

VIDEO MOSAICKING ALONG ARBITRARY VEHICLE PATHS

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Abstract—This paper presents the experimental verification of a novel method for real-time video mosaicking of the ocean floor from a semi-autonomous underwater vehicle. In order to enable mosaicking along unconstrained vehicle paths, it is essential to reduce the propagation of image alignment errors within the mosaic. We have developed iterative smoother-follower techniques to reduce these errors, and we have proven their effectiveness in the laboratory environment.

We will also present our results from a concurrent research effort to demonstrate a completely autonomous video mosaicking mission. By transferring our vision technologies to OTTER (Oceanographic Technologies Testbed for Engineering Research), we have created a prototype system for visual survey of the sea floor. In particular, we will discuss the development of a new vision processing subsystem and its integration into the AUV control system.

I. INTRODUCTION

Our primary motivation in exploring and developing key vision technologies for underwater vehicle control is to enable marine scientists to explore the ocean environment. Specifically, we wish to provide a system for autonomous mapping of the sea floor from an AUV. By aligning several camera images taken at regular intervals along the vehicle path, it is possible to form a composite image, or mosaic, of the scene. Our current research efforts have included both the development of the video mosaicking subsystem, and the integration of this sensor into an autonomous video mosaicking mission.

While autonomous video mosaicking has already been achieved on recent prototype systems [7], there are still limitations which prevent these systems from becoming

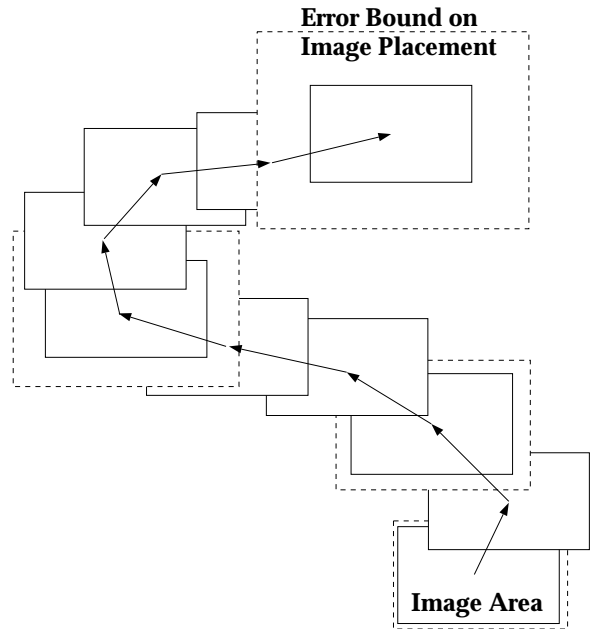


Figure 1: Error Propagation in Image Chain
For an image chain of length n , the error variance in the global position of the final image is proportional to n .

practical scientific tools. The most significant unsolved problem in real-time mosaic creation is the accumulation of image alignment errors as the mosaic increases in size (see Figure 1). Although the error between consecutive images is small, the error in placing the most recent image relative to the starting point increases without bound as more images are added to the mosaic.

If this chain of images were to loop back upon itself, the image misalignment at the crossover point would result in poor quality of the final mosaic. As a result, the vehi-

cle path length and shape is severely constrained, thereby making it impossible to map large areas of the ocean floor. In previous work, we have presented a method to alleviate this problem by optimally reducing the image alignment errors around loops in the image chain [3]. Since then, we have demonstrated experimentally the validity of our techniques. Our experimental results, as well as an overview of our methods and previous simulation work, will be presented in this paper.

