

Design and Implementation of BBAUV 3.5

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Abstract - Bumblebee 3.5 is the product of a team of undergraduates from the National University of Singapore (NUS). This vehicle is upgraded from 3.0 with considerations for RoboSub and Maritime RobotX. Specifically for Robosub, Bumblebee 3.5 aims to complete the tasks by banking on our key strengths: Acoustics Localisation, Waypoint Navigation, and Object Detection using Sensor Fusion. Given the increased difficulty of the tasks, Bumblebee 3.5's software stack is improved with new software frameworks, to include a revamped mission planner and integration of deep learning algorithms. This paper discusses their integration and performances on the 3.5.

I. COMPETITION STRATEGY

Our team's approach towards the competition is to play to our strengths; we are fully utilising our proven acoustics system to localise to pinger tasks and relying on our imaging sonar to consistently detect objects in poor visibility. These are complemented by a highly accurate waypoint navigation.

A software overhaul was also implemented to reinforce our vehicle's autonomous capabilities. This year, we have integrated new Machine Learning techniques into our perception suite to complement our traditional computer vision techniques for more reliable detection of complicated features. We have a new Mission Planner UI to improve on our work process for flexible and fast UI based mission planning by minimising coding errors during time sensitive competition runs. Our Control Panel is also refined for easier on-site debugging. We also made improvements to our dynamic positioning capabilities and control systems to hover the AUV steadily over the tasks and maintain very accurate headings for x/y maneuvers.

In order to support these changes, the hardware for Bumblebee 3.5 was also modified to ensure reliability for reduced downtime and guarantee maximum runtime during testing and the competition. Our biggest upgrade this year comes in the form of more powerful thrusters to strafe better and fight strong sea currents.

The initial aim was to complete all the tasks in Robosub 2018. However, due to difficulty in designing an all-in-one grabber/dropper mechanism and the need to provide the software team with at least 3 months of testing time in water to complete the software overhaul, the manipulation system at the point of writing this paper is ill-fitted to attempt the "Buy Gold Chip" task. Hence the decision is to skip that task while focusing on the completion of the other tasks due to our AUV's improvements.

II. DESIGN CREATIVITY

A. ACOUSTICS SUB-SYSTEM

The acoustic sub-system features several enhancements that increase the robustness of the existing system and its overall performance.

i. Custom Signal Conditioning PCB

A new signal conditioning PCB has been developed to further improve the Signal-to-Noise Ratio (SNR) of the system. It includes an enhanced pre-amplifier and bandpass filter.

ii. Enhanced ping extraction algorithm

Before the DOA is computed using the Multiple Signal Classification (MUSIC) algorithm [1], the incoming ping is extracted using Short-Time Fourier Transform (STFT) with a newly introduced dynamic thresholding method that vastly improves the susceptibility of the acoustics system to noise. This allows

the AUV to localize acoustic sources from longer distances and in noisier environments.

B. SOFTWARE SUB-SYSTEM

The new features in the software overhaul were designed with considerations for usability and smooth integration. These changes also help our new software members adapt and learn quickly.

i. Software Architecture

The software architecture was redesigned to minimize coupling, while maximizing cohesion. This enhances maintainability, extensibility and optimizes performance. In particular, the perception system is coupled to mission only via a ROS service, to request for object detections, and a ROS topic, to relay detections.

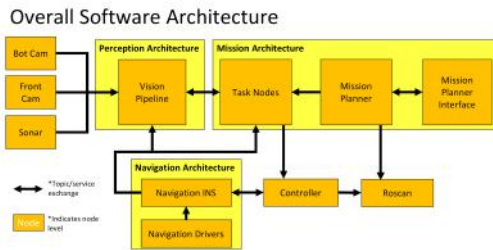


Fig 1: Overall software architecture

Inside vision pipeline, there are 3 main classes: Preprocessor, Detector and Tracker. The specific algorithms for various objects are abstracted, and the vision pipeline calls standard functions that are overridden by the children of the main classes. This design makes the vision pipeline very generic, allowing new object detection algorithms to be easily implemented on top of it.

