MC-hands-1M: A glove-wearing hand dataset for pose estimation

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Abstract. Nowadays, the need for large amounts of carefully and complexly annotated data for the training of computer vision modules continues to grow. Furthermore, although the research community presents state of the art solutions to many problems, there exist special cases, such as the pose estimation and tracking of a glove-wearing hand, where the general approaches tend to be unable to provide an accurate solution or fail completely. In this work, we are presenting a synthetic dataset\(^1\) for 3D pose estimation of glove-wearing hands, in order to depict the value of data synthesis in computer vision. The dataset is used to fine-tune a public hand joint detection model, achieving significant performance in both synthetic and real images of glove-wearing hands.

Keywords: synthetic dataset, 3D hand pose estimation, gloved hands

1 Introduction

Computer vision models, targeting more complex problems, are evolving at an incredible pace, resulting in an insatiable appetite for more datasets, whose size and annotations’ detail are becoming a limiting factor. Therefore, in literature, the utilization of synthetic visual data, from domain adaptation techniques \([12]\) to the deployment of GANs \([5]\), and from the Cut-Paste approach \([6]\) to video games’ scenes \([8]\), regularly combined with corresponding real data, has become an established technique over the last decade.

Specifically, hand pose estimation is a well-studied problem with a variety of depth- \([1]\) and color-based \([4]\) solutions, deploying different machine-learning methods \([11,10]\). However, many applications, in the context of hazardous work environments and sports, necessitate the use of gloves. Existing hand detection and tracking AI algorithms, trained on real \([3,13]\) and synthetic \([2,7]\) bare-hand datasets, exhibit significantly reduced performance or fail altogether in gloved hand scenarios, as they depend deeply on the canvas of the human skin’s colors. Hence, there is a clear need for a gloved-hand dataset with ground truth for the joints’ positions, allowing the training or re-training of AI algorithms capable of estimating poses and/or tracking hands wearing gloves of diverse size and color.

\(^1\) The dataset is public and can be found at \(https://www.zenodo.org/record/7194271/\)
As a result, the contributions of this work are: 1) a synthetic image dataset for 3D pose estimation of glove-wearing hands in outdoor environments and 2) insights on its deployment to retrain hand pose estimation and tracking modules.

2 Dataset Generation

Aiming to address the problem of 3D glove-wearing hand pose estimation, we created a Python-based, model-independent and extensible framework for the automated generation of realistic synthetic datasets, based on Blender. The adopted approach took into consideration every aspect affecting a scene’s representation: background, lighting, rendering cameras and views, model’s geometry, armature’s poses, movement constraints and texturing related properties. Its full design and methodology will be presented in a future full-length paper.

As a result, we produced \textit{MC-hands-1M}, a dataset of 1M color images of a right glove-wearing hand in outdoor environments, examples of which are depicted in Fig. 1. The employed variables were set as follows: 10 glove- and 15 cloth-like materials, 10 hand’s scales and 3 wrist’s (a priori) states, 20 combinations of outdoors background with realistic sun-like lighting and 10 views per each of the 4 different cameras.

3 Hand detection experiments and results

The hand joint detection network selected to prove the dataset’s usability is DetNet [14], which receives an RGB image as input and outputs root-relative and scale-normalized 3D, as well as 2D (image space) hand joint predictions. Its architecture comprises of a feature extractor, a 2D and a 3D detector.

Since the existing networks trained on bare-hand datasets regularly fail to recognize glove-wearing hands, in an attempt to highlight the impact of MC-hands-1M in the alleviation of this shortcoming, we conducted a series of experiments, using test sets from the Rendered Handpose Dataset (RHD) [15] of bare and from the created MC-hands-1M of glove-wearing hands. The trained networks were compared based on the AUC-PCK metric, in order to overview the performance on images of both cases.

\textsuperscript{2} Open-source 3D computer graphics software toolset, \url{https://www.blender.org/}
Regarding the experiments, a baseline network was initially trained on the CMU Panoptic Dataset (CMU) [9], the RHD and the GANerated Hands Dataset (GAN) [4]. In the second experiment, the above baseline was retrained using images solely from the MC-hands-1M dataset. Finally, the baseline network was retrained on a mixture of real (CMU) and synthetic (RHD, MC-hands-1M) images of bare (RHD, CMU) and glove-wearing hands (MC-hands-1M).

The results of Table 1 depict that a network trained on traditional datasets of bare hands achieves good performance on corresponding cases, while being unable to accurately detect the joints’ positions or even the existence of a hand wearing a glove. Conversely, the same network trained exclusively on synthetic glove-wearing hands’ images has a significantly reduced performance on bare hands’ ones. The training on a mixture of both bare and glove-wearing hand images, allows the network to achieve excellent performance for both cases. In order to examine its corresponding ability on real-life data, considering the lack of an annotated, real, non-bear hand dataset, a small collection of images exhibiting hands wearing gloves was collected.

| Training Sets                           | AUC (RHD) | AUC (MC-hands-1M) |
|----------------------------------------|-----------|-------------------|
| RHD, CMU, GANHD                        | 0.93      | 0.19              |
| MC-hands-1M                            | 0.43      | 0.97              |
| MC-hands-1M, RHD, CMU                  | **0.93**  | **0.97**          |

Fig. 2: Examples of real images with hands wearing gloves and the corresponding outcome of the network before (left) and after (right) training on our dataset. The red lines represent the index finger.
From the visual inspection of the results, one can effortlessly observe that not only the network recognizes the hand’s existence, but it also presents a decent capability to predict correctly the orientation of the hand and the majority of the different joints’ positions, as portrayed in Fig. 2.

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