Multi-initialization Optimization Network for Accurate 3D Human Pose and Shape Estimation

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\textbf{ABSTRACT}

3D human pose and shape recovery from a monocular RGB image is a challenging task. Existing learning based methods highly depend on weak supervision signals, e.g. 2D and 3D joint location, due to the lack of in-the-wild paired 3D supervision. However, considering the 2D-to-3D ambiguities exist in these weak supervision labels, the network is easy to get stuck in local optima when trained with such labels. In this paper, we reduce the ambiguity by optimizing multiple initializations. Specifically, we propose a three-stage framework named Multi-Initialization Optimization Network (MION). In the first stage, we strategically select different coarse 3D reconstruction candidates which are compatible with the 2D keypoints of input sample. Each coarse reconstruction can be regarded as an initialization leads to one optimization branch. In the second stage, we design a mesh refinement transformer (MRT) to respectively refine each coarse reconstruction result via a self-attention mechanism. Finally, a Consistency Estimation Network (CEN) is proposed to find the best result from multiple candidates by evaluating if the visual evidence in RGB image matches a given 3D reconstruction. Experiments demonstrate that our Multi-Initialization Optimization Network outperforms existing 3D mesh based methods on multiple public benchmarks.

\textbf{KEYWORDS}

3D human reconstruction, 3D pose estimation, deep learning

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\textbf{CCS CONCEPTS}

- Human-centered computing: · Computing methodologies
- Shape inference: Reconstruction:

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1 INTRODUCTION

With the help of the recent developed parametric model of the human body, monocular image 3D human pose and shape reconstruction has achieved great advancements in recent years [6, 20, 21, 30]. Nowadays optimization-based and regression-based approaches are two representative research branches of this field. Optimization-based approach optimizes model parameters by fitting the human body model to 2D keypoints or other kinds of weak supervision labels, e.g. part segmentation \[44\], densepose \[12, 45\]. However, optimizing these weak labels inevitably suffers from 2D-to-3D ambiguity problem. For example, 2D observations lack depth information, and 3D keypoints lack the information of rotation angle on limb axis. Therefore, optimization-based approaches are sensitive to the choice of initialization and easy to converge into a local optimum or unrealistic result.

Regression-based approaches apply a deep CNN to regress the 3D human pose and shape parameters from a RGB input image. Due to the difficulty of in-the-wild 3D training data acquisition, existing regression based methods also heavily rely on the supervision of weak labels, including 2D projection loss \[24\], 3D keypoints loss \[15\], body silhouette loss \[46\] and densepose loss \[34\]. Since each weak label corresponds with many possible 3D bodies, network with a single output cannot always select the real 3D reconstruction from different possible results to match with the weak supervision label, leading to the unsatisfied training quality.

In general, both two kinds of approaches suffer from the ambiguity problem caused by the weak supervision. In this paper,
we aim to solve this issue and discover the most accurate result from multiple possible 3D reconstructions which are matched with the same weak label. Instead of using a single network that outputs a single reconstruction result in one propagation, we decompose the internal analysis process of network and propose a novel three-stage framework named Multi-Initialization Optimization Network (MION) to predict the most appropriate reconstruction result through multiple optimization branches.

Specially, in the first stage, we design a reconstruction candidate optimization strategy to optimize several different coarse reconstruction candidates for each sample. To achieve this, we first generate a human mesh candidate pool by clustering a big human motion capture dataset combination [27]. Then for each candidate in the pool, we optimize its camera parameters by fitting the 3D mesh model to a weak observation of the given sample. After this, the optimized candidate with a relative small fitting loss can be selected to get into the next inference stage and regarded as an initialization to start one optimization branch. Moreover, we accelerate the parameter optimization process by directly computing its closed-form solution. Based on the multiple candidates, our method has more possibilities to avoid the local optimal and find the real 3D reconstruction.

In the second stage, we continue to push each optimization branch forward and design a mesh refinement transformer (MRT) to refine each coarse reconstruction candidate. This transformer framework has two advantages. Firstly, to achieve a refinement process, the initial 3D reconstruction information from the last stage can be effectively encoded into the transformer by a novel Projected Normalized Coordinate Code (PNCC) positional encoding. Secondly, transformer can adaptively learn the non-local relationships between different body joints during training stage, which is significant for enhancing the body structure prediction ability.

