Improved AUV Navigation using Side-scan Sonar

I. Tena Ruiz member IEEE, Y. Petillot and D. M. Lane member IEEE

Ocean Systems Laboratory
School of Engineering and Physical Sciences
Heriot-Watt University
Edinburgh EH14 4AS
Scotland, UK

Abstract— The following paper presents results from a novel solution for improving the navigation of an Autonomous Underwater Vehicle (AUV) using a side-scan sonar. It is derived from a system that has been developed to produce high quality mosaics using a Doppler Velocity Log (DVL), a tri-axial compass and a side-scan sonar. The system has been extended by incorporating a Concurrent Mapping and Localization (CML) algorithm. The CML tool chosen is the stochastic map. This is a proven tool for navigating in unknown environments. It can be used as a substitute for common absolute sensors, such as GPS or acoustic baseline systems, or it can work with them. The system concurrently builds a map of the environment using observations of landmarks extracted from side-scan sonar and uses that map an the dead-reckoning to create and estimate of the AUV's location.

I. INTRODUCTION

AUVs have become a useful tool for surveying and mapping. The data gathered by AUVs provide a good understanding of the environment at a reduced cost. Unfortunately, AUVs are generally equipped with inappropriate navigation sensors. At the core of AUV navigation systems one can generally find a dead-reckoning sensor, be it a DVL, an INS or, in some cases, both. These sensors are generally aided by attitude sensors (inclinometers and compasses), depth sensors, GPS (when close to the surface), Long Baseline (LBL), Short Baseline (SBL), Ultra Short Baseline (USBL) and/or similar acoustic solutions. In order to stop the drift of the dead-reckoning sensors the AUV must operate within a defined area (determined by the range of the acoustic solution implemented) or re-surface to obtain GPS fixes. The final navigation solution can then be used to geo-reference the payload data. In the case of side-scan sonar, the output from the geo-referencing step is a mosaic.

The *Ocean Systems Laboratory (OSL)* in *Heriot-Watt University (HWU)* has a long track record working with AUV data products. One of the outcomes of this work is SeeTrack [1], initially developed in the OSL and now licensed to See-Byte Ltd., the spin-off company commercializing OSL research. SeeTrack can be used to visualize these products. It is a *Geographic Information System (GIS)* that allows the operator to superimpose different layers of geo-referenced data. When using this system it quickly becomes apparent that errors in the navigation translate as discrepancies in the side-scan mosaic. Certain environmental landmarks can appear in different positions when re-observed.

The OSL has developed a framework where the navigation solution provided by standard AUV sensor configurations can be improved by using the side-scan sonar data [2]. This architecture is built by combining a stochastic map [3], a Concurrent Mapping and Localization (CML) strategy, with a smoothing filter [4], the Rauch-Tung-Striebel (RTS) filter. This system will be referred to as CML-RTS in the remainder of the document.
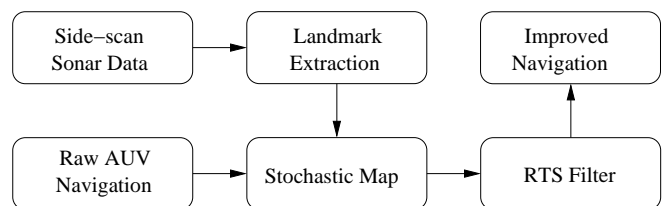

Fig. 1. Overview of the CML-RTS System

This paper will present new results obtained using such a strategy. Fig. 1 shows an overview of the system. The AUV navigation data and landmarks are

manually extracted from the side-scan images, and used to produce a new navigation solution using the stochastic map architecture, examined in section II. This new solution is further improved by implementing an RTS smoother, studied in section III. The new navigation solution can then be used to geo-reference the side-scan data. This process will be briefly discussed in section IV. Results illustrating the increased accuracy of the system will be shown in section V.

II. THE STOCHASTIC MAP USING SIDE-SCAN SONAR

Techniques for performing CML have been extensively researched by the robotics community and a number of solutions have been proposed [5]. The stochastic map is an established technique with well documented advantages [6]. It has been successfully used by the OSL to perform CML using forward-looking sonar [7]. It has now been adapted to work with side-scan sonar data as well.

