Corner Features Extraction: Part of Simultaneous Localisation and Mapping for an Autonomous Underwater Vehicle

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Abstract: Simultaneous Localisation and Mapping allows a mobile robot to map the environment and concurrently localizes itself within the map.The main contribution of this research work is the application of a sliding window technique to extract corner features from acoustic images using Mechanically Scanned Imaging Sonar. The sliding window technique has traditionally been applied to laser data obtained in indoor environments. The change in application environment and the use of Mechanically Scanned Imaging Sonar data have motivated important differences with respect to the original algorithm.

Keywords: Corner features, Feature extraction, Sliding Window Corner Detector

1. Introduction

Simultaneous Localisation and Mapping (SLAM) is a process by which a mobile robot maps the environment and concurrently localizes itself within the map. An Autonomous Underwater Vehicle (AUV) is a robotic vehicle with actuators, sensors and on-board intelligence to carry out a mission without human interference. SLAM allows a mobile robot to start at an unknown location in an unknown environment. SLAM relies on the feature extraction process to extract appropriate and reliable features with which to build stochastic maps. Feature extraction is a process by which sensor data is processed to obtain well defined entities (features) which are recognisable and can be repeatedly detected [14,15]. Underwater navigation is especially challenging because of the limited sensorial modes. Acoustic devices are the most common choice in underwater domains while the use of cameras and laser scanners is limited to applications where the vehicle operates near the surface, in clear waters or very near the sea floor [3]. Underwater SLAM systems using Mechanically Scanned Imaging Sonar (MSIS) usually model natural environments as point features corresponding to clusters of acoustic data [4,5,6,7]. Line feature extraction to take advantage of structured elements common in underwater scenarios like marinas, drilling platforms, harbours, channels, dams e.t.c. using MSIS has been reported in [4,11]. Other feature types in underwater environments have also been reported; Harris corners from cameras images [18, 19], SURF features using stereo vision [20], generalized features (blobs) by fusing camera and sonar data [21]. Something that this author found missing in underwater literature is a stochastic map or environment model based on the use of corner features from underwater acoustic data. Also missing in literature is a method to extract corner features from underwater acoustic data. Although MSISs have been used in the extraction of point features and line features, they have not been used for the extraction of corner features. The use of corner features has been traditionally related to the use of 2D laser scans in indoor environments using sliding window techniques [22, 23]. Extraction of corner features corresponding to intersecting arcs from a ring of Polaroid sonar sensors using Hough transform in an indoor environment was reported in [24]. Structured man-made underwater environments such as marinas, drilling platforms, harbours, channels and dams are not unusual environments for AUVs especially during inspection and maintenance missions. New types of features such as corners, planes and curves could offer richer representations of the environment and hence open the door for underwater SLAM systems to a wide range of environments and applications [3].

This paper describes the use of a sliding window corner detector to extract corner features from real data scans collected in a swimming pool using MSIS. The data was first segmented; this filters out the noise without loss of significant information and reduces the computational cost of processing the data. The vehicle was equipped with a MSIS which is able to perform user selectable scan sectors up 360 degrees [8].

2. Sonar theory and Operation

MSIS performs user selectable scan sectors up to 360 degrees in a horizontal 2D plane by continuously rotating a mechanically actuated transducer head at pre-defined angular increments in a process called imaging. For each of the resulting angular positions, an acoustic fan beam is produced; this fan beam has a narrow horizontal beam-width and a wide vertical beam-width. When the emitted acoustic signal travels through the water and encounter an object in its path, part of the energy returns to the transducer. Using the time of flight of the returning wave and the speed of sound in water, the range at which the signal originated can be determined. If the signal returning to the transducer head is analysed for a period of time, a series of echo amplitude vs. range measurements are produced. Each individual measurement is referred to as a bin, and the set of bins obtained from a single emitted wave is called a beam. An acoustic image of the environment is formed by accumulating this information along a scan sector [1, 3].

2.1 Sonar noise characteristics

- **Transducer reverberation noise**: When the transducer is energised and transmits the sound pulse (e.g. piezoelectric effect), the transducer continues to oscillate for a period of time until these oscillations die out completely. This would be evident out to 2m from the sonar head [16].

