Towards a Skeleton-Based Action Recognition For Realistic Scenarios

1st Çağatay Odabaşı  
*Fraunhofer IPA*  
Stuttgart, Germany  
cagatay.odabasi@ipa.fraunhofer.de

2nd Jewel Jose  
*University of Technology Chemnitz*  
Regensburg, Germany  
jewelvJose@gmail.com

Abstract—Understanding human actions is a crucial problem for service robots. However, the general trend in Action Recognition is developing and testing these systems on structured datasets. That’s why this work presents a practical Skeleton-based Action Recognition framework which can be used in realistic scenarios. Our results show that although non-augmented and non-normalized data may yield comparable results on the test split of the dataset, it is far from being useful on another dataset which is a manually collected data.

Index Terms—skeleton-based action recognition, computer vision, robotics

![Flowchart of action recognition](image)

**Fig. 1.** The flowchart of the real-world Implementation of Our Action Recognition ROS(Robot Operating System) Package.

I. INTRODUCTION

The service robots need to share the environments with people such as hospitals or care-houses. Therefore, the robots should be aware of where the people are and what they are doing by using the sensory data. However, how transferable are the action recognition systems?

II. METHODOLOGY

A. Dataset

The system is tested on two different test sets. These are NTU-RGBD [3] cross-subject test-split and our manually collected test set.

1) NTU-RGBD: It provides RGB, Depth, infrared and 3D Skeleton video collected by three Microsoft Kinect V2; however, we only use skeleton data including 25 joints per person. There are 60 action classes in the dataset and 56880 action samples in total.

2) Our Test Set: We collected a total of 85 skeleton sequences by using our data collection system. The actions are performed by three different people. However, this information is not yet used for any training or testing. There are 19 classes in the dataset which are a subset of NTU-RGBD dataset. The distribution of data can be seen in Table I. Collecting this small dataset is critical because it allows us to assess the robustness of the modern action recognition algorithms trained on a conventional dataset.

![Table of action classes and samples](image)

**Table I**  
Action classes and number of samples per each class in our dataset. All samples are stored as ROS bag files which contain the extracted human skeletons.

The general way to split this dataset is cross-view or cross-subject. Either we can use the same views or the same subjects for both training and test sets. In this work, we introduce our results just on the cross-subject split.

Although it is a standard massive benchmark dataset, the data collection system is highly structured and the data is too clean for a real-world scenario.

2) Our Test Set: We collected a total of 85 skeleton sequences by using our data collection system. The actions are performed by three different people. However, this information is not yet used for any training or testing. There are 19 classes in the dataset which are a subset of NTU-RGBD dataset. The distribution of data can be seen in Table I. Collecting this small dataset is critical because it allows us to assess the robustness of the modern action recognition algorithms trained on a conventional dataset.

B. Framework

1) Hardware: The training hardware contains NVIDIA GTX1080ti and the test hardware contains NVIDIA GTX1060 which is a laptop. The RGBD camera used in our experiment is Orbbec Astra Pro, as a standard replacement for Microsoft Kinect.
TABLE II
RESULTS ON TWO DIFFERENT DATASET. THE ACCURACIES ARE LOWER WHEN THE SYSTEM IS APPLIED TO ANOTHER DATASET. EVEN THOUGH THE AUGMENTATION, NORMALIZATION AND NOISE ADDITIONS ARE NOT REQUIRED FOR HIGHER ACCURACIES ON THE NTU-RGBD TEST SET, THEY ARE CRUCIAL FOR TRANSFERABILITY.

| Model                          | NTU-RGBD Cross-Subject Test Accuracy | Our Test set Accuracy |
|--------------------------------|--------------------------------------|-----------------------|
| Baseline                       | 74%                                  | 20.98%                |
| Baseline + noise               | 75.17%                               | 23.45%                |
| Baseline + augmentation        | 75.3%                                | 16.04%                |
| Baseline + augmentation + noise| 74.3%                                | 25.92%                |
| Baseline + normalization       | 74.6%                                | 40.71%                |
| Baseline + normalization + noise| 71.6%                                | 37.02%                |
| Baseline + normalization + augmentation| 70%                                | 49.38%                |
| Baseline + normalization + augmentation + noise| 68.9%                               | 46.91%                |

The test hardware is intentionally kept simple since it is not possible to load so much computation power on a service robot for the reasons below:
- Price,
- Heat dissipation,
- Space limitation,
- Power consumption.

