

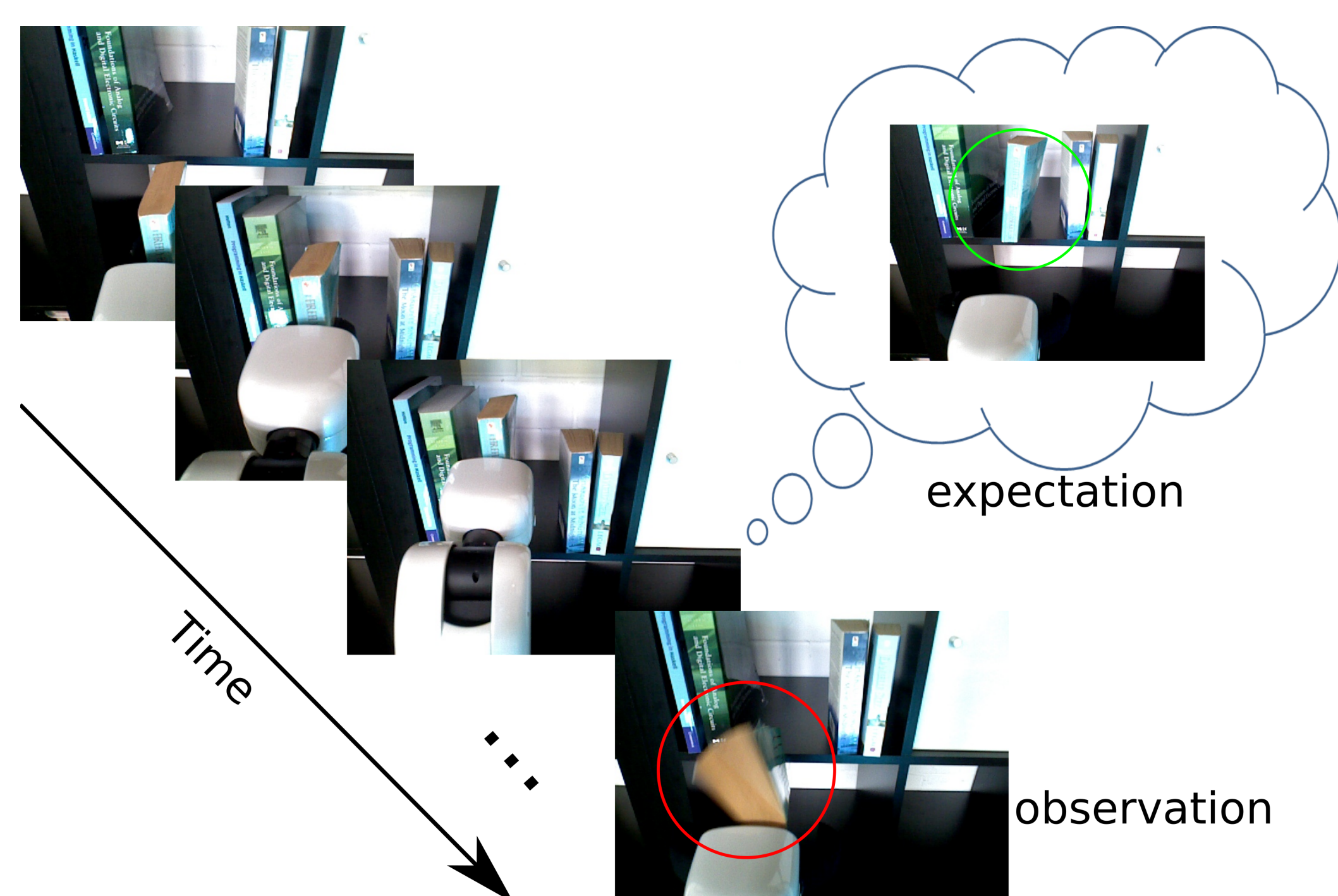
Visual Failure Detection in Robotics Using Learning

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Failures are common for robots that operate in **uncertain environments**. A robot should **detect failures** and correct them to improve its **reliability and trustworthiness**. The **robot's camera** is a rich source of information to monitor actions and detect failures. We explore visual failure detection in robotics applications using neural networks.