Finally, the refined 3D reconstruction candidates from different optimization branches need to be aggregated to one result. In the last stage, a Consistency Estimation Network (CEN) is proposed to distinguish if the form of each 3D reconstruction matches the visual evidence in the input image and select the best 3D reconstruction result. In order to get rid of the limitation of label ambiguity, CEN benefits from a specific data synthesis strategy which generates the accurate 3D ground-truth for each training sample. The overview of our Multi-Initialization Optimization Network (MION) is shown in Fig. 1.

Our contributions can be summarized as follows:

- In order to deal with the issue that weak supervision labels have ambiguities. We propose a novel three-stage framework named Multi-Initialization Optimization Network (MION) to predict appropriate human pose and shape reconstruction through multiple optimization branches.
- In our MION, instead of predicting a single result, for each sample, we calculate multiple coarse reconstruction candidates as the initializations to start different optimization branches. Compared with a single prediction, multiple candidates give more possibilities to avoid the local optimal and find the real 3D reconstruction.
- Given the different initial reconstruction candidates, we design a mesh refinement transformer (MRT) with a novel Projected Normalized Coordinate Code (PNCC) positional encoding to further refine each coarse reconstruction via a self-attention mechanism. Then a Consistency Estimation Network (CEN) is proposed to select the best 3D reconstruction result from all the optimization branches.
- Both qualitative and quantitative experiments show that our MION significantly improves the performance of monocular image 3D human reconstruction and achieves the state-of-the-art result among other methods.

2 RELATED WORKS

Optimization based methods. With the development of parametric 3D human body model, such as SCAPE [3], SMPL [25], optimization based 3D human reconstruction method becomes an important branch in the research community. This kind of method infers 3D reconstruction by fitting a parametric model to match the given 2D observation. Early optimization methods [1, 36] fit the human body model by the manually generated keypoints and silhouettes labels. These methods rely on manual intervention and
generalize badly to images in the wild. Federica et al. [5] propose first automatic 3d human model reconstruction method SMPLify which fits SMPL model to the 2D keypoints predicted by CNN detector [33]. Meanwhile, objection function contains different regular- ulation terms to ensure the optimization can produce a plausible result. In order to further improve the performance, more supervision information are incorporated into the optimization target, such as silhouette [22], scene constrains [48] and multi-view [14].

Generally, these optimization based methods are sensitive to the choice of initialization and tends to have a slow optimization speed. Meanwhile, the optimization process only converges to one local optimal result by the 2D observation input without appearance information. Thus it suffers from the problem of label ambiguities.

**Learning based methods.** Another representative method is learning base reconstruction method, which learns a human model parameter regressor by a data-driven way. Because of the lack of in-the-wild 3D reconstruction paired training data. Existing methods focus on the weak supervision way to solve this issue. HMR [18] directly regresses SMPL parameters from images by a CNN and adds iterative regression to further improve the accuracy. It also proposes an adversarial prior in case the reconstruction is not realistic. SPIN [20] incorporates a optimization into the network learning process, where the predicted parameter is refined by a optimization process to further supervise the network. These two methods both apply 2D and 3D keypoints as weak supervision signal. Inspired by the dense correspondence representation used in DensePose [12], various learning based methods [11, 34] regard IUV map as intermediate representation or weak supervision label for improving the regression CNN. On the other hand, in order to remove the limitation of SMPL parameter space, many learning based methods do not rely on the parametric model and directly regress the coordinates of each vertices on the mesh. BodyNet [39] regresses a volumetric representation of 3D human by a Voxel-CNN. Densebody [46] and DaNet [49] use a UV position map to represent 3D human body.

All the aforementioned learning based methods rely on weak supervision label during training stage. It is flawed in that the label with ambiguities cannot always lead the network to predict the real reconstruction. In this work, with the same weak supervision labels, we propose a multi-path optimization based reconstruction framework to reduce the possibility of getting into local optimal. In order to deal with the occlusion cases with ambiguities, Biggs et al. [4] also propose to predict a candidate set which contains different possible reconstruction results. However, their network is only trained on the single Human3.6m dataset [15] where each sample already has 3D reconstruction ground-truth. Thus it still cannot solve the problem raised by the weak label.