2) Software: The whole system is implemented on Robot Operating System (ROS) [2] so that it can be directly transferable to any robot. The overall structure of the system is depicted in Figure 1. First, the camera collects RGBD data and publishes it. This data is processed by the Body Tracker module to extract the skeleton joints from each frame. Then, these joints are formatted and packed so that they can be used for action recognizer. This module packs three seconds of data which is optimal for our case because if it packs less data, the information may be low and if it packs more than three seconds of data, then the latency of the system would be too high. However, this setting can be adapted according to the scenario. Finally, the Action Recognizer processes the data and publishes the action labels.

Transferability also requires modularity, since it must be possible to change only one module while deploying the system to different robots or media. For instance, if body tracker is changed in our system, only the joint formatter should be adapted.

The human skeleton detection is beyond the scope of this work; that’s why we use Orbbec Astra SDK provided with the camera for this purpose. It tracks the 19 skeleton points of human and gives 3D coordinates of each point.

The action recognition module is a convolutional neural network based on a previous work [1] because it is a fast and light network which makes it suitable for robotics applications. Also, their training routine and augmentation are used. In general, the effect of following operations are considered:
- **Removal of the joints** is done to match the joints supported by dataset and our skeleton extractor. Also, some unstable joints are removed such as hands, since their detection rate is lower than the others.
- **Adding Noise** is done via adding zero mean σ variance Gaussian noise to the raw skeleton data during the training. This helps emulating the variations between the actions of different people. Our claim is that it helps making the system more robust in real world scenarios.
- **Augmentation** is applied by shifting the skeleton sequence by a random number of frames in time. Also, the random cropping is applied to simulate the missing data in real world scenarios.
- **Normalization** is done via scaling the whole skeleton by a constant value. Additionally, all skeletons are rotated so that the line between shoulders is aligned for all skeletons in the dataset.

III. Results

The all models are trained on the cross-subject training split of NTU-RGBD dataset.

The results are presented in Table II. It is clear that there is a big gap between accuracies on two different dataset. The normalization is necessary for a practical application, because the size of the people changes a lot with the changing distance to cameras. Additive noise during training also improves the accuracy; however, it is not necessary to achieve the best results. The network trained with augmented and normalized training set yields the best results.

IV. Discussion and Conclusion

In this work, we show the challenges of designing a Skeleton-based Action Recognition system for real world scenarios. This work is important especially for service robotics domain, since the humans can be anywhere in the scene and some of the joints may not be visible to the robot’s camera. Therefore, the augmentation and the normalization become important. The results show that transferability is still an issue for these models.

In the further studies, our main focus will be transferring action recognition algorithms on a real robot in order to use it for a real scenario.

V. Acknowledgment

This work has received funding from the European Unions Horizon 2020 research and innovation programme under the Marie Skodowska-Curie grant agreement No 721619 for the SOCRATES project.
REFERENCES

[1] Tae Soo Kim and Austin Reiter. Interpretable 3d human action analysis with temporal convolutional networks. In 2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pages 1623–1631. IEEE, 2017.

[2] Morgan Quigley, Ken Conley, Brian Gerkey, Josh Faust, Tully Foote, Jeremy Leibs, Rob Wheeler, and Andrew Y Ng. Ros: an open-source robot operating system. In ICRA workshop on open source software, volume 3, page 5. Kobe, Japan, 2009.

[3] Amir Shahroudy, Jun Liu, Tian-Tsong Ng, and Gang Wang. Ntu rgb+ d: A large scale dataset for 3d human activity analysis. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1010–1019, 2016.