Abstract. We propose a viewpoint invariant model for 3D human pose estimation from a single depth image. To achieve viewpoint invariance, our deep discriminative model embeds local regions into a learned viewpoint invariant feature space. Formulated as a multi-task learning problem, our model is able to selectively predict partial poses in the presence of noise and occlusion. Our approach leverages a convolutional and recurrent network with a top-down error feedback mechanism to self-correct previous pose estimates in an end-to-end manner. We evaluate our model on a previously published depth dataset and a newly collected human pose dataset containing 100K annotated depth images from extreme viewpoints. Experiments show that our model achieves competitive performance on frontal views while achieving state-of-the-art performance on alternate viewpoints.

1 Introduction

Depth sensors are becoming ubiquitous in applications ranging from entertainment to smart spaces and from security to robotics. While recent advances in pose estimation have improved performance on front and side views, most real-world settings present challenging viewpoints such as top or angled views in retail stores, hospital settings, or surveillance applications. These viewpoints introduce high levels of occlusion making human pose estimation difficult for existing algorithms.

Humans are remarkably robust at predicting full rigid-body and articulated poses in these challenging scenarios. However, most work in the human pose estimation literature has addressed relatively constrained settings. There has been a long line of work on generative models, where a pose is estimated by constructing a skeleton using templates and priors in a top-down manner [14,7,11,13]. In contrast, discriminative methods directly identify individual body parts, labels, or positions and construct the skeleton in a bottom-up approach [45,46,9,48,10]. However, recent research in both classes primarily focus on frontal views with few occlusions despite the abundance of occlusion and partial-pose research in object detection [47,55,31,9,27,5,18]. Even modern representation learning techniques address human pose estimation from front or side views [36,12,37,53,29,5,10]. While the above methods improve human pose estimation, they fail to address viewpoint variances.

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Fig. 1: From a single depth image, our model uses learned viewpoint invariant features to perform 3D human pose estimation with iterative refinement. To provide additional three-dimensional context to the reader, a front view is shown in the lower right of each top-view frame.

In this work we address the problem of viewpoint invariant pose estimation in single depth images. There are two challenges towards this goal. The first challenge is designing a model that is not only rich enough to reason about 3D spatial information but also robust to viewpoint changes. The model must understand both local and global human pose structure. That is, it must fuse techniques from local part-based discriminative models and global skeleton-driven generative models. Additionally, it must be able to reason about 3D volumes, geometric, and viewpoint transformations. The second challenge is that existing real-world depth datasets are often small in size, both in terms of number of frames and number of classes [17,16]. As a result, the use of representation learning methods and viewpoint transfer techniques have been limited.

To address these challenges, our contributions are as follows: First, on the technical side, we embed local pose information into a learned, viewpoint invariant feature space. Furthermore, we extend the iterative error feedback model [6] to model higher-order temporal dependencies. To handle occlusions, we formulate our model with a multi-task learning objective. Second, we introduce a new dataset of 100K depth images with pixel-wise body part labels and 3D human joint locations. The dataset consists of extreme cases of viewpoint variance with front, top, and side views of people performing 15 actions with occluded body parts. We evaluate our model on an existing public dataset [17] and our newly collected dataset demonstrating state-of-the-art performance on viewpoint invariant pose estimation.

2 Related Work

RGB-Based Human Pose Estimation. Several methods have been proposed for human pose estimation, including edge-based histograms of the human-body [43] and silhouette contours [21]. More general techniques using pictorial structures [14,7,11] and deformable part models [13], continued to build appearance
models for each local body part independently. Subsequently, higher-level part-based models were developed to capture more complex body part relationships and obtain more discriminative templates \cite{45,46,48,10}.

These models continued to evolve, attempting to capture even higher-level part features. Convolutional networks \cite{34,35}, a class of representation learning methods \cite{4}, began to exhibit performance gains not only in human pose estimation, but various areas of computer vision \cite{32}. Since valid human poses represent a much lower-dimensional manifold in the high-dimensional input space, it is difficult to directly regress from input image to output poses with a convolutional network. As a solution to this, researchers framed the problem as a multi-task learning problem where human joints must be first detected then precisely localized \cite{36,12,37}. Jain et al. \cite{29} enforce global pose consistency with a Markov random field representing human anatomical constraints. Follow up work by Tompson et al. \cite{53} combines a convolutional network part-detector with a part-based spatial model into a unified framework.

