Hand-Object Pose Estimation from RGBD Images

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Abstract

Hand-object pose estimation aims to predict the pose and shape of both of the hand and held object under interaction. Although having numerous applications in the real world such as augmented and virtual reality, hand-object pose estimation concerns relatively less attention. Several methods separately estimate hand shapes and object poses but totally neglecting the correlations between hands and objects. In this work, we propose an approach that leveraging the advantage of voting mechanism to jointly learn the appearance of hand and object from RGB-D images. Our method effectively collaborates RGB and Depth features by sharing and fusing them at pixel level during the extraction process. The output features discriminate the differently meaningful distribution between color and depth information at each position to generate discriminative representations of RGB-D input. Moreover, we introduce a network to collaboratively learn voting vectors for both of the hand and object appearances to estimate their poses. This facilitates our network to examine their constrains and interactions to produce accurate outcomes. Experiments using benchmark datasets illustrate that our network achieves beyond state-of-the-art accuracy in 3D pose estimation.

1. Introduction

Estimation of hands and objects is fundamental and crucial for understanding meaningful interpretation of human action and behaviour. It provides enormous knowledge for environmental perception and teaching manipulating systems. With the advent of deep learning, pose estimation tasks have significantly made progress such as RGB-based [2, 10, 39, 46, 53], depth-based [1, 11, 22, 26, 27, 47], and RGB-D methods [19, 49]. Jointly estimation of hands objects under interaction, however, has attracted less attention due to chronic challenges. This requires simultaneously predicting the pose and shape of hands and objects during the hands handling and executing the objects. In this paper, we propose a novel network to tackle this problem from RGB-D images.

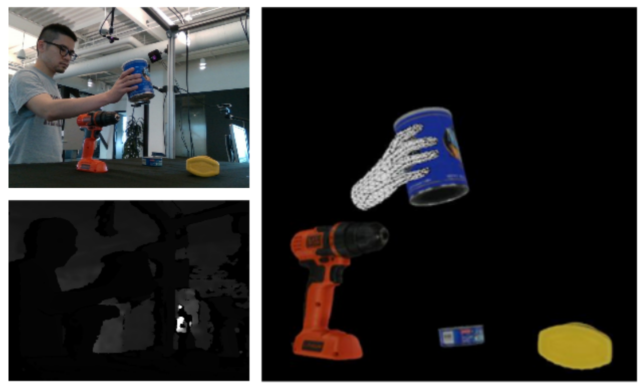

Figure 1: Example of RGB-D.

Joint hand-object pose estimation under interaction, on the other hand, is a much more challenging problem. The hand shape is notorious for being self-occlusion. This problem is adversely serious in the context when the hand manipulating an object. The naive approach is estimating the shape of the hands and objects seperately. Such methods leverage the success of object pose estimation and hand shape reconstruction independently without considering the correlations between themselves. They totally ignore the heavily dependencies of hand pose on the held object's shape, and and vice versa. Intuitively, the presence of object strongly defines and constrains the hand grasps and therefore limits the feasible hand gestures to a restricted number. Similarly, determining hand gestures provides a cue for estimating the shape and pose of the held object. Consequently, simultaneously predicting the shapes of both hand and object soonly catches the attention of computer vision researchers.

Inspired by the above perspective, some deep learning-based methods [13–15, 23, 24, 29, 36, 40, 44] joinly learn the hand and object poses from a single RGB image. Whereas, [5, 12, 28, 51] focus on another input format, depth images, to achieve the expected results. However, they pose a threat to the prediction accuracy due to lack of the other type format input. With the prevalence of depth camera, RGB-D image-based methods [21, 41] appear to be a promising solution. Although numerous research has made an impressive success in a wide range of computer vision tasks. It still puzzles the reseacher community of how to effectively using RGB-D input for joint hand-object pose estimation.

