Active Learning with Pseudo-Labels for Multi-View 3D Pose Estimation

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Abstract

Pose estimation of the human body/hand is a fundamental problem in computer vision, and learning-based solutions require a large amount of annotated data. Given limited annotation budgets, a common approach to increasing label efficiency is Active Learning (AL), which selects examples with the highest value to annotate, but choosing the selection strategy is often nontrivial.

In this work, we improve Active Learning for the problem of 3D pose estimation in a multi-view setting, which is of increasing importance in many application scenarios. We develop a framework that allows us to efficiently extend existing single-view AL strategies, and then propose two novel AL strategies that make full use of multi-view geometry. Moreover, we demonstrate additional performance gains by incorporating predicted pseudo-labels, which is a form of self-training. Our system significantly outperforms baselines in 3D body and hand pose estimation on two large-scale benchmarks: CMU Panoptic Studio and InterHand2.6M. Notably, on CMU Panoptic Studio, we are able to match the performance of a fully-supervised model using only 20% of labeled training data.

1. Introduction

Pose estimation is a fundamental problem in computer vision. Accurate pose estimates of the human body/hand allow automated systems to perform markerless motion capture [8, 36], recognize actions [5, 42], understand social interactions [17] and sign languages [15], and so on.

While supervised learning methods using deep neural networks have achieved considerable success for pose estimation [26, 37, 38, 39], the annotation of pose data is time-consuming and costly. For example, the creators of MPII [1], a popular body pose estimation benchmark, report that on average it takes an annotator one minute to annotate all body keypoints on an image. Human labels can also have inconsistent quality, especially for difficult occluded cases. On the other hand, multi-view camera systems [17, 44, 47] are increasingly being used to generate pose labels automatically, which is a major motivation for our work. However, the training of the underlying labeling models still requires significant upfront annotation.

In this paper, we propose a framework to improve the “label efficiency” for learning deep pose estimation models. Our approach is to focus the annotation budget on the most valuable samples, which is known as Active Learn-
Figure 2. An overview of the proposed active learning (AL) system for multi-view 3D pose estimation. While prior works have only considered AL for single-view pose estimation, our system is the first to work in the multi-view setting (Sec. 4), and we propose two effective strategies that make full use of multi-view geometry. Additionally, by incorporating pseudo-labels in the proposed self-training process (Sec. 4.1), we show further improvement in label efficiency without extra annotation or computational cost.

2. Related Work

2.1. 3D Pose Estimation

Pose estimation is one of the fundamental tasks in computer vision. To model human bodies that can undergo articulation and deformation, early approaches mostly take inspiration from the classical Pictorial Structures [2, 9]. Following the success of deep neural networks, and facilitated by benchmarks such as Human 3.6M [14] and MPII [1], deep CNNs have been widely applied to body and hand pose estimation. Representative methods include Convolutional Pose Machines [38], Stacked Hourglass Networks [26], PoseResNet [39], HRNet [37], etc. These methods typically work by predicting the locations of body/hand keypoints, formulated as a heatmap regression problem. Single-view 3D pose estimation methods [18, 19, 22, 47] on the other hand, directly lift 2D image evidence into 3D keypoints or mesh representations, but need more high-quality training data in order to resolve the inherent 2D-3D ambiguity.

With the increasing availability of multi-camera setups, multi-view pose estimation has gathered increased interest [11, 16, 28]. A key motivation is that these systems...
can be used to automatically or semi-automatically generate "ground truth" for single-view 3D pose estimation, and significantly reduce labeling cost. In fact, such a procedure has been adopted in benchmarks like CMU Panoptic [17] and HUMBI [44] for body pose estimation, as well as FreiHand [47] and InterHand2.6M [24] for hands. However, training multi-view models still requires large amounts of annotated 3D pose data, which strongly motivates cost-saving strategies such as active learning.

2.2. Active Learning

Active Learning (AL) [6, 32] considers a dynamic environment where an ML system selects unlabeled examples to acquire labels for, and iteratively re-trains itself using newly labeled data. This is critical in many real-world scenarios with constrained annotation budgets. A large AL literature exists for classification, including uncertainty-based sampling [29], diversity maximization [41], Bayesian methods [31], etc. Despite years of progress, in practice, the best AL strategies are often problem-dependent, and heuristics such as random sampling remain strong baselines [23, 33].

