

National Aeronautics and Space Administration



Machine-learning Solution for Automatic Spacesuit Motion Recognition and Measurement from Conventional Video

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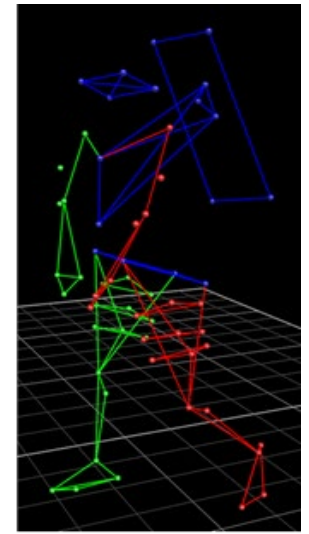
Background

- Astronauts will perform a variety of Extravehicular activities (EVA) during the planned lunar missions that range from geology to manual materials handling tasks
- Due to pressurization, added suit mass, and spacesuit mechanical configurations, the spacesuit often moves differently than when unsuited
- Kinematics measurements of spacesuits are critical for spacesuit, tool, hardware, and EVA task design

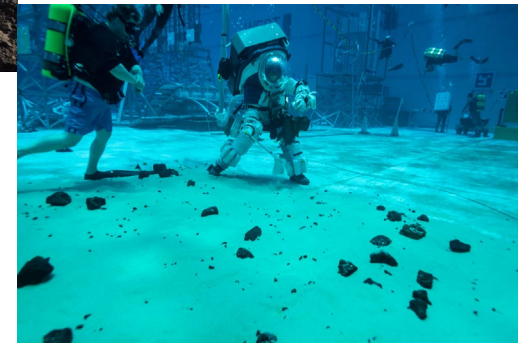


Current technology

- Optical motion capture is used to perform suited kinematic assessments
- However, there are logistical barriers to deploying optical motion capture in operational environments
 - Infrared interference
 - Limited data collection volume
 - Time-consuming to process data
- There are alternative wearable technologies such as inertial measurement unit (IMU) motion tracking
 - There are limitations in measurement accuracy and instrumentation overhead
- In most EVA training or actual EVA events, standard video and photography is collected, which can be leveraged to derive kinematics



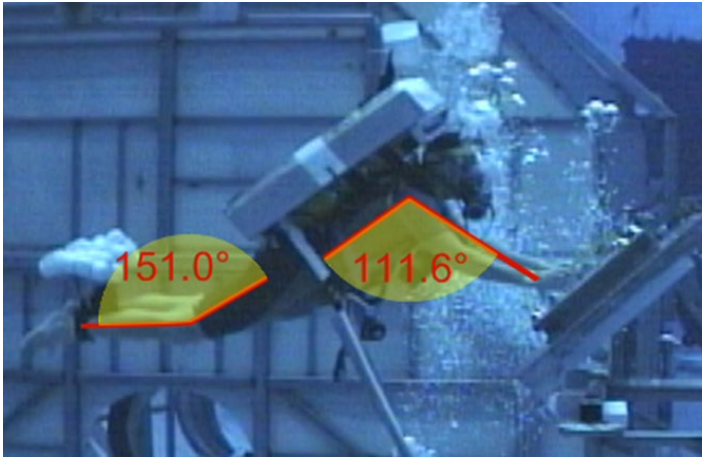
Optical motion capture



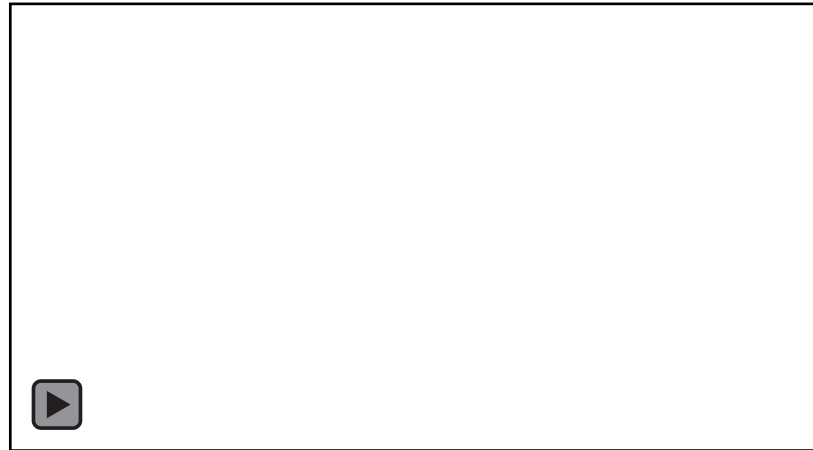
Challenging motion capture environments

Machine-learning applications

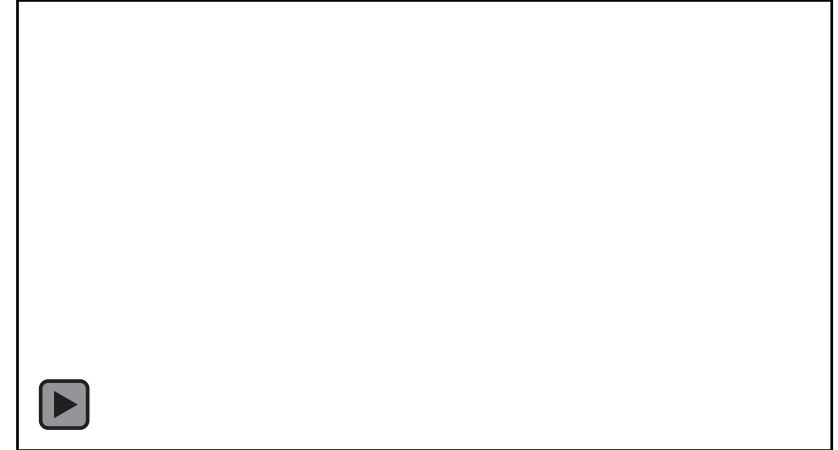
- In the past, video annotation software was used to manually determine joint angles
- New machine-learning and computer vision techniques can automatically detect objects from images and video