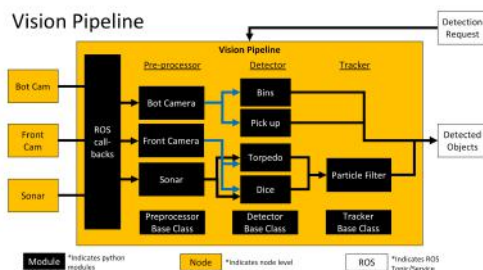


Fig 2: Vision pipeline

ii. Mission Planner Structure

The mission planner had been abstracted to reduce complexity and increase efficiency.

This also allows for the integration of a new mission UI to aid the user in planning missions. Due to the time sensitive nature of competitions, as well as in other operational situations, changing the code of the mission planner while being pressed for time has proven to be a risky maneuver as the user is prone to mistakes like syntax errors.

Integrating a new mission UI with the mission planner allows for the user to easily scan through the mission path through the graphical user interface while allowing the user to select from many predetermined missions to be run on the fly.

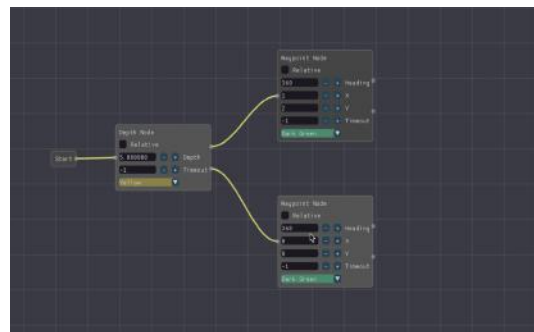


Fig 3: Interactive mission planner

It is integrated with a mapper, with important sonar features overlaid, enabling waypoints to be easily identified and set as shown in Fig. 3.



Fig 4: Interactive mapper

iii. Control Panel

The AUV control panel was developed to allow ease of on-site debugging and keyboard controls of our AUV. The control panels boast several features such as: personal configurations, camera and sonar windows, vehicle status and controller and actuation controls.

iv. Control System

Six Proportional Integral Derivative (PID) control loops have been used to control the vehicle's six degrees of freedoms.

In order for the AUV to adapt to different movement speeds, adaptive PID controllers were introduced for surge and strafe control loops, allowing for the different gains to be selected according to different setpoints.

v. Navigation Suite

The navigation sensor suite consists of a 9 axis Sparton IMU, a 6 axis STIM300 IMU, a DVL and a barometric pressure depth sensor. All the sensors are interfaced and integrated with the rest of the system over the ROS IPC framework. The data from each sensor is fused to obtain independent state data. Error state Kalman Filter is used to obtain much higher accuracy than each sensor can provide independently. This is notably more robust and suitable for dynamically changing states than the traditional full-state KF, which has inherent assumptions of vehicle motion behaviors in the state equation setup. Since error variables are used as the state vector, nonlinearities can be cancelled. In addition, motion assumptions are not necessary in formulating the state equations.

Utilising the filtered output from the sensor suite, the AUV is able to localise itself in the relative frame. By setting a predetermined origin, the local coordinates of the AUV are transformed into the global frame providing the AUV the ability to do waypoint navigation using geographic coordinate system.

vi. Perception Suite

Robustness and accuracy are two problems commonly faced in perception. Two approaches were taken to tackle these problems.

- Deep learning

Deep learning is used to detect more complex obstacles, such as dices and torpedo board. The algorithm was built upon Tensorflow Object Detection API [2] to utilise the wide variety of models implemented. Due to limited computing power and the absence of a GPU, we used the MobileNetV2 with SSDLite [3] model.

Data was collected almost daily to ensure a good mix of conditions. The data was then split into 3 groups: train, validation and

test. To prevent overfitting, data obtained on the same day are placed in the same group. A total of 1,767 train images, 408 validation images, and 644 test images were collected.