In computer vision, AL has also been widely studied for problems such as semantic segmentation [21, 34] and object detection [30]. Siddiqui et al. [34] demonstrate that incorporating multi-view geometry can improve the effectiveness of AL for semantic segmentation. Yet, the pixel classification formulation in semantic segmentation makes it easier to adapt AL approaches designed for classification, while for the keypoint localization task, multi-view adaptations are less straightforward.

For pose estimation, Yoo et al. [43] applied task-agnostic loss prediction as an AL strategy but with marginal gains over random sampling. Liu and Ferrari [20] propose the Multi-Peak Entropy metric to guide the sampling of single-view images for annotation. As we demonstrate later however, extending this metric to multi-view is a non-trivial task. More recently, Caramalau et al. [4] extend the CoreSet [31] AL algorithm to hand pose estimation with a Bayesian formulation. While we also propose an extension to CoreSet in this paper, our AL strategy relies on geometric intuitions and does not require expensive Bayesian inference. Additionally, [4] estimates 3D pose from a single depth camera, while we take RGB images from multiple calibrated cameras as input.

2.3. Self-Training and Pseudo-Labeling

Besides active learning, self-training [27, 40, 48] is another prominent approach to increasing label efficiency. Building on the principle of knowledge distillation [12], these methods perform iterative pseudo-labeling and retraining with unlabeled data. For image classification, this paradigm has been shown to improve model generalization and robustness without increasing the amount of human-annotated labels.

For the keypoint localization task in pose estimation, similar ideas have been explored in the form of semi-supervised learning and pseudo-labeling [3, 13, 25]. In this paper, inspired by the seminal work of multi-view bootstrapping [35], we also develop a pseudo-labeling method. When applied in conjunction with our AL framework, it leads to even greater gains in efficiency.

3. Problem Formulation

We assume a multi-view capture setup with $N$ synchronized and calibrated cameras, and we use the term frame $F$ to denote the collection of images from all cameras (views) $V$ at a particular time instance $t$, i.e. $F(t) = \{V_1(t), V_2(t), \ldots, V_N(t)\}$. In the following, we drop $t$ from the notation unless necessary. The entire dataset, which is a set of frames (possibly infinite), is denoted as $D = \{F_1, F_2, \ldots\}$.

The task of 3D pose estimation is to estimate the 3D locations of a set of keypoints on the human body/hand from an input frame. In this work, we focus on a well-established approach, where the 3D keypoints are obtained by triangulating 2D predictions on each camera view, using robust triangulation techniques [10], e.g. RANSAC. In particular, the 2D keypoint prediction problem is formulated as heatmap regression, where the ground truth heatmaps are commonly constructed by placing a 2D isotropic Gaussian at the ground truth location. Let $K$ be the total number of keypoints. We use $H^k$ to denote the predicted heatmap for the $k$-th keypoint, and $\hat{H}^k$ for its normalized version using softmax.

Active learning starts with an initial labeled set $\mathcal{L}_0$, and trains an initial pose estimator. Afterwards, in each iteration $i \geq 1$, an AL strategy samples a set of frames from the remaining unlabeled set $\mathcal{U}_i$, queries human annotators, and obtains labels for them. (We assume that the annotation cost for a frame is constant.) This enlarges the labeled set $\mathcal{L}_i$ into $\mathcal{L}_{i+1}$, with which the pose estimation model is re-trained. Note that $\forall i$, $\mathcal{L}_i \cup \mathcal{U}_i = D$, and that $\mathcal{L}_1 \subset \mathcal{L}_2 \cdots \subset D$. An overview of this AL framework is shown in Fig. 2.

3.1. Single-view AL for Pose Estimation

Before describing our multi-view AL framework, we review some prominent AL strategies for human pose estimation in the single-view setting.