Manual joint angle derivations from still photos



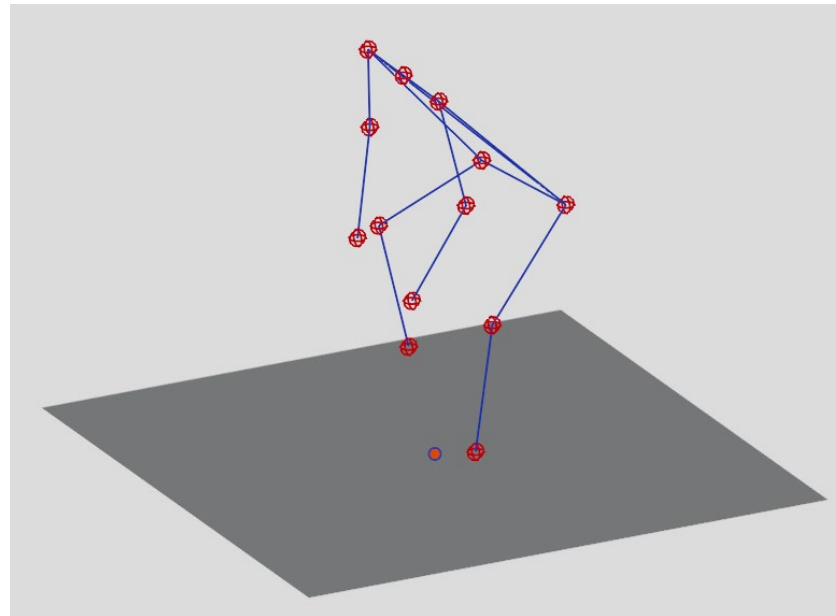
OpenPose Human joint detection



DensePose: Human Pose Estimation

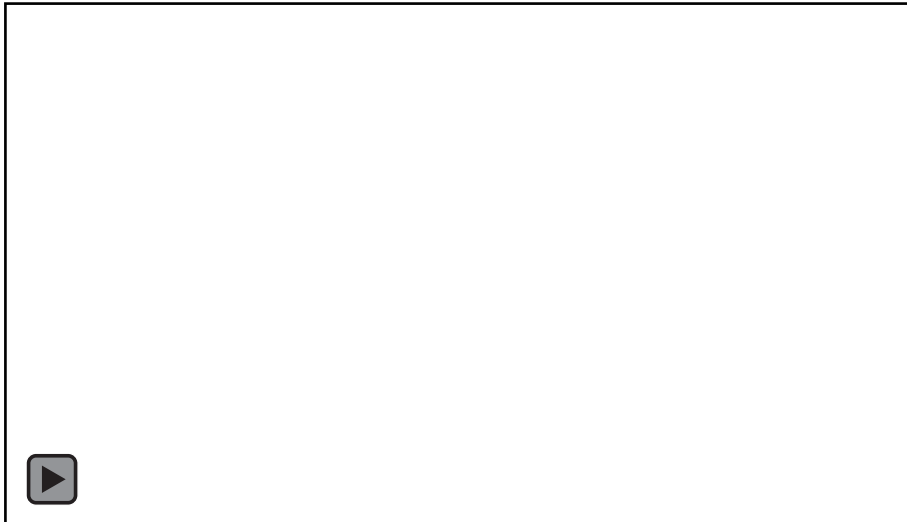
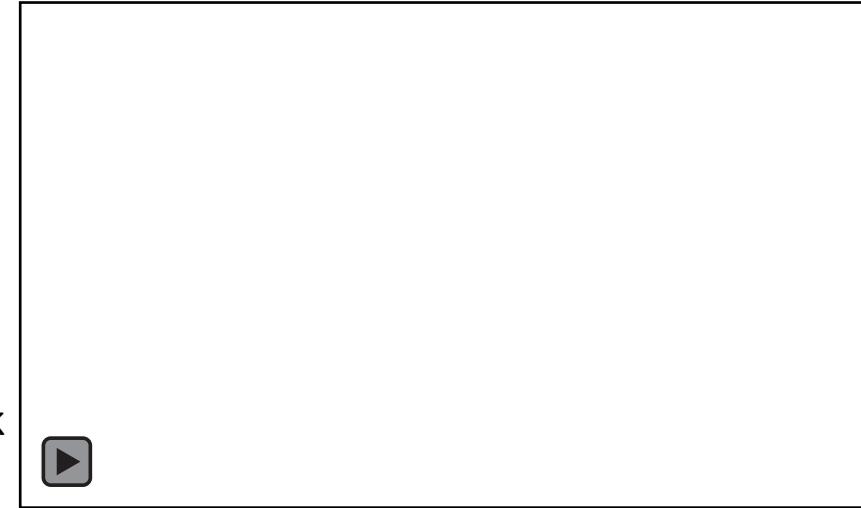
Purpose

- A similar machine learning and computer vision approach may be able to specifically identify spacesuits and automatically estimate the pose
- The developed framework would provide a useful alternative to optical motion capture
- The objective of this paper aims to present the ongoing development of machine learning solutions to quantify suit motions from conventional videos without special sensors or hardware

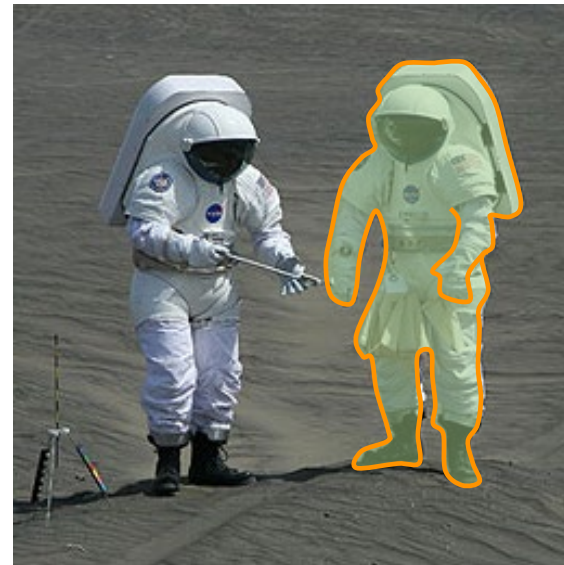


Preliminary in-house efforts

- To test the feasibility that the spacesuit can be recognized from surrounding objects, a pretrained Mask R-CNN model was applied
 - Type of object detection and instance segmentation neural network
- Additionally, a computer vision-based approach was created that could identify the 3D suit posture from the silhouette of a suit using a probabilistic classifier