Annotation was done using BBOX-label-tool [4] and converted into a TFRecord file readable by the API. Transfer learning was applied onto the pretrained model to fine tune it. Training was stopped when the validation loss is minimized.

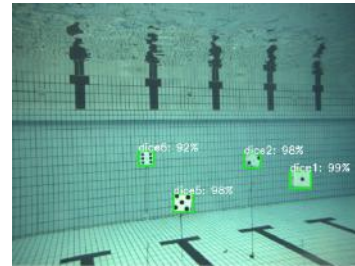


Fig 5: Dice detection

- Sensor fusion

Even with deep learning, it is still challenging to detect various objects using camera due to poor visibility underwater. However, they can be easily detected with a sonar. The AUV is equipped with a forward-looking sonar, which can provide range and azimuth of the objects from the vehicle, but not the depth, which is provided by the camera. To mitigate the sensors' individual shortcomings and increase the accuracy of detection, a particle filter was implemented, fusing data from the front camera and sonar. [5]

Initially, objects are first detected from the sonar, and the variance of particles in the z axis is large because of the unknown depth. These particles are then projected onto the camera, and particles which falls within a detection region have higher weights. This causes the particles to converge about the correct depth.

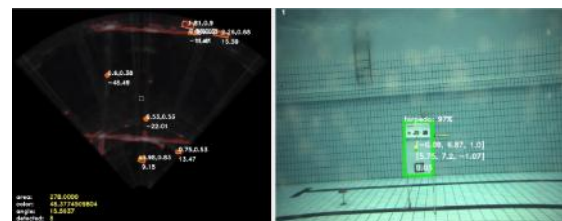


Fig 6: Sensor fusion with imaging sonar

Also, building on the navigation system, the particles are stored in world

coordinates so it is minimally affected by vehicle movements.

C. ELECTRICAL SUB-SYSTEM

Our electrical architecture was updated to cater to our hardware upgrades and to improve on reliability.

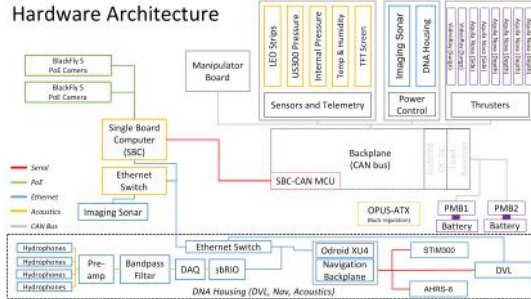


Fig 7: Hardware architecture

Ethernet and CAN are our primary methods of communication for high and low-level components respectively, allowing for ease of adding new peripherals.

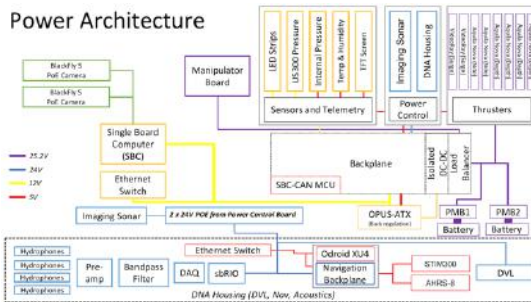


Fig 8: Power architecture

i. Backplane + Daughterboards

Our electronics in the main hull still employs a backplane system, whereby it distributes power to each of our daughter boards and provides the Controller Area Network (CAN) bus that is used for low-level communication between them. In this iteration, we also integrated a new Quad-FTDI circuitry on the backplane, allowing us to reprogram firmware of multiple daughter boards with a single USB cable. This improvement allows us to easily swap out faulty daughter boards, while allowing the on-the-fly programming, increasing the reliability and usability of our system.

