Review of Machine Vision Applications in Unmanned Underwater Vehicles

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Abstract - **This paper presents a review of recent research efforts in the field of the application of machine vision in the control of unmanned underwater vehicles (UUV). The paper focuses on five particular applications for machine vision underwater. Each application is discussed and its evolution into its present state is analysed by looking at different projects. Projects are categorised for each application and an assessment regarding the performance of the strategies is given. Their advantages and disadvantages are discussed. Based on the authors' observations, possible future trends are identified for each application.**

I. INTRODUCTION

Underwater vehicles are an important tool in many different scientific, military and commercial applications such as inspection and repair of underwater man made structures, seabed surveying and near seabed data collection. Autonomous underwater vehicles are rapidly becoming accepted as a viable alternative to remotely operated vehicles (ROV) due to their cost effectiveness and their greater manoeuvrability for use in more hazardous environments [1].

There has been a significant increase in the applications of machine vision over the last decade with improved processing capabilities of hardware and the need for sensors with greater flexibility and accuracy. Due to this evolution, the inexpensive nature of vision and its common inclusion on underwater vehicles as a payload, it was natural that machine vision has become a more commonly used sensor in control loops. Vision systems have the advantage of being light weight, inexpensive and are not limited by a minimum operating range unlike their acoustic counterparts [2]. Despite these advantages over other sensors, machine vision underwater possesses an amount of difficult obstacles to be overcome for it to be successfully incorporated into control [3]. 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 [4].

In this article, research endeavours focused on investigating five particular applications of vision systems in unmanned underwater vehicles. The five areas focused on are: station keeping, video mosaicking, feature tracking, intervention class AUVs and finally vision's usefulness in navigation and positioning. Each application is explained and different projects are discussed and categorised where applicable under each of the application headings.

II. STATION KEEPING

Station keeping is the process of maintaining a vehicle's predefined position and orientation in the presence of disturbances such as undersea currents [5]. Station keeping can be used for many different underwater applications such as repair of underwater structures and near seabed data collection. The general set up of the vision system is the same for almost all station keeping methods. A fixed downward facing camera is installed on the UUV, acquiring images of the seabed floor at a distance ranging from 1-3 meters. These images are then analyzed in order to measure offset of the vehicle from the intended station. Appropriate thruster signals are then calculated to counteract the drift of the vehicle.

Early work in the area introduced the concept of storing a reference image of the desired position and comparing subsequent images from the camera in order to measure drift from the original image. Stanford/MBARI researchers proposed a method of measuring motion using a correlation based approach to feature tracking [6]. 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. Such a method depends on having a highly textured image in order to find regions of correlation, however, in reality there is an evident lack of distinguishable features in underwater environments. Correlation based methods are essentially unable to cope with changes in images due to rotations which limits this methods capabilities.

Negahdaripour *et al* [7, 8] proposes a method of station keeping by directly measuring motion from spatio-temporal image gradient information. This technique is limited by only allowing for small changes from one image to the next. However, the method was later improved upon by computing instantaneous velocity (interframe displacement) as well as absolute position (absolute displacement from station) [5]. The limit of interframe motion for absolute position is the

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displacement from the station, whereas the instantaneous velocity limit is the interframe displacement. Consequently the limit on motion is much less restrictive. Position can be calculated by integrating the velocity over time and this 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. Low resolution images where used during experiments, possibly because of high computational expense which led to larger station errors.

Cufi *et al* [9] uses a method based on region matching in order to achieve station keeping. 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 [10]. As stated above the correlation method is incapable of dealing with rotations in images due to yaw motion of the vehicle. This problem is overcome in this case by creating an image mosaic. The mosaic creation method is based on previous work completed in the group and is further discussed in Section III [11]. The image mosaic also allows for greater interframe 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 sub sea environment and the mosaic method would be very computationally expensive to be performed in a real-time on board computer.

Different methods of station keeping have been examined each with their own advantages and disadvantages. Many different methods for stereo correspondence exist and selection of the most appropriate method is by no means a trivial task [12]. In the authors view the techniques researched are difficult to compare due to different test setups, 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 environment. While improved hardware will allow for the analysing of higher resolution images and thus superior accuracy, there still remains room for algorithm advances in order to reproduce the results seen in controlled pool trials and simulations for actual real ocean environments.

