Learning Robust Failure Recovery for Autonomous Vision Based Flight

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Overview

- Visual SLAM (Simultaneous Localization And Mapping) algorithms fail due to variable image quality in the real world.
- Such failures are often resolved by simple actions such as turning or moving to the side.
- We use a Convolution Neural Network (CNN) and Support Vector Machines (SVMs) to learn the best recovery trajectory for any failure.
- We focus on autonomous flight through forests, but our system of learning failure recovery is generalizable to many domains.

Failure Handling in Flight

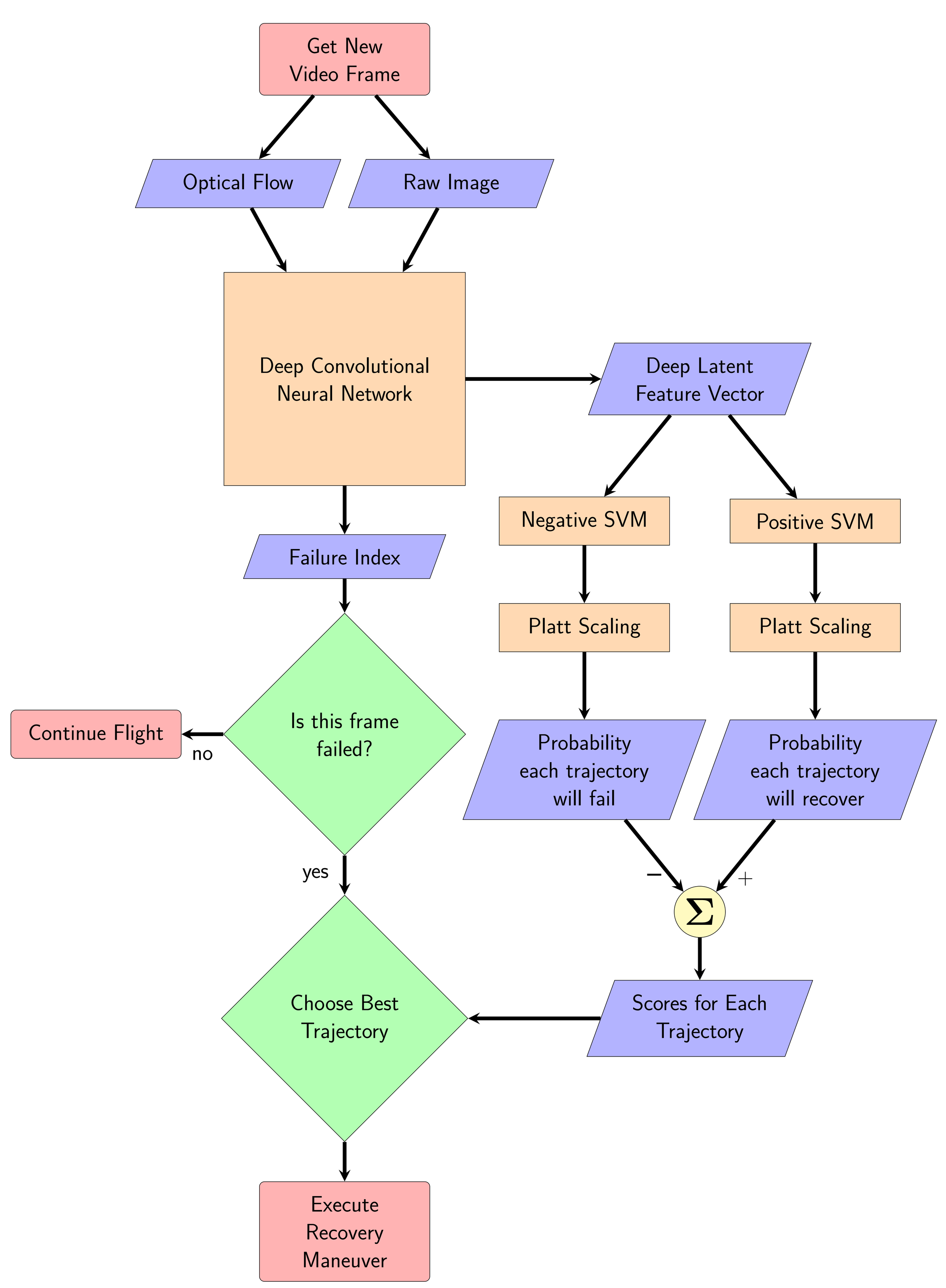

Figure 1: The algorithm in block diagram form. Failure recovery is integrated with a deep introspection framework that predicts when a failure may occur [1].

Results

Effectiveness of the approach was validated in hand held flight. Future testing will demonstrate the ability of this approach to extend flight time and reliability.