Example video processed using Mask R-CNN



Probabilistic spacesuit pose extraction from silhouettes



Iterative Outline Matching

Crowdsourcing

- To achieve this complex solution, we sought machine learning expertise found in the open-source communities outside of NASA
 - Similar machine learning solutions have been successfully developed through the accumulated knowledge found in crowdsourcing
- Through collaborations with the NASA JSC Center of Excellence for Collaborative Innovation (CoCEI) and an execution crowdsourcing platform partner TopCoder, a crowdsourcing challenge was released to the public



Dataset preparations

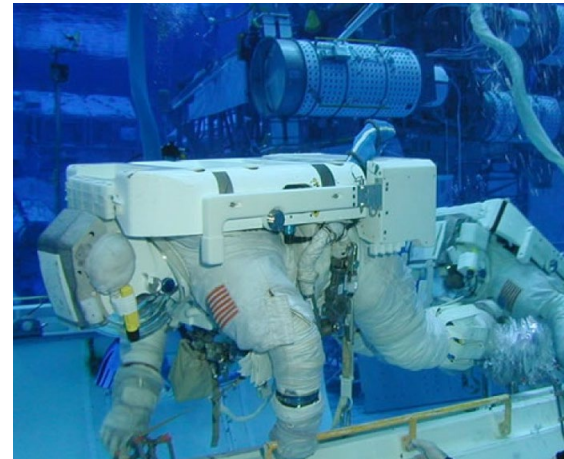
- The specific assignment of the contest was to develop novel algorithms to label and identify spacesuit motions from conventional and readily available video and photographs
- Blurring effects were simulated in the dataset
- A dataset of approved spacesuit postures was provided that consisted of ~200 images from a variety of environments
 - Apollo Lunar EVA
 - ISS EVA
 - NBL ISS EVA training
 - Neutral buoyancy lab
 - NBL Lunar EVA testing
 - Laboratory spacesuit evaluations
 - ARGOS EVA simulations
 - (Active Response Gravity Offload System)
 - Public affairs event
 - Simulated spacesuit animations



Apollo Lunar EVA



ISS EVA



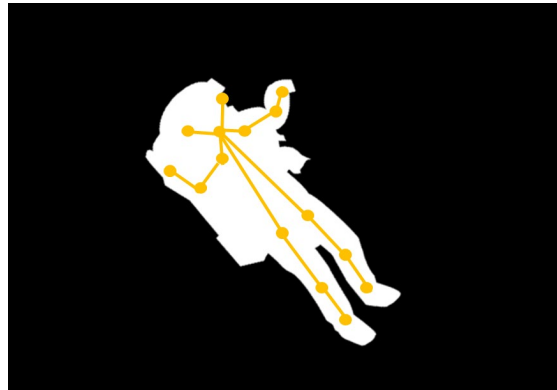
NBL ISS EVA



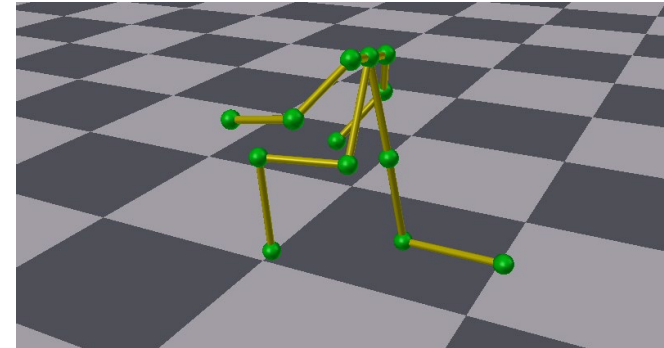
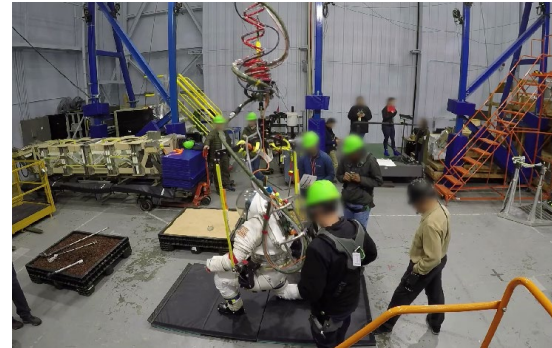
Laboratory Spacesuit evaluations

Challenge scoring

- The following data was provided: pixel coordinates from the spacesuit outline, 2D keypoint joint locations, and 3D joint center locations
- Given the limited 3D data and expected lower accuracy, a scaled scoring rubric for contenders had three components:
 - S2 – suit outline accuracy on 2D images (F-score image similarity score)
 - J2 – joint center locations on 2D images (RMSE)
 - J3 – joint center locations on 3D images (RMSE)
- $Weighted\ score = (0.4 * S2) + (0.4 * J2) + (0.2 * J3)$



Suit outline and 2D joint center locations (S2 and J2)



3D joint centers (J3)

Challenge timeline

- The crowdsourcing challenge was opened in March 2020 and ended after a month and a half
- In that timeframe, we received a total of 285 registered participants and 285 solution submissions
- Solutions were obtained from the top 5 contestants that had a final prediction of over 78%