- **Receiver Self Noise**: This is very low level background noise which is apparent in any tuner/mixer circuit. It is a low level audible hiss that will be amplified by the sonar gain application. The Micron DST Sonar used in this research has a very good signal-to-noise ratio; hence this background noise level is relatively very low and requires considerable gain to be amplified to a level that becomes obstructive to sonar imaging. A threshold value above zero would normally be set to eliminate this background noise [16].

- **Backscatter**: This is energy returned or reflected back to the receiver off any reflective object in the near vicinity. This can be any imagery on the display excluding any receiver self noise, transducer reverb noise or pickup from another acoustic device [16].

- **Aeration in the water**: Any small air bubbles (may not be visible to the naked eye) in close vicinity of the sonar will reflect the sound beam and appear as low intensity background wash on the image. This may be due to moving targets or if the swimming pool has an operative filter [16].

2.2 Interpretation of acoustic images

In some cases an acoustic image of a target will be similar to an optical image of the same target. Due to the nature of the ultrasonic signals, an acoustic image will always have less resolution than an optical image and hence it may be difficult to interpret acoustic images [1 & 3]. Darker areas depict no echo return and lighter areas shows high echo intensity returns from objects. Generally hard surfaces are good reflectors of acoustic energy; they do not absorb too much energy and one expects strong echo returns from these types of surfaces. The image contains receiver self noise which appear as low intensity returns, transducer reverberation, aeration which appear as low intensity background wash and backscatter [16]. Multiple reflections continue out to the maximum operating range and decrease in intensity as the range increases. Water surface reflections appear as low intensity circular returns equidistant from the sonar head. What is seen less than 2m from the transducer is some reverberation noise, this is evident out to 0.6m. Other reflections are ambiguous and difficult to make out [16].

Having a couple of objects located within an enclosed environment further complicates the image; the result is that the transmitted sound pulse may bounce off a number of surfaces before returning to the sonar. Filtering out these multiple reflections is a tedious process; they are not so easy to remove automatically. In those situations one may only be able to clean the image so much, leaving walls and targets reflections and also some multiple reflections in with that. There is a TVG look-up table already programmed into the Micron which automatically applies gain correction for through water attenuation. This applies around a 0.2dB/m attenuation correction for the 700 kHz transmit signal of the Micron DST. The problem of signal attenuation depends on the water and target conditions [16].

2.3 Decoding MSIS scan-line data

The sonar beam consists of a series of N_s echo amplitude bins with either 4 or 8 bit resolution. Assuming the sonar is configured to sense objects up to a maximum range R_s, the n^{th} echo amplitude bin is mapped to a discrete range r_n from the transducer head according to:

$$r_n = n\delta_r \tag{1}$$

, where δ_r is the sample range and it is given by:

$$\delta_r = R_s / N_s \tag{2}$$

This echo amplitude vs. distance information is used to detect features and obstacles within the environment [2]. Figure 1 shows echo amplitude vs. range information of a signal obtained from a swimming pool. High amplitude returns below 2m are due to amplified transducer reverberations noise. A large amplitude return at about 3m was due to the pool wall. Large amplitude returns below 2m are ignored since the sonar's operating range is from 2m to 75m; this eliminates the transducer reverberation noise.