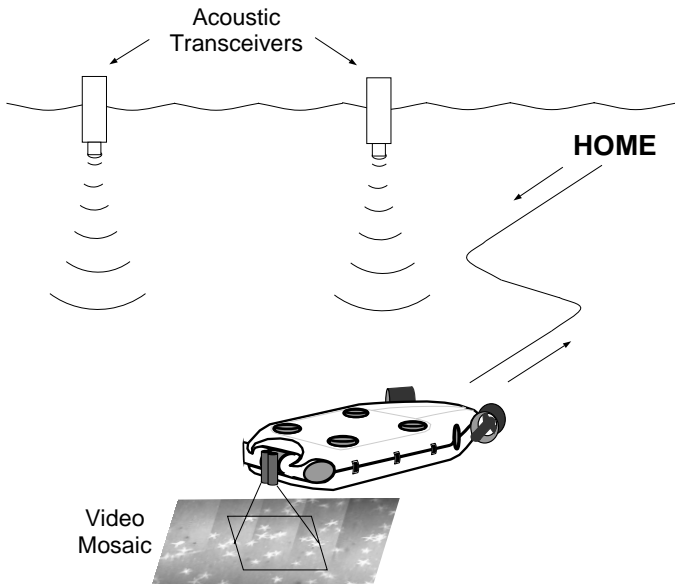


Figure 2: **Autonomous Video Mosaicking Mission**

The proposed mission consists of three phases: (1) navigate along the desired trajectory via an acoustic transceiver net, (2) mosaic the sea floor using the vision sensor for control, and (3) return home.

The second phase of our research is to demonstrate our real-time video mosaicking capability within the context of an autonomous underwater vehicle mission. Our proposed task is to start at the “home” position, navigate along a specified trajectory using an acoustic positioning system, create a mosaic of an area of the ocean floor, and return “home” (see Figure 2). By executing this mission in the test tank, we hope to demonstrate the feasibility of video mosaicking from AUV’s as a practical tool for scientific exploration.

II. BACKGROUND

Several research groups have investigated the problem of mapping the ocean floor from AUV’s. However, these other research efforts differ significantly in their choice of sensors. While several organizations have demonstrated autonomous station-keeping and biological sample collection using various types of acoustic positioning networks

and differential GPS [5, 11], these sensors have not been adapted for mosaicking tasks. Qualitative maps of the sea floor have been created with side-scan sonar [6], but according to the authors, this technology is incapable of producing the highly accurate range information required for quantitative surveys. Interesting results have been achieved in the area of constrained video mosaicking, in which a multiple-column mosaic is created by correlating the images in adjacent columns [7]. This research effort has also produced impressive single-column mosaics of the sea floor using *Ventana*, a remotely operated vehicle (ROV) owned by the Monterey Bay Aquarium Research Institute (MBARI).

Many research organizations have performed exciting AUV missions, although our concept of creating a visual multiple-image map of the sea floor is unique. Perhaps the most similar missions are those performed by the Advanced Unmanned Search System (*AUSS*), constructed and maintained by the Naval Ocean Systems Center (NOSC) [13]. This vehicle performs broad area search and survey in the deep ocean, using side-looking sonar. Upon finding an interesting item, individual images are recorded for use after the mission is completed. Surveying and inspection tasks have been the objectives of many recent AUV missions. Researchers have recently proposed autonomous environmental surveying in coastal waters off Denmark and Portugal, using the *MARIUS* AUV [12]. In an effort to reduce the cost of surveying underwater structures, a pipeline inspection task has been proposed within the context of an AUV mission [2]. Autonomous object retrieval with AUV’s is the natural extension of autonomous survey and inspection missions. This mission has recently been demonstrated on *OTTER*, a prototype AUV jointly constructed by the Stanford Aerospace Robotics Laboratory (ARL) and the Monterey Bay Aquarium Research Institute (MBARI) [14].

III. ERROR REDUCTION METHOD

To enable the task of video mosaicking along unconstrained vehicle paths, we have developed an approach to reduce the image alignment errors which propagate through the image chain (Figure 1). Our method utilizes the theory of optimal estimation and smoother-follower techniques to identify and remove these errors. These techniques and their effectiveness will be explained in the following sections.