Because human pose estimation is ultimately a structured prediction task, it is difficult for convolutional networks to correctly regress the full pose in a single pass. Recently, iterative refinement techniques have been proposed to address this issue. In \cite{52}, Sun et al. proposed a multi-stage system of convolutional networks for predicting facial point locations. Each stage refines the output from the previous stage given a local region of the input. Building on this work, DeepPose \cite{54} uses a cascade of convolutional networks for full-body pose estimation. In another body of work, instead of predicting absolute human joint locations, Carreira et al. \cite{6} refine pose estimates by predicting error feedback (i.e. corrections) at each iteration.

**Depth-Based Human Pose Estimation.** Both generative and discriminative models have been proposed. Generative models (i.e. top-down approaches) fit a human body template, with parametric or non-parametric methods, to the input data. Dense point clouds provided by depth sensors motivate the use of iterative closest point algorithms \cite{17,22,23,31} and database lookups \cite{59}. To further constrain the output space similar to RGB methods, graphical models \cite{24,16} impose kinematic constraints to improve full-body pose estimation. Other methods such as kernel methods with kinematic chain structures \cite{8} and template fitting with Gaussian mixture models \cite{60} have been proposed.

Discriminative methods (i.e. bottom-up approaches) detect instances of body parts instead of fitting a skeleton template. In \cite{50}, Shotton et al. trained a random forest classifier for body part segmentation from a single depth image and used mean shift to estimate joint locations. This work inspired an entire line of depth-based pose estimation research exploring regression tree methods: Hough forests \cite{20}, random ferns \cite{25}, and random tree walks \cite{61} have been proposed in recent years.

**Occlusion Handling and Viewpoint Invariance.** One popular approach to model occlusions is to treat visibility as a binary mask and jointly reason on this mask with the input images \cite{47,55}. Other approaches such as \cite{3,19,8},
Fig. 2: Model overview. The input to our model is a single depth image. At iteration $t$, the input to our convolutional network is a set of retina-like patches $X_t$ extracted from the input depth image. Our model predicts offsets $\hat{\delta}_t$ and selectively applies them to the pose from the previous iteration $\hat{y}_{t-1}$ based on a predicted visibility mask $\hat{\alpha}_t$. This is performed using the element-wise product operation $\otimes$. The refined pose at the end of iteration $t$ is denoted by $\hat{y}_t$.

include templates for occluded versions of each part. More sophisticated models introduce occlusion priors [27, 5] or semantic information [18].

For rigid body pose estimation and 3D object analysis, several descriptors have been proposed. Given the success of SIFT, there have been several attempts at extending SIFT [39] into the three dimensional domain [15] and embedding rotational and translational invariance [49, 56]. Other features such as viewpoint invariant 3D feature maps [38], histograms of 3D joint locations [57], multifractal spectrum [58], and volumetric convolutional network filters [40, 41] have been proposed for 3D modeling. Instead of proposing invariant features, Ozuysal et al. [44] trained a classifier for each viewpoint. Building on the success of representation learning from RGB, discriminative pose estimation from the depth domain, viewpoint invariant features, and occlusion modeling, we design a model which achieves viewpoint invariant 3D human pose estimation.

3 Model

Overview. The goal of our model is to achieve viewpoint invariant pose estimation. The iterative error feedback mechanism proposed by [6] demonstrates promising results on front and side view RGB images. However, a fundamental challenge remains unsolved: how can a model learn to be viewpoint invariant? Our core contribution is as follows: we leverage depth data to embed local patches into a learned viewpoint invariant feature space. As a result, we can train a body part detector to be invariant to viewpoint changes. Furthermore, by introducing recurrent connections and providing richer local context, our model can reason on past actions to guide downstream global pose estimation (see Figure 2).
Fig. 3: Learned viewpoint invariant embedding for a single glimpse. An input glimpse $x$ is converted into a voxel $x'$. A grid generator $g(x)$ regresses 3D transformation parameters $\theta$ which are applied to $x'$ with a trilinear sampler. The resulting 3D feature map $V$ is projected into 2D space which results in the final embedding $U$.