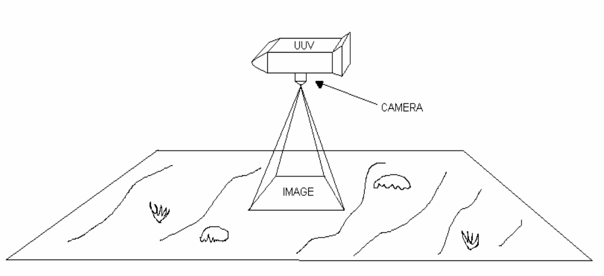

Fig 1. Camera setup for station keeping

III. VIDEO MOSAICKING

Video mosaicking is a method of creating a map of the seabed in video image form. It can be used as an aid to other applications such as navigation, wreckage visualisation and station keeping [9] and also promote a better understanding of the sea floor in areas such as biology and geology. The main problem encountered in the task of video mosaicking is alignment of all the images into a single larger composite image or map. The main contributors to this problem include the lack of image texture, object occlusions, acquisition noise and non-uniform illumination found in underwater imagery.

Marks *et al* [13] developed a method of measuring offsets and connecting the images using correlation. This method uses the incoming image to decide the position of offset rather than another type of sensor (acoustic), so it guarantees no gaps are encountered in the mosaic. Much like Marks method for station keeping [6], discussed in Section II, a stored image is correlated with live incoming images to derive the offset in pixels. The mosaic is created by repeatedly storing images and determining by the offset calculated where to place the image in the scene (see Fig 2). 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. As stated before this correlation method may suffer from a lack of features in order to correctly merge images into a composite map. Correlations inability to deal with rotations, lighting changes and lack of texture (seen from results) may hinder its ability to create two column mosaics.

Garcia *et al* [11] proposes a feature-based mosaicking also implemented in Cufi [9] as an aid for station keeping. The problem of mosaicking is tackled in four stages: feature selection and matching, estimation of dominant motion, homography computation and mosaic blending. Feature selection is performed choosing areas of high spatial gradient information using a corner detector. Matching is then accomplished by taking the textural parameters of the areas selected and correlating them with the next image in sequence. After the matching process is completed a set of displacement vectors for the candidate features from one image to the next is calculated. The least median of squares algorithm is applied to the vectors in order to minimise the effect of false matches due to moving objects (outliers) and noise. A transformation matrix can then be constructed to describe the motion between two consecutive images. Once the most appropriate transformation matrix is selected the two consecutive images can be joined in the mosaic. In this paper they also implemented the use of a colour camera, which allowed for the hue and saturation components of the image to be used to partially improve the matching process and reduce the effect of non-uniform illumination. In the testing of this particular method the mosaic was created offline, possibly because of the high computational requirements of the algorithm.

Gracias *et al* [14] has developed another approach to mosaic creation and also implemented it as an aid for navigation. The estimation of motion is performed by selecting

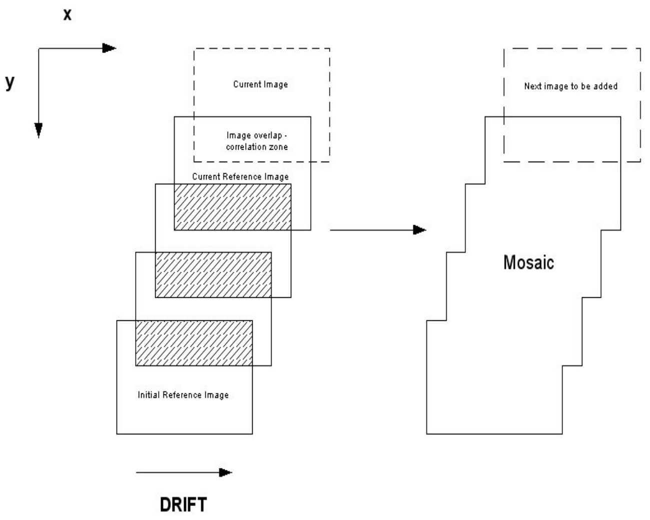

Fig 2. Mosaicking Process

point features on the image using a Harris corner detector and then finding these 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 interframe 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 that have been captured on camera. This method again has issues regarding the real-time construction of the mosaic and the assumption of a single planar surface.

All the above methods rely on the assumption that the surface is planar, but despite this, results seen from the most recent papers are encouraging. Piece-wise planar surface representation is one of the areas that is being researched to overcome this assumption. The main difficulties that remain are a lack of textures on the seabed floor and non-uniform illumination. Processing power and on-board storage are also issues for AUVs, but the reduction in unwanted image capture demonstrated in [14] may be a viable solution for slow moving vehicles. The future in this field is very much based on improving and fusing current methods to develop more robust and accurate image correspondence techniques with the goal of real-time high resolution mosaicking.