A. Optimal Estimation Theory

In attempting to reduce the propagation of alignment errors throughout the mosaic, it would seem intuitive to utilize some version of Kalman filtering to smooth the errors as additional sensor measurements are recorded. This real-time approach is applicable to dynamic systems

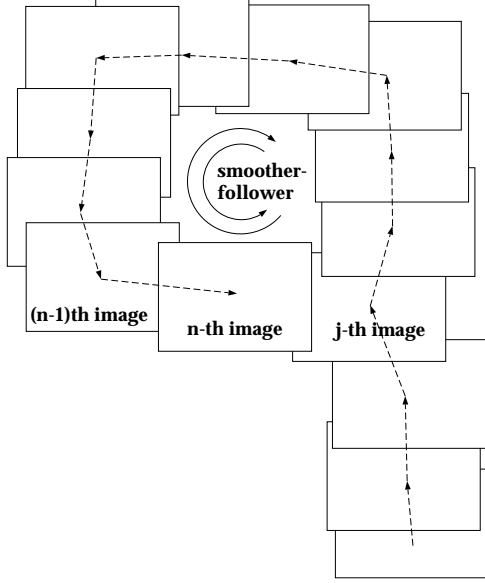


Figure 3: Geometry for a Closed Loop Image Chain
By utilizing an iterative smoother-follower, the additional information gained at the crossover point can be propagated along the entire loop to minimize the errors along that section of the image chain.

of the form [1]:

$$\begin{aligned} x(k+1) &= A(k)x(k) + B(k)\mu(k) \\ z(k) &= C(k)x(k) + D(k)\nu(k) \end{aligned} \quad (1)$$

where $\mu(k)$ and $\nu(k)$ are process and sensor noise variables, respectively. Based on the geometry of our system, the state equations can be written in similar form:

$$\begin{aligned} x(k+1) &= x(k) + \begin{pmatrix} \frac{W}{M}T(k) & 0 \\ 0 & I \end{pmatrix} u(k) \\ z(k) &= u(k) - \nu(k) \end{aligned} \quad (2)$$

where $z(k)$ is the sensor measurement. (The derivation of these equations is beyond the scope of this paper [3].) However, it becomes evident that the state, $x(k)$, is completely unobservable by the sensor, $z(k)$. As a result, it is impossible for Kalman filtering to reduce the errors in image alignment within a mosaic [1, 4].

Thus, it would seem that there is no way to bound the errors on unconstrained mosaicking. However, we can gain additional information whenever the image chain loops back upon itself. By correlating the n th image with the j th image as well as the $(n-1)$ th image (see Figure 3), we gain another measurement of the n th image global state. Furthermore, this new measurement is more accurate, since the j th image occurs earlier in the image chain and thus its global state measurement has a lower variance.

If we isolate the measurements along the loop between image j and image n , the equations of motion (2) are valid along this path. These equations can be combined as follows:

$$\begin{aligned} x(k+1) &= x(k) + \begin{pmatrix} \frac{W}{M}T(k) & 0 \\ 0 & I \end{pmatrix} z(k) \\ &+ \begin{pmatrix} \frac{W}{M}T(k) & 0 \\ 0 & I \end{pmatrix} \nu(k) \end{aligned} \quad \text{for } k = 0, \dots, (n-j) \quad (3)$$

with known initial and final states equal to the j th and n th image states, respectively. To propagate the new information throughout the loop, we can use an optimal smoother-follower [1]. Although a discussion of our smoother-follower technique is beyond the scope of this paper [3], the results of simulations and experiments running this algorithm will be presented in the following two sections.