The 2D heatmap representation naturally lends itself to entropy-based formulations, since a heatmap encodes uncertainty in the model’s prediction, and can be normalized into a probability distribution over the 2D grid using the softmax operator. For a predicted heatmap $H^k$ of keypoint $k$, let $L^k = \{l^k_1, l^k_2, \ldots\}$ be a set of 2D coordinates of local peaks obtained by applying a local maximum filter to $\hat{H}^k$, with $l^k_1$ being the argmax, and so on. In the work of
Liu and Ferrari [20], several entropy-based metrics are proposed, and a corresponding AL strategy is defined by sampling top-scoring images under each metric. We now review these metrics. A visual illustration of these metrics is shown in Fig. 3.

**Best vs. Second Best (BSB):** The Best vs. Second Best metric [29] is based on a margin sampling idea, and defined as the difference between the top two local maximums in the heatmap. Intuitively, a smaller difference means larger uncertainty or a multi-modal prediction.

\[
M_{\text{BSB}}(V) = \frac{1}{K} \sum_{k=1}^{K} \left( \hat{H}^k(t_1^k) - \hat{H}^k(t_2^k) \right),
\]

(1)

**Multiple Peak Entropy (MPE):** Multiple Peak Entropy is introduced in [20] for single-view pose estimation. The idea is that, as modes on a heatmap can be spatially diffuse, simply comparing the highest and second highest would not be able to differentiate between a single wide mode and multiple tight modes. Instead, multiple peaks are considered together to better characterize the uncertainty in a predicted heatmap.

To be concrete, MPE samples \(\hat{H}^p\) at all the local peaks \(L\), and computes the resulting entropy:

\[
M_{\text{MPE}}(V) = \frac{1}{K} \sum_{k=1}^{K} \sum_{l^k \in L^k} \Pr(t_1^k) \log \Pr(t_1^k) - \Pr(t_2^k) \log \Pr(t_2^k),
\]

(2)

where

\[
\Pr(t_1^k) = \frac{\exp H^k(t_1^k)}{\sum_{l^k \in L^k} \exp H^k(l_1^k)}.
\]

(3)

Note that the softmax operator is applied on the sparse set of local peaks only. Liu and Ferrari found that MPE performs better over the random baseline for single-view human pose estimation.

**Random:** Random sampling is a simple and very effective baseline strategy in active learning for all kinds of tasks [23, 34]. For pose estimation, random selection of frames from \(U\) ensures that the sampled poses closely follow the training distribution during the AL process.

### 4. Multi-View AL for Pose Estimation

We now discuss AL strategies under the multi-view setting. First, we consider extending single-view strategies by aggregating the per-view uncertainty metrics, without taking geometry into consideration. In particular, we focus on the average:\footnote{We also experimented with other aggregation functions such as variance, and found them to perform worse.}: if the per-view predictions have high uncertainty on average, then annotating the corresponding frame is likely helpful. We define the metric for the aforementioned entropy-based metrics as

\[
M_{\text{BSB}}(F) = \frac{1}{N} \sum_{V \in F} M_{\text{BSB}}(V),
\]

(4)

\[
M_{\text{MPE}}(F) = \frac{1}{N} \sum_{V \in F} M_{\text{MPE}}(V).
\]

(5)

Beyond simple aggregation, the camera calibrations that come with the multi-view setup provide extra information, which we can take advantage of to define geometrically-inspired AL strategies. Recall that the 3D prediction for any keypoint \(k\), denoted as \(P^k\), is obtained through robust triangulation; we will build on this fact to define novel AL strategies. But first, we give a quick recap of the relevant AL literature to motivate our approach.

An intuitive approach to AL is to sample examples that receive the most uncertain predictions, and the definition of uncertainty is usually problem-dependent. The BSB and MPE strategies fall into this category. However, focusing on uncertain examples may bias the sample distribution, leading to inferior results. On the other hand, injecting diversity into the selection process can effectively preserve statistics of the original data distribution: examples include distribution matching [46] and the influence term in [20]. Below, we propose two AL strategies: CoreSet-Poses which is based on pose diversity, and Multi-View Consistency which is based on 3D prediction uncertainty.

**CoreSet-Poses:** CoreSet [31] is a state-of-the-art AL strategy based on selecting diverse representative examples from the unlabeled set, formulated as solving a combinatorial set-cover problem. Critical to the effectiveness of CoreSet is modeling the distance between unlabeled examples; in the case of image classification, [31] uses the Euclidean distance between pretrained convolutional features.