3.1 Model Architecture

Local Input Representation. One of our goals is to use local body part context to guide downstream global pose prediction. To achieve this, we propose a two-step process. First, we extract a set of patches from the input depth image where each patch is centered around each predicted body part. By feeding these patches into our model, it can reason on low-level, local part information. We transform these patches into patches called glimpses \cite{42,33}. A glimpse is a retina-like encoding of the original input but encodes pixels further from the center with a progressively lower resolution. As a result, the model must focus on specific input regions with high resolution while maintaining some, but not all spatial information. These glimpses are stacked and denoted by $X \in \mathbb{R}^{H \times W \times C}$ where $C$ is the number of joints and $H, W$ is the glimpse height and width. Glimpses for iteration $t$ are generated using the predicted pose $\hat{y}_{t-1}$ from the previous iteration $t-1$. When $t = 0$, we use the average pose $\hat{y}_0$.

Learned Viewpoint Invariant Embedding. We embed the input into a learned, viewpoint invariant feature space (see Figure 3). Since each glimpse $x$ is a real world depth map, we can convert each glimpse into a voxel $x' \in \mathbb{R}^{H \times W \times D}$ where $D$ is the depth of the voxel. The stacked voxels are denoted by $X' \in \mathbb{R}^{H' \times W' \times D' \times C}$ where $C$ is the number of joints. In this context, voxel refers to a volumetric representation of the depth map and not a full 3D model. This representation allows us to rotate the glimpse in 3D thereby simulating occlusions which may be present from other viewpoints.

Our goal is to transform $X'$ into a viewpoint-invariant feature map $V \in \mathbb{R}^{H \times W \times D \times C}$ where $H, W'$ and $D$ are the height, width, and depth of the output feature map. This is a two-step process: First, we use a grid generator $g(x)$ which generates a set of 3D transformation parameters $\theta$. We select $g$ to be a shallow convolutional network. Second, using $\theta$ we follow \cite{28} and compute a
sampling grid $G \in \mathbb{R}^{H \times W \times C}$ which associates each element of $V$ with real-valued coordinates indexing into $X'$. If $G_{ijk} = (x_{ijk}, y_{ijk}, z_{ijk})$, then $V_{ijkc} = X'_{ijkc}$. However, since $x_{ijk}, y_{ijk}$ and $z_{ijk}$ are real-valued, we convolve the stacked voxels $X'$ with a sampling kernel $k$ and set the output feature map:

$$V_{ijkc} = \sum_{i'='1}^{H} \sum_{j'='1}^{W} \sum_{k'='1}^{D} X'_{i',j',k',c} \ker \left( \frac{i' - x_{ijk}}{H} \right) \ker \left( \frac{j' - y_{ijk}}{W} \right) \ker \left( \frac{k' - z_{ijk}}{D} \right)$$

(1)

where the kernel $\ker(d) = \max(0, 1 - |d|)$ corresponds to the trilinear sampling kernel. We further reduce the dimensionality by creating a 2D projection $U$ of the 3D feature map $V$ shown in Equation (2). Notice that (1) and (2) are linear functions of the stacked input voxels $X'$ and upstream gradients can flow smoothly through these mathematical units.

$$U_{ijc} = \sum_{k}^{D} V_{ijkc} \text{ such that } U \in \mathbb{R}^{H \times W \times C}$$

(2)

The resulting $U$ now represents two-dimensional viewpoint invariant representation of the input glimpse. At this point, $U$ is used as input into a convolutional network for human body part detection and error feedback regression.

**Convolutional and Recurrent Networks.** As previously mentioned, our goal is to use local input patches to guide downstream global pose predictions. We stack the viewpoint invariant feature maps $U$ for each joint to form a $H \times W \times C$ tensor. This tensor is input to a convolutional network. As a result, the output of the convolutional network is a global representation of the human pose. Directly regressing body part positions from the dense activation layers has proven to be difficult due to the highly non-linear mapping [53]. This is referred to as direct prediction in Table 3.

Inspired by [6]'s work in the RGB domain, we adopt an iterative refinement technique which uses multiple steps to fine-tune the pose by correcting previous estimates. Unfortunately, in [6], each refinement step is only influenced by the previous step. We claim that these iterations should have a higher-order dependency through time. Therefore, we introduce recurrent connections between each iteration. We use a long short term memory (LSTM) module [26] to model such dependencies. As a result, our model has direct access to the underlying hidden state which generated prior feedback.