B. Simulation Work

According to recent experimental data [8], the error distributions for the x , y , z , and yaw (ψ) state components are approximately uniform, with the following variances:

$$\begin{aligned} E\left[\begin{pmatrix} x \\ y \\ z \\ \theta \end{pmatrix} \begin{pmatrix} x & y & z & \theta \end{pmatrix}\right] &= \\ \begin{pmatrix} 0.0032R & 0 & 0 & 0 \\ 0 & 0.00201R & 0 & 0 \\ 0 & 0 & 0.0055R & 0 \\ 0 & 0 & 0 & 0.0085 \end{pmatrix} \end{aligned} \quad (4)$$

where R is the range from the camera to the image area. For our simulation, we have assumed these four degrees of freedom are measured by the vision sensor, and the pitch (θ) and roll (ϕ) are measured by additional sensors on the vehicle. Therefore, only the states in the above equation (4) need to be processed by our smoother-follower algorithm. Since the smoother-follower assumes Gaussian distributions for all random variables, we have modelled the above uniform distributions as Gaussian with identical means and variances.

To demonstrate the merit of our new approach to mosaicking along arbitrary vehicle paths, the following figures illustrate a typical vehicle path and its corresponding mosaic. The vehicle follows a simple rectangular trajectory in the XY plane while maintaining a constant heading. Figure 4 depicts the actual image position. The remaining two lines show the estimated position based on

the sensor data, before and after the data has been filtered by the smoother-follower. Clearly, the endpoints of the loop have the smallest error, since these points are known to the greatest degree of accuracy, while the error around the loop has been minimized. This can be seen directly in Figure 5, which shows the standard deviation of computed image position before and after the smoother-follower processing. While the original variance increases without bound, our method clearly bounds the variance around closed loops in the image chain.

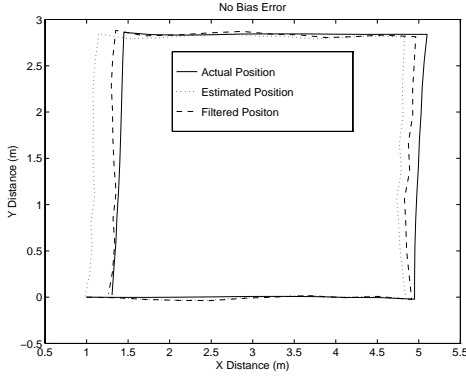


Figure 4: **Image Position within a Rectangular Mosaic**

When compared to the actual image position, the filtered data is more accurate than the position estimate based purely on noisy sensor data, particularly at the endpoints of the loop.

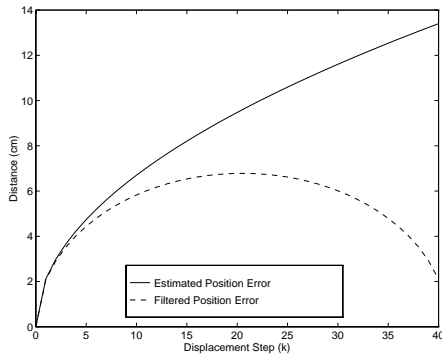


Figure 5: **Standard Deviation of State in X Direction**

Around any closed loop in the mosaic, our smoother-follower algorithm minimizes the variance, subject to the constraints of the equations of motion.

C. Experimental Verification

We have demonstrated our method in the lab, using the setup shown in Figure 6. The mobile base is a planar

(3-DOF) analogue to our 6-DOF underwater vehicle. A single downward-pointing camera is attached to the boom extending from the base. The camera video signal is input to our vision subsystem. Image digitization, storage, and display is accomplished by two VME-based processing boards created by Datacube. To perform the digital filtering and correlation of images at updates rates of up to 30 Hz, we have utilized two proprietary, real-time vision processing boards created by Teleos Research [9, 10]. These boards perform all computations in hardware, and transfer all images to and from the Datacube boards via the VME bus.