Our first strategy, CoreSet-Poses, builds on CoreSet by supplying it with a distance metric tailored for pose estimation. Specifically, given a pair of frames \((F, F')\), we define
### Algorithm 1: AL for multi-view pose estimation

| Input: Labeled set $L$, unlabeled set $U$, AL metric $M$, annotation budget $B$; |
| Sampled Data $S \leftarrow \{\}$; |
| for $F \in U$ do |
| $H_F = \{H_V | V \in F\} \leftarrow$ Model Inference; |
| $P_F, \varepsilon_F \leftarrow$ triangulate($H_F$); |
| repeat |
| $F_{\text{greedy}} \leftarrow \arg\max_{F \in U} M(F)$; $\triangleright M_{CS}, M_{MC}, \text{etc.}$; |
| $S \leftarrow S \cup \{F_{\text{greedy}}\}$; |
| $L \leftarrow L \cup \{F_{\text{greedy}}\}$; |
| $U \leftarrow U \setminus \{F_{\text{greedy}}\}$; |
| until $|S| = B$; |
| return $S$ |

Their distance $\Delta$ to be the average Euclidean distance between 3D keypoint predictions ($P_F, P_F'$) with the current model. While more sophisticated distance metrics could be defined with respect to the underlying sets of 2D heatmap predictions, the 3D predictions have already been filtered through robust triangulation, and have much lower dimensions so distance computation can be efficient. In practice, we align $P$ by shifting the root keypoint to the origin, e.g. if the root keypoint is 0, the aligned pose would be:

$$\hat{P} = P - P^0. \quad (6)$$

Given the distance metric, CoreSet-Poses solves a set-cover problem in order to maximize coverage in the pose space. While this problem is NP-hard, [4, 31] show that it can be approximately solved by a greedy $k$-center algorithm. Specifically, for each candidate unlabeled frame $F \in U$, we define the CoreSet-Poses AL metric as

$$M_{CS}(F) = \min_{F \in L} \Delta(\hat{P}_F, \hat{P}_F'), \quad (7)$$

which measures how “close” $F$ is to the current labeled set. Then, the greedy algorithm sequentially samples frames with the largest $M_{CS}$ value. Despite the improved efficiency, CoreSet-Poses would still take $O(|U|^2)$ time to compute the pairwise distances, making it potentially impractical for large datasets.

**Multi-View Consistency**: We also develop an uncertainty measure that is intrinsic to the 3D pose predictions. Our reasoning is that given a frame with multiple views, it is less likely for the frame-level prediction to be wrong if the per-view 2D predictions agree with each other. This agreement is in the geometric sense, e.g. for two views, we say two keypoint predictions exactly agree if their epipolar distance is 0. The corresponding AL strategy is then to sample frames with the largest measured disagreement. Additionally, we would like to compute this in $O(|U|)$ time, to make it practical for large datasets. We call this the Multi-View Consistency strategy.

Specifically, we take the triangulation error, or the average Euclidean distance between the 2D keypoint predictions and the reprojected 3D triangulations, as the AL metric. Note that, since this is exactly the minimization objective for triangulation, a high error directly indicates strong disagreements between 2D predictions. Formally, let the predicted 2D location of the $k$-th keypoint in view $V$ be $l^V_k$, and its reprojected location from the triangulated $P^k$ be $\hat{l}^V_k$. The triangulation error metric can be written as:

$$M_{MC}(F) = \frac{1}{N} \frac{1}{K} \sum_{V \in F} \sum_{k=1}^{K} ||l^V_k - \hat{l}^V_k||^2. \quad (8)$$

For simplicity, we use $\varepsilon_F$ to denote $M_{MC}(F)$.

Alg. 1 presents a unified view of AL for multi-view pose estimation, where different sampling strategies are realized by choosing the corresponding metric $M$.