### 3.2 Multi-Task Loss

Our primary goal is to achieve viewpoint invariance. In extreme cases such as top views, many human joints are occluded. We want our model to reason on the visibility of joints. We formulate the optimization procedure as a multi-task problem consisting of two objectives: (i) a body-part detection task, where the goal is to determine whether a body part is visible or occluded in the input; (ii) a pose regression task, where we predict the offsets to the correct real world 3D position of all visible human body joints.
**Body-Part Detection.** For body part detection, the goal is to determine whether a particular body part is visible or occluded in the input. This is denoted by the predicted visibility mask $\hat{\alpha}$ which is a $1 \times 3C$ vector of indicator variables. The ground truth visibility mask is denoted by $\alpha$. If a body part is predicted to be visible, then $\hat{\alpha}_j = 1$, otherwise $\hat{\alpha}_j = 0$ denotes occlusion. The visibility mask $\hat{\alpha}$ is computed using a softmax over the unnormalized log probabilities $p_i$. Hence, the objective is to minimize the cross-entropy. The visibility loss for a single training example $i$ is shown in Equation (3).

\[
L_{\alpha,i} = -\sum_{j=1}^{3C} \alpha_j \log(p_j) + (1 - \alpha_j) \log(1 - p_j)
\]  

(3)

Regardless of the ground truth and the predicted visibility mask, we force our model to improve its body part detection ability. As we discuss below, this is not the same for error feedback.

**Partial Error Feedback.** Ultimately, our goal is to predict the location of the joint corresponding to each visible human body part. To achieve this, we refine our previous pose prediction by learning correction offsets (i.e. feedback) denoted by $\delta$. Furthermore, we only learn correction offsets for joints that are visible. At each time step, a regression predicts offsets $\hat{\delta}$ which are used to update the current pose estimate $\hat{y}$. Specifically, $\hat{\delta}, \delta, \hat{y}$ and $y$ are $1 \times 3C$ vectors denoting real-world 3D positions of each joint or the corresponding error feedback.

\[
L_{\delta,i} = \sum_{j=1}^{3C} \mathbb{1}\{\alpha_j = 1\} ||\hat{\delta}_j - \delta_j||^2_2
\]

(4)

The loss shown in (4) is motivated by our goal of predicting partial poses. Consider the case of when the right knee is not visible in the input. If our model successfully labels the right knee as occluded, we wish to prevent the error feedback loss from backpropagating through our network. To achieve this, we include the indicator term $\mathbb{1}\{\alpha_j = 1\}$ which only backpropagates pose error feedback if a particular joint is visible in the original image. A secondary benefit is that we do not force the regressor to output dummy real values (if a joint is occluded) which may skew the model’s understanding of output magnitude.

**Global Loss.** The resulting objective is the linear combination of the error feedback cost function for all joints and the detection cost function for all body parts: $L = \lambda_{\alpha}L_{\alpha} + \lambda_{\delta}L_{\delta}$. The mixing parameters $\lambda_{\alpha}$ and $\lambda_{\delta}$ define the relative weight of each sub-objective. We describe the optimization procedure next.

### 3.3 Training and Optimization

We train the full model end-to-end in a single step of optimization. We train the convolutional and recurrent network from scratch with all weights initialized from a Gaussian with $\mu = 0, \sigma = 0.001$. We use the Adam optimizer [30] with a learning rate of $1 \times 10^{-5}$, $\beta_1 = 0.9$, and $\beta_2 = 0.999$. Our training batches
4 Datasets

We evaluate our model on a publicly available dataset that has been used by recent state-of-the-art human pose methods. To more rigorously evaluate our model, we also collected a new dataset consisting of varied camera viewpoints. See Figure 4 for samples.

4.1 Previous Depth Datasets

We use the Stanford EVAL dataset [17] which consists of 9K front-facing depth images. The dataset contains 3 people performing 8 action sequences each. The EVAL dataset was recorded using the Microsoft Kinect camera at 30 fps. Similar to leave-one-out cross validation, we adopt a leave-one-out train-test procedure. One person is selected as the test set and the other two people are designated as the training set. This is performed three times such that each person is the test set once.