In this paper, we propose a network that firstly extracts color and depth features and combines them to generate the discriminative representation of input data. The color feature is extracted by convolutional neural networks (CNNs), while the geometric information is learnt by PointNet++ [32]. The PointNet++ architecture empowers our framework to learn the physical constraints and geometric relationships between the hand and object, which are essential for estimating hand and object poses simultaneously. Differing [7], in which we find the inspiration, our architecture allows sharing information between two backbone networks. This helps the process of learning one type of input feature can absorb the presence of the other one. Therefore, our method can thoroughly investiagte the meaningfulness and the beneficial contribution of RGB and Depth values at each position across all positions. Furthermore, we develop a technique based on pixel-wise fusion [43] to attentionaly integrate geometric information into color features. We embrace the fact that the favourable features conveyed by color and depth information differ across positions. At a specific pixel, the RGB feature may be much more compelling than the physical one but the other pixel may witness the opposite situation. To handle this problem, our method introduces a learnable weight parameter to either facilitate or inhibit the feature at each pixel before fusing. In other words, our proposal network does not solely integrate the geometric feature to the color one at pixel level, but also tells to what extent the system should pay attention on each type of features at each position.

In terms of pose estimation, we adpot the voting mechanism to predict the hand and object poses simultaneously. The voting mechanism [7, 16, 45] has recently emerged as a compelling strategy for robustly forecasting the shapes. This is attributed to that voting methods can meet successful outcomes without requiring pre-known CAD object models, which are a intensive labour preparation and not always available. Such methods have ability to generalize with novel objects. Motivated by these advantages, our introduced framework computes votes for both objects and hands. Nonetheless, the main point is that the computing process aslo take the interaction conditions between the hand and the held object into account. This helps the model can learn the physical constraints and the interdependences among hands and objects.

In brief, the main contributions of our work are:

- We propose a novel architecture to empower the capability of extracting features from RGB-D images. This network can learn both color and geometric features and then attentionally fuse them together by wisely and selectively magnifying the valued features and weaken the useless one at each pixel.
- We introduce a deep voting-based model to take the strong relationship between hand poses and object shapes into account while computing voting vectors.
- Experiments on benchmark datasets demonstrate that our approach can outweigh the state-of-the-art models for hand and object 3D pose estimation.

2. Related work

2.1. Hand-object pose estimation

The naive approach for the problem is treat the hand [6, 18, 25, 27, 48] and manipulated object [31, 34, 43, 52] seperately without considering their interdependence. They underestimate the extraordinary relationship between the hand gestures and object shapes. Several approaches overcome this problem by jointly learn the shapes of both hand and object from RGB images. [8] develops two graph convolutional networks for two missions. The first one detects 2D hand joints and 2D object corners, while the second one lifts 2D keypoints to 3D coordinates. [40] proposes attention-guided graph convolution to iteratively share hand and object estimator between two branches for learning the mutual occlusion. [13] looks into photometric consistency between neighboring frames to reconstruct hand-object shape under interactions. [36] handles hand action classification to assist the process of estimating hand-object interactions. [23] introduce a semi-supervised learning framework leveraging spatial-temporal consistency to improve estimation performance. However, the absence of depth information makes the process of learning physical constraints and interactions latent. In addition, the transformation from 2D to 3D world is difficultl to accurately proceed due to high degree of non-linearity. In contrary, some methods exploit solely depth images. [5] designs an architecture that firstly predicts hand and object centers and then learn global orientations and grasps of hand configurations while interacting with objects. [12, 51] segments 2D hand and object regions from depth image and then optimizes the reconstruction process of interacting motions. This method, however, learns the depth images by 2D CNN backbone hence cannot radically observe the geometric information. [28] deploys a feedback loop to revise the flawed estimation results using depth images only. RGB-D input data, on the other hand, has received relatively less attention due to how to effectively collaborate two distinctive input format still holds a secret. [21] focuses on the physical laws of hand actions from RGB-D input to benefit hand-object interaction interpretations. [41] tracks hands and objects in dealing with a complex scenario in which manipulated objects are deformable.

2.2. RGB-D fusion

With the common of color-depth camera, a wide range of computer vision research such as object segmentation [3, 4, 30, 50] and 6D object detection [33, 37, 43] has been inspired to learn and incorporate color and depth features from RGB-D images. The RGB image and depth image belong to different modalities, so most fusing feature methods are [42]: image layer fusion, feature layer fusion, and output layer fusion. While image layer fusion concates the input data before feeding to CNNs, feature layer fusion means learning color and depth data in two distinguished architecture but sharing the learning process. Output layer fusion, on the other hand, integrate two feature maps which are seperately extracted by two backbone networks. However, fusion RGB-D features for hand-object pose estimation is less attractive because most of mentioned methods have the mutual weak point that is extracting features from depth maps by 2D CNNs. This makes the output 3D spatial feature is latent and unconcious. Motivated by [43], we develop a network of feature layer fusion that can share learning process between two backbones but can export geometric information and geometric contraints by using Pointnet++ [32] backbone for the depth map. In addition, our network adaptively and selectively adjusts features at each pixel before fusing to gain the accurate outcome.