Comparing Expectations vs Observations

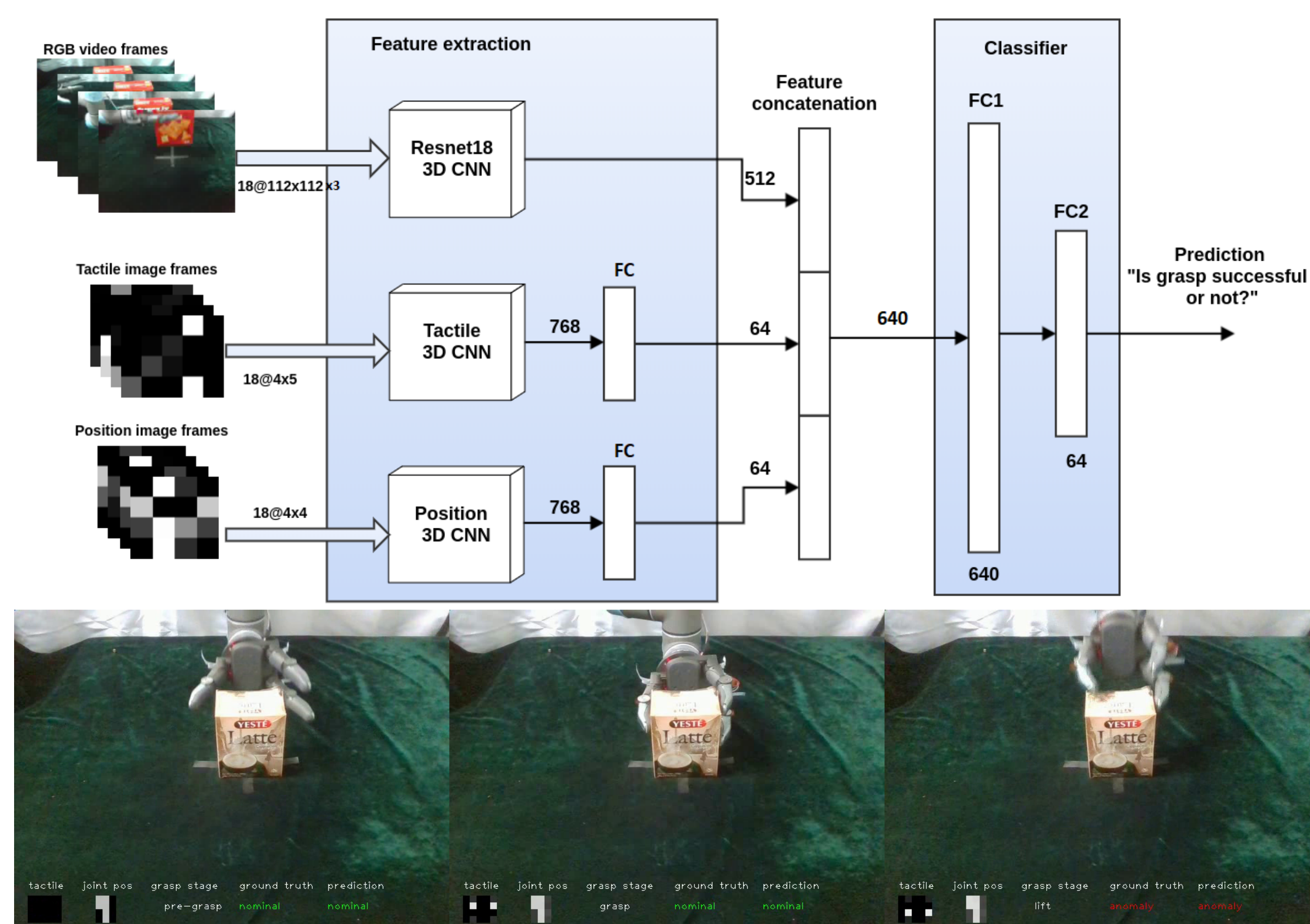
In [1], the robot learns a model of nominal motion patterns while placing a book on a shelf. During runtime, the **observed motion is compared to the expected nominal motion** to detect deviations. The method is able to detect events such as the book falling off the shelf, external disturbances to the robot, and camera occlusions.