### 4.1. Improvement via Self-Training

AL is shown to benefit from the addition of techniques like data augmentation and semi-supervised learning [23]. In this work, we want to explore a novel direction to improve it further. We leverage the fact that our measure of geometric inconsistency can also help us identify reliable frames with good pseudo-labels, which can be directly injected into the training set. In fact, this is a form of self-training, which has shown great success recently for image classification tasks [27, 40, 48]. These methods use soft pseudo-labels assigned to unlabeled frames directly, similar to knowledge distillation, and show that the richness of predictions (compared to a one-hot encoding) is crucial. In the pose estimation task, the heatmaps can play a similar role, as was demonstrated by Zhang et al. [45] in their work that distills heatmaps from an 8-stack hourglass model to a 4-stack one. However, this approach is not suitable to make

### Algorithm 2: AL + self-training w/ pseudo-labels

| Input: Unlabeled set $U$, previous pseudo-label set $P'$, target amount $M$; |
| Output: New pseudo-label set $P'$; |
| $P' \leftarrow \{\}$, $U' \leftarrow U$; $\triangleright$ Make a copy of $U$. |
| repeat |
| $F_{\text{min}} \leftarrow \arg\min_{F \in \{F \cup P'\}} \varepsilon_F$; $\triangleright$ No re-labeling. |
| $U \leftarrow U \setminus \{F_{\text{min}}\}$; |
| if $c_{F_{\text{min}}} = N$ then $\triangleright$ All views are inliers. |
| $\mathcal{P}' \leftarrow \mathcal{P}' \cup \{F_{\text{min}}\}$; |
| until $|\mathcal{P}'| = M$ OR $|U| = 0$; |
| $U = U \setminus \mathcal{P}'$; |
| return $\mathcal{P}'$ |
the best use of multi-view predictions, which is the direction that we explore.

To take full advantage of multi-view predictions, we project the 3D keypoints formed by triangulation back to each camera view, and assign pseudo-heatmaps to a set of frames with the most inliers and with the smallest triangulation error (Equation 8). These predictions are the most likely to be closest to the actual ground truth, thus they are excellent candidates to be used in self-training. We call this the pseudo-label set \( \mathcal{P} \), and we augment the training set to be \( \mathcal{P} \cup \mathcal{L} \) in each AL iteration. Similar to multi-view bootstrapping [35], our motivation is that by adding \( \mathcal{P} \) to the training set, the model is exposed to more varied data and can learn to generalize better.

Unlike AL, which in general favors samples with uncertain predictions, self-training requires the pseudo-labels to be confident and accurate, and careful selection is key. In [35], heuristics specific to hand anatomy are used to filter candidate frames, and additional human verification is conducted. Instead, our approach is fully automated. Specifically, for a pseudo-labeled frame to be considered for selection, we require that all views for all keypoints to be inliers during triangulation. Then, we take candidate frames with the smallest triangulation error \( \epsilon_F \), that are not already selected in the previous AL iteration, to form the pseudo-label set \( \mathcal{P} \). We found the latter heuristic to be critical in preventing drifting of the pseudo-labels. Our self-training algorithm is summarized in Alg. 2.

5. Experiments

5.1. Datasets and Evaluation

We use two large-scale multi-view benchmarks in our experiments: CMU Panoptic [17] is used for the body pose estimation problem, and InterHand2.6M [24] for the hand pose estimation problem.

The CMU Panoptic dataset has 9 sequences each having 31 camera views, and over 160,000 frames in total. We split them into 7 sequences for training, 1 sequence for validation and 1 sequence for test. We use 8 eye-level cameras for training and validation and 30 cameras\(^2\) for testing, including the 8 eye-level cameras used during training and validation. Sequences are temporally sub-sampled at 1 frame per second, and we end up with 5,008 training frames (40,064 images), 891 validation frames (7,128 images) and 771 test frames (23,130 images).

We use the 5fps version of InterHand2.6M. We split the dataset into 10 Captures for training, 1 Capture for validation and another 1 Capture for testing. For each capture, we use 16 cameras that are distantly-located during training and validation. Moreover, we use 32 cameras during testing. We end up with 12,123 training frames (193,968 images), 1,900 validation frames (30,400 images) and 1,762 test frames (56,384 images).

For each experiment, we conduct 3 randomized trials, and report the average and variance for the 3D Mean Key Point Error (MKPE) in millimeter (mm). As our backbone models predict 2D heatmaps for each view, to obtain the 3D prediction \( P^k \) we perform RANSAC triangulation with the 2D keypoint predictions \( l^k_i \) (argmax of the heatmap).