**Synthetic data.** Since it is difficult to collect in-the-wild samples with 3D ground-truth, synthetic data plays an important role in 3D human pose and shape estimation task. Pavlakos et al. [32] adopt joint heatmap and silhouette as intermediate representation and design two decoders to respectively predict the pose and shape parameter from the above two representations. Without introducing appearance information, the decoders can be trained by synthetic data. Xu et al. [43] propose a network to decode human body from a synthetic IUV map. Although the above methods benefit from the abundant synthetic training data, the inference process from weak label to 3D ground-truth is an ambiguity task which cannot be solved by even human.

Existing synthetic data based methods usually ignore the appearance information. Different from them, we utilize synthetic data to help the network discriminate if the visual evidence in RGB image matches a given 3D reconstruction, which can be used to select the best result from multiple candidates.

**Human structure dependence.** Human body structure in natural world has a strong prior, which builds the dependencies between different parts of the whole human body. Some existing methods explicit model such dependencies in their learning framework. CMR [21] apply a Graph-CNN [19] to model the interactions between different vertices in the inference framework. METRO [23] replaces Graph-CNN with a Transformer encoder [41] to model the interactions. However the query in its Transformer only contains the global feature of the input image and abandons detailed local information. In this work, we apply a full encoder-decoder Transformer structure which maintains the local image appearance information to refine the body structure.

### 3 METHOD

As above mentioned, the whole framework of our Multi-Initialization Optimization Network (MION) has three stages. In this section, we explain the details of each stage in sequence.

#### 3.1 reconstruction candidate selection

For common traditional CNN regression based 3D human reconstruction frameworks, training with weak supervision labels might make the network fall into local optimum. As long as the predicted 3D reconstruction matches with the provided weak supervision labels, for e.g., the 2D landmarks or masks, the network training will stop no matter if the current prediction is correct. In this work, we aim at designing a new three-stage framework begins with multiple initializations.

At our first stage, considering that nowadays 2D body keypoints telenology already achieves a high performance. For each training sample, we first utilize HRNet [38] to detect its 2D body keypoints which represents the weak supervision label. Then we expect to coarsely locate all the representative possible solutions according to this 2D keypoints in the whole solution space. To this end, a candidate selection strategy is proposed to calculate multiple possible 3D reconstruction candidates for each sample. Each candidate can be regard as an initial optimization point.

Specifically, we regard a huge human motion capture dataset named AMASS [27] as the source of our candidate and assume it contains all the possible human poses shown in natural images. Each 3D human mesh sample in AMASS is expressed by a set of SMPL [25] parameters. SMPL is a parametric model for human body mesh representation, which maps the shape parameters \( \beta \in \mathbb{R}^{10} \) and the pose parameters \( \theta \in \mathbb{R}^{72} \) to the human body mesh \( M \in \mathbb{R}^{V \times 3} \) by a linear model. Based on this, to generate the reconstruction candidates of a specific sample, we first optimize a perspective projection matrix for each candidate in AMASS by fitting the 3D keypoints from candidate meshes to the 2D keypoints from the given sample. Then the candidate with a low fitting loss
value can be selected as an possible solution to get into the next inference stage.

However, AMASS is a huge candidate dataset. It is unrealistic to optimize all the perspective projection matrix parameters for each candidate because of the high computational cost. In order to reduce the cost, we calculate the representative candidate bodies from the whole AMASS dataset by k-means clustering. Then the approximate optimal solution can be directly selected from the cluster centroids. In this work, we set the number of pose parameter clusters to 10000 and the number of camera orientation parameter clusters to 30, making the whole candidate pool contain 300000 members.