4.2 Invariant-Top View Dataset (ITOP)

Existing depth datasets for pose estimation are often small in size, both in the number of people and number of frames per person [16][17]. To address these issues, we collected a new dataset consisting of 100K real-world depth images from multiple camera viewpoints. Named ITOP, the dataset consists of 20 people performing 15 action sequences each. Each depth image is labeled with real-world 3D joint locations from the point of view of the respective camera. The dataset consists of two “views,” namely the front view and the top view. The frontal view contains 360° views of each person, although not necessarily uniformly distributed. The top view contains images captured solely from the top (i.e. camera on the ceiling pointed down to the floor).
Data Collection. Two Kinect cameras are used, one camera on the ceiling facing down while another camera is from a traditional front-facing viewpoint. To annotate each frame, we use a series of steps that progressively involves more human supervision if necessary. First, 3D joints are estimated using [50] from the front-facing camera. These coordinates are then transformed into the respective world coordinate system of each camera in the system. Second, we use an iterative ground truth error correction technique based on per-pixel labeling using k-NN and center of mass convergence. Finally, humans manually label and discard bad frames. The human labeling procedure takes one second per image.

5 Experiments

5.1 Evaluation Metrics

We evaluate our model using two metrics. As introduced in [2], we use the percentage of correct keypoints (PCKh) with a variable threshold. This metric defines a successful human joint localization if the predicted joint is within 50% of the head segment length to the ground truth joint. For summary tables and figures, we use the mean average precision (mAP) which is the average precision for all human body parts. Precision is reported for individual body parts. A successful detection occurs when the predicted joint is less than 10 cm from the ground truth in 3D space.

5.2 Implementation Details

Our model (Section 3) is implemented in TensorFlow [1]. We use mini-batches of size 10 and 10 refinement steps per batch. We use the VGG-16 [51] architecture for our convolutional network but instead modify the first layer to accommodate the increased number of input channels. The network consists of 13 layers of $3 \times 3$ convolutions interspersed with 5 layers of $2 \times 2$ max-pooling operations. Additionally, we reduce the number of neurons in the dense layers to 2048. We remove the final softmax layer and use the second dense layer activations as input into a recurrent network. For the recurrent network, we use a long short term memory (LSTM) module [26] consisting of one layer of 2048 hidden units. The LSTM hidden state is passed to a Softmax classification layer and a regression layer for loss computation and pose-error computation. Our model is trained from scratch.

To generate glimpses for the first refinement iteration, the mean 3D pose from the training set is used. Glimpses are 160 pixels in height and width and centered at each joint location (in the image plane). Each glimpse consists of 4 patches where each patch is quadratically downsampled according to the patch number (i.e. its distance from the glimpse center). The input to our convolutional network is a $160 \times 160 \times C$ tensor where $C$ is the number of human joints.
Fig. 5: Percentage of correct keypoints based on the head (PCKh). Colors indicate different methods. Solid lines indicate full body performance. Dashed lines indicate upper body performance. Higher is better.

5.3 Comparison with State-of-the-Art

We compare our model to three state-of-the-art methods: random forests [50], random tree walks (RTW) [61], and iterative error feedback (IEF) [6]. One of our primary goals is to achieve viewpoint invariance. To evaluate this, we perform three sets of experiments, progressing in level of difficulty. First, we train and test all models on front view images. This is the classical human pose estimation task. Second, we train and test all models on top view images. This is similar to the classical pose estimation task but from a different viewpoint. Third, we train on front view images and test on top view images. This is the most difficult experiment and truly tests a model’s ability to learn viewpoint transfer.

Baselines. We give a brief overview the baseline algorithms:

1. The random forest (RF) model [50] consists of multiple decision trees that traverse each pixel to find the body part labels for that pixel. Once the pixels are classified into body parts, joint positions are found with multiple mean-shifts.
2. Random tree walk (RTW) [61] trains a regression tree to estimate the probability distribution to the direction toward the particular joint, relative to the current position. At test time, the direction for the random walk is randomly chosen from a set of representative directions. The new position is found by a constant step toward the direction, and the distribution for next direction is found at the new position.
3. Iterative error feedback (IEF) [6] is a self-correcting model used to progressively make changes to an initial pose estimation by incorporating error feedback or correction offsets.

Train on front views, test on front views. Table 1 shows the average precision for each joint using a 10 cm threshold and the overall mean average precision (mAP) for all models. IEF and the random forest methods were not evaluated on the EVAL dataset. Random forest depends on a per-pixel body part labeling, which is not provided by EVAL. IEF was unable to converge to comparable results on the EVAL dataset. We discuss the ITOP results below. For frontal views, RTW achieves a mAP of 84.8% and 80.5% for the upper and full body, respectively. Our recurrent error feedback (REF) model performs similarly to RTW,
Table 1: Detection rates of body parts using a 10 cm threshold. Higher is better. Results for the left and right body part were averaged. Upper body consists of the head, neck, shoulders, elbows, and hands.

achieving a mAP of 2 to 3 points less. The random forest algorithm achieves the lowest full body mAP of 65.8%. This could be attributed to the limited amount of training data — the original algorithm by Shotton et al. [50] trains on 900K synthetic depth images.