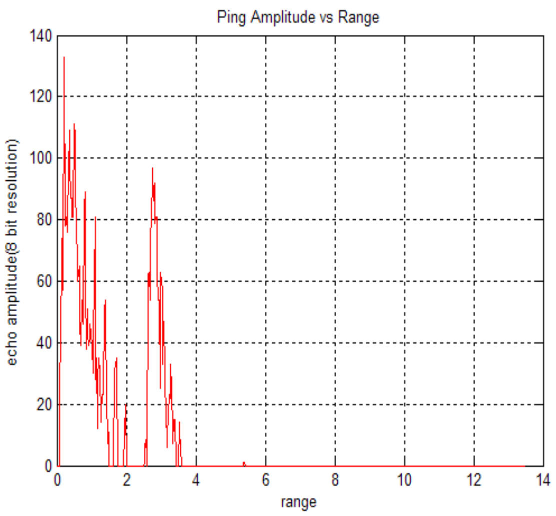

Figure 1: Echo amplitude vs. range information

2.4 Limitations of MSIS

MSIS presents some differences when compared to electronically scanned sonars. MSIS gathers data by rotating a mechanically actuated transducer head at pre-defined angular steps. This results in a continuous data flow and a low scan frequency as compared to electronically scanned sonars which take snap shots of the environment. The transducer head takes a considerable amount of time to complete a scan. To deal with continuous flow of data, data is separated into 360 degrees scan sectors. Although the first and last beams are placed near each other, there is a considerable time lapse between instances in which they were taken and at times the vehicle would have drifted. The drift leads to distortions in the acoustic image. These distortions are due to both translational and rotational motions. The amount of time to complete a scan sector also varies depending on the range settings of the sensor. Higher range settings will normally require more time to complete a scan sector because the signal travels a longer distance. These effects have to be taken into account when dealing with MSIS mounted on a vehicle. These distortions can be ignored for slow moving vehicles. For higher velocities, it is important to have a suitable localisation system in the form of dynamics model or dead reckoning sensors to provide position feedback which can then be used to correct the acoustic image [3]. Data from MSIS is in polar form, normally for easy interpretation, the acoustic image is represented in Cartesian coordinates. The author reported that with the increment of range, a loss in the measurement resolution occurs because the bins are more dispersed as a result of angular aperture between consecutive beams. This effect, which is inherently represented in polar, will produce gaps between beams in the Cartesian image. As a result of this, it is always advisable to use raw polar measurements rather than a conversion to Cartesian representation because the original data is changed [3]. Apart from all the mentioned bottlenecks of MSIS, there are some benefits of using of this sensor; it is a relatively low cost sensor as compared to electronically scanned sonars. Its capability to perform 360 degree scans sectors means that it can track features for longer periods of time even those behind the vehicle. This makes it attractive for underwater SLAM systems because there are normally fewer features in underwater environments [3].

3. Feature Extraction from MSIS

3.1 Data segmentation

Objects in the environment appear as high echo-amplitude returns in acoustic images. This means that only part of the data stored in each beam is useful for feature extraction [3,11,10]. As a result, a segmentation process can be carried out in order to extract more significant information. This process reduces the computational cost of processing the data since fewer data points are considered. The segmentation process consists of three steps which are carried out beam to beam. The first step is to consider only those bins with an intensity value above a low level noise threshold; a typical operating noise threshold value is 13 decibels [8]. This filters out low level background noise, transducer reverberation noise and noise due to aerations which might be present in the water. The second step is to apply a higher level threshold value of 22 decibels; this step filters out some of the multiple reflections off the water surface, walls and objects, and leaves behind significant information corresponding to objects. The third step involves selecting bins with the highest intensity return values above the threshold value of 22 decibels. A highest intensity return is defined as a bin with a maximum amplitude return value along a scan-line. This further segments the data without loss in significant information. Another way of doing this is to select bins that are local maxima [3, 11], this result in one or more high intensity bins being selected per scan-line. Multiple bin selection makes feature detection possible when more than one wall intersects with a single beam. This kind of scenario arises when the structured environment contains steps or ramps [3].

3.2 Corner feature characteristics sought

Corner features to take advantage of structures with intersecting planar surfaces found in man-made underwater environments such as marinas, dams, drilling platforms, channels, harbours e.t.c. are sought. In this paper corners are defined by intersecting planar surfaces making angles between 70 and 120 degrees.

3.3 Sliding window corner detector algorithm

Similarly, following the segmentation process and highest intensity return selection, ranges corresponding to the highest intensity return bins are also determined according to equations 1 and 2 and accumulated into a buffer until a required number has been stored. These ranges correspond to ranges to objects in the environment. The bearing information and the current vehicle pose corresponding to the selected scan-lines are also stored. The current vehicle pose is used to compensate for motion induced distortions in the acoustic images. The accumulated range-bearing (polar) measurements are then feed into the corner detector. The polar measurements are first transformed to Cartesian coordinates. Then a fixed size window made up of three data points is defined. The assumption made is that the three data points define the sides of a triangular window (Figure 2). The middle sample point is taken as the one of the vertices of the window, and this is the sample point where the angle is checked. The other two sample points are taken as the other vertices of the window, these are at the same number of points away from the mid-point sample. For instance, a sample window of size 13 will have a mid-point at sample point 7, and the other two vertices at sample points 1 and 13 respectively. Let k, i and j represent the mid-point, the first and the last sample points respectively in the window.