The stochastic map is an Extended Kalman Filter (EKF) [8], [9] with extra states. These new states estimate the positions of landmarks in the world. The method makes it possible to estimate and maintain the vehicle-to-vehicle, landmark-to-vehicle and landmark-to-landmark correlations. In the stochastic map the state vector looks like this:

$$\mathbf{x}(k) = \begin{bmatrix} \mathbf{x_v}(k) & \mathbf{x_1}(k) & \mathbf{x_2}(k) & \dots & \mathbf{x_n}(k) \end{bmatrix}^T \quad (1)$$

where $\mathbf{x_v}(k)$ is the vehicle state vector and $\mathbf{x_i}(k)$ are the new landmark state vectors for each landmark i. The associated covariance holds the vehicle and landmarks' covariances and correlation terms. The prediction and correction equations of the EKF [8], [9] are the same as the equations for the stochastic map. Thus the prediction update equations are:

$$\hat{\mathbf{x}}_\mathbf{v}(k) = \mathbf{f_v}[\hat{\mathbf{x}}_\mathbf{v}(k-1), \mathbf{u}(k), \mathbf{0}, k] \quad (2)$$

$$\mathbf{P}(k) = \mathbf{F_{x_v}}(k)\mathbf{P}(k-1)\mathbf{F_{x_v}^T}(k) + \mathbf{Q}(k-1) \quad (3)$$

where $\hat{\mathbf{x}}_\mathbf{v}(\cdot)$ is the vehicle's state and $\mathbf{f_v}[\hat{\mathbf{x}}_\mathbf{v}(\cdot), \mathbf{u}(k), \mathbf{0}, k]$ is the vehicle's dynamic model. The transition model uses deterministic control input functions $\mathbf{u}(k)$ if available. These functions are normally the outputs from the vehicle controller (thrust values, voltages, currents, ...). Here $\mathbf{P}(\cdot)$ is the estimated error covariance, $\mathbf{Q}(\cdot)$ is the process noise matrix and $\mathbf{F_{x_v}}(\cdot)$ is the transition matrix.

The correction equations are:

$$\mathbf{S}(k) = \mathbf{H}(k)\mathbf{P}(k)\mathbf{H}'(k) + \mathbf{R}(k) \quad (4)$$

$$\mathbf{K}(k) = \mathbf{P}(k)\mathbf{H}'(k)\mathbf{S}^{-1}(k) \quad (5)$$

$$\hat{\mathbf{x}}(k+1) = \hat{\mathbf{x}}(k) + \mathbf{K}(k)\upsilon(k) \quad (6)$$

$$\mathbf{P}(k+1) = \mathbf{P}(k) - \mathbf{K}(k)\mathbf{H}(k)\mathbf{P}(k) \quad (7)$$

where $\mathbf{H}(\cdot)$ is a matrix that stacks the Jacobians of the observed landmarks with respect to the estimated map state, the measurement noise covariance is $\mathbf{R}(\cdot)$, the innovation covariance is $\mathbf{S}(\cdot)$, with innovation $\upsilon(\cdot)$, and the Kalman gain is $\mathbf{K}(\cdot)$.

The difference between the stochastic map and the EKF is that when a new landmark is observed it is augmented. The new states represent the landmark in the world frame. The covariance and correlation terms for the new landmark can be found from:

$$\begin{aligned} \mathbf{P_{n+1\,n+1}}(k) &= \mathbf{L_{x_v}}\mathbf{P_{v\,v}}(k)\mathbf{L_{x_v}}^T + \mathbf{L_{z_{new}}}\mathbf{R_L}(k)\mathbf{L_{z_{new}}}^T \\ \mathbf{P_{n+1\,v}}(k) &= \mathbf{P_{v\,n+1}}^T(k) = \mathbf{L_{x_v}}\mathbf{P_{v\,v}}(k) \end{aligned} \quad (8)$$

where $\mathbf{P_{v\,v}}(\cdot)$ is the vehicle state covariance, $\mathbf{P_{n+1\,n+1}}(\cdot)$ is the covariance of the new landmark and $\mathbf{P_{n+1\,v}}(\cdot)$ is the correlation term between the landmark and the vehicle. Also, $\mathbf{L_v}(k)$ and $\mathbf{L_z}(k)$ are the Jacobians of the function that estimates the landmark's position in the world with respect to the robot vehicle state $\hat{\mathbf{x}}_\mathbf{v}$, evaluated at $\hat{\mathbf{x}}_\mathbf{v}(k)$, and to the new observation $\mathbf{z_{new}}$, evaluated at $\mathbf{z_{new}}$, and $\mathbf{R_L}(\cdot)$ is the measurement error covariance.
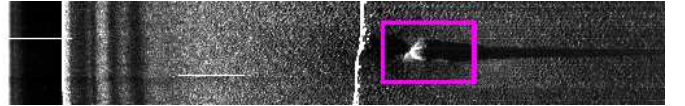