Our daughter boards consist of the Thruster Board, Sensors and Telemetry Board, and an all-new Power Control Board, which controls the power of all peripheral sensors while embedding various protection circuitry. This allows a faulty peripheral to be shutdown

safely, while the rest of our system is able to continue running, minimising downtime due to hardware faults.

ii. Propulsion System

Our eventual aim is to deploy an AUV-ASV system in open seas for RobotX and other real-world situations, thus the propulsion system was upgraded to improve performance in higher sea states. We selected thrusters with higher thrust output and power efficiency, while maintaining the same thruster configuration as our previous vehicles, as it has proven to work well.

iii. Single-Board-Computer (SBC)

In anticipation of the implementation of more computational heavy algorithms, the main SBC has been upgraded to host a new 7th generation Intel Core i7 processor. We also swapped out the unreliable USB-FTDI circuitry with RS232 for the SBC to transmit and receive data with the CAN bus.

iv. Camera Change

We also migrated from firewire to Power over Ethernet (PoE) cameras, using a PoE expansion daughter board attached to the SBC. This eliminated the bulky firewire interface cards, reduced the susceptibility of the camera feeds to interference and featured more reliable auto-exposure and better image reproduction. The bottom facing camera is also fitted with a 102.8° FOV lens to capture more area of the seabed.

v. Power Management Board (PMB)

The PMBs are redesigned to cater for the higher power draw of our vehicle. The PMOS that controls the main power line to the vehicle is substituted to one with a higher current rating and larger footprint to improve heat dissipation. A current monitoring IC was also used to provide more accurate current readings. The PCB was also imported into our battery pod CAD to ensure optimisation of space.

D. MECHANICAL SUB-SYSTEM

We designed a new grabber that is lightweight and has a small form factor. The only motion required is extending the grabber

downwards using a pneumatics powered linear actuator; no additional actuation is required to collect the balls. This grabber consists of a case and two cable ties. When pressed down against the balls, they slip behind the cable ties and are trapped inside the case. They are ejected when the grabber retracts. This mechanism merely requires the vehicle to perform a single downward motion, thus reducing possible errors during the process, improving the success rate of grabbing the balls.

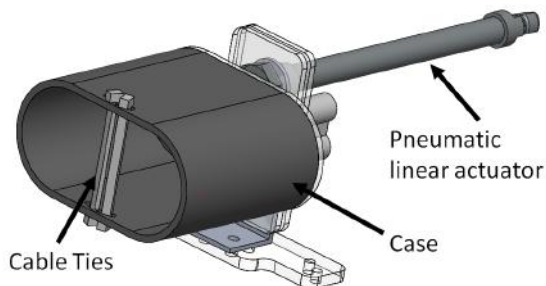


Fig 9: Grabber manipulator

III. EXPERIMENTAL RESULTS

i. Navigation Suite

The current navigation system was benchmarked for inertial navigation to evaluate the performance of the filter over distance. The filter's calculated positions were compared to coordinates in Google Maps and measured for the returning offset in position due to drift. As of time of writing, the system was evaluated over 176 meters and accrued a drift of 2.86m with 1.62% of the distance travelled.

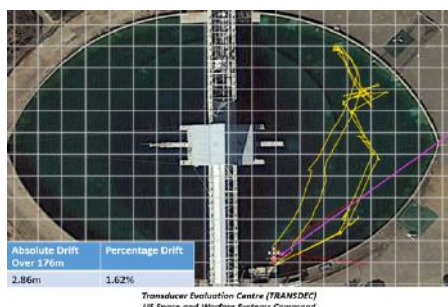


Fig 10: Navigation benchmark at Transdec

ii. Dynamic Positioning Performance results

To ensure smoother controls, the thrusters were tested in-water with a custom thruster measurement jig to verify the thrust satisfies our requirement to do dynamic positioning (DP) against open sea currents. The maximum thrust of the surge thrusters was measured to be 8.12kgf, and the downwards and

sway thrusters at 3.5kgf, which was an increase of around 50% of thrust compared to our old Seabotix thrusters measured to be at 2.14kgf.

With the more powerful thrusters, the adaptive PID controllers implemented are able to utilise the more powerful thrusters to move faster to reach setpoints further away while maintaining a steady state error of less than 3 degree in roll, pitch and yaw.

iii. Deep learning performance

The trained model is evaluated on the test set once, after it is exported for inference. The average precision for each object, as well as the mean average precision (mAP) are calculated.