5.2. Implementation Details

We use two backbone models in our experiments: PoseResNet-50 [39] and HRNet [37]. For body pose estimation, both backbones are pretrained on the MPII [1] dataset. Since MPII and CMU Panoptic define different sets of keypoints, we initialize the weights of all layers except the output layer of the PoseResNet-50. For HRNet, we use the pretrained weights of the first 4 layers and randomly initialize the remaining layers. For hand pose estimation on InterHand2.6M, as no pretrained models for our setting are available, we randomly initialize all parameters from a normal distribution.

The annotation budget \( B \) in each AL iteration is set to 100 frames for CMU Panoptic, and 2,000 frames for InterHand2.6M. Regardless of the AL strategy, frames in the first iteration (200 frames for CMU Panoptic, 2000 frames for InterHand2.6M) are always randomly sampled, to provide a reasonable starting point. Furthermore, for the sake of reproducibility, all strategies start with the same set of randomly sampled frames. As for self-training, the pseudo-label amount is set to 10%-20% of \( B \).

In each AL iteration, we train the model from scratch on the current labeled dataset, as well as the pseudo-labeled dataset if available. Both backbones are trained with a batch size of 32 images per GPU for a total of 5000 optimization steps. We use Adam optimizer with a learning rate starting at 0.001, and decayed by 1/10 at the midpoint. Following the suggestion by Mittal et al. [23], we also experiment with data augmentation. We use the recently proposed RandAugment [7] to augment the training images for CMU Panoptic. On the other hand, RandAugment does not result in better performances on InterHand2.6M, which is much larger and contains more diverse poses.

5.3. Results

We experiment with both PoseResNet-50 and HRNet on CMU Panoptic, while for the much larger InterHand2.6M we report results from PoseResNet-50. To provide upper bounds on AL performance, for each experiment we train the corresponding model in a fully-supervised fashion and plot them as dashed lines. Below, we refer to random sampling as RAND, our proposed CoreSet-Poses strategy as OURS-CS, and Multi-View Consistency strategy as OURS-MC.

\(^2\)Video from 1 test camera is missing on CMU website.
Active learning. Results with PoseResNet-50 and HRNet on CMU Panoptic and PoseResNet-50 on InterHand2.6M are reported in Fig. 4. We do not use data augmentation in this experiment in order to highlight the differences in sampling strategies.

As we mentioned earlier, the RAND strategy can be a very strong baseline for difficult tasks like pose estimation. Although MPE has been reported to outperform RAND in single-view pose estimation [20], we observe that extending MPE or BSB to multi-view by aggregating per-frame uncertainty measures fails to beat RAND. Furthermore, simple forms of aggregation also fail to account for the geometric structure in the problem: it is possible that all 2D predictions are highly confident, while being geometrically inconsistent. In such cases, the frame would fail the triangulation, yet still score low enough with MPE and BSB to evade selection.

Next, our proposed strategies OURS-MC and OURS-CS outperform RAND consistently by a large margin in all scenarios. OURS-MC is on par with OURS-CS with the PoseResNet-50 backbone, but outperforms the OURS-CS with the HRNet backbone, despite only taking a fraction of the computational cost on the unlabeled set ($O(|\mathcal{U}|)$ vs. $O(|\mathcal{U}|^2)$). It is worth noting that our AL strategies can significantly reduce the amount of annotations with a trade-off of computation: OURS-MC achieves the performance of the fully-supervised upper-bound (100% annotated) with only 20% of annotated labels on CMU Panoptic.

AL + self-training. For this experiment, we focus on building a complete system: we use pseudo-labels to augment the training set in AL iterations, and we add data augmentation (except for InterHand2.6M as previously mentioned). For clarity, we pick the overall best method from the previous experiment, OURS-MC, and compare it against RAND. Results are shown in Fig 5.

Similar to the findings in [35], the additional self-training process provides consistent improvements to active learning. In our problem setting, we also observe the benefits
to be more pronounced at the early stages: for example, on CMU Panoptic with 10% data annotated, pseudo-labels reduce the gap between OURS-MC and fully-supervised baseline by 20% with the PoseResNet-50 backbone, and by around 50% for HRNet.