Fig. 2. Manual Extraction of Landmarks

1) Manually extracting landmarks from side-scan sonar data: The stochastic map requires perfect data association. The current implementation requires that the landmark extraction and data association process is done manually. The operator has to point at the landmarks, see Fig. 2, and match them to those already stored in the map or indicate if it is a new landmark.

2) Observation models for the landmark observations: The observation vector adopted to incorporate side-scan data is as follows:

$$\mathbf{z_i}(k) = [a\ \ b]' \qquad (9)$$

where a is the cross-track distance obtained after slant-range correcting the side-scan sonar return, and b is the along-track distance computed using the pitch and the altitude of the vehicle. The prediction vector will therefore be:

$$\hat{\mathbf{z}}_\mathbf{i}(k) = \begin{bmatrix} \bar{x}_i(k)\cos\theta_v(k) - \bar{y}_i(k)\sin\theta_v(k) \\ \bar{x}_i(k)\sin\theta_v(k) + \bar{y}_i(k)\cos\theta_v(k) \end{bmatrix} \qquad (10)$$

where $\bar{x}_i(\cdot)$ and $\bar{y}_i(\cdot)$ are the predicted landmark coordinates and $\theta_v(\cdot)$ is the predicted vehicle's heading. New landmarks will be initialized given:

$$\mathbf{x_{n+1}}(k) = \begin{bmatrix} \bar{x}_v(k) + a\cos\theta_v(k) + b\sin\theta_v(k) \\ \bar{y}_v(k) - a\sin\theta_v(k) + b\cos\theta_v(k) \end{bmatrix} \qquad (11)$$

where $\bar{x}_v(\cdot)$ and $\bar{y}_v(\cdot)$ are the predicted vehicle coordinates.

III. THE RAUCH-TUNG-STRIEBEL FILTER

The RTS is a fixed-interval smoothing filter. A smoothing filter blends the estimates from a forward filter with those of a backward filter. The RTS output will consider all measurements for all times, T, when estimating at time t, where $0 \leq t \leq T$. Thus, by combining both the forward and backward filter outputs, a more accurate output can be obtained, see Fig. 3.
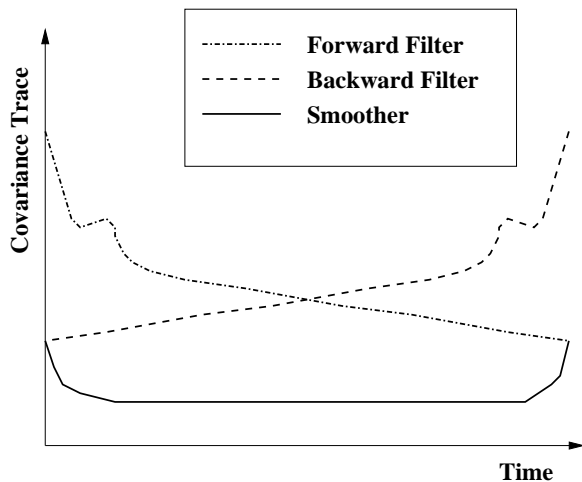

Fig. 3. The RTS combines a forward pass Kalman filter with a backward pass filter to produce a more accurate solution

The RTS uses the stored predictions and corrections of a Kalman filter to produce the smoothed signal. The OSL has shown that the RTS can be readily adapted to handle the stochastic map output [2]. The output from the combined CML-RTS solution produces an improved navigation trajectory when compared to a non CML solution.

IV. GEO-REFERENCING THE SIDE-SCAN SONAR DATA

Fig. 4 shows raw side-scan data obtained with the Florida Atlantic University's Ocean Explorer (OEX) AUV during the GOATS 2000 experiments [10]. The mosaicing software assumes that the sonar beams (each row in the raw image) sonifies a rectangular area. Thus processing is simple and fast. The mosaics are created by correcting the raw data for slant, pitch and yaw distortions. Using the knowledge of the AUVs position the samples in each sonar line are placed in a regular grid of cells that represents the world. If more than one sample falls in the same grid position these are averaged.

