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Computer Vision Applications in the Navigation of Unmanned Underwater Vehicles

Jonathan Horgan and Daniel Toal
University of Limerick
Ireland

1. Introduction

The inquisitive nature of humans has lead to the comprehensive exploration and mapping of land masses on planet earth, subsequently scientists are now turning to the oceans to discover new possibilities for telecommunications, biological & geological resources and energy sources. Underwater vehicles play an important role in this exploration as the deep ocean is a harsh and unforgiving environment for human discovery. Unmanned underwater vehicles (UUV) are utilised for many different scientific, military and commercial applications such as high resolution seabed surveying (Yoerger *et al.* 2000), mine countermeasures (Freitag *et al.* 2005), inspection and repair of underwater man-made structures (Kondo & Ura 2004) and wreck discovery and localisation (Eustice *et al.* 2005).

Accurate vehicle position knowledge is vital for all underwater missions for correct registration between sensor and navigation data and also for control and final recovery of the vehicle. The characteristics of the underwater environment pose a plethora of difficult challenges for vehicle navigation and these obstacles differ greatly from the issues encountered in land, air and space based navigation (Whitcomb 2000). The rapid attenuation of acoustic and electromagnetic radiation in water restricts the range of acoustic and optical sensors and also limits communication bandwidth. As a consequence of this severe absorption acoustic and optical sensors require submersion near to the survey mission site to gather accurate high resolution data sets. The limitation on communication bandwidth means that vehicle autonomy can only be achieved when the large majority of computation is performed onboard. Whereas land based vehicles can rely on Global Positioning System (GPS) for accurate 3D position updates, the underwater equivalent acoustic transponder network is limited by range, accuracy, the associated cost and deployment & calibration time.

Another challenge that is faced with underwater navigation is the intrinsic ambient pressure. While terrain based vehicle developers have to consider the relatively simplistic and well understood nature of atmospheric pressure in sensor and actuator design, underwater pressure, increasing at a rate of approximately 1 atmosphere (14.7 psi) every 10 meters of depth, can greatly influence and restrict sensor and actuator design. Other issues such as the inherent presence of waves and underwater currents can make the task of accurately describing vehicle motion more difficult and, as a result, affect the accuracy of vehicle navigation.

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Many of these problems cannot be overcome directly so the underwater community relies on improving the navigation sensors and the techniques in which the sensor data is interpreted. The development of more advanced navigation sensors is motivated by the need to expand the capabilities and applicability of underwater vehicles and to increase the accuracy, quantity and cost effectiveness of oceanographic data collection. Sensor selection can depend on many factors including resolution, update rate, cost, calibration time, depth rating, range, power requirements and mission objectives. In general the accuracy of a particular sensor is directly proportional to its expense. This has lead to increased research efforts to develop more precise lower cost sensors and improve data interpretation by implementing more intelligent computation techniques such as multi sensor data fusion (MSDF). Many commercially available underwater positioning sensors exist but unfortunately no one sensor yet provides the perfect solution to all underwater navigation needs so, in general, combinations of sensors are employed. The current state of the art navigation systems are based on the use of velocity measurements from a Doppler velocity log (DVL) sensor conveniently fused with accurate velocity/angular rate and position/attitude measurements derived by integration and double integration respectively of linear acceleration and angular rates from an inertial measurement unit (IMU) (Kinsey *et al.* 2006). To bound the inherent integration drift in the system position fixes from an acoustic transponder network such as Long Baseline (LBL), Ultra Short Baseline (USBL) or GPS Intelligent Buoys (GIB) are commonly used. However, this option raises the mission cost as transponders require deployment prior to the mission or a mother ship is necessary. This solution also limits the area in which the vehicle can accurately navigate to within the bounds of the transponder network (acoustic tether).

Over recent years, computer vision has been the subject of increased interest as a result of improving hardware processing capabilities and the need for more flexible, lightweight and accurate sensor solutions (Horgan & Toal 2006). Many researchers have explored the possibility of using computer vision as a primary source for UUV navigation. Techniques for implementing computer vision in order to track cables on the seabed for inspection and maintenance purposes have been researched (Balasuriya & Ura 2002; Ortiz *et al.* 2002). Station keeping, the process of maintaining a vehicle's pose, is another application that has taken advantage of vision system's inherent accuracy and high update rates (Negahdaripour *et al.* 1999; van der Zwaan *et al.* 2002). Motion estimation from vision is of particular interest for the development of intervention class vehicle navigation (Caccia 2006). Wreckage visualization and biological and geological surveying are examples of applications that use image mosaicking techniques to acquire a human interpretable view of the ocean floor but it has also been proven as an appropriate means for near seabed vehicle navigation (Negahdaripour & Xu 2002; Garcia *et al.* 2006).

This chapter gives and introduction to the field of vision based unmanned underwater vehicle navigation and details the advantages and disadvantages of such systems. A review of recent research efforts in the field of vision based UUV navigation is also presented. This review is discussed under the following headings in relation to recent literature reviewed: image mosaicking, cable tracking, station keeping and positioning & localisation. This chapter also considers the applications of sensor fusion techniques for underwater navigation and these are also considered with reference to recent literature. The author gives an opinion about the future of each application based on the presented review. Finally conclusions of the review are given.

2. Underwater optical imaging

Underwater optical imaging has many interesting and beneficial attributes for underwater vehicle navigation, as well as its ability to open up a wealth of understanding of the underwater world. However, it is not an ideal environment for optical imaging as many of its properties inherently affect the quality of image data. While image quality is a pertinent issue for vision system performance, other difficulties are also encountered such as the lack of distinguishable features found on the seafloor and the need for an artificial light source (Matsumoto & Ito 1995). For most UUV applications (below 10 meters) natural lighting is not sufficient for optical imaging so artificial lighting is essential. Light is absorbed when it propagates through water affecting the range of vision systems (Schechner & Karpel 2004). Many variables can affect the levels of light penetration including the clarity of the water, turbidity, depth (light is increasingly absorbed with increasing depth) and surface conditions (if the sea is choppy, more light will be reflected off the surface and less light transmitted to the underwater scene) (Garrison 2004).