Dice1	Dice2	Dice5	Dice6	Torpedo	mAP
0.912	0.842	0.949	0.966	0.998	0.933

Table 1: mAP of test set

The mAP result of 0.933 seems promising, but the downside is a slow inference speed of 3Hz and the possibility that it might be overfitted to images taking in our testing pool and it might not work as well at Transdec. More training will be done on-site.

iv. Robosub preparations

During the summer break, we have pool tests every day of the week for roughly 7 hours a day on weekdays and 3 hours on the weekends. The vast majority of our electrical and hardware systems were done before the summer and we have been working on the competition tasks. Additionally, we have also conducted trials at sea on Wednesdays with our AUV in conjunction with our ASV (autonomous surface vehicle) testing.

IV. ACKNOWLEDGEMENTS

Team BumbleBee would not have been where we are today without help from various organisations and people.

We would like to express our deepest gratitude to our sponsors, including our Title Sponsor - NUS, and our Platinum Sponsors - DSO National Laboratories, ST Engineering, and MacArtny Underwater Technology.

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Appendix A: SPECIFICATION OF BUMBLEBEE AUV 3.5

Component	Vendor	Model/Type	Specs	Cost (if new)
Buoyancy control	BlueRobotics	Subsea Buoyancy Foam - R3312	Density: 12 lbs/ft ³ / 192 kg/m ³ Specific Gravity: 0.19 Tested Depth (uncoated): 300 ft	USD94
Frame	Misumi Automation Systems Pte Ltd Cititech	Material: Acetal Copolymer, Stainless Steel 316 Fabrication: CNC	<u>Acetal</u> Density: 1.41 g/cm ³ Strengths Tensile: 9500 psi Flexural: 12,000 psi Compressive: 15,000 psi	SGD900
Waterproof Housings	Achieve Engineering Feimus Engineering	Material: Black Delrin, Aluminium 6061-T6 Fabrication: CNC	<u>Black Delrin</u> Density: 1420 kg/m ³ Yield Stress: 72 MPa Yield Strain: 22 MPa	SGD1000
Waterproof connectors	SubConn	Assorted Micro and Low Profile Series	Depth rating PEEK: 300 bar, 4,350 psi	
Thrusters	Videoray	Pro 4	4.8 kgf thrust @ 12V 200W consumption	
	ROVEEE	Brushless Thruster	3.6 kg-force thrust 122 watts consumption	SGD1440
Motor Control	Tekin	RX8	Forward/Brake/Reverse Input Voltage: 6S LiPo Max Current: 300A Burst Current: 1000A	USD136
High Level Control	Atmega	Embedded Atmega2560 & Atmega 328		
	National Instruments	sbRIO-9606 Embedded Device		

		NI-9223 Analog Input Module		
	Odroid	XU-4	Samsung Exynos5422 Cortex™-A15 2Ghz and Cortex™-A7 Octa core CPUs 2Gbyte LPDDR3 RAM PoP stacked eMMC5.0 HS400 Flash Storage	
Actuators	Festo (Pneumatics)	VUVG-L10- P53C-T-M5- 1P3	5/3 Way Solenoid Valve 3-8 bar	-
	Ninja (Gas Tank)	MHE2-MS1H- 5/2-QS-4K	5/2 Way Solenoid Valve 0.9-8 bar	
	PalmersPursuit (Output Regulator)	Ninja Paintball Aluminum HPA Tank	3000 PSI 13 Cubic Inch	
		Female Stabilizer Co2 Air Pneumatic Regulator, Adjustable 0- 250 psi output	0-250 PSI Output	
Battery	Revoelectix	XHSA10000	6 Cell 10000mAh	
Regulator	OPUS	DCX1.250 250W ATX PSU	250W	
	Murata	UWQ-12/17- Q48PB-C	204W Isolated 24V-12V DC-DC Converter	
		UVQ-24/4.5- D24P-C	108W Isolated 24V-12V DC-DC Converter	
CPU	Aaeon	GENE-KBU6	Intel Core i7-7600U 16GB DDR4 RAM 512GB mSATA Mini SSD	SGD818
CPU Daughter Board	Aaeon	BIO-ST03- P2U1	Intel® i210, 10/100/1000Base-TX x	SGD118