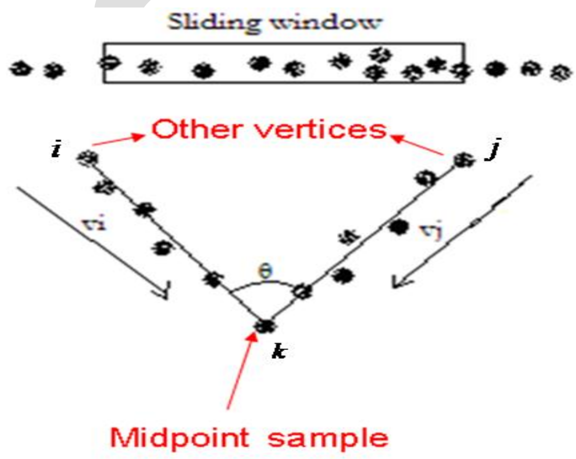

Figure 2: Window for the corner detector

After a window has been defined, the process of corner searching starts by computing the distance $dis(i, j)$ between the vertices at i and j. This distance is determined by:

$$dis(i, j) = sqrt\left(\sqrt{(\Delta x_{ij})^2 + (\Delta y_{ij})^2}\right) \quad (3)$$

If the distance $dis(i, j)$ is greater than a pre-defined threshold value then the mid-point of the window is shifted to the next data point and the process is repeated. If the distance $dis(i, j)$ is lower than a pre-defined threshold value, then an angle check is performed. But first, the distance $dis(k, j)$ between vertices at k and j, and the distance $dis(k, i)$ between vertices at k and i have to be determined, these are given as follows:

$$dis(k, j) = sqrt\left(\sqrt{(\Delta x_{kj})^2 + (\Delta y_{kj})^2}\right) \quad (4)$$

$$dis(k, i) = sqrt\left(\sqrt{(\Delta x_{ki})^2 + (\Delta y_{ki})^2}\right) \quad (5)$$

This information is then used to determine the angle θ at the mid-point sample. The angle θ is determined using a re-arranged dot product rule according to:

$$\theta = \arccos\left(\frac{a_i . b_j}{|a_i||b_j|}\right) \tag{6}$$

where the vectors a_i and b_i are given as:

$$a_i = \left(\Delta x_{ki} \quad \Delta y_{ki}\right) \tag{7}$$

$$b_i = \left(\Delta x_{kj} \quad \Delta y_{kj}\right) \tag{8}$$

If the angle θ is outside the pre-defined minimum and maximum threshold values then the mid-point of the window is shifted to the next data point and the process is repeated. If the angle θ is within the pre-defined minimum and maximum threshold values, then an inward validation is performed by picking corresponding sample points from each side of the window centred at the current mid-point and repeating the corner validation all the way to the last two points closest to the mid-point. All this point pairs must pass the distance and angle tests for a corner to be initialised at the current mid-point. This makes sure that corners are not initialised at outlier sample points but on the other hand it makes the algorithm computationally expensive if the window selected is too wide. Figure 3 shows the execution of the corner feature extraction algorithm.