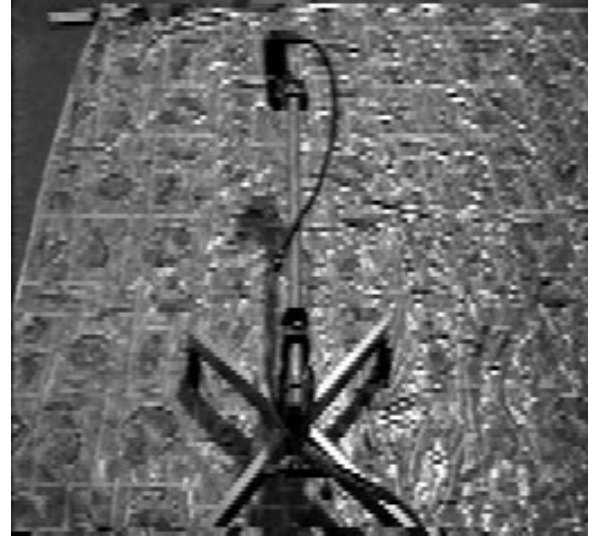


Figure 6: **Experimental Setup**

This photograph depicts the mobile base and camera used for our experiments. The plastic sheet simulates the ocean floor, in both the lab and test tank environments.

By moving the mobile base along a square trajectory, we have created a loop mosaic which depicts poor image alignment at the crossover point (Figure 7). By correlating the initial and final images in the mosaic, a more accurate estimate of the final image position was calculated. Using this additional information and the offset data for all other images, we used our smoother-follower algorithm to calculate an improved estimate for the global position of each image. As seen in Figure 8, the visual quality of the mosaic is greatly improved at the crossover point, while the quality of the rest of the mosaic has not been degraded.

IV. VIDEO MOSAICKING MISSION

In order to demonstrate the potential benefits of utilizing autonomous underwater vehicles for scientific research, we have integrated our existing vision sensing and

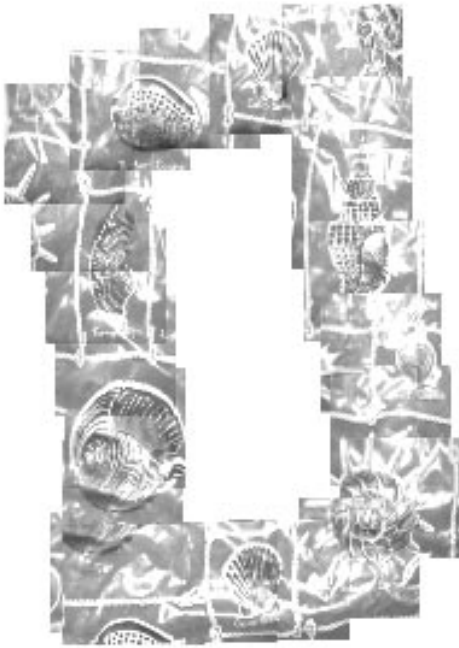


Figure 7: **Unconstrained Mosaic (Estimated Image Alignment Data)**

This mosaic was created autonomously while the mobile base followed a square trajectory. Note the poor image alignment between the initial and final images, in the lower left corner of the mosaic.

control technologies into a complete video mosaicking mission. The following sections describe the details of this research.

A. Mission Specification

The objective of our mission is to create a visual map of the sea floor, using vision as the primary sensor for vehicle control. To accomplish this goal, starting at the vehicle's initial entry point into the water, three distinct phases are required (see Figure 2).

The first phase involves the computation and execution of a vehicle trajectory from the initial entry point to the desired mapping site. During this phase, the primary sensor for navigation and control is SHARPS, an acoustic positioning system created by Marquest, Inc.