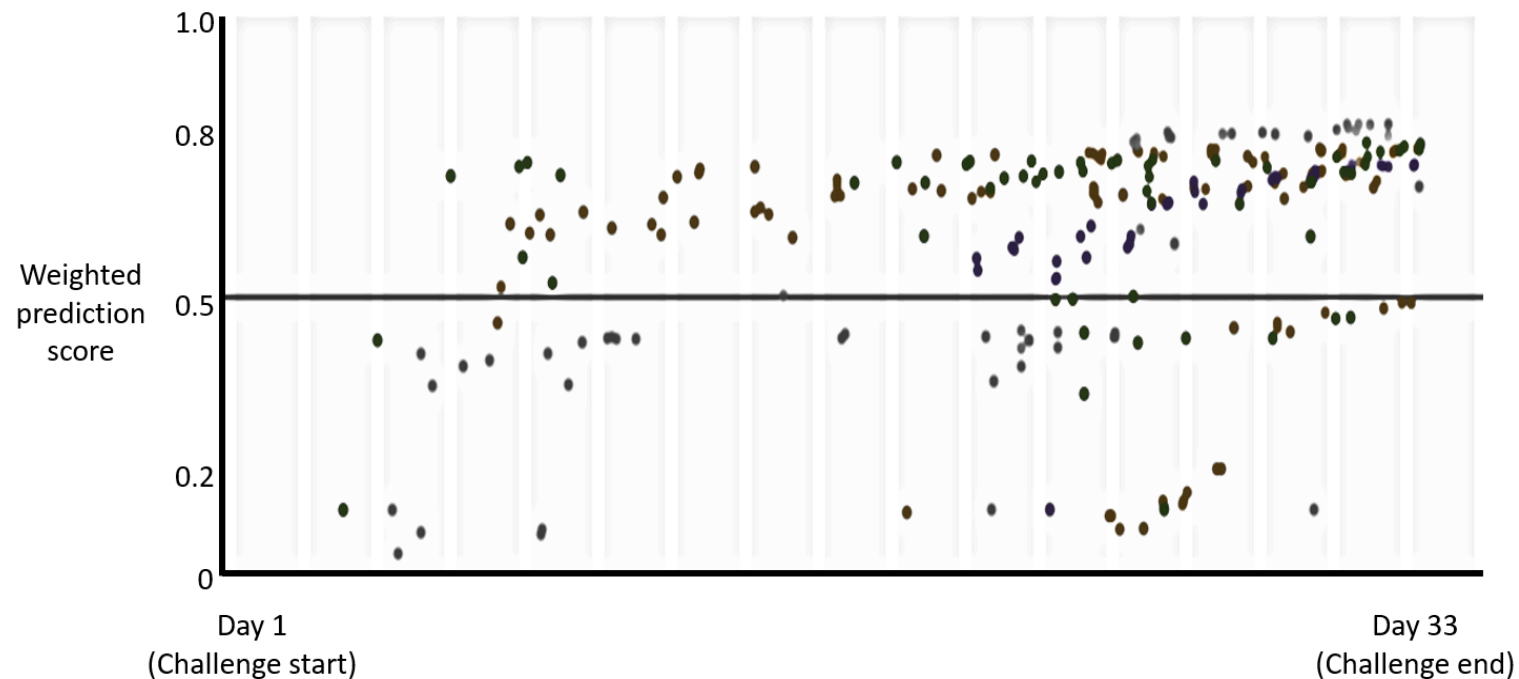


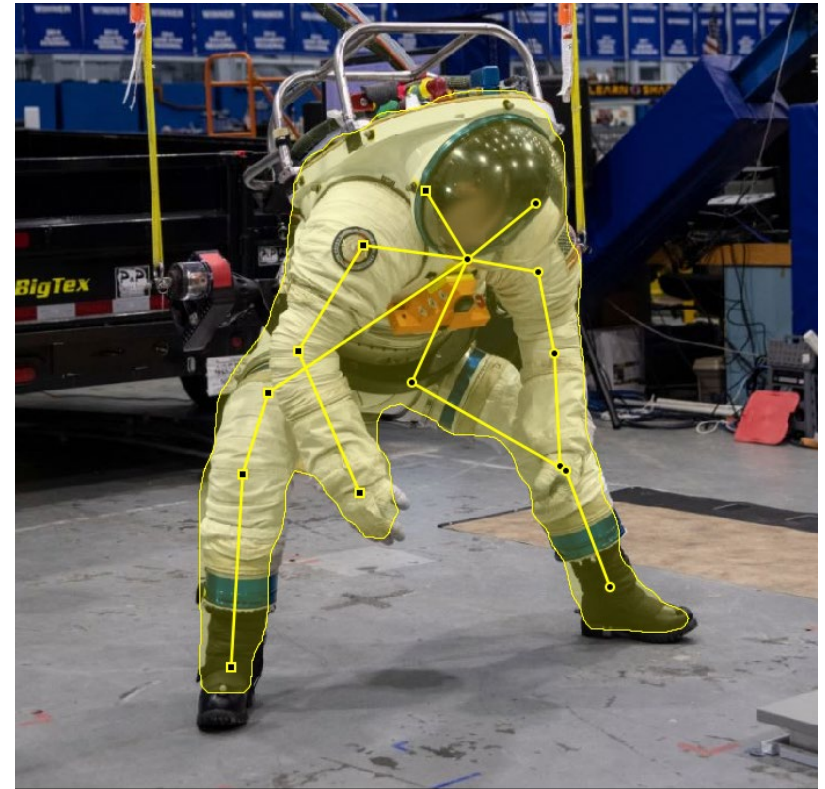
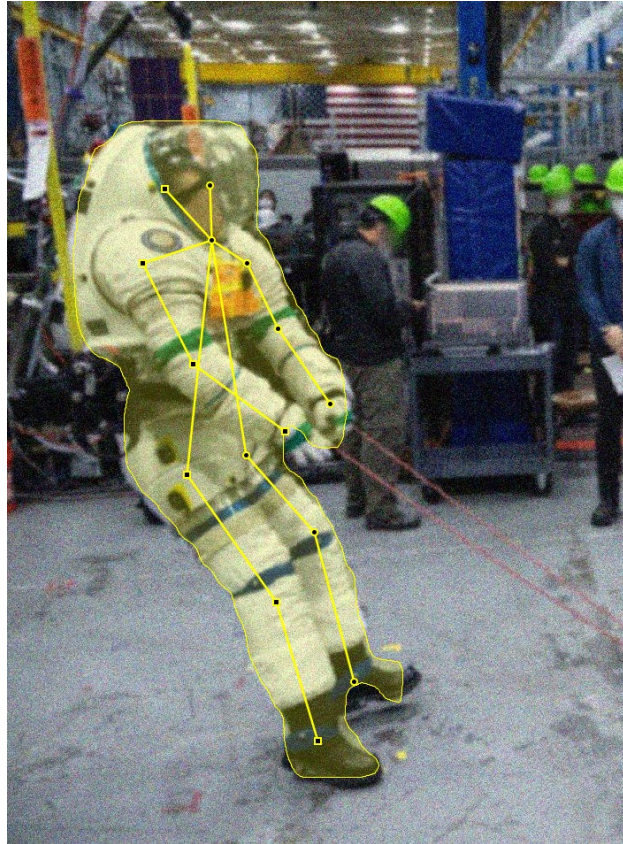
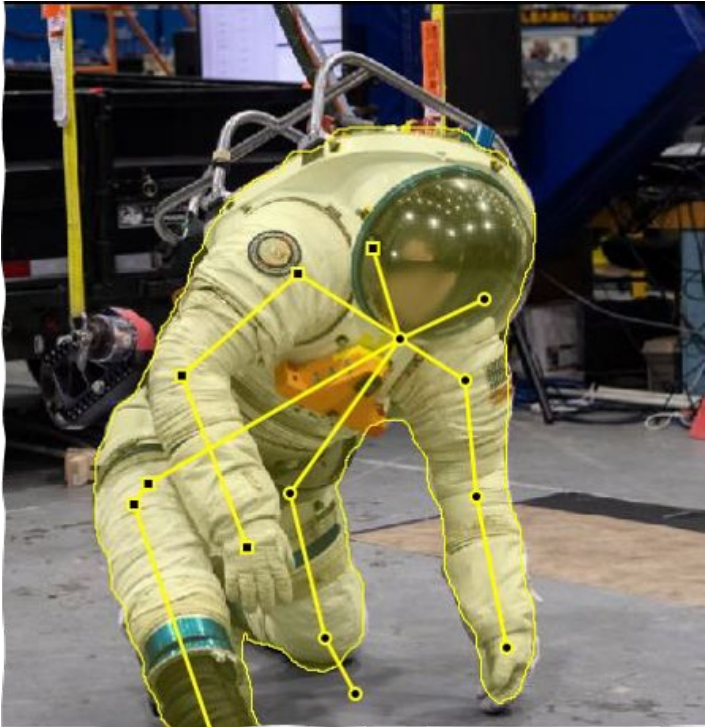
Image accuracy overview