We show qualitative results in Figure 6. The front-view ITOP dataset is shown in columns (c) and (d). Both our model and IEF make similar mistakes: both models sometimes fail to learn sufficient feedback to converge to the correct body part location. Since we do not impose joint position constraints or enforce strong skeleton priors, our method wrongly predicts the elbow to be off the body completely.

Train on top view, test on top view. Figure 6 shows examples of qualitative results from frontal and top down views for Shotton et al. [50] and random tree walk (RTW) [61]. For the top-down view, we show only 8 joints on the upper body (i.e. head, neck, left shoulder, right shoulder, left elbow, right elbow, left hand, and right hand) as the lower body joints are almost always occluded. Shotton and RTW give reasonable results when all joints are visible (see Figure 6a and 6c) but do not perform well in the case of occlusion (Figure 6b and 6d). For the random forest method, we can see from figure 6b that the prediction for the occluded right elbow is topologically invalid though both right shoulder and hand are visible and correctly predicted. This is because the model doesn’t take into account the topological information among joints, so it is not able to modify its prediction for one joint base on the predicted positions of neighboring joints. For RTW, figure 6b shows that the predicted position for right hand goes to the right leg. Though legs and hands possess very different depth information, the model mistook the right leg for right hand when the hand is occluded and the leg appears in the common spatial location of a hand.

Train on frontal views, test on top views. This is the most difficult task for 3D pose estimation algorithms since the test set contains significant scale and shape differences from the training data. Results are shown in Table
Fig. 6: Qualitative results without viewpoint transfer. Each row shows a different algorithm. Red arrows indicate locations.

| Body Part   | RTW | RF  | IEF  | Our Model |
|-------------|-----|-----|------|-----------|
| Head        | 0.6 | 48.1| 40.3 | 55.6      |
| Neck        | 9.6 | 5.9 | 40.2 | 40.9      |
| Torso       | 4.3 | 4.7 | 27.9 | 35.0      |
| Upper Body  | 2.2 | 19.7| 19.5 | 29.4      |
| Full Body   | 1.9 | 10.8| 13.4 | 20.4      |

Table 2: Detection rate for the viewpoint transfer task. Full results and figures can be found in the supplemental material.

RTW gives the lowest performance as the model relies heavily on topological information across joints – if the prediction for an initial joint fails, predictions for subsequent joints will also fail.

Both representation learning methods are able to localize joints despite the viewpoint change. IEF achieves a 40.3 detection rate for the head while our model achieves a 55.6 detection rate. This can be attributed to the proximity of upper body joints in both viewpoints. The head, neck, and torso locations are similarly positioned across viewpoints.

Runtime Analysis. Methods which employ representation learning techniques often require overhead for forward-propagation through their networks. As expected, our model requires 1.7 seconds per frame (10 iterations) while the random tree walk takes 0.3 seconds per frame. While this is dependent on implementation details, it does illustrate the tradeoff between speed and performance.
Table 3: Detection rate of our model with different feedback mechanisms on the ITOP front dataset. Rows denote a different body parts. Model is trained without viewpoint transfer and the detection threshold is 10 cm.

| Body Part     | Direct Prediction | Iterative Feedback | Recurrent Feedback |
|---------------|-------------------|--------------------|--------------------|
|               | Front     | Top    | Front | Top    | Front | Top    |
| Head          | 27.8      | 32.1   | 95.9  | 91.0   | 98.1  | 98.1   |
| Hands         | 1.3       | 1.8    | 44.6  | 50.2   | 68.6  | 85.5   |
| Upper Body    | 15.0      | 17.8   | 77.4  | 82.1   | 84.0  | 91.4   |
| Full Body     | 21.8      | 23.8   | 73.7  | 62.1   | 77.4  | 75.5   |

Fig. 7: Our model’s estimated pose at different iterations of the refinement process. Initialized with the mean pose, it converges to the correct pose over time.

5.4 Model Ablation Studies

To further gauge the effectiveness of our model, we analyze each component of our model and provide both quantitative and qualitative analyses. Specifically, we evaluate the effect of error feedback and discuss the relevance of the input representation (e.g. glimpses).