The system requires good navigation. In Fig. 5 the side-scan image shown in Fig. 4 has been processed and mosaiced using the AUV's raw navigation information. The errors in the navigation become apparent when observing the image, especially when compared to Fig. 6, where the navigation data has been processed by a Kalman-RTS system.

V. RESULTS

These results show the outcome of processing the side-scan and navigation data recorded by the OEX AUV during the GOATS trials, organized by NATO SACLANT Undersea Research Centre.

The system was run for six vehicle transects along an area of interest. The following results show qualitatively that the proposed system can improve the results. For an in depth analysis of the system and extensive quantitative results the interested reader should refer to [2].

Fig. 7 and Fig. 8 illustrate two typical mosaics obtained when running the system using only the information for single transects. The system uses the navigation information from the AUV to run a Kalman-RTS and this information is used to create the mosaics.

Five landmarks where consistently re-observed in the six transects and these were used by the CML-RTS system. The landmarks, when plotted in
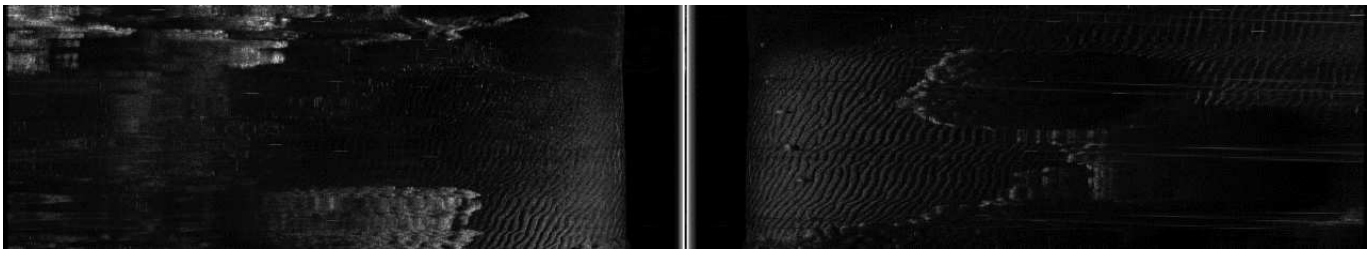
Fig. 4.   A raw unprocessed side-scan sonar image.

Fig. 5.   A geo-referenced side-scan mosaic created using the AUVs output.

Fig. 6.   A geo-referenced side-scan mosaic created using a Kalman-RTS system.

a local East, North and Up (ENU) navigation frame, clearly show the error in the position estimates for the transects, see Fig. 9. The landmark observations are spread over a region of approximately 20 meters across-track and 12 meters along-track. The outcome of the CML-RTS system produces a set of smoothed transects and one estimate for each landmark position. This is a useful feature of the system that could be adapted for many different applications where landmarks (pipe junctions, corals, underwater structures, wrecks, etc.) need to be inspected and mapped.

