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Real-time Mosaicing of Large Scale Areas with Forward Looking Sonar

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Abstract: Mosaicing of large scale areas is an important application in the field of underwater computer vision. Although most of the works use optical cameras for that purpose, Forward Looking Sonars, also called acoustic cameras, are becoming more popular due to recent advances with respect to resolution. Mapping a large area in real-time can be extremely important in certain applications such as search and rescue, post-disaster survey, surveillance or automatic target detection. In particular, the possibility of having a map created in real-time of the surveyed area can diminish the Post-Mission Analysis time and allow mission replanning. Results obtained for a marina dataset are hereby presented and the possible applications of this work are discussed.

Keywords: forward looking sonar, mosaicing, real-time, mapping, underwater

1. INTRODUCTION

Mosaicing large areas of underwater environments has been one of the most prominent applications in the field of underwater computer vision. The applications for mosaicing include coral reef mapping (Shihavuddin et al., 2013), navigation (Negahdaripour and Xu, 2002) and archaeological site mapping (Pizarro and Singh, 2003), among others. All these works use optical cameras, but in the last years sonars have become more popular due to their performance under conditions where optical cameras fail. For instance, sonars can be very useful under conditions of turbidity and lack of illumination. In underwater vehicles without artificial light, optical cameras are not very useful in deeper water due to the light attenuation. The same happens for surface vehicles, where optical cameras have good performance only in shallow waters.

Typically, sonars have been used in applications such as obstacle avoidance (Petillot et al., 2001), chain inspection (Yong, 2011) or Automatic Target Recognition (ATR) (Beaujean et al., 2011; Williams and Groen, 2011). Most of these applications use high resolution sonars either, Side-Scan Sonars (SSS), Synthetic Aperture Sonars (SAS), or sometimes Forward Looking Sonars (FLS). Their high resolution prevents real-time mosaicing without special hardware such as Graphical Processing Units (GPUs) and considerable subsampling. However, lower resolution FLS can be used for that purpose. They are also low cost and small enough to be easily mounted on Remotely Operated Vehicles (ROVs), Autonoumous Underwater Vehicles (AUVs) and Autonoumous Surface Vehicles (ASVs) of medium size.

Few works have been published on mosaicing for FLS data and even less in real-time mosaicing. However, the current developments of the state of the art are quite promising. Namely, a prototype of a FLS system developed by the authors (non-commercial) is presented in (Cervenka and Marchal, 2004). The focus of that article is on the system design and calibration, but initial results of mosaicing are presented. Partial mosaics of large areas are presented. During the experiments, not all the area of the survey was insonified resulting in mosaics with huge gaps. This mosaicing technique is not performed in real-time.

In (Kim et al., 2008), a mosaicing algorithm for high resolution FLS images is performed in a ship-hull inspection. In this case, the mosaic is built from 80 images of a high resolution sonar (DIDSON). It is shown that the algorithm is implemented to work in real-time, but it is uncertain if it can provide the claimed resolution with the enhancement (up to 10 times the original) in real-time. As a result of this work a commercial software for sonar image enhancement and mosaicing (processing time of 3.5 frames/sec) is available (Acoustic View). The mosaic of up to 1000 frames depending on the level of free memory is claimed. In (Yong, 2011), mosaicing techniques were

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investigated for FLS data, where the algorithm works near real-time, but the results are focused only on ship-hull inspection covering a small area.

An innovative phase correlation-based mosaicing algorithm initially introduced in (Hurtos et al., 2012) was extended and the latest results can be found in (Hurtos et al., 2014b). Most of the work from these authors was not focused on real-time capability, but very recently the first experiments on real-time mosaicing of FLS data were presented in (Hurtos et al., 2014a). Nonetheless, the covered area is relatively small and the sonar used is a high resolution one with relatively short range, thus the results are not as suitable for wide-area survey applications where the depth can be higher and ASVs are used.

Finally, a very interesting work on mosaicing of FLS data together with SSS data is presented in (Reed, 2011). Although this method does not work in real time, it is very useful for wide areas. By filling the gap produced by the nadir of the SSS with FLS data, the mission time reduces considerably as less transects are needed to cover the same area without losing the nadir area. This is extremely useful for fast assessment of the area in applications such as post-tsunami or other catastrophe surveys. This method was tested in a post-tsunami survey with good results, in that were found objects that would not be seen in SSS data. Unfortunately, no details about computational time are given in this article.