- In-depth statistical analysis and verification is on-going,
- As expected, contenders scored best at:
 - 2D suit outline extraction (0.90, SD: 0.02),
 - followed by 2D joint detection (0.79, SD: 0.03),
 - followed by 3D joint prediction (0.66, SD: 0.05)
- The top winner had a S2, J2, and J3 accuracy score of 0.92, 0.84, and 0.72, respectively, with a total weighted score of 0.85
 - The top solution used a modified Mask R-CNN network with custom dataset augmentations
 - Results and highlights from the top solution were provided in the following slides



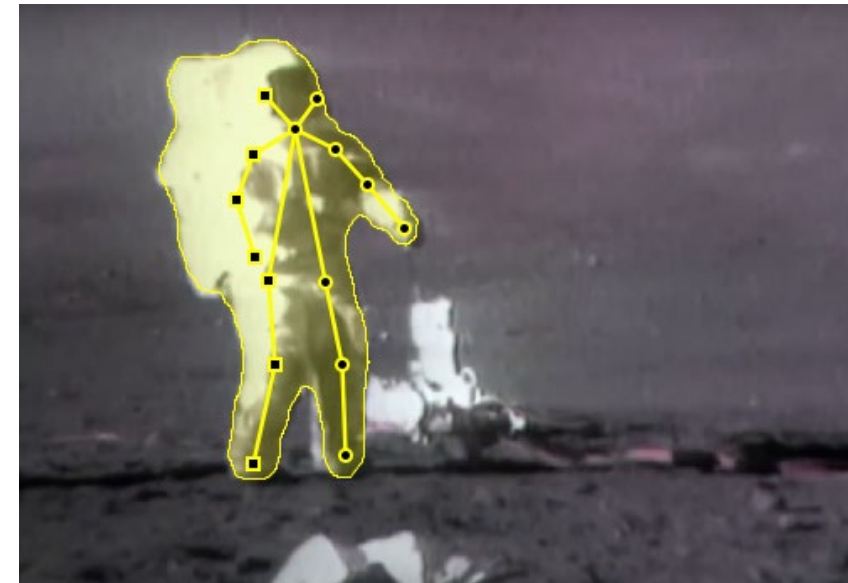
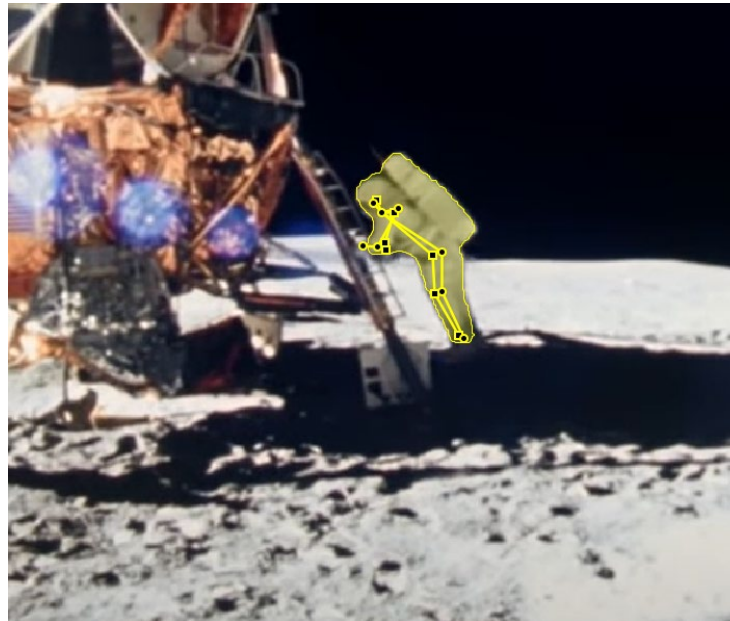
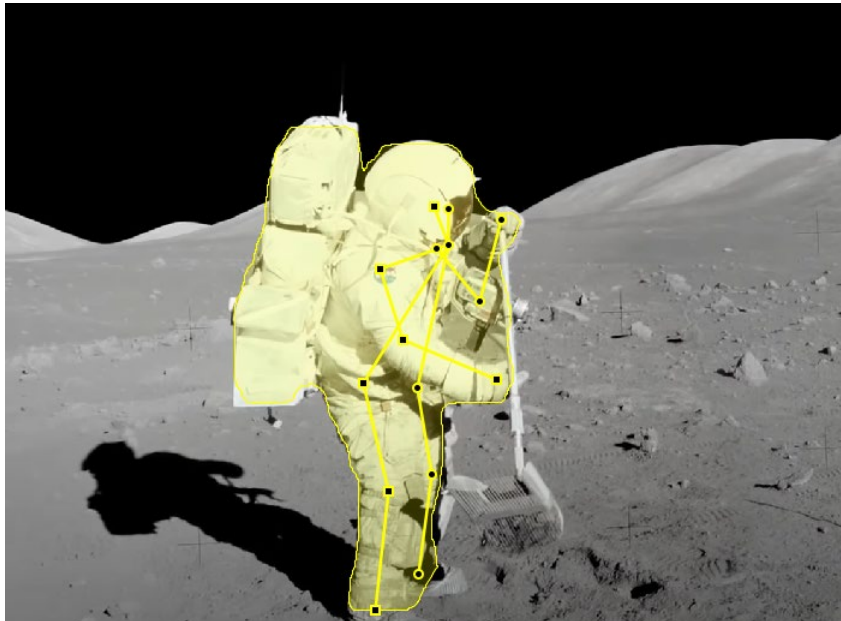
ARGOS/Laboratory suit posture prediction