The accuracy of the system can be easily appreci-

ated when comparing two mosaics created with the six transects. In the first mosaic, Fig. 10, the AUV navigation is used to run a Kalman-RTS filter. The system is unable to correct the drift in the navigation between transects and the data is diluted as it is averaged across transects. The resulting mosaic is of poor quality. The second mosaic, Fig. 11, results from running the CML-RTS system. This mosaic does not suffer from severe dilution despite the fact that six images were used to create it. The landmarks are also clearly visible (and numbered for the reader). The system is able to produce larger mosaics (by combining transects) coherently and
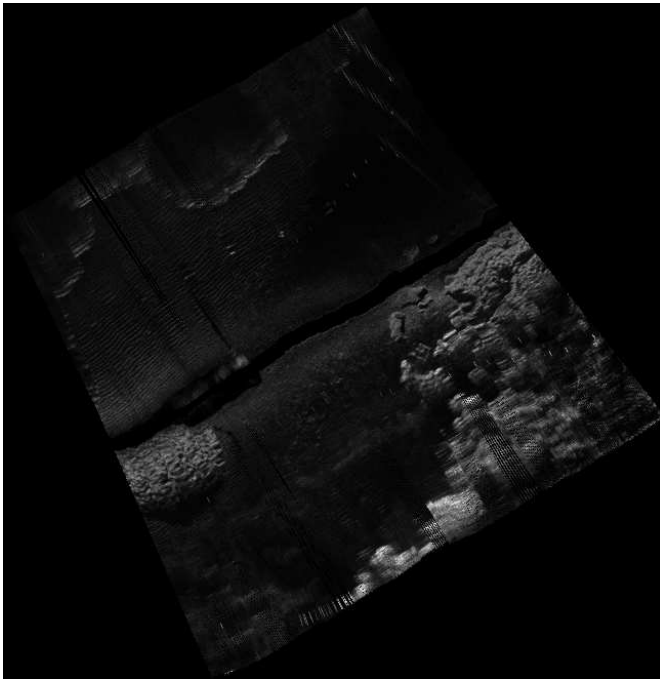
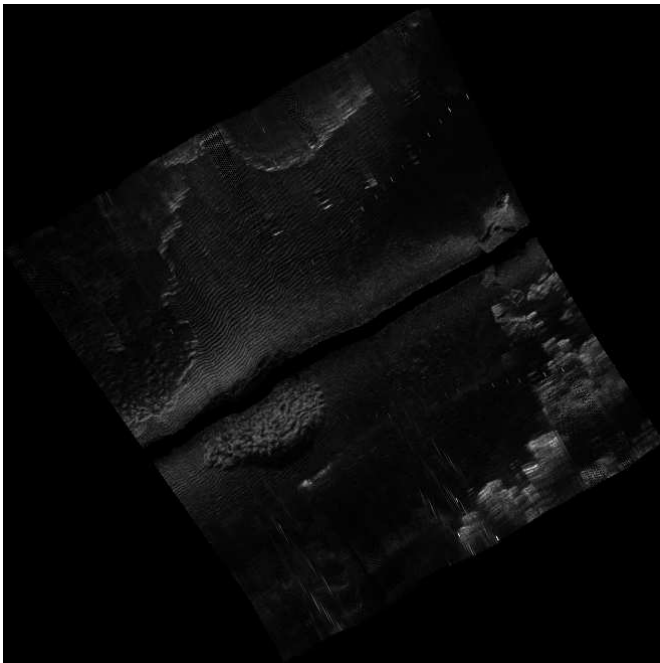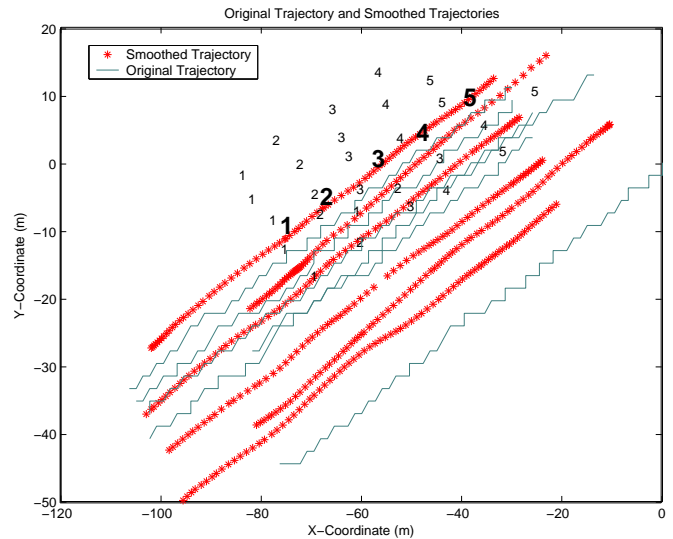Fig. 7.   Mosaic created using data from single transect (092357).

Fig. 9.   Here the landmark observations (small numbers) are displayed alongside the OEX output trajectories. The final estimated landmark positions (large numbers) and smoothed vehicle trajectories are also shown for comparison.

used to coherently blend mosaics from different transects. It can also be used to more accurately map the position of landmarks in the environment.

The OSL will use this work in the AMASON project. The AMASON project is funded by the 5th Framework Program of research of the European Community. The AMASON project will provide scientific users with a fusion [11] and classification framework for underwater applications.