Underwater optical imaging has four main issues associated with it: scattering, attenuation, image distortion and image processing. Scattering is as a result of suspended particles or bubbles in the water deflecting photons from their straight trajectory between the light source and the object to be viewed. There are two different types of scattering; backscatter and forward scatter (see Fig. 1). Backscatter is the reflection of light from the light source back to the lens of the camera. This backscattering can result in bright specs appearing on the images, sometimes referred to as marine snow, while also affecting image contrast and the ability to extract features during image processing. Forward scatter occurs when the light from the light source is deflected from its original path by a small angle. This can result in reduced image contrast and blurring of object edges. The affect of forward scatter also increases with range.

The rapid absorption of light in water imposes great difficulty in underwater imaging. This attenuation necessitates the use of artificial lighting for all but the shallowest of underwater missions (less than 10m, dependent on water clarity). The visible spectrum consists of several colours ranging from the red end of the spectrum (wavelength of <780nm) to the blue (wavelength of >390nm). Water effectively works as a filter of light, being more efficient at filtering the longer wavelength end of the visible spectrum, thus absorbing up to 99% of red light by a depth of approximately 4m in seawater (Garrison 2004). Absorption intensifies with increasing depth until no light remains (see Fig. 1). The effects of absorption discussed apply not only to increasing depth but also to distance.

Due to the extreme pressures associated with deep-sea exploration there is need for high pressure housing around each sensor. In the case of a camera a depth rated lens is also required. Imperfections in the design and production of the lens can lead to non-linear distortion in the images. Moreover, the refraction of light at the water/glass and glass/air interface due to the changes in medium density/refractive-index can result in non-linear image deformation (Garcia 2001). To account for this distortion the intrinsic parameters of the camera must be found through calibration and using radial and tangential models the lens distortion effects can be compensated for. The characteristics of the underwater environment not only create issues for collection of clear and undistorted images but also affect the subsequent image processing. Due to the severe absorption of light and the effects of scattering (marine snow etc.) it is essential to decrease range to the objects being viewed in order to obtain higher resolution clearer images. This has the consequence of limiting the field of view (FOV) of the camera and thus not allowing for wide area images of the seafloor while also challenging the assumption that changes in floor relief are negligible compared to camera altitude.

The motion of the artificial light source attached to the vehicle leads to non-uniform illumination of the scene thus causing moving shadows which makes image to image correspondence more difficult. The lack of structure and unique features in the subsea environment can also lead to difficulties in image matching. While terrestrial applications can make use of man-made structures, including relatively easily defined points and lines, the subsea environment lacks distinguishable features. This is in part due to the lack of man-made structures but also due to the effects of forward scattering blurring edges and points.

An issue that affects all real-time image processing applications is whether the hardware and software employed are capable of handling the large amounts of visual data at high speed. This often requires a trade-off in image processing between the frame rate and the image resolution which can be detrimental to the performance of the application.

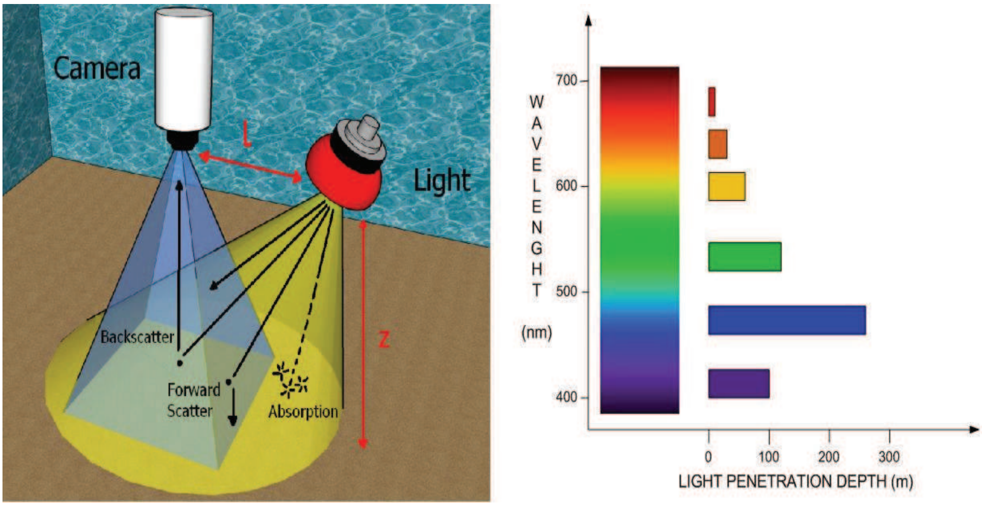

Fig. 1. Scattering and light attenuation (left), colour absorption (right) (Garrison 2004).

3. Vision based navigation

Cameras are found on almost all underwater vehicles to provide feedback to the operator or information for oceanic researchers. Vision based navigation involves the use of one or more video cameras mounted on the vehicle, a video digitizer, a processor and, in general, depending on depth, a light source. By performing image processing on the received frames, the required navigation tasks can be completed or required navigation information can be calculated. The usual setup for the vision system is a single downward facing camera taking images of the sea floor at an altitude of between 1 and 5 meters (see Fig. 2). The use of optical systems, like all navigation sensors, has both advantages and disadvantages. If the challenges of underwater optical imaging, described in section 2, can be successfully addressed some of the potential advantages of vision based underwater navigation include:

- Underwater vehicles are commonly fitted with vision sensors for biological, geological and archaeological survey needs. As such, they have become standard equipment onboard submersibles. As a readily available sensor, vision can be incorporated into a navigation framework to provide alternative vehicle motion estimates when working near the seafloor in relatively clear water.
- The visual data received from optical systems can be easily interpreted by humans and thus provides an effective man-machine interface. Further processing of the visual data can be processed to perform vehicle navigation.
- Optical imaging systems are relatively inexpensive sensors and only require the camera itself, an image digitizer, a host computer and a light source dependent on conditions. The depth rating, low light sensitivity, resolution and whether the camera is zoom or non-zoom, colour or monochrome can all affect pricing.
- Cameras are relatively light weight with small form factors and low power consumption. These can be important issues for deployment on autonomous craft. Unfortunately most missions require artificial lighting which adds significantly to both the weight and power demands of the system.
- Optical imaging has a very high update rate or frame rate and thus allows for high update rate navigation data. The image digitizing hardware and the computation cost of the image processing algorithms are the constraints of the system rather than the optical imager itself.
- Optical imaging systems provide high resolution data with measurement accuracies in the order of millimetres when working near the seafloor.
- Imaging systems can provide 3D position (stereovision) and orientation information, in a fixed world coordinate frame, without requiring the deployment of artificial landmarks or transponders.
- Optical systems have been proven to be capable of providing underwater vehicle navigation without the aid of other sensors.
- Optical imaging systems are very diverse and can be implemented to perform many navigation and positioning applications including: cable tracking, mosaicking, station keeping and motion estimation.

