. In ROS, odometry message comprises of position, orientation and twist (linear and angular velocity). The message represents the transformation of the base link frame of the mobile system viewed from the odometry frame. The odometry message is published in odometry frame (*odom*) as the message itself the transformation of the base link observed from odometry frame. However, the odometry has gradual error accumulation when the robot moves over the time. This gradual drift in odometry is compensated as a transform message from map to odometry frame and most of the SLAM techniques based on feature or grid-based will provide this transform.

In this architecture the state estimation of the UGV is based on cascading the odometry locally and globally from different modalities. The scan-match odometry from 2D LiDAR scan data at 40Hz and filtered IMU data from xsens is fused with *local_ekf_localization* node which provides robust local state estimation of UGV at local frame. Finally this odometry message is used by local planner in navigation stack. The *navsat_transform_node* provides odometry message which takes heading of the UGV from IMU and fused odometry message from *global_ekf_localization* node. It finally provides odometry message which is cascaded with *global_ekf_localization* along with GNSS and odometry message from *local_ekf_localization* node. The resultant state estimation from *global_ekf_localization* node is published in consistent with UGV's world frame is highly accurate state of the UGV in world frame.

C. Mapping

SLAM is a technique used to localize the mobile system and generate a physical map of the environment simultaneously. And this is always considered to be a complex problem because for mapping the environment a good estimate of the robot's location is needed and to localize a robot, a consistent map of the environment is required. Hence, there is mutual dependency between the estimates about the pose of the robot and the map of the environment. As the task does not require dense model of the environment, we have adopted

occupancy grid method rather dense 3D SLAM approaches. In this architecture there are two mapping capabilities. The OctoMaps were used to generate 3D occupancy grid which is more computationally efficient to generate rather graph based RGBD-SLAM such RTAB-Map which is GPU intensive and computationally its not efficient for the given task and storage consumes more space. The OctoMaps are generated from the 3D scan data from velodyne and the projected grid map is used for global and local path planning.

Fig. 4: 2D Hector Map(Top) and 3D OctoMap(Bottom) of the warehouse

In addition to this graph based 2D LiDAR Hector map is used by local planner to avoid obstacles more computationally effective and faster when the global planner is carot planner, this is used when the base controller in MANUAL mode and overrides by joystick. The base link frame of UGV is stabilised with IMU and it uses scan match odometry generated from 2D LiDAR scans, no EKF fusion is performed from other modalities for Hector SLAM. This promises faster convergence of estimation for mapping compared to EKF based SLAM. As the frequency of the 2D LiDAR is 40Hz the system can generate robust map even in long corridors more accurately in large warehouse with corridors larger than 15 meters. The Figure 4 depicts both 2D and 3D maps generated by Hector Map and OctoMap. Also the hector map testing in GUIDED mode boosted the performance of local planner for the navigation because of significant reduction in CPU load with same controller and planner frequencies. Overall, both the mapping has different advantages from convergence of local planner, computation and projection of 3D obstacles stand point.

D. Navigation

This is the most crucial part of the overall architecture of Mörr, UGV. Time Elastic Band (TEB) [13] local planner is used for dynamic obstacle avoidance in Mörr. TEB provide multiple path with different topologies which are time optimal solutions. However, TEB solves for unconstrained

optimization problem which is much faster than constrained optimization problems, the performance of TEB is based on size of the map, size of the obstacle (polygon or circle) and computational power. In this system the parameters are tuned for optimal results considering the computation power with maximum CPU load of other packages and achieving maximum speed for completing the task faster. The maximum velocity achieved was 0.7m/sec - 1.2m/sec along x-axis without compensating the performance of the controller's stability. Figure 8 show the local and global path generated by planners in different scenarios. Navigating in tight corners is much easier with circular footprint as most of the unconstrained problem is now convex optimization problem with smooth costmaps.

