Learning Robust Failure Response for Autonomous Vision Based Flight

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***Abstract*— The ability of autonomous mobile robots to react to and recover from potential failures of on-board systems is an important area of ongoing robotics research. With increasing emphasis on robust systems and long-term autonomy, mobile robots must be able to respond safely and intelligently to dangerous situations. Recent developments in computer vision have made autonomous vision based navigation possible. However, vision systems are known to be imperfect and prone to failure due to variable lighting, terrain changes, and other environmental variables. We describe a system for learning simple failure recovery maneuvers based on experience. This involves both recognizing when the vision system is prone to failure, and associating failures with appropriate responses that will most likely help the robot recover. We implement this system on an autonomous quadrotor and demonstrate that behaviors learned with our system are effective in recovering from situational perception failure, thereby improving reliability in cluttered and uncertain forest environments.**

I. INTRODUCTION

Vision systems are known to be imperfect, which makes the vision system on any mobile robot prone to failures [1]. A number of different ideas have been explored in the robotics and computer vision literature that try to qualitatively assess the reliability of vision systems. Similarly, there is ongoing research that tries to predict failures in perception systems. However, we believe that it is equally important to make intelligent decisions once a failure has been predicted or recognized in order to mitigate any dangerous situations that might ensue. This is important to ensure long-term autonomy of mobile robots, and make them robust to the widespread situational changes that may occur in the environment the robot is operating in. An example of this from our system is shown in Fig. 1.

The task of associating failures with recovery maneuvers is challenging for three primary reasons. First, as robots become more robust due to advances in hardware and software, they will encounter failures less frequently. In this sense, the failures make up the long tail of the distribution of situations the robot will find itself in. The importance of learning about the long tail has been widely studied in the vision community in terms of object and pose detection [2]. Even though failures are encountered less frequently, it is critical for a mobile robot to be able to recover from them to ensure safe long-term operation. Second, associating failures with recovery maneuvers to some extent depends on domain knowledge related to the environment a robot operates in.

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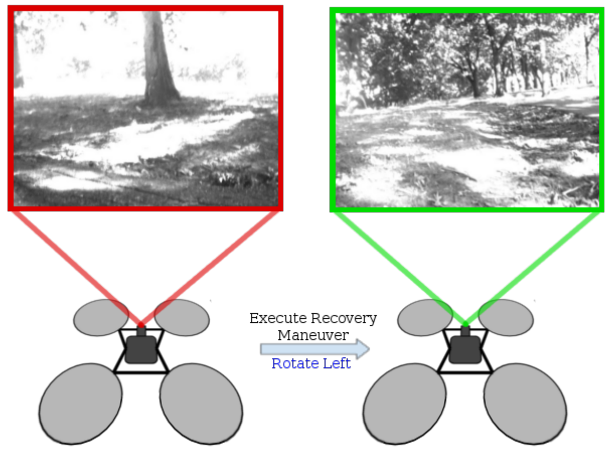

Fig. 1. After the quadrotor is alerted of a failure (possibly due to a combination of over-exposure and lack of features in the scene) on the left, our system tells it to execute the *rotate left* maneuver. At the end of this maneuver as shown on the right, the quadrotor has turned away from the source of illumination, and has enough information in the scene to continue its monocular flight. This is deemed a successful recovery from the perception failure.

This will cause different robots to possibly learn different recovery maneuvers. This paper presents a framework that allows a robot to associate failure modes with recovery maneuvers that have been selected by leveraging the domain knowledge available to us. Finally, since mobile robots work on real-time data streams, they will almost certainly run into situations that could not possibly have been accounted for in any training set presented to the robot. It is therefore important to continue to learn from past experience for as long as possible. It is also difficult to manually label the different modes of failure. For mobile robot vision systems, over- or under-exposed images, motion blur, large inter-frame rotation, lack of texture, shadows etc. could all potentially cause failures. Fig. 2 shows example images from our actual flight tests that triggered perception failures, which were then resolved by one of the recovery maneuvers. The supervised learning task of classifying failures thus becomes intractable since it is almost impossible to label images in a training set with the cause of failure. A large number of factors could cause a vision system to fail. Rather than identifying the cause of failure, it then becomes more important to identify the recovery maneuver most likely to succeed in mitigating the failure.

An integral part of the framework presented in this paper is the ability of a robot to predict failures in their vision systems ahead of time. In the associated literature, this