Fig 2(a) visualizes different cluster centroids of camera orientation parameter. The optimization target function can be defined as:

$$\max_T \mathcal{L} = \| \Pi_K (J_{3d}^{cand}, T) - J_{2d}^{gt} \|_2^2$$  \hspace{1cm} (1)

$$\Pi_T (J_{3d}^{cand}, T) = \begin{bmatrix} f & 0 & c_1 \\ 0 & f & c_2 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} f_T \frac{f_T + f_s}{f_s} \\ f_s \frac{f_T + f_s}{f_s} \\ 1 \end{bmatrix}$$  \hspace{1cm} (2)

where $J_{3d}^{cand} \in \mathbb{R}^{N \times 3}$ denotes the coordinates of a set of 3D keypoints regressed from a candidate mesh, and $J_{2d}^{gt} \in \mathbb{R}^{N \times 2}$ is the corresponding 2D keypoint. $\Pi_K$ is the perspective projection function from 3D to 2D. $T$ is camera translation parameters for optimizing. $f$ is the pre-defined focal length of camera, $c_1$ and $c_2$ are the pre-defined camera center parameters. Since the camera orientation parameters and pose parameters are already known, only the three camera translation parameters are required to be optimized. To further accelerate the computing speed, we directly compute the closed-form solution of the ternary homogeneous linear equations.

After fitting all the 3D candidates to the given 2D keypoints, we select a set of candidates with low fitting loss and a large pose variance, although the selected candidates match with the same 2D keypoints, they still might distribute dispersedly in the pose solution space to give more initializations for avoiding the local optimal. The selected reconstruction candidates of two samples is shown in Fig. 2(b).

### 3.2 Mesh Refinement Transformer

Most selected candidates from the first stage are corasely optimized and need further refinement. In order to alleviate local optimal solutions and increase the possibility of finding the real 3D reconstruction, in this stage, we provide an individual optimization branch to refine each coarse candidate. Each branch only focuses on refining the details to make the initialization more compatible with the weak supervision label.

Inspired by a series of recent vision transformer (ViT) works [6, 7, 10, 50], we determine to use the ViT architecture which has two advantages for the body reconstruction refinement task. Firstly, ViT follows a sequence prediction format by regarding the input image as a sequence of different local patches. This manner allows the whole inference framework pay attention on the details of each local patch, which is suitable for the refinement task. Secondly, the self-attention mechanism of transformers, which explicitly models all pairwise interactions between elements in a sequence makes our architectures particularly suitable for learning the relationship of different body parts.

To construct our transformer network, we first use a backbone network (e.g. resnet) to extract image feature [7]. Then three deconvolution layers are added to the top layer of backbone to upsample the feature map and recover more spatial information. Finally we flatten feature map to make a feature vector sequence and input it into a transformer encoder, as shown in Fig. 4. Thus each element in the sequence represents a local patch of input image.

In order to refine the SMPL parameter of a given candidate, we need to encode the candidate as a 2D map for CNN, which
We regard the three channel normalized coordinate code (NCC) of \( p_{\text{pos}} \) where \( \theta \) is denotes the spatial position index on PNCC map, \( \mathbf{S} \in \mathbb{R}^{V \times 3} \) is the point cloud tensor of mean SMPL model, the sine and cosine functions used in original transformer positional encoding [41] are applied in Fig. 3. After we get PNCC map, the sine and cosine functions can be represented to transfer the 3-channel PNCC into the final positional encoding used in 3D face alignment work 3DDFA [51], we propose a Projected Normalized Coordinate Code based positional encoding (PNCC-PE) which encodes the initial SMPL parameter information (PNCC) into the transformer input. Based on this, PNCC-PE builds the positional encoding of decoder is the refined pose parameter. Meanwhile, we add two MLP networks which respectively predict the camera parameter and shape parameter from the top sequence feature. Therefore, all the weak supervision labels (e.g. 2D keypoints) can be involved into the training by a perspective projection. The overview of our MRT is shown in Fig. 4.

The total loss of our MRT is as follows:

\[
L = w_1 \cdot L_{\text{smpl}} + w_2 \cdot (L_{D_j}^3 + L_{D_j}^2)
\]

\[
L_{\text{smpl}} = \| \theta_{\text{reg}} \cdot \beta_{\text{reg}} - \| \theta_{\text{gt}} \cdot \beta_{\text{gt}} \|_2^2
\]

\[
L_{D_j}^3 = \| f_{\text{gt}} - R(V_{\text{reg}}) \|_2^2
\]

\[
L_{D_j}^2 = \| g_{\text{gt}j} - \Pi_K (R(V_{\text{reg}})) \|_2^2
\]

where \( L_{\text{gt}}, L_{D_j}^3 \) and \( L_{D_j}^2 \) are the vertex loss, 3D joint loss and 2D joint projection loss. \( w_1 \) and \( w_2 \) are the weights of different loss functions.

