Robot Adaptation to Environment Changes in Long-Term Autonomy

Sriram Siva and Hao Zhang

***Abstract*— Long-term autonomy introduces new challenges to robot perception, due to long-term changes of robot operation environments. In this paper, we propose learning-based approach that adapts robot perception according to environment variations. Our approach jointly performs feature learning, multisensory fusion, and adaptation under a unified regularized optimization framework. To evaluate the performance of our approach, we collected a dataset from physical robots in the underground and field environments. Experimental results have shown that our approach enables robots to adapt to long-term environment changes.**

I. Introduction

Long-term autonomy receives an increasing attention in the robotics community, with the overall objective to enable robots to operate over long periods of time, e.g., hours, days, years, and ultimately in a lifetime. Long-term autonomy introduces new challenges on robot perception. For example, in a search and rescue operation, a robot may need to track and follow a human rescuer under significantly different lighting conditions across various environment scenarios and times of a day, as illustrated in Figure 1. These changes often result in ineffective task execution and even failures.

Adaptation is considered as one of the viable solutions to address long-term autonomy and to enable robots to operate over long periods of time autonomously. Although methods are actively studied in the past years to adapt robot behaviors [1], [2], the challenges of adapting to environmental changes (e.g., lighting conditions) have not been well addressed.

In this paper, we present our ongoing research on developing a real-time robot adaptation method for dynamically fusing different sensor modalities and adapting to short-term and long-term environmental changes. We formulate robot adaptation as a joint learning problem that simultaneously learns important features and an adaptation model under the unified mathematical framework of regularized optimization. The contribution of this paper is twofold:

- We introduce a new approach to address robot adaptation in long-term autonomy. We also implement a new method to solve the formulated optimization problem, which possesses a theoretical guarantee to converge to the optimal solution.
- We collect a new dataset from mobile robots to benchmark methods for robot adaptation to short and long-term environment changes.

Experiments are conducted using the new benchmark dataset to evaluate our approach.

S. Siva and H. Zhang are with Human-Centered Robotics Lab in the Computer Science Department, Colorado School of Mines, Golden, CO 80401, USA {sivasriram,hzhang}@mines.edu

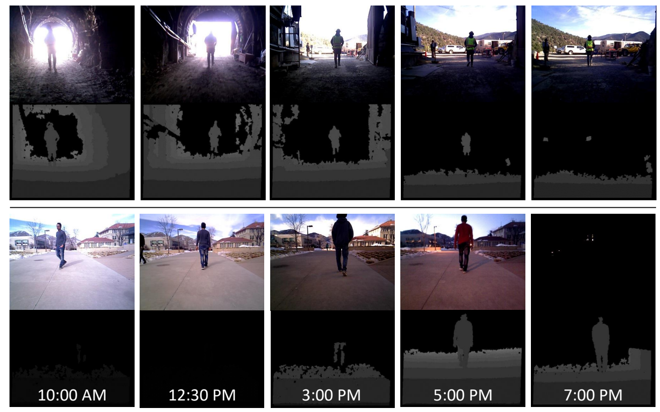

Fig. 1. Motivating examples of *robot adaptation*. When a mobile robot follows a human rescuer during a long-term search and rescue mission, the robot requires the perceptual adaptation capability of adapting to various long-term (e.g., different times of the day) and short-term (e.g., when moving from a dark tunnel to a bright open area) environment variations, in order to avoid perception failures.

II. The Dataset

Before this research, no dataset is publicly available for benchmarking robot perceptual adaptation. A practical contribution of this research is the collection of a new dataset that consists of multisensory perception data collected in real-world field applications under short-term and long-term environment changes. We used Clearpath Husky and Jackal robots (e.g., Figure 2) that are equipped with structured-light cameras and other sensors including luminosity sensors to collect multisensory information during outdoor and underground operations.

During data collection, we assume the robot is performing a human following task, which is a desired capability in field robotics applications (e.g., to carry rescue gears in a long-term search and rescue operation). To follow a human subject, the robot is manually control by a sperate operator. The current dataset contains two different scenarios:

- Scenario I (Mine-Entering-Exiting): The mobile robot follows a human subject to enter and exit two different mine drifts [3] (i.e., horizontal openings in a mine). One drift is dark, and the other has light bulbs installed in the drift. When the robot travels from the inside to the outside of the mine drift (or vise versa), the environment exhibits significant lighting changes. This testing scenario represents possible situations when robot performs underground search and rescue, for example, in mine, cave, and subway environments.