E. Object Detection

To perform object detection, we use the data-sets that provides information about the fire simulator through the camera. The objects are detected using the information from the Realsense D435i camera, then they are classified and the distance of the object relative to the Mörrri is measured. The object detection is attained using the integration of feature based and appearance based modeling. As compared to other sensors the images from the camera have more information that can be used to identify objects.

There are plenty of convolutional neural network(CNN) architectures that performs object detection method using feature extractor which are performed better than other methods, this shows development in object detection. During the training process CNN learns the features in object and it can also generalize the object feature. Here, we used existing method which is Darknet object detection and it uses a hierarchical dimension of object classification[1]. Using this method we trained Mörrri Object detection network that can detect targeted objects in real-time. Figure 5 shows the real-time detection from Mörrri view with the bounding boxes. To find the depth of the object we used depth frame in realsense D435i, we overlapped the bounding box parameters from RGB frame to depth frame to find the depth parameter of the targeted object.

Fig. 5: Trained Mörrri network can detect fire simulator and soft ball(Mörrri Camera View)

F. Training Network

To analyse the quality and other attributes of FSB data-set, we utilized widely used open source neural network

framework Darknet. The darknet model is trained with high resolution images and shown promising results in object recognition. Figure 6 shows the average training loss of 0.1351 for 4000 iterations on Mörrri network which got trained using FSB data-set.

Fig. 6: Plot for average training loss of 4000 iterations

Again under training the model we developed networks with different training regimes, parameters or data-sets, which can also be train depends on system architecture. The Mörrri network consists of 19 convolutional layers which got modified with the extraction to be faster with high accuracy. The other parameters for training such as batch size, subdivisions, iterations, etc., are decided based on the number of classes i.e 2 in this task. However, performance rises significantly as the IOU threshold decreases indicating promising results to get the boxes perfectly aligned with the object[1].

VII. EXPERIMENTAL RESULTS

All the network is trained with the identical parameters and tested at 512 x 512, the Mörrri network which is suitable for high end system architecture and it gives mean average precision of 90.89% with ~ 32 FPS, on the other hand it might affect the processing speed of low level configuration system, because it has plenty of layers in its network, Table II shows the mean average precision of three different networks. To overcome the processing speed issue we developed some other networks which have less number of layers and its very precise for low level architecture with mAP of 86.16% with ~ 25 FPS. During the test we experimented the object detection under different scenarios and distance, we could see promising results under different lighting conditions with distance of $\sim 6-7$ metres. The visualization of 3D bounding boxes were perfectly aligned with the map frame in proper time synchronization[15]. Figure 7 illustrates the real world implementation for Mörrri's autonomous navigation, it navigates in the local path generated by TEB planner in GUIDED mode by generating way-points of the target in real-time.

TABLE II: Three Networks trained for different system architecture

Network	Object	Average Precision	mAP
Mörri	Fire Simulator	90.91%	90.89%
	Soft Ball	90.87%	
Copter	Fire Simulator	84.72%	86.16%
	Soft Ball	87.59%	
Tiny	Fire Simulator	84.79%	85.76%
	Soft Ball	86.73%

Fig. 7: Real world implementation of Mörri's navigation

Some of the results from object detection and navigation visualization is shown in Figure 8 where 3D bounding boxes in different colors represent different classes. In the bottom image of Figure 8 which is showing two different object got detected in the same frame, in that you can see difference in cost map which doesn't show for soft ball, especially the small objects. This is the reason we showed marker visualization for object detection so that it reduces the collision. Finally, the overall results are provided and accomplished the task specific object detection and autonomous navigation in real-time has been achieved successfully and demonstrate with the Mörri UGV robot.

Fig. 8: Detected objects as markers in Rviz and TEB local planner solutions for target way-points

VIII. CONCLUSION

In this paper, we have successfully presented a working system for task-oriented autonomous UGV navigation with obstacle avoidance and object detection in a large warehouse. In future, overall brain node that contains the actions and plans for mapping the area autonomously and planning and scheduling other task should be implemented and also implementation of semantic segmentation to find the exact boundaries of the target.

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