### 3.3 Consistency Estimation Network

Applying multiple initializations usually leads to different optimized results. Some results might fall into local optimum and some results might be close to the real 3D ground-truth. Therefore, it is necessary to find the best reconstruction candidate among all the refined candidates. To this end, in the last stage, we consider the optimum path selection as a scoring problem and propose a Consistency Estimation Network (CEN) to solve this problem by utilizing the synthesis training data SURREAL [40].

The target of the network is to identify if one 3D reconstruction matches the visual evidence of input human image. For this purpose, we need a dataset with ground-truth 3D body mesh, which can be achieved by data synthesis. Specifically, when generating a synthesis sample, we select one training sample and randomly pick two candidates from its candidate collection generated in the.
which has the largest pose parameter distance with the selected

where \( i \) is the index of one vertice on the body point cloud, \( P_{\text{reg}} \) is the \( i \)th output of our CEN, meaning the regressed score of \( i \)th vertice. \( \| V_{gt}^i - V_{\text{cand}}^i \|_2 \) denotes the distance between the PNCC encoding body and RGB image encoding body in a normalized point cloud space. During the inference stage, we compute the average distance of all the output vertice distance and choose the reconstruction result in the optimization branch with the lowest distance as our final result.

3.4 Implementation details

For our candidate selection strategy in the first stage, after we fit all the candidates to the 2D keypoints of current sample, all the candidates with a fitting loss lower than 2000 are chosen to be an available candidate. Then we iteratively select the candidate which has the largest pose parameter distance with the selected candidates and put it into the final candidate collection.

For the Mesh Refinement Transformer (MRT), the backbone network adopts the architecture of ResNet-50 [13]. Note that we remove the last fully connection layers in original ResNet-50 and add three deconvolution layers to make a fully convolution network (FCN) as our backbone. The FCN receives the 224×224 input image and produces 56 × 56 feature maps with 384 channels. In order to match with image feature, the rendered PNCC has the same resolution of 56 × 56 and each channel of PNCC is transferred into a position encoding map with 128 channel. During MRT training stage, the loss weight of SMPL parameter regression is set to 1 and the loss weight of 2D keypoints and 3D keypoints regression is set to 5. The data augmentation techniques includes rotation \([-60^\circ, 60^\circ]\) color jittinging \([0.6, 1.4]\) and flipping, are applied randomly to input images. We adopt the AdamW [26] optimizer with an initial learning rate of \(5 \times 10^{-5}\) to train the MRT model, and reduce the learning rate to \(5 \times 10^{-6}\) after 20 epochs. The training process stops after 60 epochs. MRT is trained on 4 Titan X GPUs with a batch size of 64. During training and inference stage, all the 2D keypoints used in the first stage are predicted by the HRNet-W48 network in MMPose [9].

For training the Consistency Estimation Network (CEN), we adopts a ResNet-34 network as backbone. The initial learning rate is set to 0.01. We train our model for 100 epochs and lower the learning rate by a factor of 10 after 50 epochs.

4 EXPERIMENTS

This section focuses on the empirical evaluation of the proposed method. First, we present the datasets and evaluation metrics that we employed for quantitative and qualitative evaluation. Then, we conduct extensive ablation experiments and comparsion experiments to verify the effectiveness of our method.

4.1 Datasets and Evaluation Metrics

The networks mentioned in this work are trained on various datasets. Specifically, the training sets of our Mesh Refinement Transformer (MRT) is dominated by weak supervision datasets, including Human3.6M [15], LSP [16], MPII [2], COCO [24], LSP-Extended [17], MPI-INF-3DHP [28]. Our Consistency Estimation Network (CEN) is trained on UP-3D [22] and SURREAL [40] which have 3D ground-truth. We conduct the evaluations on the test set of Human3.6M and 3DPW [42]. To get a pair comparison with earlier state-of-the-art method, we use the same evaluation metric with SPIN [20].