As described by the authors the algorithms presented in the literature are not suitable to work for a wide range of applications, or to work in real-time, or large scale areas. This has also to do with the complexity of FLS data. For a review of the most important issues and challenges that mosaicing FLS brings, the reader can refer to (Negahdaripour et al., 2011). The existing methods try to solve a specific problem and are not focused on the real-time constraint, using in certain cases MATLAB implementations. Our algorithm tries to be as generic as possible while maintaining the real-time constraint and working in any area of any dimension. We also georeference the mosaic so that it can be easily overlapped in a satellite map. Inspired by work done on real-time mosaicing of optical camera data (Ferreira et al., 2012), a novel algorithm for mosaicing of FLS data in real-time is hereby presented. It can be considered for large scale areas as the results will show, but also to other applications such as Automatic Target Recognition (Ferreira et al., 2014a). The algorithm is flexible to work with various sonars (BlueView and Reson tested thus far) and in different setups (fixed to a pier, mounted onto a moving ASV, and mounted onto a moving ROV tested thus far).

The reasons that motivate the use of FLS to mosaic large scale areas are various. First, there is a reduction of the noise and an increase in the Signal-to-Noise Ratio (SNR). This is due to the averaging effect of the mosaic. Noise is intrinsically present in these kinds of sonars due to the physics of the sensor. Backscatter is always present, and noise due to reflections coming from the water column occur independently of the stability of the platform. If the sonar is onboard an ASV, noise can increase with stronger sea states. The ASV is not overactuated and the effect of the waves can be considerable. The instability in pitch and roll can get problematic with high sea states, but even with calmer sea states, small changes in pitch mean significant changes in insonification. Indeed, inhomogeneous insonification is a natural phenomenon in acoustic camera images that one cannot eliminate in raw data. A mosaic averages over several frames with different insonifications and diminishes the effect of the insonification variability.

Second, the presence of other acoustic sensors on board can interfere with the FLS. Namely, echosounders and Doppler Velocity Loggers (DVL) working in frequencies within the operational range of the FLS are easily noticed in the raw data. Again, the averaging effect of mosaicing can mitigate this source of noise. Finally, mosaics can also help improve the contrast of the image and the definition of objects present on the seabed. That comes naturally from the fact that several images are stitched together, and therefore an object will be seen in more than one view.

The remainder of the document is organized as follows. Section 2 presents the mosaicing algorithm. Section 3 describes some of the applications used to test the algorithm. Then, Section 4 shows the results obtained for a large scale area. Finally, conclusions and future work are described in Section 5.

2. METHOD

The mosaicing algorithm is inspired by the one presented in (Ferreira et al., 2012). In this work, we apply a similar mosaicing algorithm to FLS data. In (Ferreira et al., 2012), the algorithm was purely based on optical data (with acoustic altimeters only used in the case of failure). For the FLS data used here, the algorithm can take advantage of other sensors on-board the ASV or the ROV. In (Ferreira et al., 2012), vision-based motion estimates were used to get an initial guess of the best transformation between the actual frame and the mosaic. For FLS data, instead we use other on-board sensors of the vehicle and not the sonar itself. In particular, for the ASV case, motion estimates are available from a Differential GPS (DGPS) system and heading information is available from the same DGPS system. For the ROV case, motion and heading can come from a unit that integrates high-end inertial, DVL, and Ultra-Short Baseline sensors.

In the case of the ASV, the sonar head is mounted on a variable depth pole and has a pan-and-tilt unit that has to be considered for mosaicing purposes. As in similar work in the literature (Hurtos et al., 2012; Aykin and Negahdaripour, 2013), the 3D point is projected onto 2D using an orthographic projection as an approximation. This approximation is valid as long as the scene relief is small when compared to the sonar range. This is true if the vertical beam width and the tilt angle are small, since $cos(\phi) \approx 1$ and $sin(\phi) \approx 0$ for small angles. In our typical missions and for the sonars tested, the tilt angle is smaller than 5° and the beam width is 10°, thus this assumption holds. A study on the effect of this approximation in the images registration can be found in (Johannsson et al., 2010). Equation (1) defines the 3D coordinates in spherical coordinates (r, θ, ϕ), with r being the sonar's range and θ and ϕ the bearing and elevation angles respectively. Equation (2) presents the projected 2D point.