For the purposes of the review the general setup and assumptions about the state of the vehicle and the environment conditions are described. These assumptions are adhered to by all literature and algorithms described unless specifically stated otherwise.

- The underwater vehicle carries a single down-looking calibrated camera to perform seabed imaging.
- The underwater vehicle and thus the camera is piloted at an altitude above the seafloor which allows the acquisition of satisfactory seafloor imagery. This altitude can be affected by external conditions affecting the maximum imaging range.
- The imaged underwater terrain is planar. In most underwater environments this is not the case but the affects of this assumption are reduced using robust statistics for more accurate vehicle motion recovery. This assumption can also be relaxed due the fact that the differences in depth within the imaged seabed are negligible with respect to the average distance from the camera to the seabed.
- The turbidity of the water allows for sufficient visibility for reasonable optical imaging of the working area.
- The light present in the scene is sufficient to allow the camera to obtain satisfactory seafloor imagery.

- An instrumented platform which allows for comparison of results or measurement data fusion is employed.
- Known reference frames between the vehicle and the camera and the vehicle and any other sensors utilized in the navigation technique.

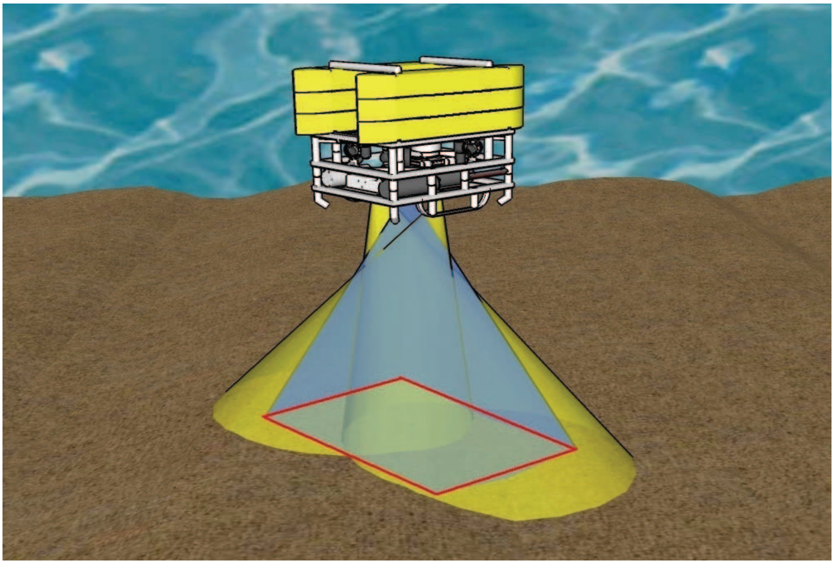

Fig. 2. Camera and lights setup (red box illustrates image frame)

4. Cable tracking

The necessity for frequent underwater cable/pipe inspection is becoming more apparent with increased construction of subsea piping networks for the oil and gas industry and heavy international telecommunication traffic. Current methods for the surveillance, inspection and repair of undersea cables/pipes utilize remotely operated vehicles (ROV) controlled from the surface. This work can prove to be very tedious and time consuming while also being prone to human error due to loss of concentration and fatigue. Cables can be covered along sections of their length thus making it difficult to recover cable trajectory after losing track. A reliable image processing based cable tracking system would prove much less expensive and less prone to error than current solutions, as the need for constant operator supervision is removed. The development of the vision based cable tracking system for use on autonomous vehicles would also be beneficial because of the reduced cost as a mother ship is no longer necessary and such systems are beginning to appear in commercial use (Hydro-International 2008). Vision systems also possess advantages over magnetometer and sonar based solutions for cable tracking (Ito *et al.* 1994). Vision systems prove less expensive, have the ability to identify faults and require a smaller less powerful vehicle for operation (Ortiz *et al*. 2002).

An early attempt at a cable tracking system using machine vision was developed by Matsumoto and Ito (Matsumoto & Ito 1995). The method, like most underwater cable tracking techniques, takes advantage of the lack of straight line edges found in the underwater environment. An edge image of the sea floor is acquired using a Laplacian of Gaussian filter. The Hough transform is then applied to the edge pixel image in order to find the most likely pipe edge candidates. A method of candidate evaluation is implemented by examining the length and width of each edge pixel line candidate. The direction of the cable in the present image and the previous image are used to predict the angle of the Hough transform to be applied to the subsequent image to reduce computation time. This cable following algorithm also attempts to address the problems of sediment covered pipes and non-uniform illumination. While achieving reasonable results in a controlled environment, factors such as spurious edge detection from other pipes or elements, abrupt pipe direction changes and a search algorithm (when cable is undetected) have not been accounted for and result in reduced performance.

Balisuriya *et al.* developed on previous work (Balasuriya *et al.* 1997) by adding an *a priori* map of the cable location to his technique (Balasuriya & Ura 2002). The main features of the method are the ability to follow the cable when it is not visible to the vision system and selection of the correct cable in the image (in the case of multiple cable presence). These objectives are addressed by assuming that an *a priori* map of the cable is available. The *a priori* map serves three purposes; to predict the region of interest (ROI), to avoid misinterpretations with other cables in the image and to be used as a navigation map in the case where the cable disappears from view. A similar method to Matsumoto and Ito is implemented to locate the cable in the image by utilizing the Hough transform. The technique described fuses inputs other than optical information to track the cable and has attempted to overcome the issues of tracking a cable when it becomes partially or fully obscured to the vision system (due to sediment or algae coverage). It also addresses the difficulty associated with correct cable selection. The method demonstrates that the extra information, in the form of a map, fused with optical sensing can greatly improve performance. Unfortunately, having an *a priori* map of the cable location is not always a realistic assumption especially in the case of older installations.