- Seemed to perform well at predicting joint coordinates in a variety of active EVA postures (squatting, crawling, etc.)
- Algorithms can robustly distinguish between hardware or unsuited people in these lab environments



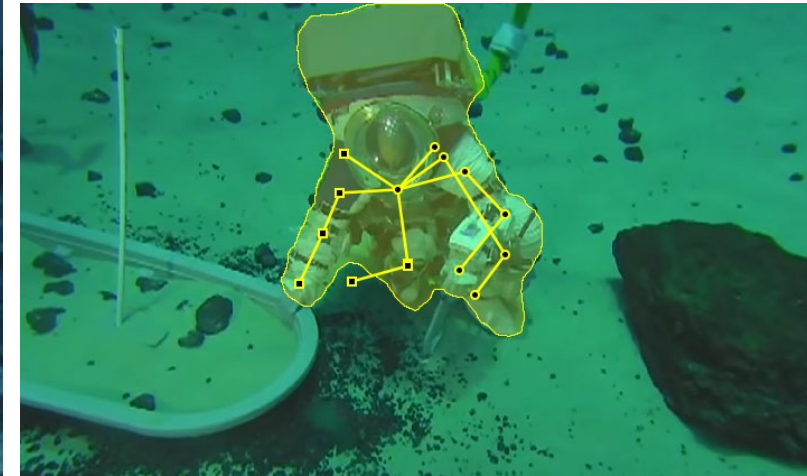
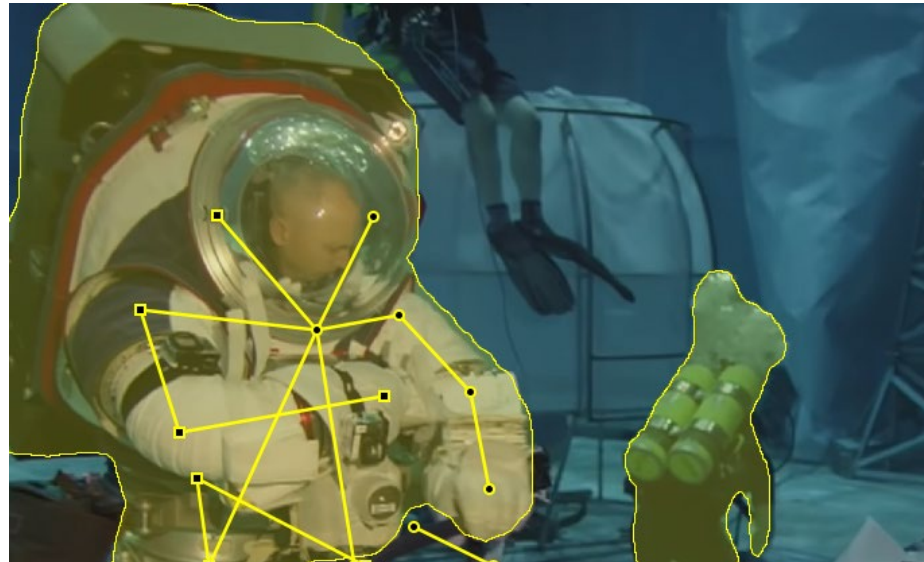
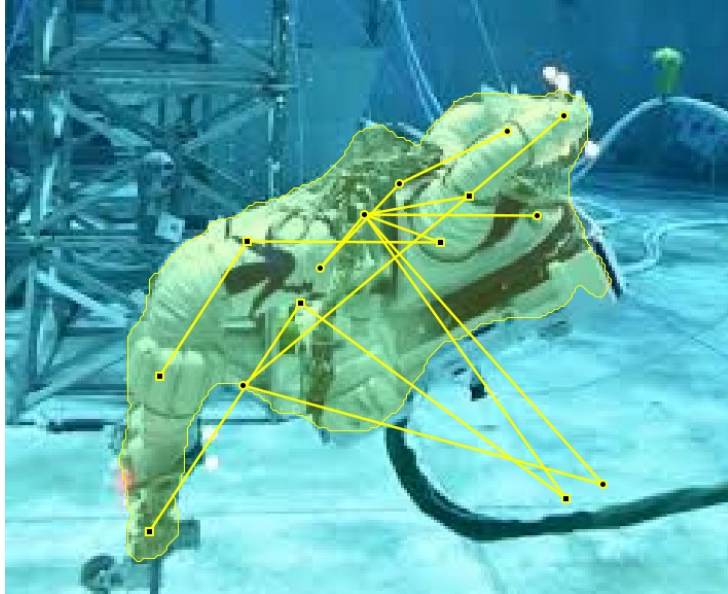
Apollo and ISS EVA posture prediction

- The solution was robust to image resolution and quality, as performance did not decrease in low resolution images or images with mainly black and white hues