**Human3.6M:** It is an indoor benchmark for 3D human pose estimation. It includes multiple subjects performing actions like Eating, Sitting and Walking. Following typical protocols, e.g., [20], we use subjects S1, S5, S6, S7, S8 for training and we evaluate on subjects S9 and S11.

**LSP:** LSP with its extension is a standard 2D human pose estimation dataset which is collected by the images from sports activities. This dataset has large variance in terms of appearance and especially articulations. Each person in this dataset is labeled with total 14 joints which are used for weak supervision by the perspective projection.

**MPII:** MPII is a 2D human pose estimation dataset which covers a wide range of human activities with 25k images containing over 40k people. We use it for weak supervision during training stage.

**MPI-INF-3DHP:** It is a dataset captured with a multi-view setup mostly in indoor environments. No markers are used for the capture, so 3D pose data tend to be less accurate compared to other datasets. We use the provided training set (subjects S1 to S8) for training.

**UP-3D:** It is a recent dataset that collects color images from 2D human pose benchmarks. SMPLify [5] is utilized to generate 3D human shape candidates for each sample. The candidates were evaluated by human annotators to select only the images with good
When applying more candidates into the whole framework, the performance is continuously improved until the number of candidates reaches 5. This phenomenon indicates that applying multiple different optimization initializations is an effective way to alleviate falling into local optimum and improve the overall performance in 3D human reconstruction task.

### Effectiveness of PNCC position encoding
To demonstrate the superiority of our Projected Normalized Coordinate Code based positional encoding (PNCC-PE) over traditional position encoding method, we further conduct experiment to investigate the impact of PNCC-PE. Tab. 2 shows the ablation study on Human3.6M. MION (w/o PNCC-PE) replaces the PNCC-PE by the traditional sinusoidal position encoding [41]. As we can see, compared with traditional position encoding, the proposed PNCC-PE significantly improve the performance on 3D human reconstruction task: 56.88% vs 61.14%. We attribute this phenomenon to the initialization information brought by the PNCC-PE makes the joint queries of decoder easily focus on the corresponding local patch feature.

### Effectiveness of Consistency Estimation Network
Consistency Estimation Network (CEN) is one of the key steps in our pipeline. As indicated in Tab. 3, compared with random selection strategy MION w/o CEN, our CEN reduces the MPJPE error from 62.47% to 56.88%, which proves the effectiveness of CEN on predicting the consistency between RGB image and given human body parameter. We also evaluate the upper bound of CEN by always selecting the result with lowest error. As we can see, the performance gets further improvement: from 56.88% to 52.17%, meaning that the multiple initialization method has the potential to achieve a better result.

### 4.2 Ablation experiment
To evaluate the effectiveness of each component proposed in our method, we conduct ablation experiments on Human3.6M under various settings.

| Method            | MPJPE | PA-MPJPE |
|-------------------|-------|----------|
| 1-path (MRT)      | 62.31 | 45.48    |
| 2-path (MION)     | 61.59 | 44.75    |
| 3-path (MION)     | 59.98 | 42.81    |
| 4-path (MION)     | 58.78 | 41.86    |
| 5-path (MION)     | 56.88 | 41.59    |
| 6-path (MION)     | 58.71 | 42.02    |

Table 1: Analysis of the difference of using different number of optimization paths. MPJPE and PA-MPJPE are used as evaluation metric.

### Comparison experiment

#### Comparison on the In-door Dataset.
We evaluate the performance of our methods on the in-door dataset Human3.6M in terms of 3D pose estimation accuracy. We train our model following the setting of SPIN [20] and utilize Human3.6M, LSP, MPII, COCO and MPI-INF-3DHP as the training set. Quantitative results are reported in Tab. 4. It shows the results of our approach against other the state of the art methods which output a full mesh of the human body (SMPL, in particular). As we can see, training with the same amount of weak supervision label, our method significantly outperforms other methods on MPJPE metric and achieves a competitive performance on PA-MPJPE metric.