In the second phase of operation, the mosaicking task is executed, which commands the vehicle to follow a specific coverage pattern based on position data from the vision sensor. The individual images and mosaic are stored for later perusal by scientists upon mission completion. Alternatively, these images may be transmitted directly for immediate use by scientists around the world, provided

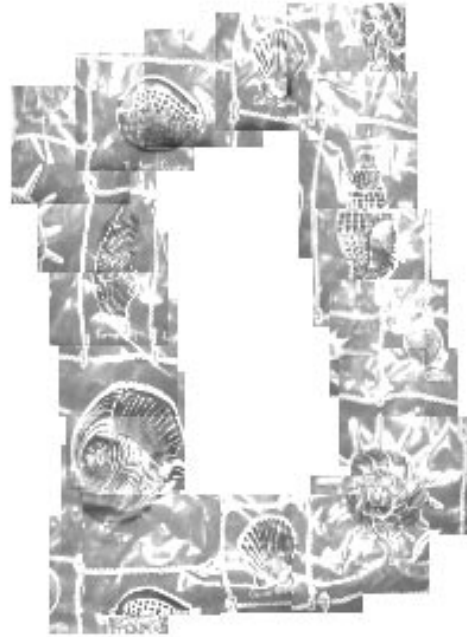


Figure 8: **Unconstrained Mosaic (Filtered Image Alignment Data)**

This mosaic was created using filtered image alignment data from our smoother-follower approach. Note the greatly improved alignment at crossover (lower left corner), while the rest of the mosaic has not degraded in quality.

there is enough bandwidth in the AUV-to-surface ship connection to handle the data in a timely fashion.

The final phase of this mission is the return to the entry point. This portion of the mission is relatively straightforward, since it is performed in the same way as the initial transect to the mapping site. The successful execution of each phase in this mission requires a higher level of logic to switch between control modes during a phase transition. This logic, implemented as a finite state machine (FSM) on our system, will be explained in the next section.

B. Hardware/Software Integration

Since completing our experiments in mosaic error reduction, we have upgraded our vision subsystem to a more flexible processing environment. We have developed a new vision sensor based on the Advanced Vision Processing (AVP) software library from Teleos Research. Our software runs under Windows NT on a dual 133 MHz Pentium PC.

This vision system resides off-board our AUV, which

sends video data to the AVP via the fiber-optic tether. The *OTTER* robot (Oceanographic Technology Testbed for Engineering Research) is roughly 2 meters long, 1 meter wide, and has a dry mass of 145 kg (Figure 9). It is made up of three pressure housings surrounded by 8 ducted thrusters and covered by a fiberglass shell. One housing holds two independent VME card cages with 68040 single board computers for control and sensor processing. The other two hold NiCad batteries which provide approximately 750 W-hrs of power. Currently, a fiber-optic tether is used to trickle charge the batteries, provide ethernet communications, and send video back to the remote control station. The sensor suite includes pitch and roll gravity sensors, a small inertial measurement unit with 3 accelerometers and 3 rate gyros, a flux-gate compass, and a pressure depth sensor. Two black/white CCD video cameras are mounted as a stereo pair on a custom pan/tilt unit. Main propulsion is provided by two 2 hp brushless DC variable reluctance motors. Six 1/2 hp VR motors are used for lateral and vertical motions as well as attitude control.



Figure 9: *OTTER* Underwater Vehicle

In order to incorporate our vision technology into an autonomous mission scenario, we modified several levels of the *OTTER* software control structure. To provide communications and control with our AVP vision processing subsystem, we modified our low-level control system to receive vision sensor data. From a mission perspective, the capability for complete autonomy must be reflected in the highest level of our control structure. We have implemented our mission as a finite state machine (FSM) in ControlShell, a software package for control system design developed by Real-Time Innovations, Inc. (Figure 10). Each state in this FSM represents a different phase of our mission. In order to transition from one state to the next, an external event is received by the FSM, indicating completion of that particular task. For instance, to transition from the Mosaicking to Homing states, the vision subsystem must send an event to *OTTER* after the mosaic has been created. This level of logic provides the vehicle with enough intelligence to complete the entire mission autonomously.

