A Prototype for AUV Post-mission Debrief Generation from Metadata (Demonstration)

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ABSTRACT

A prototype system will be demonstrated that can automatically generate natural language reports from metadata from Autonomous Underwater Vehicles (AUVs). The system takes time-series sensor data, mission logs, together with mission plans as its input, and generates post-mission debriefs for human operators in a concise and easy-to-understand manner. The state-of-the-art systems tackling similar issues are usually designed for simulated environments or can only interpret plans. To the best of our knowledge, this is the first system that directly deals with noise-prone real data from mission logs combined with mission plans.

Categories and Subject Descriptors

I.2.9 [**Robotics**]: Autonomous vehicles, Operator interfaces; I.2.1 [**Applications and Expert Systems**]: Natural language interfaces

Keywords

AUV behaviour recognition, NLG, metadata, sensors

1. INTRODUCTION

As autonomous systems become more common place, it is important to address the lack of opacity and trust between the system and the human operator. Autonomous systems by their very nature are able to adapt, modifying preset plans and behaving in a less observably deterministic fashion [1]. Previous attempts have been made to build state-of-the-art natural language interfaces to bring mission states and purposes closer to human operators in simulated environments for pre-mission verifications for Autonomous Underwater Vehicles (AUVs) [1, 2]. However, in real world missions, the data collected by AUVs will be more noise-prone, due to imperfect sensors and irregular trajectories (partially caused by noisy environmental factors). Therefore, in this paper, we introduce a prototype system that can generate natural language debriefs for real AUV missions and is able to achieve reasonable robustness to data noise. The prototype system described here is rule-based at this stage, but could feasibly be extended by applying advanced machine learning techniques to this problem. Other previous work has looked at enabling the mission plan to be more scrutable and less opaque [4]. However, this work looks at explaining only the plans whereas our work combines the plans with from logs of real missions in order generate accurate reports of what actually happened.

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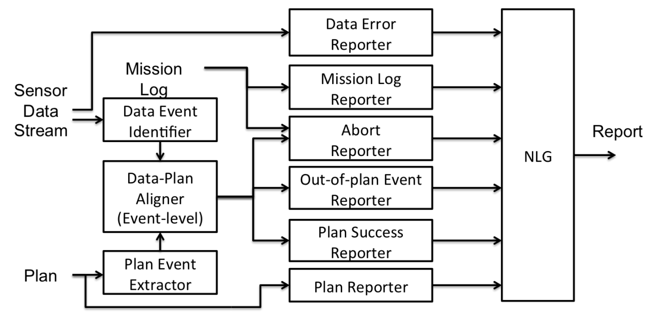


Figure 1: The overall architecture of the system.

2. SYSTEM ARCHITECTURE

The prototype system takes three types of data sources as its input, including the mission plan, time-series sensor data and mission logs[1]. The overall system architecture is illustrated in Figure 1.

Firstly, the system starts from a **Plan Event Extractor** that describes the events of interest in the mission plan. However, as vehicles are enabled with more autonomy and as missions plans are not always executed exactly, it is important to look at the data from the mission in conjunction with the plan. Therefore, given a sensor data stream from the logs, a sequence of events of interest is extracted by the **Data Event Identifier**. This sequence of events is then aligned to the sequence of events of interest recognised in the plan using the Smith-Waterman algorithm. We give detailed description of the **Data Event Identifier** and the **Plan Event Aligner** below.

The set of aligned events are then sent to the NLG component. This is broken down into a number of individual reporter modules that use rule-based generation. The **Plan Success Reporter** debriefs the planned events successfully executed by the AUV. If any unplanned events are conducted by the vehicle, these will be reported by the **Out-of-plan Event Reporter**. When a mission is recognised as aborted, the **Abort Reporter** seeks the reason for the

[1]These data are exported from the REMUS Vehicle Interface Program (REMUS VIP).

