DEVELOPING METHODS FOR EXERCISE SYSTEM KINEMATIC TRACKING

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BACKGROUND

How to quantify the load and forces produced by exercise equipment and their Vibration Isolation and Stabilization (VIS) platforms in-flight is an active area of investigation. Kinematic tracking paired with system modeling can provide insights as well as verification and validation of simulations used for system design and development. Traditional motion capture methods can require significant cost in equipment procurement and crew-time, but newer lessons learned can be leveraged [1]. The VIS systems of current and future exercise hardware on the International Space Station (ISS) such as the Cycle Ergometer with Vibration Isolation System (CEVIS) and the European Enhanced Exploration Exercise Device (E4D) are not currently outfitted with IMUs or similar measurement devices. Video-based methods would enable use of multi-purpose, crew-familiar flight equipment. An initial exploration of video-based solutions was performed utilizing 2-camera video from crew cycling on Teal-CEVIS on the ISS.

METHODS AND RESULTS

Our group has scoped a variety of video-based object tracking methods. To date, we have primarily investigated computer vision toolkits such as openCV. Techniques explored include key-point detection, background subtraction, region-of interest tracking, color-based tracking, tag masking and tracking, and corner detection.

Although object-tracking and 6D pose estimation is a rich field, space applications are a unique problem that are challenging for existing software and toolkits. The majority of the existing object-tracking applications involve vehicles/pedestrians and household objects with simple backgrounds. We have identified the following features which pose particular challenges for on-station exercise equipment tracking:

1. Busy and visually cluttered background
2. Low-textured tracking object with relatively small motions
3. Occlusions and motion by human subject and loose, floating objects
4. Limited number of video cameras with no fixed global references
5. Limited ability to add tags, markers, or visual references to the tracking object
6. Lack of training data for Machine Learning (ML) algorithms

CONCLUSION

We will summarize the efficacy of techniques tested for a ground mock-trial and the on-station exercise trial. It is likely that human-in-loop feedback or a conglomerate of methods is required. ML-based methods, like those implemented for human body tracking [2], may still be a viable option, but more training data and validation is needed.

REFERENCES

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