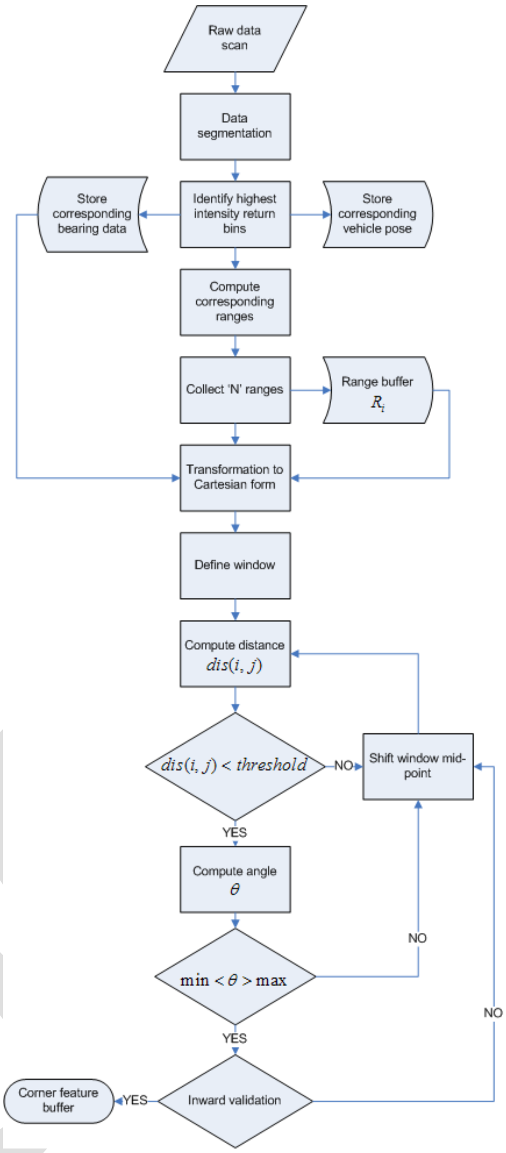

Figure 3: Corner feature extraction flow chart

4. Experimental set-up

The experiment involved an AUV navigating in a swimming pool and at the same time logging data from the on-board sensors. Real data collected from the sensors was then used to evaluate the corner feature extraction algorithm. Section 4.1 describes the swimming pool in Pretoria-Hatfield where the tests were performed. Section 4.2 briefly describes the experimental platform used during the data collection. Section 4.3 describes the MSIS used to scan the environment for map building purposes. Sections 4.4 and 4.5 describe the acoustic beaconing system used to provide the absolute vehicle position estimates and the electronic compass used estimate the vehicle heading respectively. Section 4.6 describes the water pressure sensor used to estimate the depth of the vehicle.

4.1 Test environment

The tests were performed in a 15m by 15m, and 5m deep public swimming pool located in the Pretoria-Hatfield. Figure 4 shows the swimming pool during one of the experiments.

Figure 4: Swimming pool in Pretoria-Hatfield

4.2 Experimental platform

The AUV used for the work reported in this paper is shown in Figure 5. The vehicle was designed and built by the Mechatronics and Micro Manufacturing (MMM) group in the division of Material Science and Manufacturing (MSM) of the Council for Scientific and Industrial Research (CSIR) Pretoria. The AUV is a simple, small and low-cost vehicle comprising a water tight compartment made from aluminium. The compartment houses the computer system, batteries, ballast tanks, sensors and the electronic components. A metal frame is mounted around the vehicle to protect the compartment and external sensors from damage. The vehicle has been designed to be neutrally buoyant. The vehicle was also equipped with a water pressure sensor, an electronic compass and an acoustic beaconing system described in sections below.

Figure 5: AUV; the experimental platform

4.3 Mechanically Scanned Imaging Sonar

The experiments were carried out using the Micron DST Sonar (see Figure 6). The sonar was mounted underneath the AUV in an inverted mode and used to scan the environment in which the vehicle was operating. The sonar's operating range was set at 13.5m and it was sampled at 0.0225m. A mechanical step angle of 0.9 degrees was used to generate 360 degrees scan sectors. With these range settings, 600 data bins were returned by the sonar head, each bin was sampled at 0.00003 seconds. Individual sonar beams had a return signal travel time of about 0.018 seconds. The sample time between individual beams was about 0.1 seconds which is about five times the signal travel time. As a result, there was enough waiting time before the sonar could be ping again and hence this avoided interference from consecutive echo returns. An 8-bit mode was used; bin return values were represented by numbers in the range of 0 to 256. For the range settings used in this thesis, the sonar head required about 40 seconds to complete a 360 degrees scan sector.

Figure 6: Tritech Micron DST Sonar

4.4 Acoustic Beaconing System

An acoustic beaconing system was used to determine the absolute positions of the AUV. This provided ground truth about the positions of the vehicle. The system uses four sonar transducers; three were placed at known positions and were used as beacons. One receiving transducer was mounted on top of the vehicle. The beacon positions were used to estimate the absolute positions of the vehicle. The system has a maximum 2D position error of 0.21m [17].

4.5 Electronic Compass

An electronic compass was used to estimate the heading of the AUV. The device used is a HMC6343 by Honeywell. This device was calibrated before every dive to reduce the effects of disturbances due to other magnetic objects [17].

4.6 Water pressure sensor

An LM series low-pressure media-isolated pressure sensor was used to estimate the vehicle depth. The device used is an LM series low-pressure media-isolated pressure sensor [17].