We find that pseudo-labels would negatively drift if the pseudo-labeled frames are sampled from $U$ instead of $U \setminus P$ in each iteration. Essentially, the same frames would keep re-entering $P$ and their labels become worse and worse. The number of frames to include, $M$, is also a crucial parameter. We present more ablative studies regarding these design choices in the appendix.

In summary, the above results show that our proposed AL strategies outperform the baselines steadily by a large margin, for both body and hand pose estimation. Additionally, with a carefully tuned self-training process, we can further improve label efficiency, with no extra cost.

5.4. Ablation Studies

Diversity of samples. We take one trial of our experiments with PoseResNet-50 on CMU Panoptic where $B = 50$, and study the distribution of sampled poses. Intuitively, sampling more diverse poses (while still following the data distribution) should help generalization. The ground truth 3D poses are shifted to have keypoint 2 (waist) at origin, and clustered into 10 clusters using K-means. We visualize the distribution of frames sampled by each AL strategy based on this clustering in Fig. 6, along with the entropy computed from the discrete distributions.

The long-tail nature of the pose distribution can be seen from Fig. 6(a): samples from RAND are unevenly distributed, and dominated by clusters 1 and 8 in particular, which are common standing poses. Compared to RAND, the MPE strategy actually samples common pose clusters more heavily, and frames from minority clusters (5, 7, and 9) are almost never sampled. Interestingly, the proposed OURS-MC, being based on an uncertainty measure, attains much better pose diversity (higher entropy), especially in the early iterations. This is likely because OURS-MC looks for geometric disagreements in the predictions, which are largely decoupled from the prediction targets (pose) and their distribution.

Accuracy of pseudo-labels. The main challenge with pseudo-labels is to ensure their accuracy and avoid drifting. In Fig. 7, we visualize the distribution of MKPE between pseudo-labeled frames and their actual ground truth, over several AL iterations. Our selection strategy maintains high accuracy ($< 1.5$ mm MKPE on average), resulting in consistent improvements over the course of AL.

6. Conclusion

In this paper, we propose an active learning framework for 3D pose estimation from multi-view input. We first
extend existing entropy-based single-view AL strategies to multi-view, and then propose two AL strategies utilizing 3D keypoint triangulation. The proposed CoreSet-Poses and Multi-View Consistency strategies consistently outperform all baselines, for both body and hand pose estimation problems. In addition, we introduce a self-training procedure using pseudo-labels, and further improve the label efficiency with minimal cost. Our complete system achieves state-of-the-art performance on CMU Panoptic and InterHand2.6M.

A limitation of this work is that, we limit our attention to the most established approach to 3D keypoint localization: per-view 2D prediction followed by triangulation. As such, the framework currently does not handle volumetric methods [16] and direct shape regression [18, 47]. We will explore these directions in future work.

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This appendix provides details and additional ablative studies of supporting experiments that are not presented in the main paper. In the following, we first present the visualizations of the pose clusters used in Fig. 6 in the main paper. Then, we discuss the design considerations in our pseudo-labeling algorithm. Next, we conduct ablative studies on self-training and data augmentation. Finally, we present our main results in the main paper (Fig. 4 and Fig. 5) from a different perspective to give a complete picture of the proposed methods.

A. Visualization of 3D Pose

As stated in our main paper, we study the distribution of sampled frames with respect to a discrete clustering of ground truth poses. In Fig. 6 of the main paper, we have visualized the distribution of frames sampled by each AL strategy, along with the entropy values computed from the discrete distributions. The ground truth 3D poses are shifted in 3D to have keypoint 2 (waist) at origin, and then we use K-means to cluster them into 10 clusters. Sample images from each cluster are visualized in Fig 8. The visualization confirms the findings that the proposed OURS-MC samples frames with better diversity in poses (higher entropy), especially in the early iterations.

B. Ablative Studies on Pseudo-labeling

In addition to the differences between the proposed self-training algorithm and the multi-view bootstrapping method [35] mentioned in the main paper, self-training produces new and more accurate pseudo-labels as the amount of human-annotated data increases with the AL iteration. Here, we detail the design choices for our specific pseudo-labeling strategy.

We have considered the following three strategies. In Fig. 2, we plot the distributions of MKPE between pseudo-labels in \( P \) and their corresponding ground truth, over the first four AL iterations.