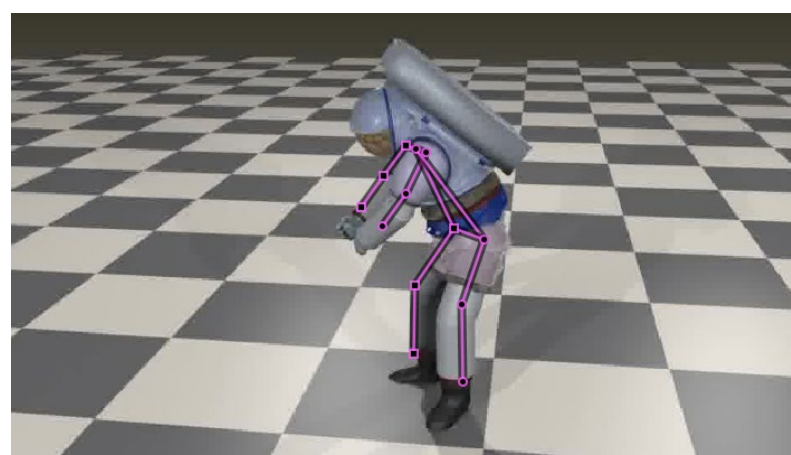
NBL suit posture prediction

- Due to optical distortions and possible color desaturation, algorithm performance degraded for the images taken at the NBL
- Further algorithm refinements are needed



3D suit posture prediction

- 3D suit posture predictions were more accurate in computer-generated images
 - Camera project matrix can be more easily estimated in synthetic images



Discussion

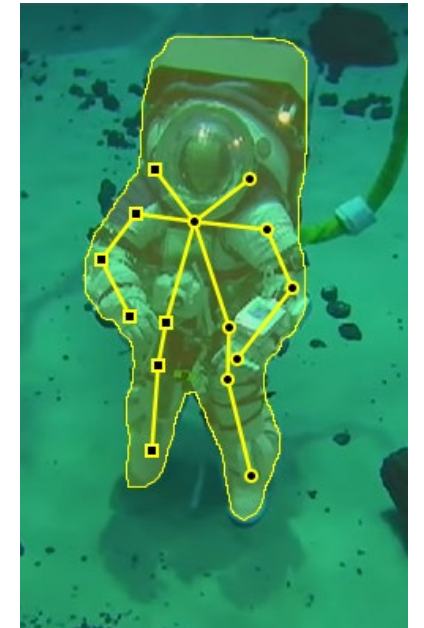
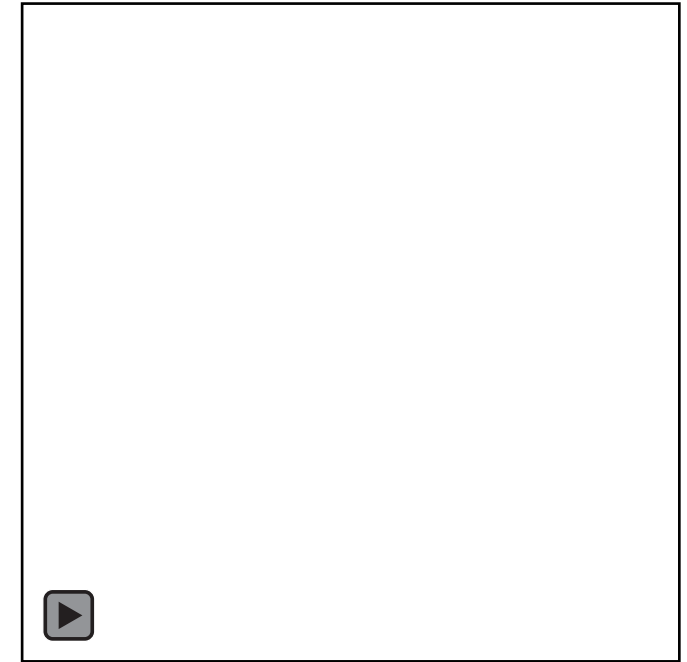
- Overall, the suited posture extraction accuracy was good in a variety of operational environments
- Based on the received solutions, it is promising that the spacesuit can be recognized as an independent object in most of the images
- The crowdsourcing challenge has greatly accelerated the technology readiness level of this approach
- Algorithms can be improved on by leveraging the larger internal NASA datasets and suit expertise

Limitations

- Dataset was sparse for this type of machine-learning approach, particularly the 3D joint center dataset
- There may be inherent limitations in accuracy due to camera distortion properties
 - The approximate postural information will still be useful for full-body kinematic^s assessments such as ergonomic evaluations

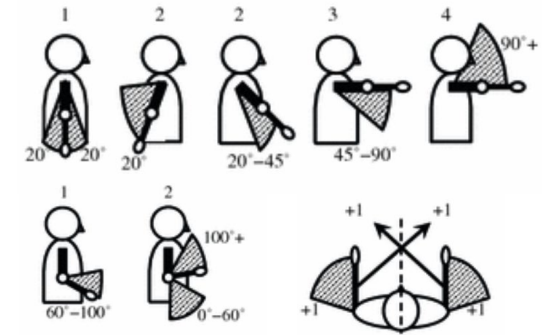
Future work

- Since different approaches were taken by contenders, the top algorithms can be combined to improve prediction accuracy
- Algorithms will be retrained with larger datasets
 - Internal NASA dataset of suited motions
 - High-quality rendered images of the 3D suit CAD
- A probabilistic suit posture model can be developed to reduce estimations containing unlikely or infeasible postures
- After refinements of the framework, the new method will be tested and validated on xEMU spacesuit testing data
 - Compared against gold standard optical motion capture data



Suit design and EVA applications

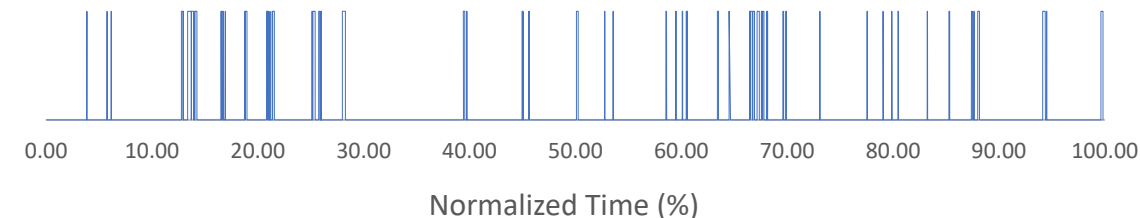
- Once validated for reliability, this tool can have a variety of applications for suit, hardware, and EVA task design
 - Joint cycle tracking
 - EVA injury assessments
 - Historical EVA task and timeline analysis
 - Active kinematics monitoring
 - Joint mobility data for suit design
- Through additional model training, this framework can be easily adapted to future suit architecture
- In a more generalized form, this same framework can be used for exoskeleton and robot kinematics applications