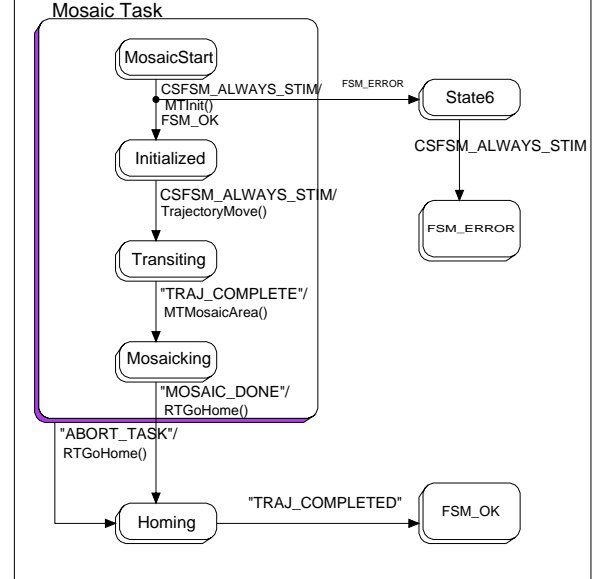


Figure 10: **Finite State Machine for Video Mosaicking Mission**

This diagram represents the progression of states of OTTER during mission execution.

C. Experimental Results

We have successfully demonstrated the video mosaicking mission with *OTTER* in the test tank at the Monterey Bay Aquarium Research Institute (MBARI). Under autonomous control, the vehicle followed the specified trajectory to hover over the desired mapping site, created a single-column mosaic composed of five images, and returned to its home position. One of the many mosaics created during the mission trials is illustrated in Figure 11. This achievement opens up new possibilities for unmanned scientific exploration of the open ocean.

V. CONCLUSIONS

We have presented a new technique for the real-time creation and on-line improvement of unconstrained video mosaics. To achieve this, we have extended the theory of smoother-follower estimation for our specific type of dynamic system. Our simulations and experimental work in the lab have verified the validity and feasibility of this method.

Secondly, we have demonstrated the task of video mosaicking in an autonomous mission scenario. By combining our vision sensing and control capabilities with our expertise in hierarchical control of AUV's to form a complete system, we will provide scientists with a new capability for undersea exploration, namely, the ability to remotely explore the marine environment by autonomously mapping the ocean floor.

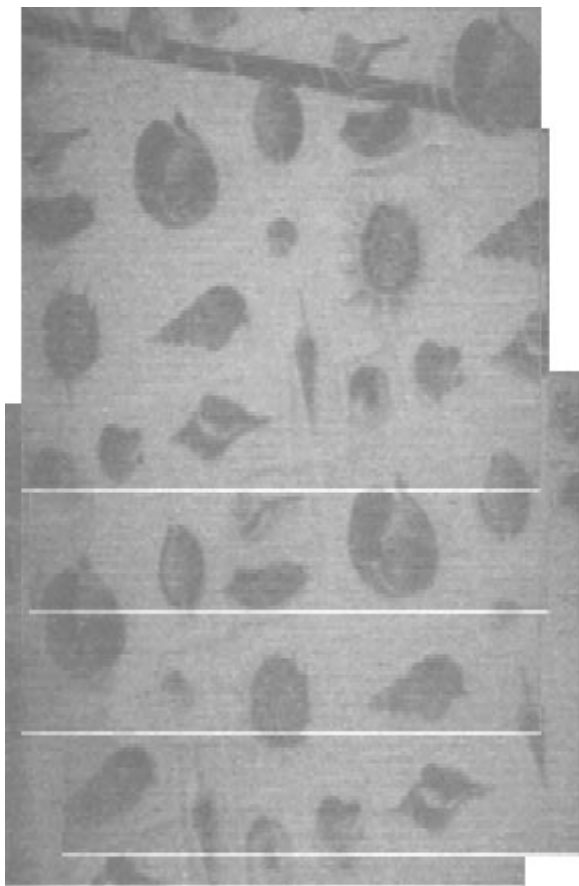


Figure 11: **Mosaic Mission**

This single-column mosaic was created under autonomous vehicle control during the video mosaicking mission.

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