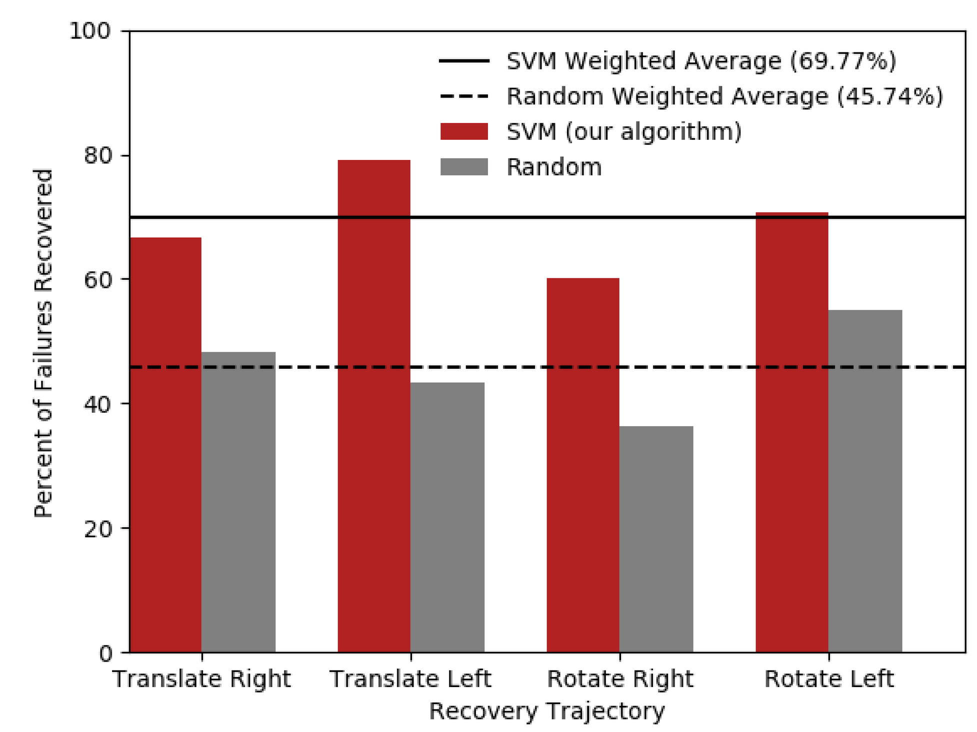

Figure 2: Failure Recovery by Percent

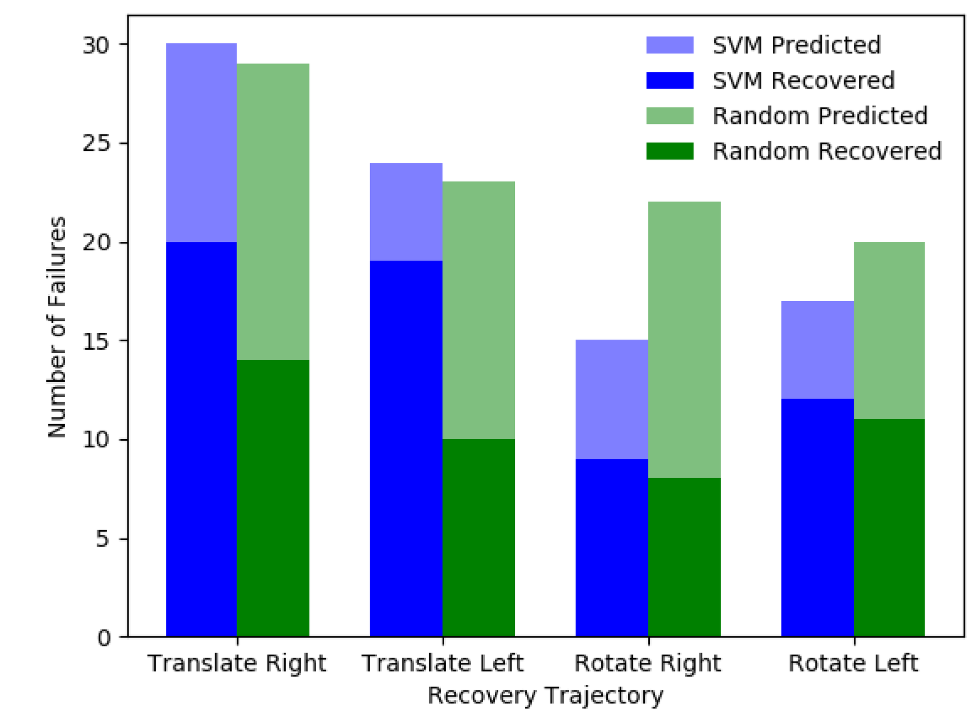

Figure 3: Failure Recovery by Number

Classifying Images by Best Recovery Trajectory

Figure 4: Translate Right

Figure 5: Translate Left

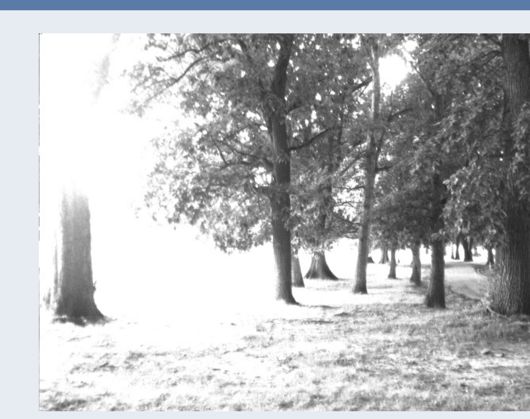

Figure 6: Rotate Right

Figure 7: Rotate left

Examples of failed images from the training set. Our algorithm used these images, and thousands like them, to learn which trajectories recover from different failures.

