Self-Explainable Robots in Remote Environments

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ABSTRACT

As robots and autonomous systems become more adept at handling complex scenarios, their underlying mechanisms also become increasingly complex and opaque. This lack of transparency can give rise to unverifiable behaviours, limiting the use of robots in a number of applications including high-stakes scenarios, e.g. self-driving cars or first responders. In this paper and accompanying video, we present a system that learns from demonstrations to inspect areas in a remote environment and to explain robot behaviour. Using semi-supervised learning, the robot is able to inspect an offshore platform autonomously, whilst explaining its decision process both through both image-based and natural language-based interfaces.

KEYWORDS

Explainable robot, semi-supervised learning, autonomous control, transparent interfaces, remote location, NLG

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1 INTRODUCTION

Recent advancements have made robots and autonomous systems a valuable asset in unsafe environments as a way to keep humans out of danger, such as in the nuclear or energy domains [6, 7, 10, 13, 17, 20]. These domains often require navigating highly dynamic scenarios and executing time-critical actions successfully. We focus here on offshore energy platforms as part of the EPSRC ORCA Hub programme [6], where robots are expected to maintain and operate parts of the platform autonomously, whilst communicating with remote operators through a human-robot interface.

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Machine learning is an important part of modern robots, with more accurate and sophisticated algorithms being deployed over time. However, it requires a high amount of data, which is challenging and costly to obtain, particularly in hazardous domains. Using semi-supervised machine learning, we have shown that a robot can learn inspection strategies from a demonstration by a human operator [19]. This method provides several advantages over both supervised and unsupervised machine learning algorithms: it does not require expensive data collections and it leverages unsupervised learning methods to extract information not explicitly available. More importantly, the robot successfully adapts to unseen conditions, which is imperative in changing situations.

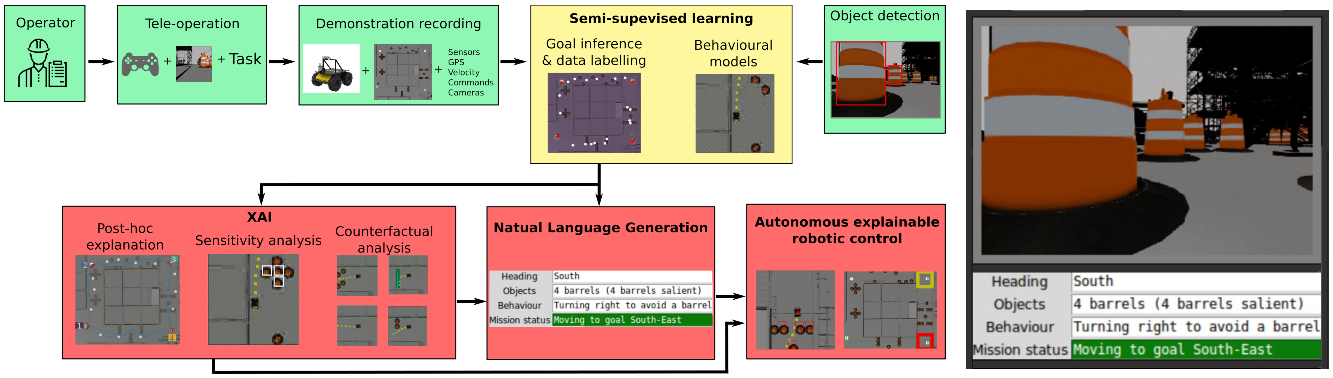
Nevertheless, typically a single robot is not able to perform the multitude of tasks needed for complex operations. Thus, operators often have to supervise several types of robots at the same time (e.g. ground robots with hoses to extinguish fires and aerial drones for inspections). This is exacerbated by the remote nature of the environment, as remotely-controlled robots often instil less trust than those co-located [1, 9]. Maintaining a correct and clear operator mental model is thus necessary for the deployment of multiple adaptive robots simultaneously.

Dynamic robot behaviours may be difficult to understand, in particular to non-experts and novice operators. We provide a way to communicate these clearly through natural language messages synthesised from the semi-supervised learning algorithm. Presenting the robot behaviour in words can increase situation awareness, helping to better understand what the robot is doing and why, as well as helping the operator know when to intercede if the robot is not operating correctly [4, 16].

