

Users in Wheelchairs (UIW) – A Human Centered RGB Dataset of Wheelchair Users

William Huang, Sam Ghahremani, Siyou Pei, Yang Zhang

Introduction & Background

Able-Bodied Users - Users with no physical disabilities. For the context of this research, focused on users who are not in a wheelchair.

Markerless Motion Capture (MMC) - Motion capture systems, that rely on deep learning models to identify joint positions from camera images.

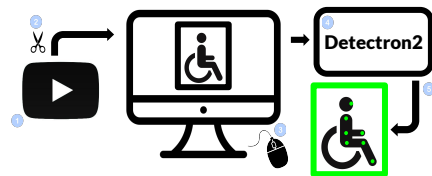
Kinematic analysis from MMC has played a key role in fields including rehabilitation, sports performance and robotics in large part due to its accessibility and cost. MMC is severely limited by the quality of the data used in training. Common algorithms (BlazePose, OpenPose, Detectron2) are trained off large **able-bodied** datasets like COCO. The lack of wheelchair users in these data sets leads to a disparity in performance between able-bodied users and users in wheelchairs.



Figure 1: Example output of OpenPose, a common MMC algorithm

Objective

- Develop and collect a new dataset of RGB images of users in wheelchairs.
- Dataset is large and diverse enough to capture idiosyncrasies of movement in wheelchairs and the unique settings users in wheelchairs may be found.
- Validate new dataset to identify performance changes when testing on users in wheelchairs with new dataset.



- Select a set of wheelchair videos to annotate from publicly available sources.
- Collect frames with unique poses for annotation.
- Annotate data through crowd worker involvement.
- Boost existing Detectron2 object and pose detection models with data.
- Validate performance changes of boosted model.

Defining Action Groups

- In order to maintain consistency, define a set of actions and motions to collect videos of.
- Identified set of **common tasks both able-bodied and wheelchair users perform**.
- Selected most popular **wheelchair sports** for unique poses that may not be captured in everyday motions.

Daily Life Examples

- Stretches
- Daily Chores
- Wheelchair Skills

Sports Examples

- Basketball
- Rugby
- Dance

Collecting Videos

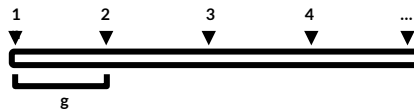
- Selected **83 videos** in corresponding action groups.
- Collect from existing datasets and YouTube.
- Individual videos are labeled as the corresponding action group for crowd worker efficiency.

Example Video Topics

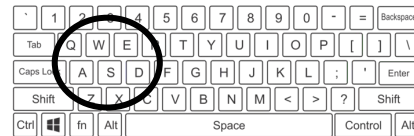
- Top 3 Stretches for Someone in a Wheelchair
- Shooting a Basketball From a Wheelchair
- Wheelchair Dance

Frame Selector Application

- All videos must be analyzed manually before sending to crowd workers to select individual frames.
- Annotator is looking for motions and poses that sufficient differ from previously collected frames.
- Videos are collected through a custom multithreaded video scraper.
- Naive algorithm splits video into frames for annotator to analyze.



- For each video, select $n=500$ frames with a minimum of $g=60$ frames between each frame.
- If there are not $g*n$ frames in the video, select as many frames with g frames between each.



Each frame is displayed before the annotator has a set of options. Key bindings are designed for efficiency.

- D - Go to next frame
- W/S - Mark current frame as unique enough to save or not save. Defaulted to false.
- Q/E - Mark current frame as a frame with multiple people. Defaulted to false.

Collected Frames

- Collected **2491 frames** from all videos.
- Each frame is labeled with the corresponding action of the video and whether knot the frame contains multiple people for crowd worker reference.

Action Type	Number of Frames	% of Dataset
Talking	458	18.38%
Daily Routine	285	11.44%
Basketball	231	9.27%
Dance	225	9.03%
Wheelchair Skills	171	6.86%
Moving	153	6.14%
Tennis	130	5.22%
Extreme Sports	119	4.78%
Household Chores	70	2.81%
Other	295	11.84%
Total	2491	

Figure 2: Table of distribution of actions in dataset

Crowd Worker Validation

- Crowd workers are recruited to annotate keypoints and bounding boxes around users in wheelchairs.
- Some images are misannotated and must be manually reviewed and corrected.



Figure 3: Example of incorrect annotation. Knee is duplicated.



Figure 4: Example of correct annotation.

Images from MobilityAIDS [3], a publicly available disability dataset. Labels by our crowd workers

Results & Discussion

Detectron2 was selected as the MMC model for testing. All models were boosted from the base COCO R50 model trained on the COCO Keypoint dataset. UIW was separated into a 1.5k training set and trained for 30 epochs with default hyperparameters and a learning rate of .00025 tested on a 1k testing set. Base COCO R50 was used as the control.



Figure 5: Comparison of UIW vs COCO R50 bounding boxes AP



Figure 5: Comparison of UIW vs COCO R50 keypoint AP

Conclusions

- Developed a wheelchair-focused RGB dataset.
- Enable fast improvements in performance on users in wheelchairs in common models for better equity.
- Develop an end to end pipeline for further expansion into the existing UIW dataset.

Next Steps

- Expand upon UIW dataset.
- Test other common MMC models.
- Test efficacy of synthetic data and comparisons with the existing UIW.

Acknowledgements & References

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[1] Lin, Tsung-Yi, Michael Maire, Serge Belongie, Lubomir Bourdev, Ross Girshick, James Hays, Pietro Perona, Deva Ramanan, C. Lawrence Zitnick, and Piotr Dollár. "Microsoft COCO: Common Objects in Context." arXiv, February 20, 2015. <https://doi.org/10.48550/arXiv.1405.0312>.
 [2] Yuxin Wu and Alexander Kirillov and Francisco Massa and Wan-Yen Lo and Ross Girshick. "Detectron2". 2019. <https://github.com/facebookresearch/detectron2>.
 [3] Andres Vazquez, Marina Kollmitz, Andreas Eitel, & Wolfram Burgard (2017). Deep Detection of People and their Mobility Aids for a Hospital Robot. In Proc.-of the IEEE Eur.-Conf.-on Mobile Robotics (ECMR).