Ortiz *et al.* developed a method for real-time cable tracking using only visual information that again takes advantage of the cables shape to locate strong alignment features along its side (Ortiz *et al.* 2002). After the initial image segmentation step the contour pixels are examined to locate pixel alignments that display strong pipe characteristics (long pixel alignments, parallel alignments and alignments in a y direction on the image). Once the cable has been located in the image a Kalman filter is implemented to reduce the ROI for the subsequent image to reduce computation time. When anomalies occur in the prediction phase actions are taken in order to correct the algorithm; either the frame causing the anomaly is discarded or, if a number of consecutive frames are incorrect, the Kalman filter is reset. This method achieved a 90 percent success rate for trials at 25 frames/sec performed on old cable installations. The technique dealt reasonably well with partially covered cables however, a minimal presence of the cable is required in the image at all times. No backup system in the scenario where the cable becomes undetectable by the system is described. The performance of the method discussed by Ortiz *et al.* (Ortiz *et al.* 2002) was later improved upon while also reducing the complexity of the system (Antich & Ortiz 2005). This new technique also includes a first approximation to the vehicle control architecture for locating and tracking the cable autonomously using the vision system and a method is proposed for unsupervised tuning of the control system. Both the control system and the tuning strategy were validated using 3D object-oriented simulator implemented in C++ using the OpenGL graphics library. Only simulation results have been published to date but results for the implemented control architecture are promising.

Recently Wirth *et al.* developed a method for cable tracking by implementing a particle filter in an attempt to predict the location of the cable when it is partially obscured and thus the number of extracted image features is reduced (Wirth *et al.* 2008). A motion model is calculated to describe the cable parameters' changes over time using previously captured cable inspection footage. An observation model is also described to detect cable edges in the image. These models are then combined in a particle filter which sequentially estimates the likelihood of the cable position in subsequent frames. Experimental results concluded that the system was capable of working online in real time and showed good performance even in situations where the cable was scarcely visible. A method for dealing with multiple cable presence has yet to be developed for the system.

Different methods for cable tracking systems exist each with their own advantages and disadvantages. The work reviewed uses similar techniques for cable detection (looking for straight line edges) but differ in their approaches to cable direction prediction to save on computational expense and improve detection robustness. The need for a robust system for tracking a cable that is partially obscured for a short segment remains a priority. Sensor fusion has been proved to be a good approach to robust cable following when the cable is in view. The future will focus on refining tracking methods and working towards the development of vision systems for inspection, fault identification and localisation with the hope of fully automating the process of cable tracking and inspection and reducing human input. There remains a lot of room for improvement in these systems but despite this there is a surprising lack of publications in the field over recent years.

5. Station keeping

The ability for submersible vehicles to accurately maintain position and orientation is a necessity. The process of maintaining a vehicle's predefined pose in the presence of disturbances (undersea currents and reaction forces from manipulators attached to vehicle) is known as station keeping. Station keeping can be used for many different underwater applications such as repair of underwater structures and near seabed data collection. Station keeping using a vision system has the advantage of being able to use natural rather than manmade beacons for motion detection while inherently having a high resolution and update rate. The camera is setup in a similar fashion to that of image mosaicking and the methods for motion estimation overlap greatly between the two applications (see Fig. 2). The general method for visual station keeping is to maintain a reference image acquired from the station and compare live incoming frames with this image to estimate and correct for vehicle drift.

Stanford/MBARI researchers proposed a method of measuring vehicle drift using a texture tracking strategy (Marks *et al.* 1994). The method of motion estimation is the same process as described in video mosaicking (Marks, *et al.*, 1995). Firstly the spatial intensity gradient of the images is filtered to highlight zero crossings using a Laplacian of Gaussian filter. The incoming images are then correlated with the reference image in order to measure movement of features. Filtering in this case is an attempt to highlight image textures and reduce the effect of noise and non-uniform illumination. Tests were performed in a test tank while the vehicle was on the surface but no external measurements were taken in order to thoroughly evaluate the performance of the system. The result consisted of the plots of commanded control effort to counteract the disturbances in order to hold station. Such a method depends on having a highly textured image in order to find regions of correlation. Correlation-based methods' inability to deal with changes in the image due to rotations will inhibit accurate motion estimation.

Negahdaripour *et al.* proposed a method of station keeping by directly measuring motion from spatio-temporal image gradient information (optical flow) (Negahdaripour *et al.* 1998; Negahdaripour *et al.* 1999). This method allows for the estimation of 3D motion directly using the spatio–temporal derivatives of incremental images captured over a short period of time (Negahdaripour & Horn 1987). A generalized dynamic image motion model was later developed (Negahdaripour 1998) to account for variations in the scene radiance due to lighting and medium conditions underwater. This is of particular importance when using flow–based methods in underwater imagery due to the artificial light source motion. A technique for calculating both instantaneous velocity and absolute position is implemented to increase the limit of inter-frame motion. The position calculated by integrating the velocity over time is used for course correction before the absolute position is used for finer adjustment. This method is susceptible to sporadic miscalculations in velocity, which, accumulated over time, can result in inaccurate position estimations.

Cufi *et al.* (Cufi *et al.* 2002) make use of a technique previously developed for a mosaicking application (Garcia *et al.* 2001b). The acquired images are convolved with high pass filters in both the x and y direction in order to find small windows with the highest spatial gradient (interest points). These windows are then compared to the reference image using two methods. Firstly a correlation based strategy is used to find candidate matches for each interest point. Then a texture characterisation method is performed on each point to select the best correspondence using different configurations of the energy filters (Garcia *et al.* 2001a). As stated above the correlation method is incapable of dealing with large rotations in images due to yaw motion of the vehicle. This problem is overcome in this case by simultaneously creating an image mosaic. The mosaic creation method is based on previous work completed by Garcia *et al.* and is discussed further in section 6 (Garcia *et al.* 2001b). The implementation of the image mosaic also allows for greater inter-frame motion. No overlap between image iterations is needed as the mosaic can be referenced for motion estimation. This method improves on previous correlation based approaches but could again suffer from a lack of distinct textures in the subsea environment while the execution of the mosaicking system may be too computationally expensive to be performed in a real-time on board computer.