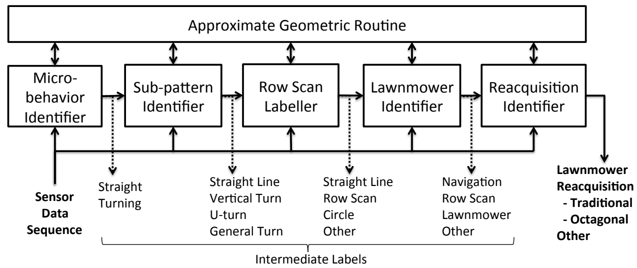


Figure 2: The hierarchical classifier for event identification from real sensor data (the Data Event Identifier)

Table 1: Performance of the Data Event Identifier

	Precision	Recall
Lawnmower Scan	0.948	0.848
Traditional Reacquisition	0.933	0.609
Octagonal Reacquisition	0.704	0.528
Overall Event Accuracy	0.743	
Mission Accuracy	0.720	

abort from the mission log, locates and reports the aborted mission objective. In addition, important messages in the mission log, such as automatic parameter adjustments by the AUV, the thruster controller errors during the mission, etc., are summarised by the **Mission Log Reporter**, while potential errors identified in the sensor data such as coordinate jumps (e.g. due to LBL failures) are reported by the **Data Error Reporter**.

Our system focuses on three major event types: lawnmower scans, traditional multi-view reacquisitions and octagonal spiral reacquisitions [3] (see Figure 3 for examples).

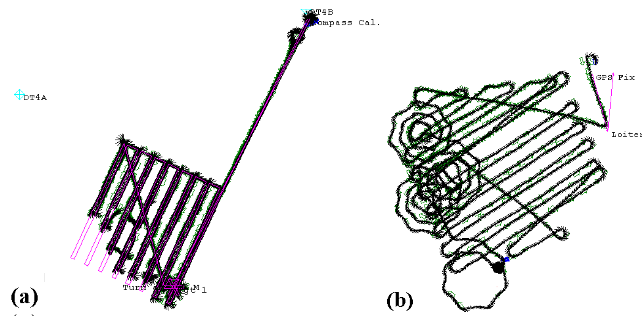
3. EVENT IDENTIFICATION FROM REAL SENSOR DATA

In order to identify events of interest in noise-prone real sensor data, we construct a rule-based hierarchical classifier as shown in Figure 2. To relieve the error accumulation problem, each layer is designed to be robust to imperfect labels from the previous layer. In addition, there are a set of approximate geometric functions specifically designed for this problem to confer robustness to data noise (such as unevenness in row scans or coordinate jumps during navigations).

We tested this Event Identifier on a set of 215 real world REMUS AUV missions conducted by the Heriot-Watt Oceans Systems Lab. These missions were manually annotated with event sequences. Table 1 shows the performance with the overall event accuracy of around 74% and high Precision and Recall for lawnmower scans and traditional reacquisitions. 72% of the missions have all events accurately identified.

4. DEMONSTRATION

The prototype will demonstrate the generation of debriefs from AUV missions, showing the mission tracks, events identified and generation process. Two examples of such debriefs generated by the system are shown in Figure 3. The graphical illustrations are exported from the REMUS VIP software, where the magenta lines indicate the plan trajectories and the dark bold lines are the actual trajectories travelled by the AUV.



(**a**) `This mission includes a lawnmower scan and a reacquisition. The target to reacquire is [26.5134, -30.38255]. The mission was successful. A few thruster controller errors were noticed, but not critical. The vehicle altitude was adjusted from 2.5M to 3M to optimise scan range. Minimum altitude was reached during lawnmower scanning, therefore some inshore legs were shortened. Navigation jumps due to LBL error might lead to imperfect data coverage.`

(**b**) `This is an unknown test mission. A lawnmower scan was conducted in addition to the planned mission. Extra reacquisitions were conducted around objects [26.3825, -35.27893], [52.3822, -6.27864] and [51.3818, -35.27895]. The mission was aborted before the vehicle navigated to [51.383, -20.27577], due to time out.`

Figure 3: Example debriefs generated for two real missions.

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