The OSL has recently extended the CML-RTS system presented in this paper to provide automatic landmark extraction and data association facilities [12]. This work builds on the OSL's broad experience in Computer Aided Detection and Computer Aided Classification [13], [14] and landmark feature descriptors and data association algorithms [7], [15].

Fig. 8.   Mosaic created using data from single transect (093811).

produce better and more accurate trajectories.

VI. CONCLUSIONS

This paper has demonstrated that side-scan sonar returns can be used to improve an AUV's navigation estimates. The CML-RTS system proposed can be
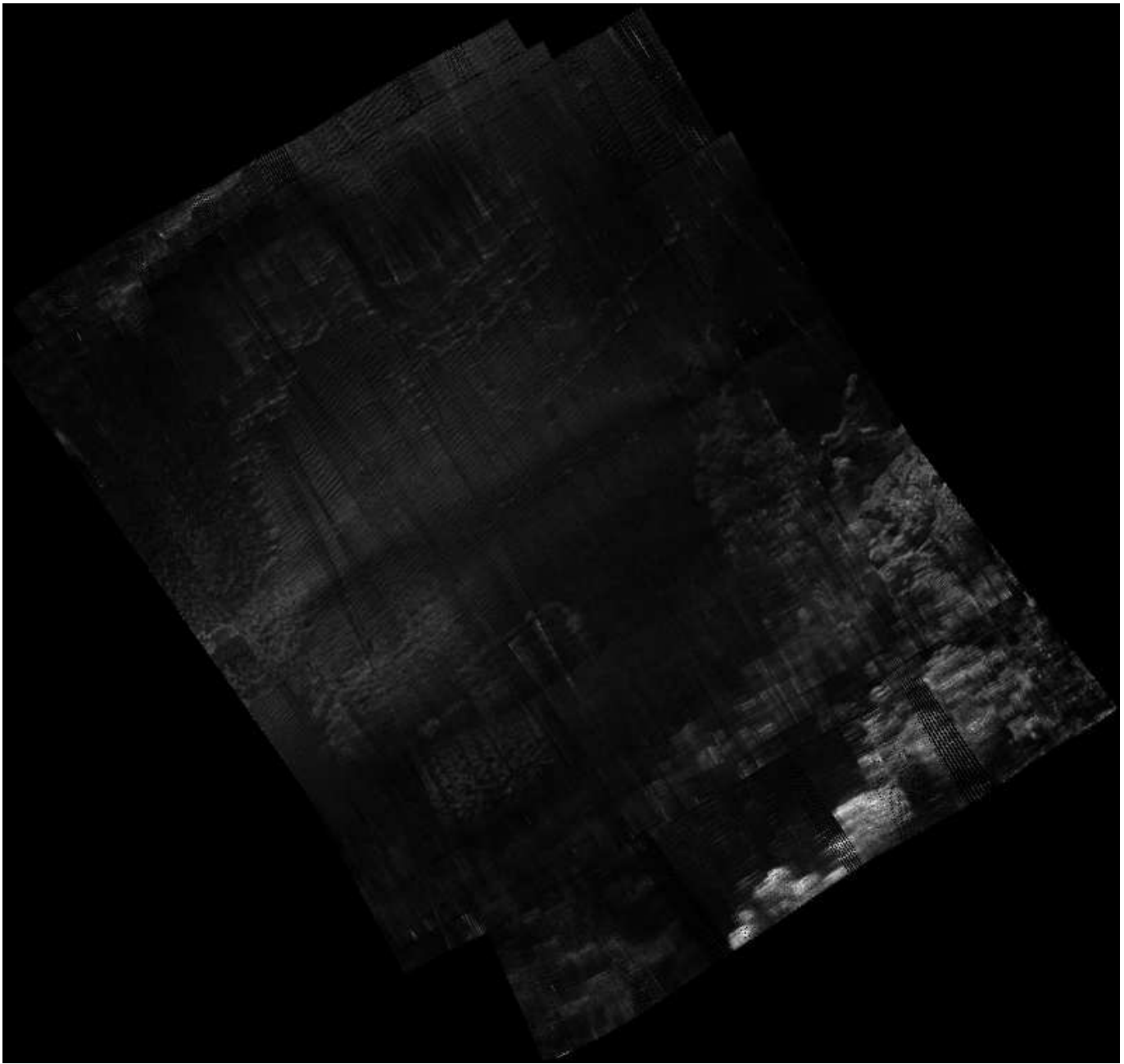
Fig. 10. Mosaic created using data fom six transects and a Kalman-RTS system.