Other methods implement a combination of methods to achieve station keeping. Van Der Zwaan *et al.* use a technique of integrating both optic flow information with template matching in order to estimate motion (van der Zwaan *et al.* 2002). The station keeping system tracks an automatically selected naturally textured landmark in the image plane whose temporal deformations are then used to recover image motion. A prediction of the location of the landmark is made by utilizing optical flow information. This estimate is then refined by matching the image with the selected reference frame. This system performed in real-time and showed robust results even in the case of limited image textures however, experiments were performed on poor resolution images thus decreasing accuracy and improving algorithm speed.

Station keeping, much like mosaicking, has many methods for tracking motion from vision: correlation based, feature based, optical flow based etc and selection of the most appropriate method is by no means a trivial task. Many factors have to be considered to obtain accurate results with the final goal of creating an autonomous real-time station keeping system. The methods discussed are hard to compare due to differing test setups and vehicle dynamics, however, none of the methods mentioned appears fully capable of overcoming the difficulties of station keeping faced in underwater environments, at least in a real-time on board system in an unstructured environment. While improved hardware will allow for the analysis of higher resolution images and thus superior accuracy, there still remains room for algorithm advances and sensor fusion research in order to reproduce the results gained in controlled pool trials and simulations in actual real ocean environments.

6. Mosaicking

Light attenuation and backscatter inhibit the ability of a vision system to capture large area images of the sea floor. Image mosaicking is an attempt to overcome this limitation using a process of aligning short range images of the seabed to create one large composite map. Image mosaicking can be used as an aid to other applications such as navigation, wreckage visualisation, station keeping and also to promote a better understanding of the sea floor in areas such as biology and geology. Mosaicking involves the accurate estimation of vehicle motion in order to accurately position each frame in the composite image (mosaic). The general setup of the vision system remains the same for almost all mosaicking implementations. A single CCD camera is used to acquire images at a right angle to the seabed at an altitude ranging from 1-10 meters depending on water turbidity (see Fig. 2).

One of the very earliest attempts at fusing underwater images to make a larger composite seafloor picture was published by Haywood (Haywood 1986). The simple method described did not take advantage of any image processing techniques but instead used the known vehicle offsets to merge the images in post processing. This method led to aesthetically poor results and gaps in the mosaic. Early attempts at automated image mosaicking were developed by Marks *et al.* who proposed a method of measuring offsets and connecting the images using correlation to create an accurate real-time mosaicking system (Marks *et al.* 1995). This method uses the incoming images to decide the position offset, rather than another type of sensor (acoustic), so it guarantees no gaps are encountered in the mosaic. Much like Marks *et al.* method for station keeping, discussed in the previous section, a stored image is correlated with live incoming images to derive the offset in pixels (Marks *et al.* 1994). The images are filtered using a Laplacian of Gaussian filter in order to highlight zero crossings and pronounce the image textures. The filtering reduces the image noise and also the effect of non-uniform illumination from artificial sources. The mosaic is created by repeatedly storing images and determining by the offset calculated where to place the image in the scene. The images are stored at intervals determined by predefined positional offsets in the x and y planes. Each time an image is stored, the system waits until the x and y value change limit has been reached and the process repeats itself. The system produced was capable of creating single column mosaics in real time using special purpose hardware. This correlation based method relies on well contrasted images in order to locate regions of correlation; a lack of texture will inhibit the system from correctly positioning images in the mosaic. A simple motion model is assumed as correlations inability to deal with rotations, scale changes and undersea currents (seen from results) may hinder its ability to create multiple column mosaics. This method was later extended by Fleisher *et al.* in order to reduce the effect of error growth due to image misalignments, in a similar fashion to current

Simultaneous Localisation and Mapping (SLAM) algorithms (Fleischer 2000). This involved the detection of vehicle trajectory crossover paths in order to register the current images with the stored frames to constrain the navigation error in real time. The use of either an augmented state Kalman filter or a least-squares batch formulation for image realignment estimation was proposed. The same image registration method is implemented thus the system continues to use a simplistic 2D translation image registration model.

Garcia *et al.* proposed a method of feature characterisation to improve the correspondences between images in order to create a more accurate mosaic to position an underwater vehicle (Garcia 2001; Garcia *et al.* 2001b). Firstly regions of high spatial gradient are selected from the image using a corner detector. Image matching is accomplished by taking the textural parameters of the areas selected and correlating them with the next image in sequence. A colour camera improves the process as the matching is implemented on the hue and saturation components of the image as well as the intensity of the image. A set of displacement vectors for the candidate features from one image to the next is calculated. A transformation matrix can then be constructed to merge the images in the correct location in the final mosaic. The paper also implements a smoother filter which is an improvement on techniques first proposed by Fleischer *et al*. (Fleischer 2000). An augmented Kalman filter is used as the optimal estimator for image placement and has the advantage over batch methods of being able to handle multiple loops, real time dynamic optimisation and gives knowledge of the image position variance.

Negadaripour *et al.* extend previously discussed work in station keeping (Negahdaripour *et al.* 1999) and early work in image mosaicking (Negahdaripour *et al.* 1998) to create a fully automatic mosaicking system to aid submersible vehicle navigation (Negahdaripour & Xu 2002). As with the previously discussed station keeping methods, spatio-temporal image gradients are used to measure inter-frame vehicle motion directly which is then integrated over time to provide an estimate of vehicle position. Two methods are proposed for reducing the drift inherent in the system. The first method is based around trying to correct for the biases associated with the optical flow image registration to improve the inter-frame motion estimation and thus reduce accumulated system drift. The second addition attempts to bound the drift in the system by correcting errors in position and orientation at each mosaic update. This is performed by comparing the current image to a region extracted from the mosaic according to the current position estimate. The comparison between the expected image and the current image is used to feedback the correct position estimate and update the mosaic; thus constraining the error growth to the mosaic accuracy.