$$P = \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} r\cos\theta\cos\phi \\ r\sin\theta\cos\phi \\ r\sin\phi \end{bmatrix}, \quad (1)$$

$$\hat{p} = \begin{bmatrix} m \\ n \end{bmatrix} = \begin{bmatrix} r\cos\theta \\ r\sin\theta \end{bmatrix}. \quad (2)$$

By using the orthographic projected point, an affine transformation can relate two consecutive frames. The rotation matrix and translation parameters for the affine transformation can be directly obtained from the DGPS and the pan-and-tilt unit, with the pan being treated as a pure rotation around the elevation axis for the ASV case. In the case of the ROV, the sonar was fixed, but the robot was fully actuated and able to control all translational and rotational degrees of freedom providing accurate measures for heading and pitch. The pitch angle was purposely kept at 0°, and the robot depth was controlled to obtain optimal sonar position with respect to the sea bottom. Therefore, the same rotation matrix and translation vector can be obtained from the ROV navigational system. Skipping the details, the final relation between two frames can be described as in (3). For convenience, rewriting (3) using homogeneous coordinates for the projected point $(m, n, 1)$ gives us the final formula in (4) with $\mathbf{R}$ being the rotation matrix and $\mathbf{t}$ a vector with the translations in x and y directions.

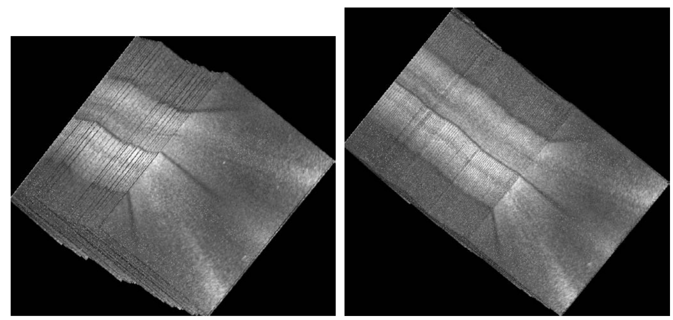
$$\begin{bmatrix} m_2 \\ n_2 \end{bmatrix} = \mathbf{R} \begin{bmatrix} m_1 \\ n_1 \end{bmatrix} + \mathbf{t}, \quad (3)$$

$$\begin{bmatrix} m_2 \\ n_2 \\ 1 \end{bmatrix} = \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ 0_{1x2} & 1 \end{bmatrix} \begin{bmatrix} m_1 \\ n_1 \\ 1 \end{bmatrix}. \quad (4)$$

As in (Ferreira et al., 2012), the motion estimates (now coming from DGPS/INS instead of the camera) can be used as an initial guess of the point where the images should be stitched together to form the mosaic. Then, a correlation method can be applied in a neighborhood of that initial guess instead of the full frame in order to improve computational efficiency and take advantage of the DGPS/INS.

Nonetheless, in featureless environments, the correlation or feature-based methods have poor performance and the use of the DGPS/ROV navigation motion estimates is recommended, with a careful filtering of the estimates. For instance, the correlation method used in (Caccia, 2006) or other feature-based methods like the ones of (Ferreira et al., 2014b) fail for particular datasets that are quite featureless. This can happen in a sandy bottom with no artificial or natural objects of interest. If one applies a feature-based method to refine the mosaic, the algorithm estimates that the robot is practically stopped as the actual image is very similar to the mosaic leading to a maximum correlation coefficient for a zero pixel translation.

Figure 1 shows an example of this situation with the same area represented in a mosaic that only uses DGPS estimates and one that uses the correlation method. As it can be easily observed, several frames map to the same location in the case of the correlation method. There is also an error in the direction perpendicular to the movement of the robot due to the noise sensitivity of the correlation method to very similar images. For the BlueView sonar tested, two sonar heads are joined together and a thin line departing from the origin represents the border of each sonar head. The lack of continuity of these lines means that the algorithm is drifting. In the case where only DGPS estimates are available, these lines are continuous. In these situations, using only DGPS gives a better result than the correlation method. Current work tries to identify environments that are featureless, and switch between using correlation or only DGPS (or other on-board navigation sensors for underwater vehicles).



(a) (b)

Fig. 1. On the left, a partial of the mosaic built using the correlation method. On the right, a partial of the mosaic built using only the DGPS estimates.