IV. FEATURE TRACKING

Feature tracking is the process in which an underwater vehicle can detect and follow a natural or man made element on the seabed floor such as a power or telecommunication cable. Feature tracking can be used for underwater applications such as cable inspection and repair, and can eliminate the need for tedious and error prone human inspections that are necessary for ROV based solutions. This system would also prove much less expensive than an ROV method, as the need for a mother ship is removed. Vision also has advantages over magnetometer methods for cable tracking, not only because of its expense but also its ability to detect cable cracks or defects. The camera setup remains similar to the station keeping configuration seen in Fig 1.

The first example of a cable tracking system takes advantage of the lack of straight line edges found in the underwater environment [3]. The incoming images from the camera are filtered by a combination of Laplacian and Laplacian of Gaussian in order to obtain an edge image. Only pixels with certain threshold contrast and LoG filtered values are regarded as edge pixels. The threshold value for contrast is changed dynamically in order to identify even the finest contrast pixel edges that have a long linear characteristic. The Hough transform (Fig 3) is then applied to the image in order to find the most likely candidates for a cable edge. The distance and direction of the edges with the greatest votes in the Hough transform are measured. Those that produce an evaluation value greater than a pre-defined value are selected as the final candidates. A process of predicting the angle range of the Hough transform is used to save on computation time by examining the difference between direction of the present cable edge and the previous one. This method achieved good results in a controlled environment but features such as sediment covered pipes, non-uniform illumination or spurious edge detection from other pipes or elements could have reduced performance. Another limiting factor was the speed at which the cable could be tracked due to the processing time of the images.

Ortiz *et al* [15] developed a method for real-time cable tracking using only visual information and again takes advantage of the cables shape to locate strong alignment features along its side. 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

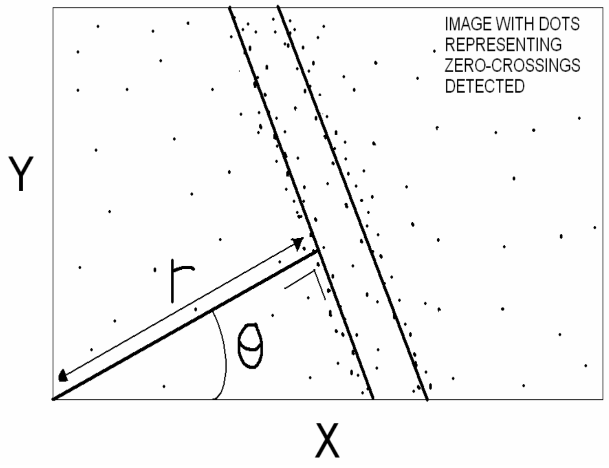

Fig 3. Hough transform detecting pipe edge pixels

the image a Kalman filter is implemented in an attempt to predict the location and orientation of the cable in the following image. This prediction reduces the computation time by choosing a region of interest (window of pixels) where the cable is most likely to be located. In the event of a failure of the prediction algorithm, the region of interest window is expanded to the whole image and all previous knowledge of the orientation and location of the cable is discarded. The technique achieved good results for partially covered cables, however, a minimal presence of the cable is required in the image at all times. No backup system exists in the scenario where the cable becomes completely invisible to the camera.

Balasuriya *et al* [16] proposes a system where information other than the optical information is used in the process of tracking the cable. An *a priori* map of the cable is assumed so an estimate of the location of the cable in the proceeding image can be predicted. The cable is detected by filtering the image with a Sign of Laplacian of Gaussian filter and highlighting the zero crossings. This filtering will create a high pixel concentration in a particular direction. The region of this line is predicted in the Hough plane using the *a priori* map. This method reduces the amount of image processing, due to the Hough angle prediction, as the region of interest has been greatly reduced. It also has the advantage of avoiding possible misinterpretations of similar features or other cables appearing in the image.If the cable is not detected in the region of interest then the vehicle can simply continue to follow the model line (*a priori* map) until the cable is again detected in the image. This paper has attempted to overcome the issues of tracking when the cable is invisible due to sediment or algae and the problem associated with correct cable selection in the presence of other cables or linear features. The results show that it has achieved these goals, but an *a priori* map of the cable location is not always available in cable tracking applications.

Good results have been achieved in all the papers discussed in partially controlled environments. No solution to the problem of tracking a cable that is invisible for a short segment has yet been produced, except in the case of having an *a priori* map of the cables location. The prediction systems also fall short in the case of abrupt changes in direction of the cable. Improvements in image processing to reduce the effects of marine snow, blurring and distance limitations would undoubtedly improve algorithm performance [4]. Another step to improve such systems is to develop a robust technique for cable inspection, fault identification and localisation.