Gracias *et al.* developed another approach to mosaic creation while also implemented it as an aid for navigation (Gracias 2002; Gracias *et al.* 2003). The estimation of motion is performed by selecting point features on the image using a Harris corner detector (Harris & Stephens 1988) and registering these control points on the proceeding images through a correlation based method. A two step variant of the least median of squares algorithm referred to as the *MEDSERE* is used to eliminate outliers. After estimating the inter-frame motion, the parameters are cascaded to form a global registration where all the frames are mapped to a single reference frame. After registration the mosaic is created by joining the images using the global registration transformation matrix. Where images overlap there are multiple contributions to a single point on the output image. A method of taking the median of the contributors is employed, as it is particularly effective in removing transient data, like moving fish or algae, which has been captured on camera. The creation of the mosaic is performed offline and then used for real time vehicle navigation. This technique has been experimentally tested for relatively small coverage areas and may not extend well to more expansive surveys due to the assumption of an extended planar scene. The method does not account for lens distortion, which can have a significant impact at larger scales (Pizarro & Singh 2003).

Pizarro *et al.* attempts to tackle the issues associated with the creation of large scale underwater image mosaicking using only image information in a global mosaicking framework (Pizarro & Singh 2003). The problem is broken down in three main parts: radial-distortion compensation, topology estimation and global registration. The proposed method uses feature descriptors invariant to changes in image rotation, scaling and affine changes in intensity and is capable of dealing with low overlap imagery. Radial distortion is accounted for by image warping in a pre-processing step prior to mosaicking. The mosaicking system uses all overlap information, including overlap from images that are not consecutive in time, in order to create a more accurate mosaic by partially limiting the effects of drift. The mosaic is rendered by multi-frequency blending to form a more globally consistent mosaic. The paper claims to have created the largest known published automatically generated underwater mosaic.

Gracias and Neighadaripour present two methods of creating mosaics using video sequences captured at different altitudes (Gracias & Negahdaripour 2005). The first method relies on a rendered mosaic of higher altitude images to act as a map to guide the position of the images in the lower altitude mosaic ('image to mosaic'). The second method does not require rendering of the higher altitude mosaic, just the topology to match each particular image of the lower altitude sequence against the higher altitude images ('image to image'). Ground truth points were used to compare the two methods presented. Both methods obtained good results but while the 'image to image' method showed less distortion, it had the disadvantage of higher computational expense. Unfortunately the method requires a small amount of user input to select correspondences and the flat, static and constant lighting of the environment are assumptions of the technique. Time efficiency is another factor to be considered due to the method requiring runs at different altitudes.

It is difficult to compare and evaluate the performance of each of the methods described. Each technique has been tested in scenarios where different assumptions are made regarding the environment, vehicle dynamics and processing power available. Negahdaripour and Firoozfam attempted to compare methods (using a common data set) implemented by different institutions to document the various approaches and performances of different techniques to the marine world (Negahdaripour & Firoozfam 2001). Unfortunately, due to time constraints, only comparative results for feature–based and direct methods are reported. A more comprehensive report would give a better understanding of the strengths and weaknesses of current techniques available. Some recent research efforts in the area have investigated the construction of 3D mosaics, a further step forward in the evolution of mosaicking methods (Nicosevici *et al.* 2005). Video mosaicking remains a very complex and challenging application because of the inherent difficulties faced with accounting for 3D vehicle motion and the difficulty using optics underwater (Singh *et al.* 2004). 3D mosaicking is a glimpse of what the future could possibly hold for this application and what research institutes will be improving upon with advances in processing capability and vision systems.

7. Positioning & localisation

The possibilities of using vision systems for navigation have already been discussed in the case of mosaicking, station keeping and cable tracking. For the purposes of this review vision based navigation will be discussed in relation to mosaic based localisation, Simultaneous Localisation and Mapping (SLAM) and motion estimation.

Image mosaics are a large area composite view of the seafloor. This composite view is effectively a map of the area over which the vehicle has passed during the mission. If the mosaic updates in real-time and thus the most recent visual information is available it allows for comparison between current camera frames and the composite image in order to improve the mosaic but also to localise the vehicle within the composite image. This technique has been used in both station keeping and mosaicking. Cufi *et al*. compare the live image with the most recently updated mosaic to allow for greater inter-frame motion and improve the robustness of the station keeping system (Cufi *et al.* 2002). Gracias *et al.* used a technique in which the mosaic is created offline and then implemented for a subsequent mission as a map of the site to aid vehicle navigation (Gracias 2002; Gracias *et al.* 2003). Negadaripour and Xu take advantage of the mosaic by calculating the inter-frame motion in order to estimate vehicle position and subsequently use the rendered mosaic to improve the placement of image at the mosaic update stage (Negahdaripour & Xu 2002).

Simultaneous Localisation and Mapping (SLAM) also known as concurrent mapping and localisation (CML) is the process in which a vehicle, starting at an unknown location in an unknown environment, incrementally builds a map within the environment while concurrently using the map to update is current position. Following vehicle motion, if at the next iteration of map building the measured distance and direction travelled has a slight inaccuracy than any features being added to the map will contain corresponding errors. If unchecked, these positional errors build cumulatively, grossly distorting the map and therefore the robot's ability to know its precise location. There are various techniques to compensate for this such as recognising features that it has come across previously and re-skewing recent parts of the map to make sure the two instances of that feature become one. The SLAM community has focused on optimal Bayesian filtering and many techniques exist including laser range scanning (Estrada *et al.* 2005) , sonar (Tardos *et al.* 2002) and video (Davison *et al.* 2007) . Almost all the literature is based on terrestrial environments where vehicle dynamics are more limited and manmade structures provide an abundance of robust scene features. Very little literature exists which has tackled the issues of SLAM based navigation in an underwater environment. The strong majority of research that has taken place in the underwater environment has focused on acoustic data (Tena Ruiz *et al.* 2004; Ribas *et al.* 2006). The key to successful visual SLAM for underwater vehicle navigation lies in the selection of robust features on the sea floor to allow for accurate correspondence in the presence of changing view points and non uniform illumination. Another important factor to be considered is the likely sparseness of image points due to the environment and the necessary selection of robust features.