5. Results and Discussions

5.1 Validation of the corner feature extraction algorithm

The tests were carried out in a 15m by 15m by 5m deep swimming pool at Hatfield-Pretoria. The vehicle was equipped with MSIS. Its operating range was set to 13.5m using equation 1 and 2, at a step angle of 0.9 degrees and a 360 degrees scan sector mode was used. A range of 2m from the sonar head was ignored because its operational range settings are 2m to 75m and therefore any echo returns less 2m were considered to be due noise. An acoustic beaconing system was used to provide absolute vehicle positions. The vehicle maintained a constant depth of 1m using feedback from the pressure sensor. The vehicle also maintained a constant heading using feedback from the compass. The vehicle was assumed to be static during the environment scanning process.

Figure 7 shows a raw acoustic image in polar form. The image was colour coded to distinguish between strong intensity returns from objects and weak intensity returns as a result of noise and multiple reflections. Regions with intensity return values > 0 but < 13 decibels were sampled at a blue colour, regions with intensity return values >13 but < 22 decibels were sampled at a green colour, regions with intensity return values > 22 decibels were sampled at a red colour. The expected swimming pool walls are shown with thick black lines.

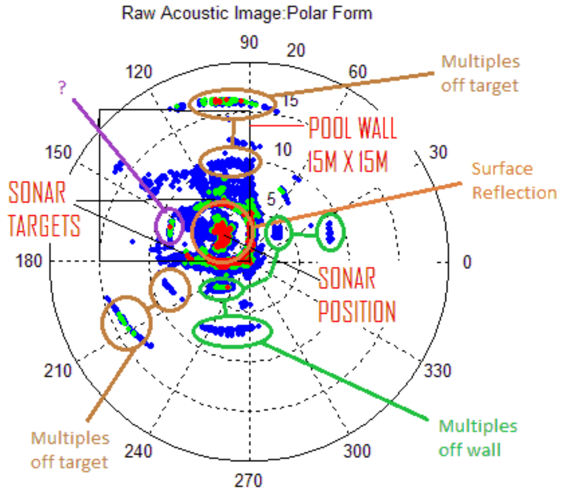

Figure 7: Showing a 360 degrees sector acoustic image

The more targets you have within an enclosed environment such as a swimming pool, the harder it becomes to identify some of the reflections because sound bounces off a number of targets before returning to the sonar head. This causes multiple reflections off targets. The process of interpretation of acoustic images was further complicated by such issues as receiver self noise, transducer reverberation noise and backscatter. In Figure 7, some of the reflections are quite clear. Others are a bit ambiguous and are difficult to make out. Multiples off the wall reflections are annotated in green; these continue out to the maximum range and decreases in intensity as the range increases. Multiples off targets reflections are annotated in brown; these continue out to the maximum range and increases in intensity as the range increases. Reflections from the water surface appear as low intensity circular returns equidistant from the sonar head. Bottom reflections also make up the noise but they are generally of a higher intensity than surfaces reflections because of the hardness of the reflecting material. There is a further high amplitude reflection annotated in purple that looks to be a bottom reflection. There are also a lot of low level returns sampled at blue on the image which are likely to be receiver self noise that is amplified and aerations in the water. So when tries to filter out these multiple reflections, they are not easy to remove automatically. In these situations the image may only be cleaned so much, leaving behind walls and targets returns and also some multiple reflections in with that. Very little or no signal from the walls further away was reflected back to the direction of the transducer, this appears to be a result the oblique grazing angle that the beam strikes the wall surface, e.g. most of the sound energy reflects outward with very little signal reflected back in direction of the transducer. The walls were also obscured to some extend by the targets.

Figure 8 shows the first step of segmentation; after applying a low level noise threshold value of 13 decibels. Low level background noise was eliminated. Some of the low intensity multiple reflections off walls and targets, some low intensity surface and bottom reflections were also eliminated. A range of 2m from the sonar was ignored; this eliminated the transducer reverberation noise.

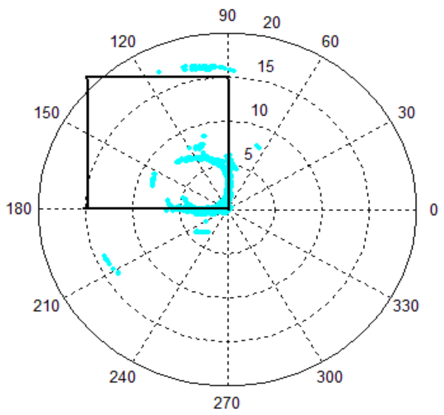

Figure 8: The first step of the segmentation

Figure 9 shows the second step of the segmentation; applying a threshold value of 22 decibels. This process left behind significant information corresponding to objects in the environment. Reflections from the swimming pool walls are clearly visible. Some of the high intensity multiple reflections off walls and targets and, some high intensity surface and bottom reflections were further eliminated.