V. INTERVENTION CLASS AUV (IAUV)

The next step in the evolution of the AUV is the development of manipulators (robot arms) in order to make it a true intervention class vehicle (IAUV). Manipulators are useful for many undersea applications such as repair of undersea cables and pipes, programming tasks such as valve operation (ALIVE IAUV [17]), environment interaction and sample taking. Some of the design and implementation issues to be addressed are, reliable behaviour within the workspace, avoiding collisions, system instabilities, unwanted drift, target recognition and target interaction. At present, most underwater manipulation tasks are performed by manned submersibles or ROVs. One of the main factors limiting human interaction during manipulation tasks is the low bandwidth and time delay inherent in acoustic sub sea communication [18]. Vision can be a useful sensor to overcome some of the issues involved with making robot arm control autonomous. As stated earlier, in Section II, vision systems can be implemented to measure and control drift but they can also be utilized for target recognition and interaction.

Early attempts at a robotic arm vision control system were made by Smith *et al* [19]. The developed vision system had two objectives, identifying target objects in real-time and to produce a range measurement to effectively change the image from 2D to 3D. The target identification method uses a combination of edge detection and corner detection to identify simple shapes like pyramids or cubes by comparing them with reference objects. Range measurement was achieved by a laser triangulation scheme. The method described in this paper is only capable of identifying and interacting with known referenced objects. Unfortunately in a real unstructured marine environment the manipulator may encounter unidentified and unrecognised potential objectives of interest in random locations, with unknown position, size and orientation.

A more recent commercial development in the area has been the ALIVE (Autonomous Light Intervention Vehicle) project [17]. This vehicle was developed with the aim of replacing costly tethered ROVs, with intervention class AUVs for reliable exploitation and maintenance of sub sea equipment for the oil and gas industry. This vehicle does not use vision in the manipulation of a robotic arm, but instead uses it in an Autonomous Docking System (ADS). The Vision Docking Systems (VDS) task is to perform accurate vehicle orientation estimation in the final docking phase. Edge detection is preformed on the incoming images utilising the Canny algorithm, in order to determine the edges of three circular valves that should be present. It is the centre of these circles that are then used along with a CAD (Computer Aided Design) model, in order to estimate the pose of the vehicle. The ALIVE system is currently in commercial use and has shown impressive reliability. The offshore oil and gas industry's' attention has been drawn to IAUVs and the potential savings this technology may bring. This system is developed for docking and then manipulating known objects and uses other sensors in its operation besides optical. The system is proficient at its intended application but as yet is unable to cope with unidentified and unmodelled environments.

To overcome the problems of manipulation in unstructured environments Toal *et al* [20, 21] proposed a method of interacting with objects using a technique called 'Pull to Position' a direction based variant on visual servoing. Current techniques require prior knowledge of the position and orientation of the object of interest relative to the robot arm. 'Pull to Position', on the other hand, does not require any knowledge of the object in question. Vision is used to determine the required direction of 'pull' to the object of interest. This pull is then applied to a simple model of the robot arm in simulation. The joint angle changes in the simulation model are then recorded and the same changes are applied to the actual robot arm. The process then repeats itself by finding the direction to target using the vision system. Good results were achieved in early experiments using an array of light dependent resistors (LDRs) mounted in a honeycomb arrangement of an insect eye, instead of a camera. The use of the simple sensor array and point light source target was for the purpose of simplifying vision processing during the motion control development. This technique has since been tested with camera systems in the laboratory [22]. The robot arm under this control proved capable of tracking a moving target using the 'Pull to position' method (see Fig 4).

The ALIVE project has shown the great potential of IAUVs in the commercial sector in just one of the many application fields that it can enjoy success. IAUVs can eliminate the need for costly manned submersibles and tethered ROVs in applications such as cable repair and sample collection. However, the need for an IAUV that can operate without prior knowledge is vital to make them more commercially viable and reduce the need for customised solutions. Underwater robotic arm control is quite a new area of research and is likely to see rapid development in the coming years. The future could possible see a fusion of an array of different sensors in order for reliable robotic arm function.