			2 (Supports PoE 802.3af) USB 3.0 x 1	
Internal Comm Network	In-House	Controller Area Network	1000Kbps	
		Ethernet	1000 Mbps	
External Comm Interface	In-House	Ethernet	1000 Mbps Ethernet tether	
Programming Language 1	C++			
Programming Language 2	Python			
Inertial Measurement Unit (IMU)	Sparton	AHRS-8	Dynamic Heading Accuracy 1.0° RMS Static Heading Accuracy 0.2° RMS Heading Repeatability 0.1° RMS Dynamic Pitch/Roll Accuracy 1.0° RMS Static Pitch/Roll Accuracy 0.2° RMS Pitch/Roll Repeatability 0.1° RMS Pitch/Roll Range ±90°, ±180° Accelerometer Range ± 4g or ± 8g (± 1g) Gyro Dynamic Range ± 480°/sec (± 300°/sec) ² Magnetic Range ±1.2 Gauss (±900 MGauss) ² Maximum Magnetic Inclination (Dip) ± 80°	
	Sensoror	STIM300	0.3 °/h gyro bias instability 0.15 °/√h angular random walk ±400 °/s angular rate input range 10 °/h gyro bias error over temperature gradients 0.05 mg	

			<p>accelerometer bias instability</p> <p>± 10 g acceleration input range</p> <p>3 inclinometers for accurate levelling</p>	
Doppler Velocity Log (DVL)	Teledyne Marine	Pathfinder	<p>600kHz Phased Array DVL</p> <p>Maximum Altitude 89 m</p> <p>Minimum Altitude 0.2 m (<20 cm altitude mode available)</p> <p>Velocity Range ± 9 m/s</p> <p>Long Term Accuracy $\pm 0.2\%$ ± 0.2 cm/s</p> <p>Long Term Accuracy $\pm 1.15\%$ ± 0.2 cm/s</p> <p>Precision @ 1 m/s ± 0.5 cm/s @ $\frac{1}{2}$ alt.</p> <p>Precision @ 3 m/s ± 1.5 cm/s @ $\frac{1}{2}$ alt.</p> <p>Precision @ 5 m/s ± 2.3 cm/s @ $\frac{1}{2}$ alt.</p> <p>Resolution 0.01 mm/s (0.1 cm/s default)</p>	USD15000
Camera(s)	FLIR	BFS-PGE-31S4C-C	<p>2448 x 2048 at 22 FPS</p> <p>Sony IMX264 CMOS</p> <p>Global shutter</p> <p>Color</p> <p>C-mount</p>	SGD850
Acoustics Embedded Platform	National Instruments	sbRIO-9606	<p>Processor: 400 MHz PowerPC</p> <p>FPGA: Xilinx Spartan-6 LX45</p> <p>DRAM: 256 MB</p> <p>Storage: 512 MB</p>	
Acoustics Voltage Input Module	National Instruments	NI-9223	<p>Voltage Range: ± 10 V</p> <p>Sampling Rate: 1 MS/s</p> <p>Channels: 4</p> <p>Resolution: 16-bit</p>	
Hydrophones	Teledyne Reson	TC4013	<p>Usable Frequency range: 1Hz to 170kHz</p> <p>Receiving Sensitivity: -211dB ± 3dB re 1V/μPa</p> <p>Transmitting Sensitivity: 130dB ± 3dB re 1μPa/V at 1m at 100kHz</p>	