Effect of Recurrent Connections. We analyze the effect of recurrent connections compared to regular iterative error feedback and direct prediction. To evaluate iterative feedback, we use our final model but remove the LSTM module and regress the visibility mask $\hat{\alpha}$ and error feedback $\hat{\delta}$ using the dense layer activations. Note that we still use a multi-task loss and glimpse inputs. Direct prediction does not involve feedback but instead attempts to directly regress correct pose locations in a single pass.

Quantitative results are shown in Table 3. Direct prediction, as expected, performs poorly as it is very difficult to regress exact 3D joint locations in a single pass. Iterative-based approaches significantly improve performance by 50 points. It is clear that recurrent connections improve performance, especially in the top-view case where recurrent feedback achieves 91.4 upper body mAP while iterative feedback achieves 82.1 upper body mAP.

Figure 7 shows how our model updates the pose over time. Consistent across all images, the first iteration always involves a large, seemingly random transformation of the pose. This can be thought of as the model is “looking around” the initial pose estimate. Once the model understands the initial surrounding
Fig. 8: Comparison of heatmap and glimpse input representations. (a) shows the multi-channel heatmap and glimpse input projected onto a 2D image. Explicitly, the difference between the glimpse image and the input image is increased blurring further from the center. (b) shows localization error as a function of refinement iterations. Lower error is better.

Effect of Glimpses. Our motivation for glimpses is to provide additional local context to our model to guide downstream, global pose estimation. In Figure 8 we evaluate the performance of glimpses vs indicator masks (i.e. heatmaps). Figure 8 shows that glimpses do provide more context for the global pose prediction task. As the number of refinement iterations increases, using glimpses, the localization error for each joint is less than the error with heatmaps. By looking at Figure 8, it becomes apparent that heatmaps provide limited spatial information. The indicator mask is a way of encoding 2D body part coordinates but does not explicitly provide local context information. Glimpses are able to provide such context from the input image. We observe that in the presence of noisy labels, such as some frames of EVAL, both the heatmap and glimpse strategy outperform methods that require single 3D point precision (Table 1). Heatmaps and glimpses provide “slack” for our model during training. If the noisy label is close to the true ground truth, IEF and our method can learn and perform correctly.

6 Conclusion

We introduced a viewpoint invariant model that estimates 3D human pose from a single depth image. Our model is formulated as a deep discriminative model that attends to glimpses in the input. Using a multi-task optimization objective, our model is able to selectively predict partial poses by using a predicted visibility mask. This enables our model to iteratively improve its pose estimates by predicting occlusion and human joint offsets. We showed that our model achieves competitive performance on an existing depth-based pose estimation dataset and achieves state-of-the-art performance on a newly collected dataset containing 100K annotated depth images from several view points.
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Appendices

A Localization Heatmaps

To further analyze the viewpoint transfer task (train on front and side views, test on top views), we visualize the localization heatmap in the figures below. For each body part, we plot the predicted test-set locations with respect to the ground truth. Clusters closer to (0,0) are better. All axes denote centimeters.

Figure 9 shows our model’s outputs for the viewpoint transfer task. For lower body parts, our model makes a systemic error of predicting joints to be lower (i.e. closer to the ground) than the ground truth. From the top view, the lower body parts are not only further from the camera but they are also often occluded which forces our model to reason based on global pose structure as opposed to fine-tuned local information. For the upper body, most joints are visible which lead to more correct predictions.

Fig. 9: Predicted joint locations for our method (iteration 10) for the viewpoint transfer task. The point (0,0) indicates the ground truth location.
Below, Figures 10 and 11 show the differences between the initialization strategies of IEF and our method.

Fig. 10: Predicted joint locations for iterative error feedback (iteration 0) for the viewpoint transfer task. The point (0,0) indicates the ground truth location.

Fig. 11: Predicted joint locations for our method (iteration 0) for the viewpoint transfer task. The point (0,0) indicates the ground truth location.
Random tree walk tends to perform poorly on the viewpoint transfer task. The heatmaps below show predictions very far from the ground truth.

**Fig. 12:** Predicted joint locations for random tree walk (step 0) for the viewpoint transfer task. The point $(0,0)$ indicates the ground truth location.