For the blending of several images into the mosaic, special care has to be taken. Most of the pixels close to the origin of the sonar head should be discarded as they do not represent accurately the bottom, but include instead reflections from the water column. Only a valid region of interest should be mosaiced. The blending strategy can not be the same as the one used for optical cameras. In that case, only new pixels were added to regions that were empty. For FLS data, that approach does not apply. For instance, in circular missions, that would mean adding only pixels in the boundaries and not filtering any noise in the overlapped areas. In the more common lawn mowing patterns, that strategy can be used, but it is still suboptimal as does not improve areas that are seen in more than one frame whereas it is exactly on that that the mosaic can be useful. Due to the changes in insonification, an object can be clearly seen in one frame and then not any more in the next one. If the blending technique would add only new pixels in a case where the object was not seen on the previous frame, then that object could not be seen at all. Hence, a different approach is used here based on an average of both images. The overlapping area between the mosaic and the frame to be added is computed. On this area, an average of the mosaic and the new frame is copied to the mosaic. This ensures that some of the noise is filtered and gives more importance to the new frame than what was done with the optical camera. This simplified technique works sufficiently well for many missions. Other more complicated techniques like the ones described in (Yong, 2011) include different weights for each of the images or for each region of the image. They can be used in a non real-time context, but in this case the real-time constraint led the authors to choose the simplest yet effective solution.

3. APPLICATIONS

The method described in Section 2 can be applied in different contexts such as chain inspection, hull inspection, target detection, obstacle avoidance and surveys. The survey of large scale areas can be an interesting application of this method. Although a survey of a large area might not require real-time capability, an algorithm that works in real-time and gives on-the-fly results can be very useful. For instance, in search and rescue operations after natural catastrophes such as a flooding, a typhoon, a tsunami or naval accidents, a rapid assessment of the area can provide critical information to the rescue teams. It is possible to cover a large area quite fast by using some FLS that have long ranges (e.g., Blueview at 450kHz - about $50m$ and Reson at 400kHz - about $100m$) and large field of view (e.g., Blueview 130° and Reson 128°). The possible drawback of performing real-time mosaicing without global optimization is that for a lawn mowing pattern mission, artifacts can occur naturally in parallel tracks in cases of high overlap of the consecutive search legs. It is worth noticing that in future work, the mission planning can take into account the area covered by the sonar in the definition of transects to avoid artifacts. The data collected and used to test the method was not acquired with that in mind.

The mosaic can be built in real-time and can be sent to an operator as it shall be seen in Section 4. This person can inspect immediately the area while the survey is being conducted without the need of waiting until the end. As the mosaics that are optimized in post-processing can take some hours to finish, this represents another important advantage of this method. Due to the flexibility of the method, one can also get partial mosaics corresponding to each parallel track. During mission planning, the operator can give start and stop geographic coordinates that correspond to a transect, avoiding artifacts and getting important information in real-time. Finally, large scale and complex environments such as marinas can be extremely helpful for proving the usefulness of the algorithm as they represent a series of situations that can occur in other environments such as structured man-made objects, unstructured objects, sandy bottoms, etc.

In a particular context of Mine Countermeasures, real-time mosaics of a large area are extremely important. Nowadays, the data collected either with SSS or FLS requires the operators' involvement for Post-Mission Analysis (PMA). This analysis is generally very time consuming and exhausting for operators that spend long hours looking at the waterfall display of the data in order to find potential mine-like objects. Nonetheless, human operators still outperform software implemented ATR algorithms due to the false-alarm rates of the algorithms. This is not desirable at all as additional search patterns are implemented to take a closer look at the computer ATR targets, increasing dramatically the overall mission time. If target recognition is performed by an operator based in real-time mosaics, both the false-alarm rate will be low and the time spent on data analysis will be considerably reduced.

4. RESULTS

The results presented in this section were obtained both with surface and underwater vehicles. The data were obtained by the BlueView sonar model P450-130 working at 450kHz and with 130° Field of View (FOV) mounted onboard an ASV; and with a Reson SeaBat 7128 onboard the ROV Latis from University of Limerick. The algorithm can run at a frame rate between 1Hz and 4Hz depending on the number of mosaics saved for post-processing and data analysis (parameter configurable).