By comparing the current observation with a learned expectation, the robot is able to detect failures

Multimodal Data for Grasp Failure Detection

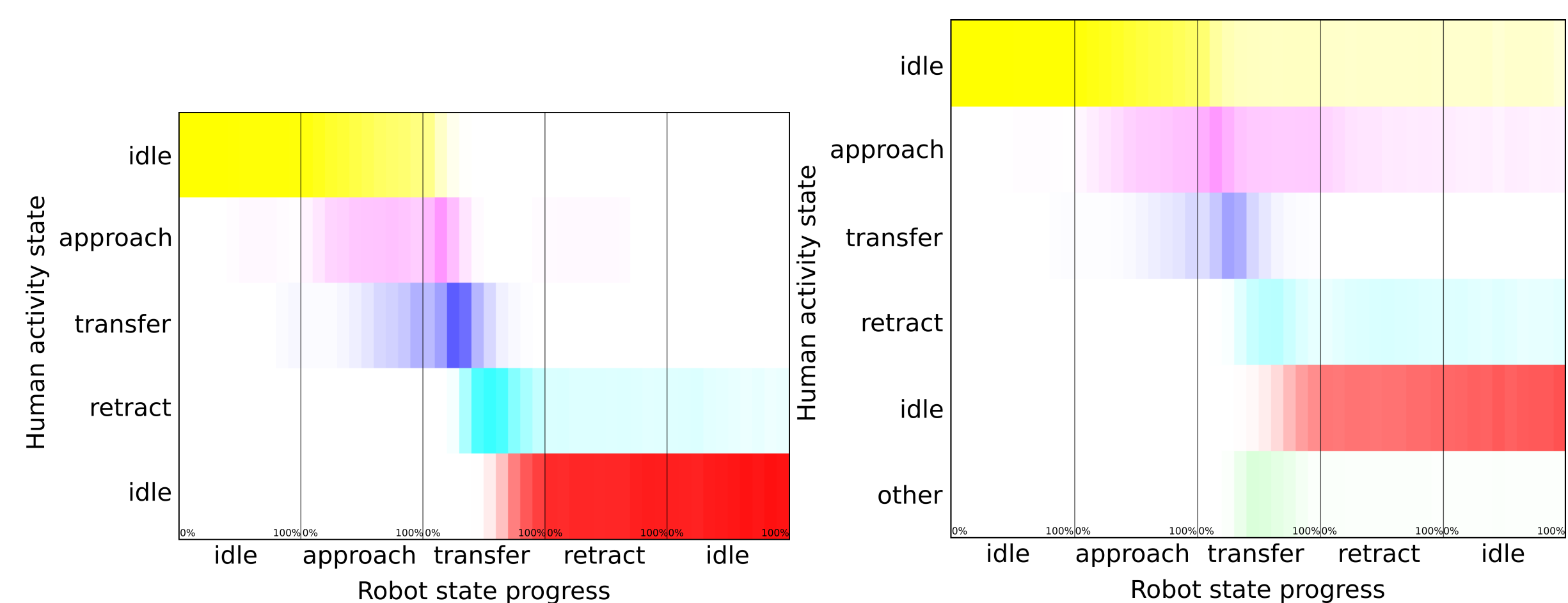
The visual-tactile dataset [2] contains video, tactile and finger position data for successful and failed grasps by a robot arm. Our method [3] represents **tactile and position data as images** and uses 3D CNNs as feature extractors before fusing the features from all three modalities for **grasp outcome classification**. We find that an **intermediate fusion strategy** produces the best results.



For a grasping task, it is beneficial to fuse data from the camera, tactile sensors, and finger position encoders to detect failed grasps [3]

Object Handover Failure Detection

We focus on **failures which are induced by humans** during object handovers between robots and humans. By **classifying the activity state of the human**, we can determine if their activity is expected during the current phase of the handover. We collect a **dataset of 591 object handovers**, including successful and failed executions. Our classification method using visual features and 2D skeleton poses achieves a true positive rate of 0.55 for robot-to-human handovers and 0.71 for human-to-robot handovers.



Ground truth annotations of the human activity state in relation to the current robot state for only successful (left) and all (right) executions

Pipe Defect Detection



Defects in sewer pipes observed by a remote-controlled robot [4]

The QV-Pipe dataset [4] consists of short video clips from a remote-controlled robot in a sewer pipe, which may have one of 16 defect categories. We fuse intermediate CNN features from individual frames before classifying each clip, and were able to achieve an mAP of 59.91, placing third in the VideoPipe Video Defect Classification Challenge.

Acknowledgements

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References

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- [2] Wang T, Yang C, Kirchner F, Du P, Sun F, Fang B. Multimodal grasp data set: A novel visual-tactile data set for robotic manipulation. International Journal of Advanced Robotic Systems. 2019;16(1). doi:10.1177/1729881418821571
- [3] P. Gohil, S. Thoduka, and P. G. Plöger, "Sensor Fusion and Multimodal Learning for Robotic Grasp Verification Using Neural Networks," in 26th International Conference on Pattern Recognition (ICPR), 2022.
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