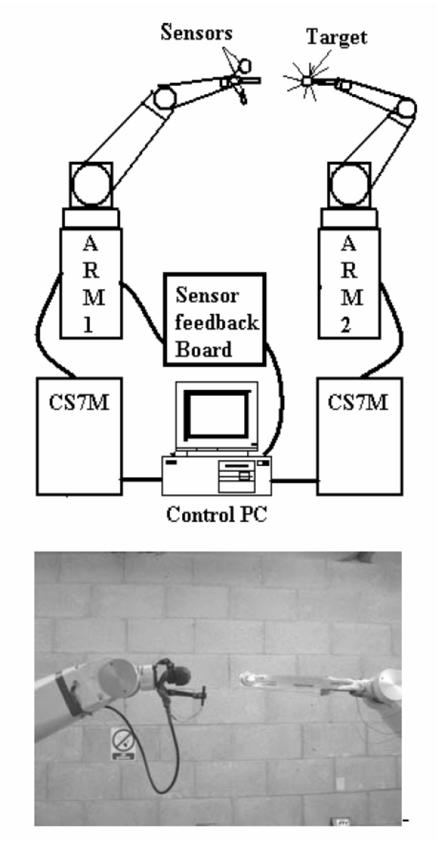

Fig 4. Experimental setup for target tracking

VI. VISION IN NAVIGATION AND POSITIONING

Navigation underwater is an important issue for autonomous underwater vehicles as the operator needs to know the vehicles position and orientation in respect to the position of the mission's goal. Different methods for motion detection have already been discussed in Section II. A mosaicking method that incorporates a navigation system has also been examined [11]. However, the main difficulty faced with navigation underwater is that GPS is unavailable. In general navigation is achieved with combinations of: acoustic positioning (ultra short baseline (USBL) or long baseline (LBL)); inertial navigation systems (with Kalman filter); Doppler velocity log (DVL), pressure depth and other integrated sensors. Acoustic positioning systems generally have accuracies of the order of 1% of slant range between beacons and transponders. Inertial navigation with Kalman filter fusing position estimates from a complex of different sensors gives the best possible navigation/position estimates. In this scenario DVL is a common INS aiding sensor.

At low velocities DVL performance degrades [23]. DVL as with all acoustic instruments has a minimum (blanking) range from the sea bed below which it does not function and it is often a bulky sensor which is an issue for AUVs. Another possible solution to aid INS is a vision system. If motion of the platform over the seabed can be derived from vision this could be used in INS aiding. UUVs generally have camera systems and this approach would thereby use the already present camera in navigation. This would have the advantage over DVL with regard to cost and performance that wouldn't degrade at lower speeds and sub meter altitudes. To date no such system has been developed for an underwater application, but a small number of attempts have been made for autonomous land based vehicles. The camera setup for land based vehicles would differ from underwater vehicles. Instead of observing the surface the camera would face to the side or front of the vehicle.

One of the first basic land based applications of vision as an aid to INS was developed by Roberts *et al* [24]. The system developed used vision as well as an odometer in order to allow an autonomous vehicle to retrace a narrow road over a long distance. The vehicle is first piloted along the road to its destination while the vision system takes note of significant landmark features that satisfy a predefined model. These landmarks are then used during the autonomous retrace to correct any positional errors that may have occurred. This system is a greatly simplified version of what would be required for an AUV.

Another land based vision aided INS system was developed at MIT by Deil *et al* [25]. The purpose of this development was to lengthen the period of time during which a vehicle can maintain correct positional information in GPS-deprived environments. The vision system is used to locate corner features in the surrounding terrain using a Harris corner detector. These features are then tracked over multiple frames using normalised cross-correlation. A single feature over multiple frames creates a plane between the feature and the camera in 2 different locations. This relationship is known as the epipolar constraint. This epipolar constraint that is created by multiple features is used along with a Kalman Filter in order to update an inertial measurement unit (IMU) and remove translation error. This method is capable of dealing with an unstructured land setting; however, it is not directly transferable to a sub sea scheme, as distinct features are sparser in an underwater environment. Such an approach though would potentially aid INS navigation in occluded areas where acoustic positioning drops out e.g. in channels, caves or wrecks.

Researching the currently available solutions for underwater navigation, it is apparent that there is a need for more flexibility and choice. The author believes that with improved hardware and further research, vision systems have a role to play in the development of enhanced navigation & positioning systems.

VII. DISCUSSION AND CONCLUSIONS

In this paper different applications for machine vision underwater have been examined. Despite the difficulties of incorporating optics into underwater environments, research into the field appears to be growing stronger due to its obvious advantages over other sensors. The ALIVE project is just one of many projects where machine vision has been incorporated into a commercially successful vehicle. The presented examples of various applications for vision in UUVs show that it is by no means a trivial task to identify the most promising systems to use. From this research it can be seen that vision systems can be assured a strong future in the research and development of underwater vehicles.

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