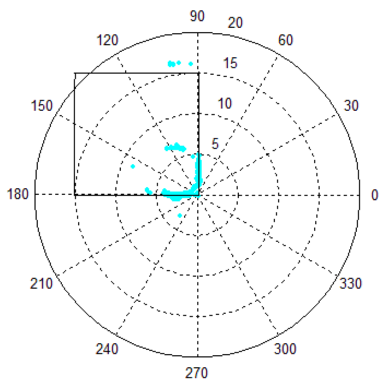

Figure 9: The second step of segmentation

Following the application of a threshold value of 22 decibels, bins with the highest intensity return values were selected along individual beams; the third step of the segmentation process. Figure 10 shows an image in polar form obtained after selecting the highest intensity returns. This process further segmented the data and left behind significant information corresponding to swimming pool walls.

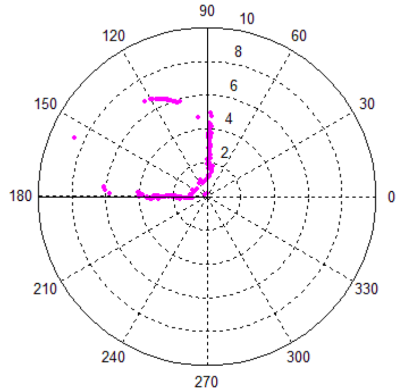

Figure 10: The third step of segmentation

Following the highest intensity return selection, a sliding window corner detector was then applied to search for corner features in the scan. Figure 11 shows the extracted corner features (blue stars). The expected swimming pool wall is shown with the black lines. Although the algorithm manages to detect a corner where it was expected, two corners were extracted. The second 'ghost' corner was due to an outlier point in the data. This is because acoustic data is sparsely distributed. Mapping outliers or 'ghost corners' can have catastrophic effects on the real time implementation of EKF SLAM because the computational complexity of the SLAM process is quadratic the number of features mapped, and hence the outliers or 'ghost' features corrupt the EKF SLAM process. A smoothing filter is applied to make data points evenly distributed. This will get rid of outlier points and hence make corner extraction more reliable. Reliable corner feature extraction means that underwater SLAM systems can be employed in a wider range of environments and applications.

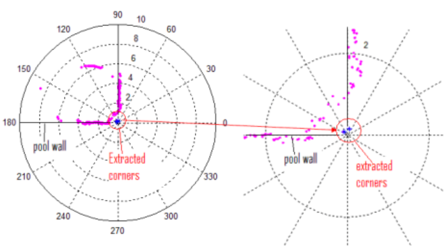

Figure 11: Extracted corner features

6. Recommendations for Further Work

Further work needs to be done by applying a smoothing filter to achieve an even distribution of data samples and hence reduce the effects of outlier points. Mapping outliers or 'ghost corners' can have catastrophic effects on the real time implementation of EKF SLAM.

7. Conclusion

This work presents the use of a sliding window corner detector to extract corner features from real data scans using MSIS. The algorithm has traditionally been applied to laser data obtained in indoor environments. The application of the sliding window technique in underwater environment using MSIS to scan the environment present important differences which must be taken into consideration when processing the data. A segmentation process is carried out to extract more significant information from the scans since only part of the data is useful. This also reduces the computational cost of processing the data since fewer data points are considered..The current vehicle pose is used to compensate for motion induced distortions in the acoustic images. The results presented show the viability of the proposed method.

8. References

[1] Imagenex Technology Corp, "Sonar Theory and Applications", Available: http://www.imagenex.com/sonar_theory.pdf, date accessed: [2009, 05/20].

[2] P. Newman: On the Structure and Solution of the Simultaneous Localisation and Map Building Problem, *Phd Thesis*, 1999, The University of Sydney.

[3] D. Ribas: Underwater SLAM For Structured Environments Using Imaging Sonar, *Phd Thesis*, 2008, University of Girona.

[4] D. Ribas: 2005, Towards Simultaneous Localization & Mapping for an AUV using an Imaging Sonar, *Masters Thesis*, University of Girona.