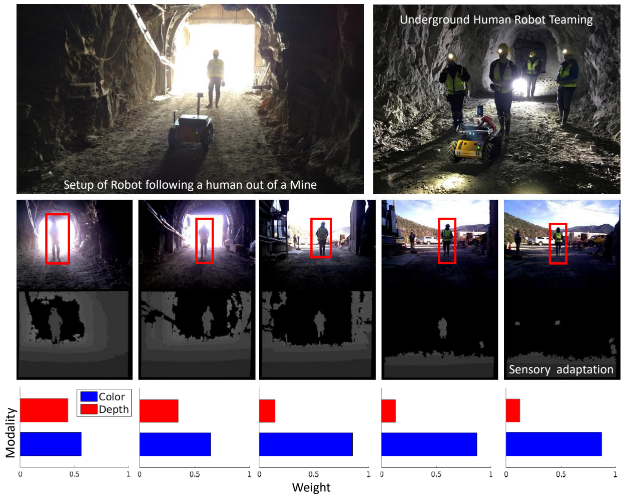

Fig. 2. Robot following humans in the underground environments, and the preliminary results on robot adaptation.

- Scenario II (All-Day-Following): A mobile robot follows a human subject in an outdoor environment at different time of the day from dawn to dusk, and across different months. The environment changes dramatically, especially lighting levels from noon to late evening. In the daytime under strong sunshine, structured-light depth sensors fail. In evenings with poor lighting conditions, color camera cannot work well. This Scenario II includes significant challenges caused by long-term environment changes across a day and seasons.

In each scenario, we collect 20 instances of human following, each consisting of 700-1000 color-depth images. In addition, we collect the light level data (in lux) using Adafruit TSL2561 digital luminosity sensors installed on the robots to document environments' lighting variations. The ground truth of human detection is manually labeled by bounding human subjects in the color-depth scene with a box.

III. Preliminary Results on Robot Adaptation

We developed our approach for robot adaptation based on joint learning that simultaneously learns important features and an adaptation model under the unified mathematical framework of regularized optimization.

We evaluate our approach in Scenario I, in which a mobile robot follows a human subject to go into and get out of the mine drifts. Beyond the conventional perception difficulties including human body deformation and camera motion, the robot must also address the challenge of swiftly adapting to the fast lighting change when it navigates from the inside to the outside of the mine (and vise versa).

We show the qualitative result in Figure 2, which graphically illustrates that our approach allows the robot to accurately recognize the subject when navigating from a dark mine drift into a bright outdoor open area under significant lighting variations.

In addition, we compute numerical results to quantitatively assess our approach. To evaluate how well to identify humans under lighting changes, accuracy is employed as an evaluation metric. Our method obtains an average accuracy of 96.91% in Scenario I. In order to demonstrate the advantages of our approach, we also implement several baseline methods for comparison, including the optimization-based classifiers using a single type of features as the input (i.e., HOG, LBP, or GIST features extracted from color or depth images). Moreover, we implement a Multi-Sensory Fusion (MSF) approach [4], as a baseline to compare with our approach. The results of comparison is listed in Table I. It is observed that (1) methods based on color features (i.e., HOG, LBP, and GIST) generally perform better than methods using depth features (i.e., HOG-D, LBP-D, and GIST-D), (2) through fusing all multisensory multimodal features, MSF outperforms techniques using single types of features, and (3) our approach greatly improves performance and obtains the best accuracy, due to its capability to calibrate perception and adapt to environment changes.

TABLE I
Comparison of average accuracy over all robot operation scenarios in the newly collected benchmark dataset

Methods	Scenario-I
HOG	89.22%
LBP	81.40%
GIST	79.53%
HOG-D	70.11%
LBP-D	61.07%
GIST-D	67.57%
MSF	92.30%
Our Approach	**96.91%**

Besides accuracy, we also evaluate how our approach can adapt to environment changes by analyzing the importance of different sensor modalities, i.e., color and depth in this experiment. The quantitative results are graphically presented in Figure 2. It is observed that, when the robot stays outside of the mine under direct sunshine, it completely relies on color cues to recognize the subject. This is because structured-light depth sensors fail under direct sunshine, and cannot provide depth information. Our approach is capable to automatically learn this fact from data without the requirement of hard coding. When the robot follows the subject into the mine drift with a reduced lighting, we observe that the proposed approach starts using the depth information to combine with color cues to recognize the humans, which demonstrates the on-the-fly adaptation to lighting changes of the surrounding environment.

References

[1] M. W. Floyd, M. Drinkwater, and D. W. Aha, "Trust-guided behavior adaptation using case-based reasoning," tech. rep., Naval Research Laboratory Washington United States, 2015.

[2] Q. Zhang, H. Qian, and M. Zhu, "Parameter adaptation by case-based mission-planning of outdoor autonomous mobile robot," in *Proceedings of Intelligent Vehicles Symposium, 2005.*, IEEE.

[3] Colorado School of Mines, "The edgar experimental mine." `https://mining.mines.edu/edgar-experimental-mine`.

[4] H. Zhang, F. Han, and H. Wang, "Robust multimodal sequence-based loop closure detection via structured sparsity.," in *Robotics: Science and Systems*, 2016.