One of the few examples of underwater optical SLAM was developed by Eustice who implemented a vision based SLAM algorithm that performs even in the cases of low overlap imagery (Eustice 2005). Inertial sensors are also taken advantage of in the technique developed to improve the production of detailed seabed image reconstructions. Using an efficient sparse information filter the approach scales well to large-scale mapping in testing where an impressive image mosaic of the RMS Titanic was constructed (Eustice *et al.* 2005).

Williams *et al.* describes a method of underwater SLAM that takes advantage of both sonar and visual information for feature extraction in reef environments (Williams & Mahon 2004). Unfortunately the performance of the system during testing is difficult to evaluate as no ground truth was available for comparison. Saez *et al.* detail a technique for visual SLAM that takes advantage of a trinocular stereo vision (Saez *et al.* 2006). A global rectification strategy is employed to maintain the global consistency of the trajectory and improve accuracy. While experiments showed good results all testing was carried out offline. The algorithm for global rectification becomes increasingly computational complex with time and as a result is unsuitable for large scale environments. Petillot *et al.* presents an approach to perform underwater 3D reconstruction of the seabed aided by SLAM techniques and the use of a stereo camera system (Petillot *et al.* 2008). A Rauch-Tung-Striebel (RTS) smoother is used to improve the trajectory information outputted by the implemented Kalman filter. This paper is unique in the way it uses a combination of SLAM and RTS techniques for the optical 3D reconstruction of the seabed.

The issues associated with metric motion estimation from vision are dealt with more directly by Caccia (Caccia 2003) and later developed into a more complete system with ocean environment experimental results (Caccia 2007). The system is based on an optical feature correlation system to detect motion between consecutive camera frames. This motion is converted into its metric equivalent with the implementation of a laser triangulation scheme to measure the altitude of the vehicle (Caccia 2006). The current system only allows for horizontal linear translation and doesn't account for changes in yaw but promising results were achieved using the Romeo vehicle for a constant heading and altitude in the Ligurian Sea. Cufi also calculates direct metric motion estimation for evaluation of a station keeping algorithm (Cufi *et al.* 2002). This technique uses altitude measurements gained from ultrasonic altimeter to convert offsets from images produced by a calibrated camera into metric displacements.

Machine vision techniques have been proven as a viable localisation and motion sensor in an unstructured land setting; unfortunately it is by no means a trivial task to transfer these techniques to subsea systems. The underwater environment adds the complexity of 3D motion and the inherent difficulties associated with optics underwater. However, recent work in the area of vision based SLAM and motion estimation techniques have proved that imaging systems can be complementary sensor to current sonar and inertial motion estimation solutions with the advantages of having high accuracy and update rate and being especially beneficial in near intervention environments. The SLAM community is focused on improving algorithms to allow for real time mapping of larger environments while improving robustness in the case of sparse features, changing illumination and highly dynamic motion.

8. Navigation using sensor fusion

Sensor fusion, also known as multi-sensor data fusion (MSDF), is the combination of sensory data or data derived from sensory data from different sources in order to achieve better information than would be possible when these sources are used individually. The term better in this case refers to the data and can mean: more accurate, noise tolerant, more complete, sensor failure tolerant or data with reduced uncertainty. There are many different issues that require consideration when performing sensor fusion such as data alignment, data association, fusion, inference and sensor management (Loebis *et al.* 2002). The fusion process can also be further categorized by the different levels at which it can take place. A commonly used categorisation identifies four fusion levels signal, pixel, feature and symbol and these are discussed in more detail in references (Loebis *et al.* 2002; Luo *et al.* 2002).

All sensors available for underwater vehicle navigation have their own advantages and disadvantages. Sensor fusion techniques allow for the fusion of data from many sources to improve the overall navigation accuracy and reliability while taking advantage of the available sensors complementary attributes. A well established sensor fusion application is between a Doppler velocity log (DVL) and an inertial navigation system (INS) (Kinsey *et al.* 2006). This sensor fusion is used to combat the issue of INS integration drift: small errors in the measurement of acceleration and angular velocity are integrated into progressively larger errors in velocity, which is compounded into still greater errors in position. Inertial measurement units (IMU) typically employ another type of sensor such as DVL measurements and position measurements from GPS or acoustic navigation systems to correct for errors in the IMU state estimate and limit the effect of integration drift. Whitcomb *et al.* reported preliminary results from the first deployment of an early prototype of a combined long base line (LBL) acoustic network positioning and Doppler navigation (Whitcomb *et al.* 1999). This system was later extended upon by Kinsey *et al.* who indentified that solutions and experimental results for underwater vehicle navigation in the x and y horizontal plane were particularly rare in literature (Kinsey & Whitcomb 2004). The system developed, *DVLNAV* supports many of the sensors available on today's UUVs including DVL, LBL, compass, depth sensors, altimeters and GPS. Results demonstrated that the system provides more accurate navigation at a higher precision and update rate than LBL alone while also proving that accurate estimates of sound velocity, heading, and attitude data in computing underwater vehicle position significantly improves the accuracy of Doppler based navigation.

Loebis *et al.* published a review of MSDF and its application to UUV navigation (Loebis *et al.* 2002). It was concluded that accurate navigation cannot be performed by one navigation system alone and the best way to improve is by implementing MSDF between a number of complementary navigation systems. A method of cable tracking that utilizes MSDF between an INS, GPS, and vision based dead reckoning is also proposed but to the authors' knowledge no results for the system have been published to date. Nicosevici *et al.* presented a classification of currently used sensor fusion techniques that focuses on its application to UUV navigation (Nicosevici *et al.* 2004). Many of systems reviewed implement the extended Kalman filter for sensor data fusion. The main conclusions drawn from the literature for sensor fusion implementation is to first be aware of the goal of the sensor fusion (the improvement brought by the system) and second be aware of the constraints imposed by the sensors involved (sensor data model etc.).