**Fig. 13:** Predicted joint locations for random tree walk (step 300) for the viewpoint transfer task. The point $(0,0)$ indicates the ground truth location.
| Body Part | ITOP (front-view) | ITOP (top-view) | EVAL | ITOP (transfer) |
|-----------|------------------|----------------|------|-----------------|
|           | RTW  | RF  | IEF | Ours | RTW  | IEF | Ours | RTW  | Ours | RTW  | RF  | Ours |
| Head      | 97.8 | 63.8 | 89.8 | 98.1 | 98.3 | 95.4 | 52.1 | 98.1 | 90.9 | 93.9 | 1.5 | 48.1 | 55.6 |
| Neck      | 95.9 | 86.4 | 57.5 | 97.5 | 82.2 | 98.5 | 36.6 | 97.6 | 87.4 | 94.7 | 8.1 | 5.9  | 40.9 |
| L Shoulder| 93.4 | 84.5 | 62.4 | 97.6 | 91.1 | 87.8 | 35.7 | 96  | 88.5 | 84.4 | 2.0 | 4.8  | 31.2 |
| R Shoulder| 94.7 | 82.1 | 60.7 | 95.4 | 92.4 | 90.1 | 43.7 | 96.1 | 87.1 | 89.5 | 1.7 | 15.8 | 32.0 |
| L Elbow   | 79.8 | 79.1 | 37.2 | 73.9 | 77.1 | 58.9 | 15.5 | 86.6 | 26.4 | 58.8 | 1.0 | 38.9 | 20.1 |
| R Elbow   | 76.1 | 67.3 | 48.6 | 72.7 | 83.1 | 55.9 | 18.1 | 85.8 | 28.5 | 32.2 | 1.5 | 36.1 | 19.8 |
| L Hand    | 72.0 | 48.9 | 37.2 | 68.4 | 72.9 | 46.6 | 14.7 | 85.6 | 36.1 | 63.3 | 0.8 | 4.2  | 17.2 |
| R Hand    | 69.0 | 53.7 | 35.0 | 68.9 | 80.9 | 51.6 | 13.0 | 85.4 | 28.4 | 15.8 | 0.8 | 3.7  | 18.2 |
| Torso     | 93.8 | 65.0 | 61.3 | 85.6 | 68.2 | 80.5 | 27.7 | 72.9 | —    | —    | 3.9 | 4.7  | 35.0 |
| L Hip     | 79.9 | 54.2 | 69.7 | 71.8 | 53.6 | 11.7 | 36.4 | 61.7 | —    | —    | 3.1 | 0.0  | 11.9 |
| R Hip     | 80.7 | 47.4 | 64.4 | 72.2 | 57.8 | 28.3 | 29.7 | 60.6 | —    | —    | 3.8 | 0.0  | 12.0 |
| L Knee    | 66.0 | 69.0 | 72.1 | 68.7 | 56.1 | 1.6  | 52.9 | 50.6 | 81.9 | 87.1 | 0.2 | 0.1  | 4.0  |
| R Knee    | 71.6 | 62.3 | 78.3 | 69.3 | 51.6 | 3.6  | 48.3 | 52.5 | 84.9 | 84.9 | 1.9 | 0.0  | 4.0  |
| L Foot    | 69.0 | 57.9 | 77.2 | 61.0 | 34.5 | 0.0  | 64.6 | 52  | 88.7 | 98.6 | 0.1 | 0.1  | 2.1  |
| R Foot    | 67.9 | 64.6 | 80.1 | 60.6 | 22.7 | 0.0  | 60.0 | 50.9 | 91.2 | 85.9 | 0.1 | 0.1  | 2.2  |
| Upper Body| 84.8 | 70.7 | 53.6 | 77.4 | 84.7 | 73.1 | 28.7 | 75.5 | 59.2 | 73.8 | 2.2 | 19.7 | 29.4 |
| Lower Body| 72.5 | 59.3 | 73.6 | 67.3 | 46.1 | 7.5  | 48.7 | 54.7 | 86.7 | 89.2 | 1.5 | 0.1  | 6.0  |
| Full Body | 80.5 | 65.8 | 62.1 | 77.4 | 68.2 | 47.4 | 36.6 | 75.5 | 68.3 | 74.1 | 2.0 | 10.8 | 20.4 |

Table 4: Detection rates of body parts using a 10 cm threshold. Higher is better. The EVAL dataset does not provide torso or hip locations. ITOP (transfer) denotes the viewpoint transfer task.