			Horizontal Directivity Pattern: Omnidirectional $\pm 2\text{dB}$ at 100kHz Vertical Directivity Pattern: $270^\circ \pm 3\text{dB}$ at 100kHz	
Sonar	Teledyne Blueview	M900	Field-of View 90° Max Range 100 m Optimum Range 2-60 m Beam Width $1 \times 20^\circ$ Beam Spacing 0.18° No. of Beams (90, 130 FOV) 512 Range Resolution 1.3 cm Update Rate within Optimum Range Up to 25 Hz Operating Frequency 900k Hz	
Manipulator	In-House	-	-	-
Algorithm: Vision			Thresholding Particle filter Machine learning	
Algorithm: Acoustics			Multiple Signal Classification (MUSIC) Localization with Short- Time Fourier Transform (STFT) based Ping Extraction	
Algorithm: Localisation and Mapping			Error State Kalman Filter	
Algorithm: Autonomy			ROS SMACH	
Open source Software			OpenCV, ROS, Tensorflow Object Detection API	
Team size	29			
HW/ SW expert ratio	7:3			
Testing time: simulation			2 hours a day	
Testing time: in-water			328 hours	

Appendix B:

Team Bumblebee strongly believes in public outreach and we try our best to engage people from different communities. Through exhibitions and lab tours, we explain and showcase our technology, so that more people can better understand our vision.

A. PUBLIC SHOWCASE

During the past year, we participated in Singapore Week of Innovation and Technology (SWITCH) in 2017 and Innovfest Unbound in 2018, which aim to showcase the latest development in technologies and innovations to the public. Through this, we are share with members of public more about autonomous systems.



Fig 11: SWITCH event

We also participated in the Singapore Civil Defence Force (SCDF) Workplan Seminar 2018, where we gained the opportunity to share about the potential of using underwater robotics in their search operations.



Fig 12: SCDF Workplan seminar

We also participated in different University showcases, which we exhibited our AUV to students from all Junior College students, freshmen, senior year students as well as industrial

partners to increase the awareness of the potential of our autonomous systems especially considering the fact that Singapore is an island being surrounded by water.



Fig 13: Junior college showcase

B. LAB TOUR AND SHARING SESSION

Team Bumblebee was one of the projects being featured for the Innovation Mission Robotics to Singapore which consists of delegates from the Dutch Embassy as well as representatives from various Dutch robotics companies.

We also hosted City University Underwater Robotics, one of the oldest underwater robotics team in Hong Kong, to visit us during their visit to Singapore, where we exchanged and gained from each other's experiences.



Fig 14: City University Underwater Robotics visit

We also welcome any teams that happen to be in Singapore for a visit of our lab! You are able to arrange for a session at bumblebeeauv@gmail.com.

In addition to hosting lab tours, we have organised an industrial tour to Fugro Subsea Technologies. We were given a tour around their hangar of their fleet of ROVs and AUVs, where team members gained a first-hand exposure to the practices and techniques adopted by industries. We also took part in design review session with them, gaining valuable insights to approach the design of our autonomous systems.



Fig 15: Fugro subsea technologies visit

C. HORNET

Since its inception 2 years ago, the Hornet Training Program has evolved to a staple element of our training of newer members. Through this program, we provide new members a platform to build an AUV to compete in the Singapore AUV Challenge. The main aim of this programme is the challenge the team to explore and implement bold designs instead of trying to replicate what others have achieved successfully.



Fig 16: Hornet team 2017

Appendix C:

OUR SPONSORS

Title Sponsor

• NUS (Faculty of Engineering, School of Computing, Advanced Robotics Centre, Engineering Design and Innovation Centre, Department of Mechanical Engineering, Department of Electrical and Computer Engineering): For their cash support, equipment procurement, and academic support in our project.

Platinum Sponsor

- DSO National Laboratories: For cash support and technical guidance
- ST Engineering: For cash support
- MacArtney Underwater Technology: For provision of underwater connectors and potting services

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- Teledyne Reson
- National Instruments

Supporting Organisations (Resources)

Republic of Singapore Yacht Club (RSYC), Sports Singapore, NOAA Southwest Fisheries Science Center (SFSC), Sentosa Development Corporation (SDC)

Supporting Organisations (Equipment)

Deep Sea Power and Lights, Southco, Tekin, SeaBotix, Samtec, Aquila Nova, Techkinetics, MV Asia Informatix Pte Ltd, Sterling Comms