#### Comparison on In-the-wild Dataset.
Since the lack of in-the-wild 3D supervision labels, reconstructing 3D human model on in-the-wild outdoor images is much more challenging due to factors such as extreme poses, appearance variations and heavy occlusions. We conduct evaluation experiments on 3DPW datasets to compare...
our MION with previous 3D human pose and shape estimation methods. As indicated in Tab. 5, we can see our method outperforms all the other methods under the challenging scenarios, which proves the robustness and generalization of our framework.

### 4.4 Analysis experiment

**Running speed analysis.** We evaluate the inference speed of our method and the state of the art method SPIN [20] on the same hardware platform (one Titan X Pascal GPU). Both two methods apply the same ResNet50 as the backbone. The whole running time of our MION is 128 ms. Note that our candidate selection process from 300k candidate pool only takes 18 ms, which is much less than the following CNN inference stages spend (63 ms for the second stage, 47 ms for the third stage). In general, since the running time of SPIN is 59ms and we perform much better than SPIN on 3DPW dataset, 52.34 vs 59.2 in terms of PA-MPJPE, we believe it is worth taking more time for this better solution.

**The performance on shape recovery.** In order to verify the effectiveness of our method on shape recovery, we evaluate the shape accuracy of three different methods on 3DPW dataset, including baseline (1-path), MION (5-path) and the state of art method SPIN. We apply two evaluation metrics in the experiment, the first one is mean vertex L2 error of two body clouds, the second one is the L2 distance between two SMPL shape parameter vectors. The results are shown in Tab. 6

### 5 CONCLUSION

This work aims to solve the 2D-to-3D ambiguity problem of training with weak supervision labels. Instead of training a regression network with one output, we propose to apply multiple initializations and different optimization branches to avoid the network easily get stuck in local optimum. Specifically, we propose a three-stage framework named Multi-Initialization Optimization Network (MION). In the first stage, we strategically select different coarse 3D reconstruction candidates which are compatible with the 2D keypoints of input sample. Regarding each candidate as an initialization, in the second stage, we design a mesh refinement transformer (MRT) to respectively refine each coarse reconstruction result via a self-attention mechanism. Finally, a Consistency Estimation Network (CEN) is proposed to find the best result from multiple candidates by evaluating if the visual evidence in RGB image matches a given 3D reconstruction. Experiments demonstrate that our framework outperforms existing 3D mesh based methods on multiple public benchmarks. Future work can focus on improving the efficiency of this framework.

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### Table 4: Comparison with state of the art on Human3.6M dataset. MPJPE and PA-MPJPE are used as evaluation metric.

| Method         | MPJPE | PA-MPJPE |
|----------------|-------|----------|
| SMPLify [5]    | -     | 82.3     |
| NBF [30]       | -     | 59.9     |
| HMR [18]       | 88.0  | 56.8     |
| GraphCMR [21]  | -     | 50.1     |
| Holopose [11]  | 64.3  | 50.6     |
| TexturePose [31]| -  | 49.7     |
| DenseRaC [43]  | 76.8  | 48.0     |
| Pose2Mesh [8]  | 64.9  | 47.0     |
| SPIN [20]      | 62.3  | 41.1     |
| **MION**       | **56.88** | **41.59** |

### Table 5: Comparison with state of the art on 3DPW dataset. MPJPE and PA-MPJPE are used as evaluation metric.

| Method         | MPJPE | PA-MPJPE |
|----------------|-------|----------|
| HMR [18]       | -     | 81.3     |
| GraphCMR [21]  | -     | 70.2     |
| STRAPS [35]    | -     | 66.8     |
| SPIN [20]      | -     | 59.2     |
| Pose2Mesh [8]  | 89.2  | 58.9     |
| I2LMeshNet [29]| 93.2  | 57.7     |
| Song et al. [37]| -  | 55.9     |
| **MION**       | **81.98** | **52.34** |

### Table 6: The comparison of different methods in terms of shape recovery accuracy. Mean vertex L2 error and Shape Parameter L2 error are used as evaluation metric.

| Method         | Vertex L2 error | Shape Param L2 error |
|----------------|-----------------|----------------------|
| Baseline (1-path) | 0.142           | 5.383                |
| SPIN            | 0.116           | 4.398                |
| **MION (5-path)** | **0.094**       | **3.227**            |