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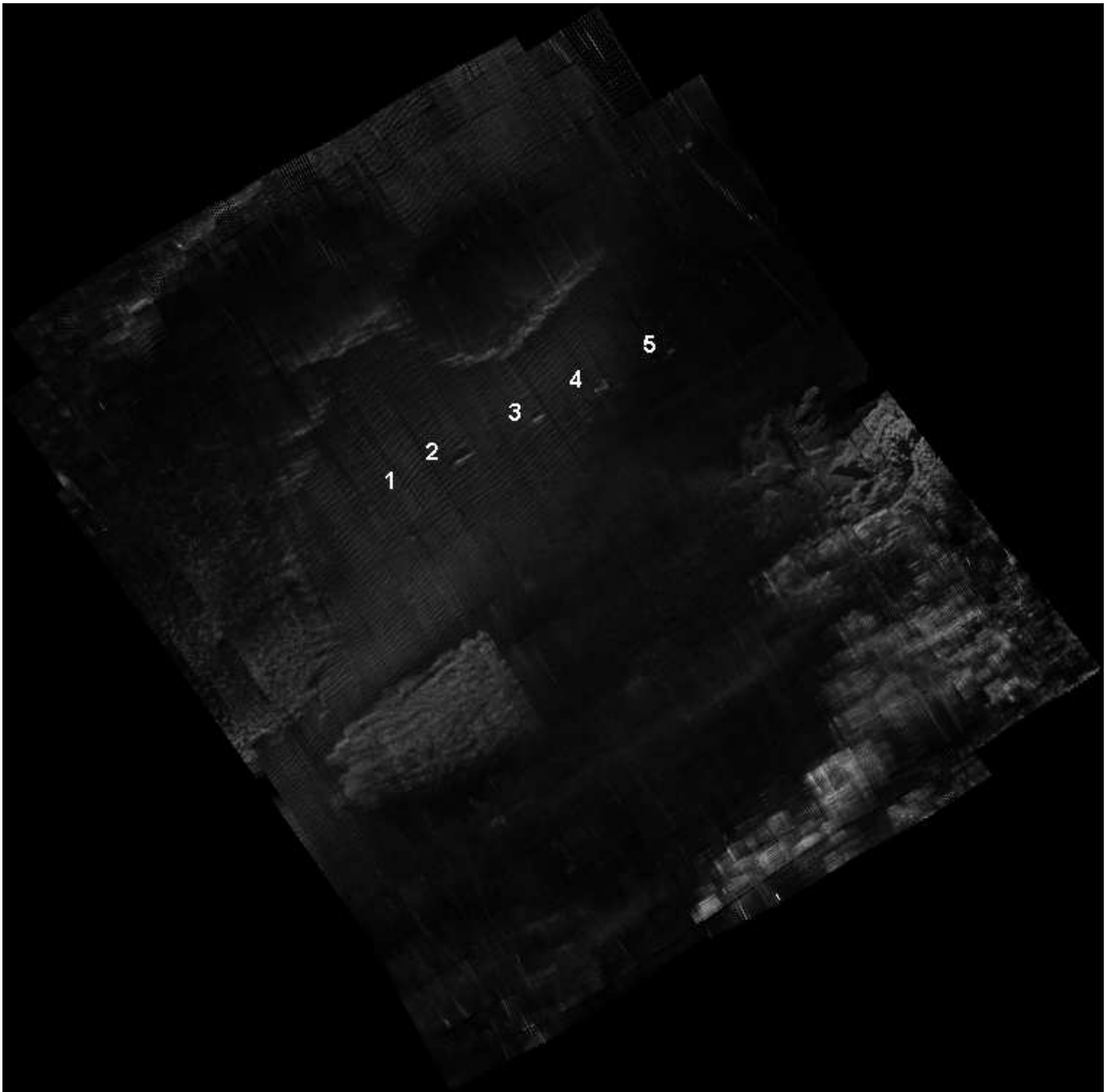[7] I. Tena Ruiz, "Enhanced concurrent mapping and localisation

Fig. 11. Mosaic created using data fom six transects and a CML-RTS system.

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