[5] S. Williams, G. Dissanayake, and H.D. Whyte: Towards Terrain-Aided Navigation for UnderwaterRobotics. Available: http://www.cas.edu.au/download.php/Williams2001-AdvRobotics-underwaterRobotics.pdf?id=1297, date accessed: [2009, 05/20].

[6] S.B. Williams, P. Newman, J. Rosenblatt, G. Dissanayake and H.D Whyte: Autonomous Underwater Navigation and Control. Available: http://www.robots.ox.ac.uk/~pnewman/papers/Robotica.pdf, date accessed: [2009, 05/20].

[7] S.B. Williams, P. Newman, J. Rosenblatt, G. Dissanayake and H.D Whyte: Autonomous Underwater Simultaneous and Localisation and Map Building. Available: http://www.robots.ox.ac.uk/~pnewman/papers/Robotica.pdf., date accessed: [2009, 05/20].

[8] Tritech International Limited a,Web page: Available: http://www.tritech.co.uk/products/products-micron_sonar.htm [2009, 06/05].

[9] I. Tena, Y. Petillot, D.M. Lane and C. Salson: Feature Extraction and Data Association for AUV Concurrent Mapping and Localisation. *Proceedings of the 2001 IEEE, International Conference on Robotics & Automation*. Seoul, Korea, May 21-26, 2001.

[10] D. Ribas, P. Ridao, J. Neira and J.D. Tardos: SLAM using an Imaging Sonar for Partially Structured Underwater Enviroments. *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, Beijin, China, 2006.

[11] D. Ribas, P. Ridao, J. Neira and J.D. Tardos: Line Extraction from Mechanically Scanned Imaging Sonar. Available: http://www.springerlink.com/content/45178xuw0708k5j4/fulltext.pdf?page=1, date accessed: [2009, 06/20].

[12] S. Majumder: Sensor Fusion and Feature Based Navigation for Subsea Robots. *Phd Thesis*, The University of Sydney, 2001.

[13] J.J Leornard, R.N Carpenter and H.J.S. Feader: Stochastic Mapping Using Forward Look Sonar. *Robotica*, Vol. 19. 341 (2001).

[14] H.D. White, T. Bailey: Simultaneous Localisation and Mapping: Part I The Essential Algorithms. *Robotics and Automation Magazine*, June, 2006.

[15] H.D. White, T. Bailey: Simultaneous Localisation and Mapping: Part I The Essential Algorithms. *Robotics and Automation Magazine*, September, 2006.

[16] K. Matson: (Kevin-Matson@tritech.co.uk). 2010, DST Micron Sonar. [E-mail to:] Matsebe, O. (omatsebe@csir.co.za). Dec. 12.

[17] S. Holtzhausen: 2010, *Design of an Autonomous Underwater Vehicle: Vehicle Tracking and Position Control*, MSc. thesis, University of KwaZulu-Natal.

[18] J. Horgan, J. Riordan and D. Toal: 2008, "Near Seabed Navigation of Unmanned Underwater Vehicles Employing Vision Systems; Experimental Approaches", *11th Mechatronics Forum Biennial International Conferencem*, Ireland.

[19] M.J. Roberson, O. Pizarro, S.B. Williams and I. Mahon: 2010, "Generation and Visualization of Large-Scale Three-Dimensional Reconstructions from Underwater Robotic Surveys", *In Journal of Field Robotics*, vol. 27, pp. 22-51.

[20] I. Mahon, S.B. Williams, O. Pizarro, Y. Petillot and M.J. Robertson: 2008, "Efficient View-Based SLAM Using Visual Loop Closures", *IEEE TRANSACTIONS ON ROBOTICS*, vol. 24, no. 5, pp. 1002-1014.

[21] S. Majumder: 2001, *Sensor Fusion and Feature Based Navigation for Subsea Robots*, PhD. thesis, The University of Sydney.

[22] M. Namoshe, O. Matsebe and N. Tlale: 2010, *Feature based Navigation System for Indoor Mobile Robot*.

[23] L. Spinello: .2007, *Corner extraction*. Available: http://www.asl.ethz.ch/education/master/mobile_robotics/year2008/year2007, [2009, 06/05].

[24] D. Tardos, J. Neira, P. Newman and J.J. Leonrard: 2002, "Robust Mapping and Localization in Indoor Environments Using Sonar Data".

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