While vision based sensor fusion techniques are growing in popularity for terrestrial robot navigation applications (Dong-Xue et al. 2007; Jia *et al.* 2008) very little literature exists for underwater vision based sensor fusion as most of the navigation applications reviewed rely purely on optical information (Eustice 2005). One of the few underwater vision based sensor fusion techniques is proposed by Balasuriya *et al.* to tackle the issues of cable tracking when the cable becomes invisible to the camera for a short period of time and also correct cable selection in the presence of multiple possibilities (Balasuriya & Ura 2001). A combination of image data, a prior map of the cable location and inertial data are fused together in order to implement reliable cable tracking. Testing of the algorithm using the Twin-Burger 2 AUV in a test tank proved that the sensor fusion greatly improved system performance. Majunder *et al.* describe an algorithm that takes advantage of low level sensor fusion techniques in order to provide a more robust scene description by combining both vision and sonar information (Majumder *et al.* 2001). Huster *et al.* propose a system to improve station keeping by using accelerometer and gyrocompass measurements as well as monocular vision displacements to counteract drift from a fixed location. The use of inertial measurements also reduces the amount of visual information required for extraction from the vision system resulting in a more simple and robust solution (Huster *et al.* 2002).While vision based motion estimation techniques rely on the fusion of altitude measurements from sensors to estimate metric displacement (Cufi *et al.* 2002), Eustice (Eustice 2005) also takes advantage of other sensor information (attitude) in order to overcome many of the challenging issues involved in visual SLAM based navigation in an unstructured environment.

The authors of this chapter, Horgan *et al.* propose a real-time navigation system for a UUV that takes advantage of the complementary performance of a sensor suite including a DVL, a compass, a depth sensor and altimeter sensors with a feature based motion estimator using vision (Horgan *et al.* 2007). The compass and the depth sensors are used to bound the drift of the heading and depth estimations respectively. The altimeter is required in order to translate the feature displacements measured from the images into the metric displacements of the robot. While the robot must rely on DVL navigation above a certain altitude where vision is less effective, DVL measurements can be complemented with higher frequency accurate motion estimates from the vision system when navigating close to the seafloor. When a vehicle comes close to the seabed, DVL can drop out due to minimum blanking range, however at such short ranges vision systems are at their most effective.

From the reviewed papers it is apparent that sensor fusion can greatly improve robot navigation accuracy while also decreasing the need for expensive individual sensors. However, there is a relative lack of publications in the area which can be explained by the fact that sensor fusion can be quite difficult to implement due to sensors having different physical properties, data types, update rates and resolutions. MSDF that takes advantage of visual information is an appealing prospect as it has complementary attributes to many commercially available sonar sensors as vision system’s performance improves with decreasing range making it a very good candidate for near intervention underwater missions. Very little research has taken place into fusion between inertial and vision measurements but the author believes that vision is a viable solution for aiding INS in a near seabed environment where acoustic positioning may be prone to inaccuracy e.g. in channels, caves or wrecks.

9. Conclusion

The presented review illustrates the growing popularity of vision based UUV navigation methods. The diversity of optical imaging has been demonstrated with regard to applications of cable tracking and inspection, mosaicking, positioning & localisation and sensor fusion. Vision systems are a very useful sensor for the navigation of underwater vehicles and have been the subject of increased interest over the last decade as a result of improved processing capabilities of hardware and the need for more flexible and accurate sensor solutions. The increase in research efforts into vision systems is due to its inexpensive nature and its common inclusion on underwater vehicles as a payload sensor. Vision also has a number of advantages over other types of sensors for underwater applications.

Cameras are light weight and do not possess a minimum operating range unlike their acoustic counterparts (Nolan 2006). Despite these advantages over other sensors, machine vision underwater poses an amount of difficult challenges to be overcome for it to be successfully incorporated into control (Matsumoto & Ito 1995). Marine snow, low contrast, non-uniform illumination and a lack of distinguishable features on the seabed are just some of the inherent difficulties faced when using optics underwater (Cufi *et al.* 2002).
Kinsey *et al.* indentified that solutions and experimental results for underwater vehicle navigation in the x and y horizontal plane were particularly rare in literature (Kinsey & Whitcomb 2004). This is of particular interest as vision is a very useful sensor for horizontal plane navigation in the correct conditions while near the seafloor. It was later stated by Kinsey *et al.* that there is a distinct need for improved near seabed (near intervention) UUV navigation systems for the exploitation of scientific data and the near seabed operations (Kinsey *et al.* 2006). Current systems while sufficiently precise and fast for dynamic positioning remain unconvincing in near intervention operations. Vision systems have inherently fast frame rates (update rates) depending on the capability of both the hardware and software while also having resolutions of sub centimetre accuracy depending on vehicle altitude and resolution. These attributes as well as the other advantages discussed previously make vision based methods ideal for near intervention class missions.
Sensor fusion techniques will allow for more complementary synthesis of vision algorithms with DVL, INS, compass and altimeters proven to provide a more robust navigation solution. While online processing of optical data has been an issue in the past improving hardware capabilities should now allow for real-time implementation of vision based algorithms with sufficient accuracy and update rates.

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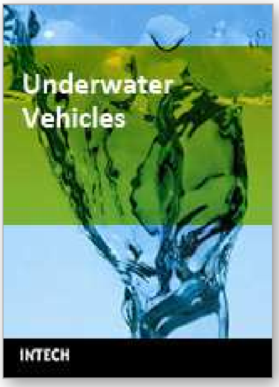

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For the latest twenty to thirty years, a significant number of AUVs has been created for the solving of wide spectrum of scientific and applied tasks of ocean development and research. For the short time period the AUVs have shown the efficiency at performance of complex search and inspection works and opened a number of new important applications. Initially the information about AUVs had mainly review-advertising character but now more attention is paid to practical achievements, problems and systems technologies. AUVs are losing their prototype status and have become a fully operational, reliable and effective tool and modern multi-purpose AUVs represent the new class of underwater robotic objects with inherent tasks and practical applications, particular features of technology, systems structure and functional properties.