Candidate Trajectories

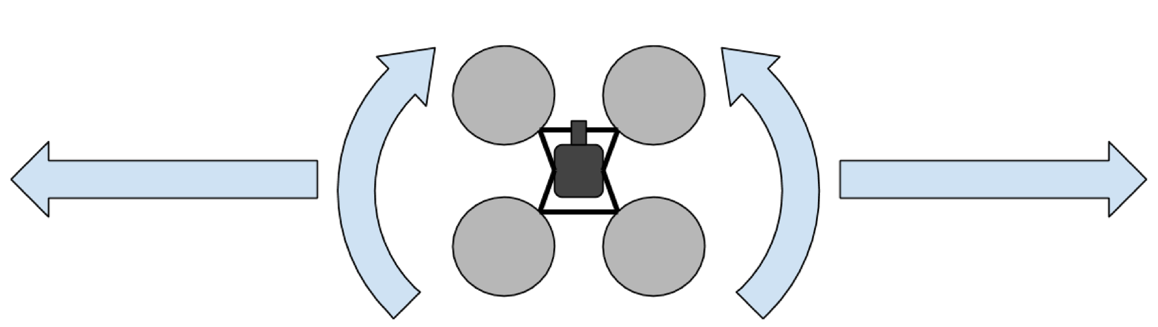

Figure 8: Each candidate trajectory has the potential to resolve different failures, but which trajectory is best for a given failure is not always intuitive.

Two SVM classifiers output independent probabilities that each trajectory will recover or fail.

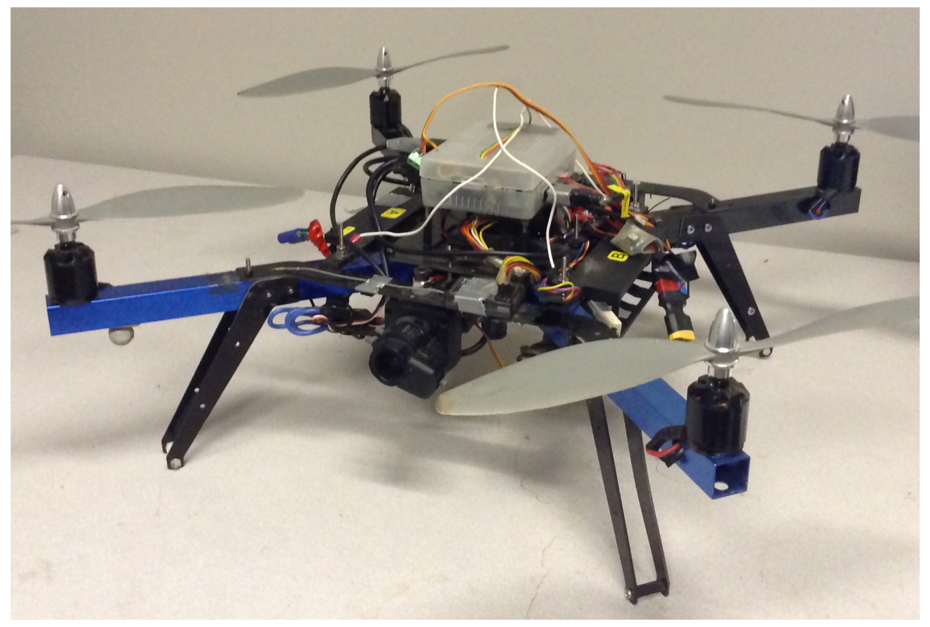

Figure 9: The testbed: an autonomous quadcopter for flight through dense forests with a camera as the primary sensor [2]

Training Data

7539 images were collected by holding the quadcopter while walking and executing a given trajectory when alerted of a failure.

Trajectory	Recovered	Failed
Translate Right	745	631
Translate Left	738	530
Rotate Right	1280	863
Rotate Left	1234	1518

Table 1: Images in the training set

Images from throughout **825 trajectories** were used. Highly similar images were removed by comparing L1 distances in feature space.

Conclusion

This framework could be used to improve reliability of small autonomous aircraft in exploration, disaster response, mapping, and many other applications.

Additionally, our data driven approach to failure recovery can be used to improve reliability in many fields, from autonomous ground vehicles to robot manipulation.

References

[1] S. Daftry, "Towards scalable visual navigation of micro aerial vehicles," Master's thesis, Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, April 2016.

[2] D. Dey *et al.*, "Vision and learning for deliberative monocular cluttered flight," in *Field and Service Robotics (FSR)*, June 2015.

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