Score	Level of Musculoskeletal Disorder Risk
1-2	negligible risk, no action required
3-4	low risk, change may be needed
5-6	medium risk, further investigation, change soon
6+	very high risk, implement change now

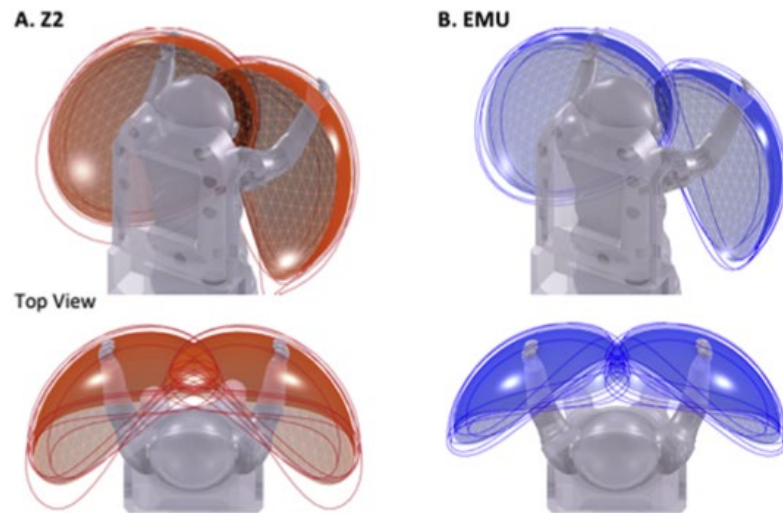


Arm Raise Events

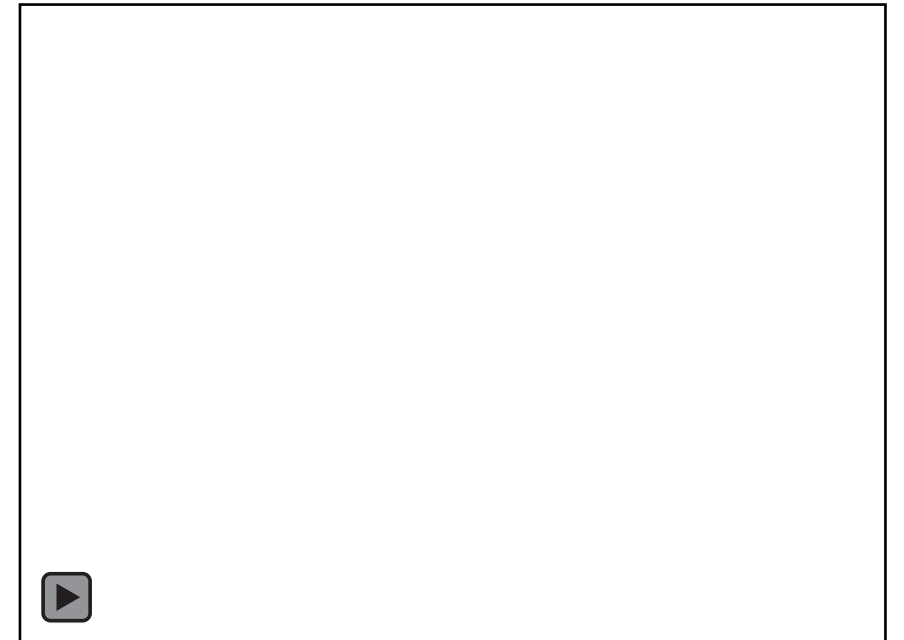
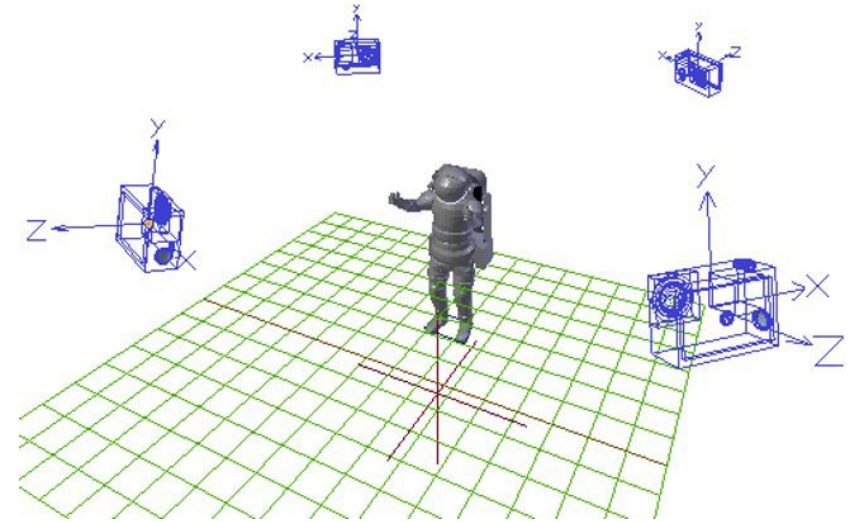


Use Case: Suit mobility

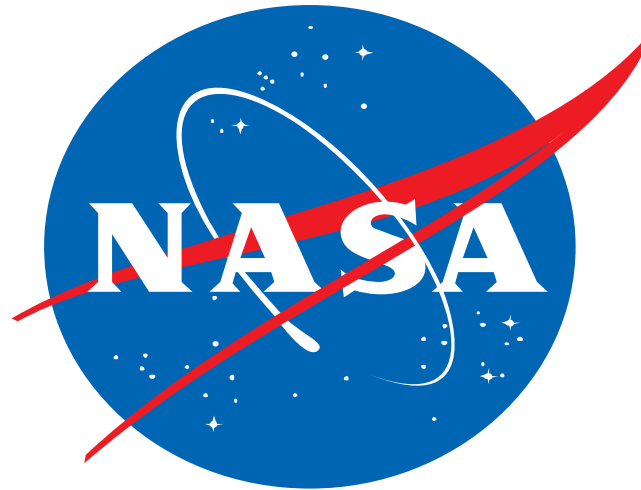
- Upon improvements through multi-camera triangulation, 3D accuracy can be improved greatly and provide useful metrics
- This type of method may assist with the standardization of suited motion capture
 - Reduce variability in optical motion capture marker definitions



Suit benchmarking example: Z2 vs. EMU range of motion



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