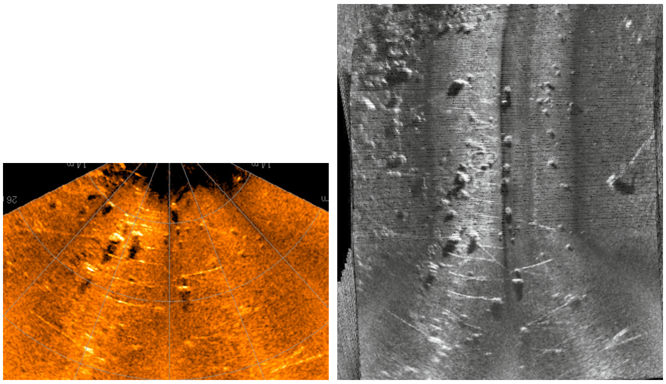
4.1 Mapping a marina

The data here presented were obtained with a BlueView P450-130 sonar that was mounted onboard the ASV Gemellina. The data were collected in Marciana Marina, a marina at the Island of Elba, during the ANT'11 trial conducted by the Centre for Maritime Research and Experimentation (CMRE), formerly known as NURC.

The full mosaic is presented in Fig 2. It is built at half the resolution of the original raw data. As it was expected, the differences between tracks are easily seen due to the lack of optimization and complex blending. The goal of the work is to show real-time useful mosaics with no need of waiting for hours of post-processing. The characteristic inhomogeneous insonification is the main reason for these artifacts. As described above, for future trials, the mission planning can be done in way that decreases overlapping while guaranteeing no gaps. Alternatively, defining starting and stopping points for the mosaicing correspondent to each transect, gives partial mosaics that can later be registered in post-processing. The dimension of the area and other quantitative data will be given in Subsection 4.3.

Fig. 2. The full mosaic of Marciana Marina overlaid in a Google Earth satellite image

A small area of this data set is shown in Fig. 3 together with a frame of raw data for the same area. As it can easily be seen, the mosaic improves the image contrast and gives a much better definition of the shadow. It also shows details hardly seen on the raw data such as several mooring ropes. While in the raw data sometimes it is hard to see that there is a mooring rope, in the mosaic it is very clear and identifiable.



(a) (b)

Fig. 3. On the left, one frame of raw data. On the right, a partial mosaic of the same area.

4.2 Mapping an area for Automatic Target Recognition

Another large area was mapped with a Reson SeaBat 7128 onboard the ROV Latis from University of Limerick during the ANT'12 trials near La Spezia, Italy. This sonar has a much better resolution than BlueView and a lower level of noise. Only slight changes were needed on the side of the mosaicing algorithm due to its flexibility. One of the motivations to use FLS mosaics is the lower SNR. In this particular case, the original raw data has already a low SNR and thus the improvement is not as noticeable as for BlueView data. Nonetheless, the quality of the mosaic is still superior to the one of the raw data, and the same improvement in contrast and shadow can be seen in Fig. 4. This mosaic is composed of 2511 frames obtained in a cross-pattern mission for Autonomous Target Recognition. In the middle of the mosaic, a cylindrical shape target can be identified with a very well defined shadow. It is important to notice that although this sonar produces higher resolution images of larger dimensions, the algorithm still works in real-time. To show that feature, a video is attached to this document.

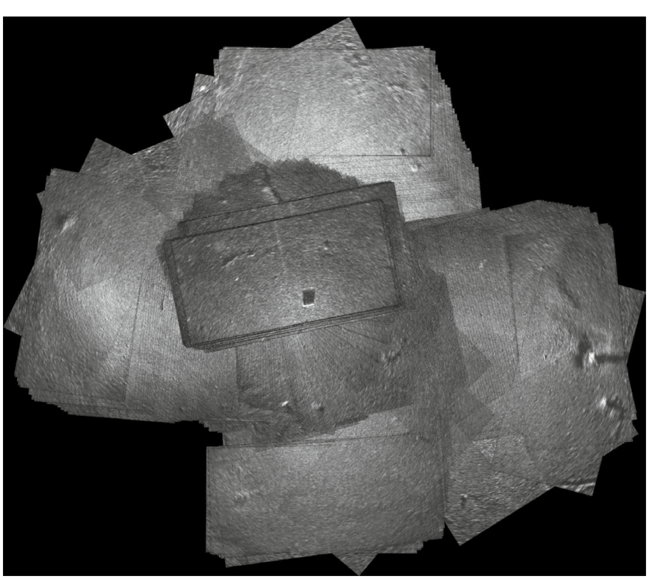


Fig. 4. Mosaic of a cross-pattern mission.

