DEVELOPING METHODS FOR EXERCISE SYSTEM KINEMATIC TRACKING

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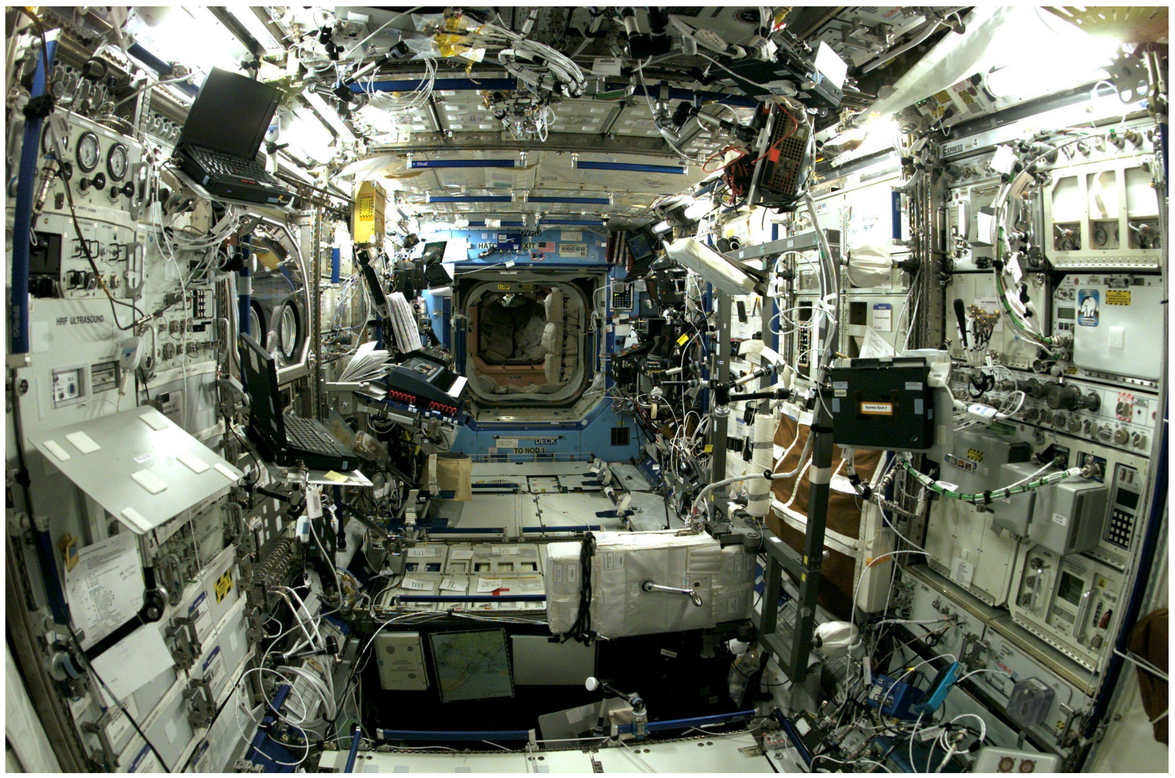


Fig. 1 Destiny module containing CEVIS Image Credit: NASA [ISS007-E-11800]

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- ❑ Visually cluttered background
- ❑ Occlusions from objects and crew members
- ❑ Subject motion
- ❑ Low-textured object with small motions
- ❑ Loose floating objects
- ❑ Limited camera views
- ❑ No global references for camera positions
- ❑ Lack of training data for AI/ML
- ❑ Operational challenges such as camera stability and synchronization

Background

Quantifying the loads produced by exercise equipment and their Vibrational Isolation and Stabilization (VIS) platforms in-flight is critical for simulation verification and validation to inform system development, future design requirements, and understanding interactions between countermeasure devices and crew members. Analytical approaches are currently driven by kinematic inputs. In addition to tracking the kinematics of the crew member, using tools such as Southwest Research Institute's ENABLE [1], hardware object tracking is a remaining gap. While motion capture of exercise on the International Space Station (ISS) is now being collected [2], historical lack of and inadequacy of tracking systems in-flight, like inertial measurement units or traditional marker-based infrared motion capture, make video-based methods attractive. The unique challenges video-based methods have in space flight are presented here by using a two camera RGB video trial with the Teal CEVIS (Cycle Ergometer and Vibration Isolation and Stabilization System) as a case study (Fig. 2).