1. Fig. 9a. Enlarge \( P \) in each AL iteration with the top pseudo-labeled frames. (Selection criterion is discussed in the main paper.)

2. Fig. 9b. Keep the size of \( P \) constant, and pick the top pseudo-labeled frames in each AL iteration.

3. Fig. 9c. Alternating schedule (described in the paper): in each AL iteration \( i \), pick top frames that are not already in \( P_{i-1} \) from the last iteration, to form \( P_i \) for the current iteration.

To begin with, the first strategy is easily susceptible to label drifting, as more and less accurate pseudo-labels would enter \( P \) and pollute the training set over time. Somewhat surprisingly, the second strategy of keeping the size of \( P \) constant does not work either. We have empirically verified that, in this scenario, the set of frames selected to form \( P \) is very stable across iterations. Then, with every passing iteration, this strategy essentially re-labels a same set of frames, using a new model trained on a training set containing them, and the errors would accumulate. Note that in this case, the model needs to achieve zero training error on \( P_i \) in every AL iteration \( i \) for the pseudo-labels to remain the same, let alone improve.

Lastly, we found the alternating schedule to be robust against label drifting. In each iteration \( i \), all frames in \( P_{i-1} \) are evicted, and prevented from re-entering until the next iteration. This effectively avoids the above error accumulation problem, as a model trained on frames from \( P_i \) (among others) is never used to infer pseudo-labels on the same set of frames.

C. Ablative Studies on Data Augmentation

We present the effect of RandAugment on CMU Panoptic in Fig. 10 that is presented separately in Fig. 4 and Fig. 5 in the main paper. For each training image, we randomly apply two of the following augmentation operations:

- Rotate (within ±30°)
- AutoContrast
- Equalize
- Invert
- Posterize
- Solarize
- Color
- Contrast
- Brightness
- Sharpness

In the case of image rotation, we also rotate the target heatmap by the same amount. All other operations are label-preserving and do not alter the heatmap.

Overall, we find that the choice of AL strategy outweighs data augmentation. For example, OURS-MC without data augmentation even outperforms RAND + RANDAUG with PoseResNet-50 backbone. For OURS-MC with the HR-Net backbone, the performance gain from data augmentation gets smaller as it saturates more quickly towards the fully-supervised baseline.

Additionally, we compare performances of self-training on RAND and OURS-MC without RandAugment and present the comparison in Fig. 11 to complement Fig. 5 in the main paper. Self-training suffers from the fact that no
D. Data augmentation, self-training, and AL

The comparison between AL, AL+ST, AL+RANDAUG, and AL+ST+RANDAUG for different backbones and AL strategies are shown in Fig. 12. Data augmentation would improve the label-efficiency of an AL framework, especially at an earlier stage. Larger performance gains can be observed on RAN and PoseResNet-50 based AL systems.

Self-training shows possible additional gains for all variations of experiments with different AL strategies and data augmentation. However, performance improvements from self-training saturates with higher performance models, i.e. when the performance gets closer the upper bound (a fully-supervised model). Nonetheless, self-training can provide additional gains “for free” in our AL framework, since it does not incur additional computational or annotation costs.

Finally, as we stated earlier, the choice of AL strategy outweigh data augmentation and self-training in terms of the label-efficiency. Our proposed OURS-MC and OURS-CS would outperform other compared ALs under all different setups for pose estimation problems.
Figure 10. Effects of data augmentation using RandAugment on CMU Panoptic. OURS-MC achieves better label efficiency than RAND + AUG without data augmentation.

Figure 11. AL + self-training (ST) on CMU Panoptic without data augmentation. X-axis: percent of dataset labeled. FS: fully-supervised baseline. When combined with AL, our automated self-training strategy enables additional label efficiency gains at no extra computational cost, especially for RAND and during the early stages of training. Best viewed in color.
Figure 12. Comparison between AL, AL + self-training (ST), AL + Randaug, and AL + ST + Randaug on CMU Panoptic. X-axis: percent of dataset labeled. FS: fully-supervised baseline. When combined with AL, our automated self-training strategy enables additional label efficiency gains at no extra computational cost, especially for RAND and during the early stages of training. Best viewed in color.