Table 1. Comparison between raw data size and mosaic size for a small area survey and high resolution sonar

Area [m^2]	# frames	Mission time [min]
3650	141	9
Raw data [MB]	Mosaic data [kB]	Ratio raw/mosaic
170	400	425

4.3 Data size reduction

Table 1 shows quantitative data relative to a small dataset obtained with the Reson sonar on-board the ROV Latis. The quantities presented are the area covered by the survey, number of frames, mission time, total raw data size, mosaic data size and ratio between these two. Total raw data size sums all the sonar data collected, while the mosaic data size is referred to the global mosaic at the end of the mission. Even though the mission takes only 9 min and the area covered is not very large, 170 MB of data are produced by the sonar system due to high frame rate (50 pings per second) and resolution of Reson which corresponds to 1.2MB of data per raw frame in .png format. Mosaicing that data at half the resolution does not decrease the quality in a considerable way, while reducing impressively the amount of data generated to 400 kB by saving the mosaic in the .png format. This represents a ratio of 425 between the amount of raw data and the size of the mosaic. This ratio can be further increased by compressing the mosaic to a .jpg format, e.g. with a 85% compression factor the size decreases to half (200 kB). It should be noted that the first frame covers an important part of the area and weights considerably in the mosaic. For a data set like the one of Fig. 2 where a substantial area is covered, the importance of that initial frame decreases and the ratio raw data/mosaic increases dramatically.

Table 2 presents the same kind of quantitative data as Table 1 for the data set obtained with the BlueView sonar and shown in Fig. 2. For an area of 75000 m^2 covered in 42 min of mission, 4.4 GB of raw data are produced. Instead, the full mosaic can be represented with only 3.2 MB. This gives a ratio of 1375 between the raw data size and the mosaic size without any compression. Such a ratio is impressive and it is extremely important for the aforementioned scenario where an underwater vehicle builds the mosaic and sends it through acoustic messages to a surface vehicle. The same applies if a surface vehicle performs the mission and tries to exchange the data through WiFi, radio or satellite link to an aerial vehicle or on-shore control station. By reducing the amount of data and allowing the exchange of information between vehicles or between a vehicle and a control station, the mosaic can be seen as an enabler for mission replanning and PMA. A fast assessment of the covered area can be performed by an operator or an algorithm, and a new mission can be initiated to look better in a particular area of interest.

5. CONCLUSION

This paper showed how it is possible to map a large scale area with a FLS in real-time without the need of waiting for a global optimization process. The simplicity of the method does not compromise its effectiveness and usefulness. Real-time mosaics of large areas can be very useful

Table 2. Comparison between raw data size and mosaic size for a large area survey and lower resolution sonar

Area [m^2]	# frames	Mission time [min]
75000	8827	42
Raw data [MB]	Mosaic data [kB]	Ratio raw/mosaic
4400	3200	1375

in a myriad of applications. Compared to previous works, this work presents a real-time performance suitable for both small and large scale surveys and able to work with different sonars and resolutions. Several improvements can be included in future work. Namely, the use of a GUI for mission replanning based on human feedback and the exchange of mosaic data between vehicles/shore station. Another possible research avenue is the use of FLS as a gap filler when fused together with SSS data to reduce mission time. Mission time and PMA time reduction are two main advantages of real-time mosaicing with FLS and shall be exploited in the future. Finally, distinguishing between feature rich and featureless environments will allow to use Simultaneous Localization and Mapping (SLAM).

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Title

Real-time mosaicing of large scale areas with forward looking sonar

Abstract

Mosaicing of large scale areas is an important application in the field of underwater computer vision. Although most of the works use optical cameras for that purpose, Forward Looking Sonars, also called acoustic cameras, are becoming more popular due to recent advances with respect to resolution. Mapping a large area in real-time can be extremely important in certain applications such as search and rescue, post-disaster survey, surveillance or automatic target detection. In particular, the possibility of having a map created in real-time of the surveyed area can diminish the Post-Mission Analysis time and allow mission replanning. Results obtained for a marina dataset are hereby presented and the possible applications of this work are discussed.

Keywords

Forward looking sonar, mosaicing, real-time, mapping, underwater

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