2.3. Voting mechanism for pose estimation

The Hough voting is originally introduced to detect 2D defined shapes [9, 17] and then developed to futher complex computer vision tasks [35, 38]. The deep learning-based voting methods [7, 16, 20, 45] have recently appeared to be a promising approach for object detection and pose estimation due to its robustness and ability to novel object.

3. Method

In Figure 2, we provide an overall pipeline of our method for 3D hand mesh estimation. Our proposed network consists of backbone, Attention, voting and cluster and hand pose Estimation.

3.1. Feature Extraction and Attentional Fusion

Given a color map $I_{rgb} \in \mathbb{R}^{H \times W \times 3}$, the color features $f_{rgb} = \{f_i^{rgb}\}_{i=1}^{H \times W}$ are normally extracted by a CNN architecture. Where $f_{rgb} \in \mathbb{R}^{H \times W \times d_{rgb}}$ and each pixel is mapped into a color feature space $f_i^{rgb} \in \mathbb{R}^{d_{rgb}}$. The geometric features, on the other hand, are extracted by converting depth maps to point cloud and then feeding into PointNet [?]. In our work, differing from the original work, we conduct PointNet++ [32], an upgraded version, to replace the original backbone. Moreover, instead of only extracting the 3D point cloud feature of points inside the segmented region, our method applies the whole depth map without requiring semantic segmentation as in DenFusion. However, most of the pixels and points are background, which is redundant and harms hand pose estimation. We overcome this problem by adding an attention model to find out where should pay more attention to. Given a depth map $I_d \in \mathbb{R}^{H \times W \times 1}$, the point cloud features $f_{geo} = \{f_i^{geo}\}_{i=1}^{H \times W}$. Where $f_{geo} = \in \mathbb{R}^{H \times W \times d_{geo}}$ and point cloud pixel at each position is $f_i^{geo} \in \mathbb{R}^{d_{geo}}$.

$$f_i = A \times f_i^{rgb} \oplus B \times f_i^{geo} \tag{1}$$

3.2. Hand and Object Voting

3.3. Hand-Object Interation Learning

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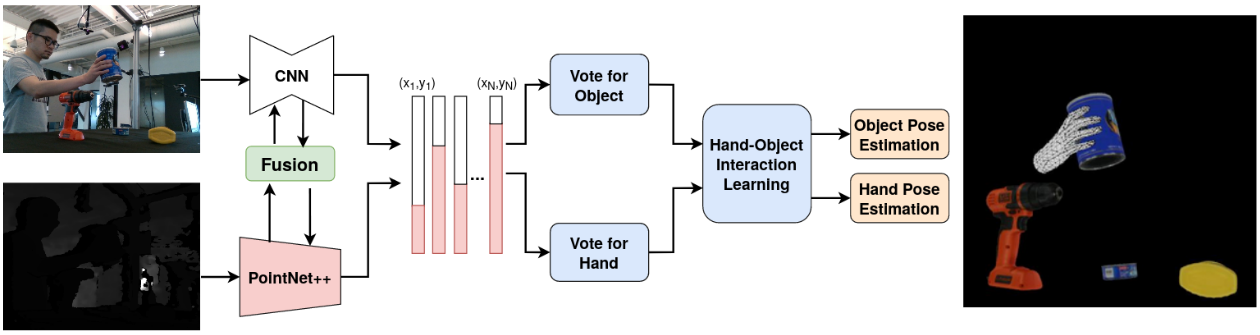

Figure 2: Overview of our proposal. Our method takes both color and depth maps as input data. The color features are extracted by a CNN, while the 3D features are calculated by PointNet++ architecture. These two types of features are then fused together at pixel-level to obtain the new distinctive features. The attention mechanism is applied for the such new features to learn the contribution disparity of the context to the hand pose. The votes are computed and then regressed to estimate the MANO parameters.

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