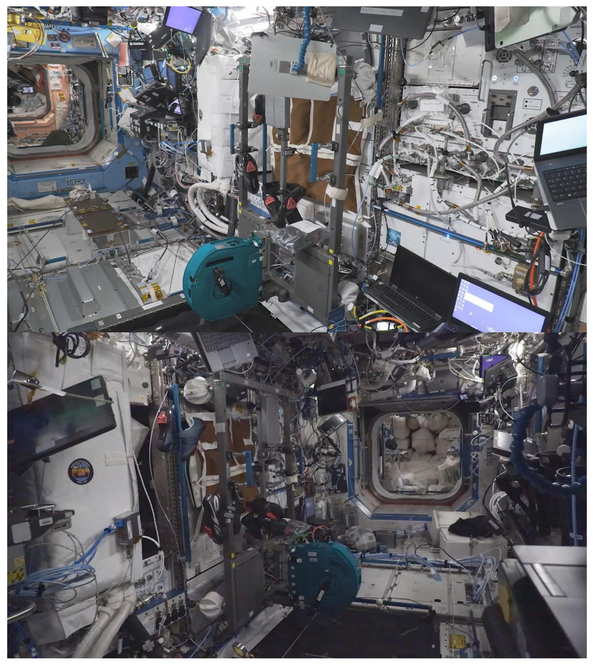


Fig. 2 Left/right views of Teal CEVIS during the 2-camera video data collection

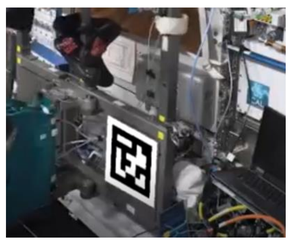


Fig. 4 April tag masking

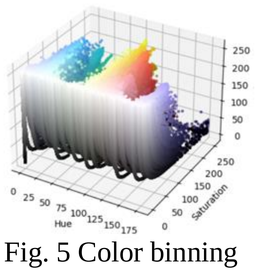


Fig. 5 Color binning by pixel

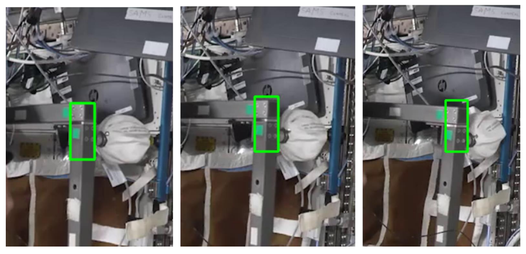


Fig. 6 Region of Interest tracking drift

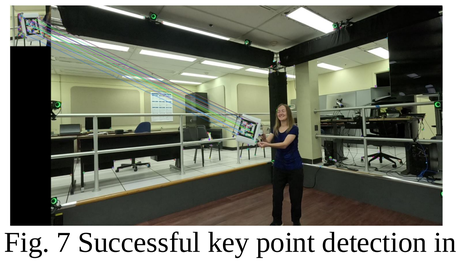


Fig. 7 Successful key point detection in video/motion capture April tag collection

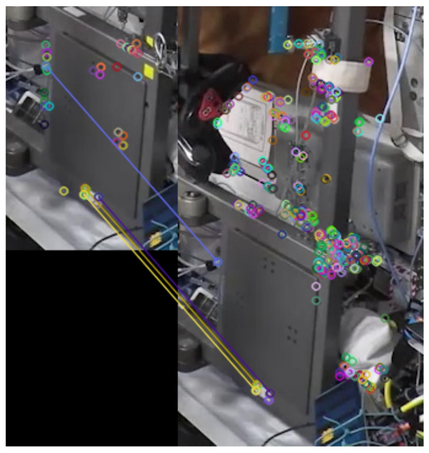


Fig. 3 Key point detection

Methods & Results:

Keypoint Detection (using ORB algorithm [3] in OpenCV [4])

- The lack of distinguishing features on the CEVIS and busy background may be insurmountable for a keypoint detector on an unprocessed RGB video (Fig. 3,7).

Background Subtraction (using OpenCV)

- Motion-based background subtraction is complicated by relatively fast human motion, camera wobble and lighting changes frame-to-frame. The relatively slow motion and low texture of the CEVIS results in a noisy and ineffective subtraction.
- Artificial Intelligence/Machine Learning (AI/ML)-based segmentation tools are a promising solution currently being investigated. Some of these tools are object agnostic and do not require extensive training on ISS-like imagery [5].

Feature Detection (using OpenCV)

- Corner detection was briefly explored: low object texture and high background texture presented challenges that would require manual input to resolve.
- Color masking to reveal key features (colorful stickers) is effective, but too few colorful features are present for sufficient post processing (Fig. 5).
- Region of interest tracking over even the highest textured areas resulted in drift (Fig. 6). A loose floating object that entered the region of interest caused the tracked object to be fully lost.

Planar Tracking

- A flat section of the CEVIS was masked with an April Tag using VEGAS Pro video editing software (Fig. 4). There was visible drift, but this method should be explored further. Other planar tracking algorithms could also be used.

Conclusions & Recommendations

No single method explored produced high fidelity 6-DOF poses that could be used to determine the loads on ISS by exercise equipment and VIS platforms. Human feedback/manual inputs, a conglomerate of techniques, or custom ML-based methods may be required unless dedicated tracking aids, such as fiducial markers, can be included on the hardware. We will be exploring two ML-based object detection and tracking methods in future work [6-7].

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