In this video and paper, we describe a system that combines semi-supervised learning and natural language explanations of behaviour to learn from demonstrations and clarify or verify the behaviours displayed by the robot.

2 BEHAVIOURAL MODEL LEARNING

We train DNNs as behavioural models based on demonstrations carried out by robot operators [19]. In this LfD (learning from demonstration) configuration (Fig. 1a), a user teleoperates a Husky robot in an inspection scenario. The operator receives exteroceptive information about the robot from an on-board camera and drives it controlling linear and angular velocities. We recorded five demonstrations varying the location of obstacles, but maintaining the same points on the remote platform as inspection goals.



(a) System architecture **(b) Explainable inteface**

Figure 1: (a) Explainable learning from demonstration architecture. Green blocks represent input modules to the system. The yellow blocks represent the semi-supervised learning of behavioural models. Red blocks are the main outputs of the system in graphical and natural language form. (b) Interface including Natural Language Generation (NLG).

First, following [3], we extract goals in the demonstrations as the most likely position on the platform to where the robot is being directed. Using a sequential importance sampling algorithm, we extract the goals and parameters of the proportional controllers that satisfy them. We filter the goals using their likelihood of being part of the actual path taken by the robot and their saliency in a path-prediction model. Once the system has inferred the goals, we label each step of the original demonstration to learn goal-based Deep Neural Networks (DNNs). These models take the state of the robot as input and predict the most likely path to be followed by the robot for the next 5 seconds.

We use the behavioural models for different tasks (red blocks in 1a). First, we can control the robot in an MPC (model-predictive control) way. Second, we explain the path prediction from the models with causal inference. Using sensitivity analysis, we are able to point out the objects around the robot that are important for behaviour prediction. Also, using counterfactual analysis, the system can inform a user about the required modifications to follow a specific path [18]. Finally, the combination of these behavioural explanations can be translated to natural language.

3 NATURAL LANGUAGE INTERFACE

Although robots that adapt are more useful in certain environments, this ability to adapt can make their behaviour obscure to non-experts. This decreased understanding can have a negative effect on the operator's trust, and thus on the human-robot collaboration. Improving the robot's transparency is important for explainability and trust [14, 21] and it is crucial for a clear operator mental model, which can prevent issues such as wrong assumptions, misuse, disuse or over-trust [4]. A more faithful mental model also helps to increase the operator's confidence and performance [2, 11].

Previous works have communicated the robot's actions through natural language during and after the tasks [4, 8, 12, 15]. They provide information through automatic reports or real-time dialogue, yet, unlike our case, these robots often have well-defined behaviour that could be initially described by an expert or coded from domain-specific knowledge.

The system, described here (see Fig. 1b) and illustrated in the video generates updates about the actual direction of the robot ('Heading') based on the robot's internal measurement unit (IMU), a list of objects that are sensitive for the prediction ('Objects'), the current behaviour ('Behaviour') based on the predicted path followed by the MPC and the position of salient objects, and an overall mission status. Combining these outputs using template based generation, the system provides easy-to-digest explanations about the robot's behaviour and deviations from its standard trajectory. Some examples are "Turning left to avoid a barrel" or "Making a u-turn towards South-West goal". These are shown on the operator's user interface to help increase understanding and situation awareness.

4 CONCLUSION AND FUTURE WORK

In this demonstration, we have shown a robot that autonomously navigates an environment and produces updates about what it is doing and why. The robot's behaviour is learned from an operator demonstration, from which a program is synthesised and then executed using a semi-supervised learning algorithm. The updates adapt to the robot's behavioural model and can be used to keep operators informed about what the robot is thinking of doing next. In the future, we would like to extend this to more types of updates and allow one to more closely examine the robot's actions through free-chat. Explanations could become crucial if we want to better understand highly autonomous, adaptive robots that show behaviour that may be too complicated even for experts to understand. Evaluating and optimising natural language explanations is also left for future work [5]. Finally, this work could also open the door to live debugging of robots and automatically-synthesised programs, to verify that the robot is acting as it should or explain why it did not correctly learn from the demonstration.

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