Project-4: Hand Pose Estimation

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Autumn, 2024

Outline

- What is hand pose?
  - 2D keypoints
  - 3D keypoints
  - Mesh representation
- How to estimate hand pose?

2D Hand Keypoints

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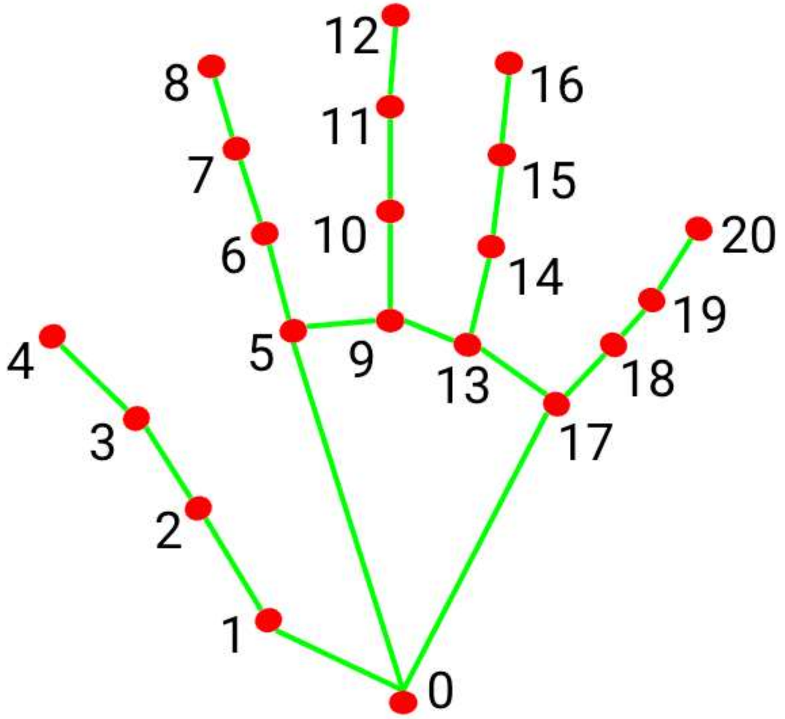

0. WRIST
1. THUMB_CMC
2. THUMB_MCP
3. THUMB_IP
4. THUMB_TIP
5. INDEX_FINGER_MCP
6. INDEX_FINGER_PIP
7. INDEX_FINGER_DIP
8. INDEX_FINGER_TIP
9. MIDDLE_FINGER_MCP
10. MIDDLE_FINGER_PIP
11. MIDDLE_FINGER_DIP
12. MIDDLE_FINGER_TIP
13. RING_FINGER_MCP
14. RING_FINGER_PIP
15. RING_FINGER_DIP
16. RING_FINGER_TIP
17. PINKY_MCP
18. PINKY_PIP
19. PINKY_DIP
20. PINKY_TIP

2D Hand Keypoints

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How to estimate 2D Hand Keypoints?

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Input： RGB image

How to define output?

How to estimate 2D hand keypoints?

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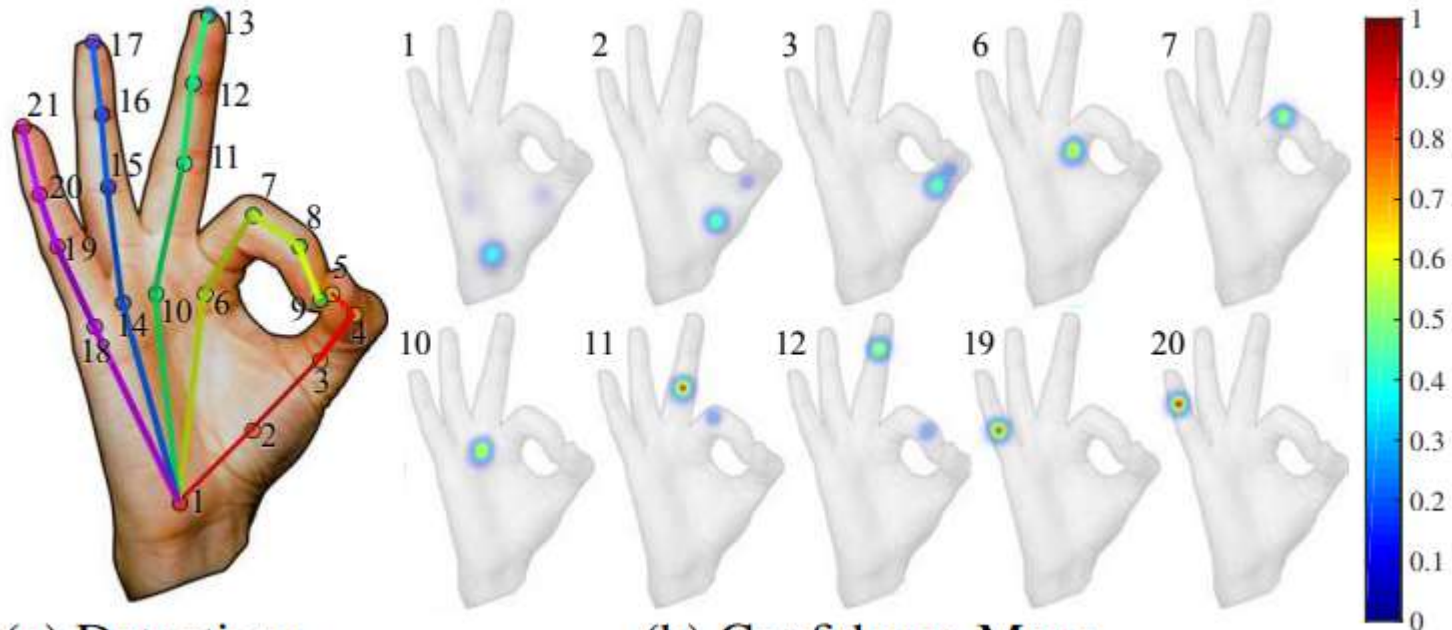
Input

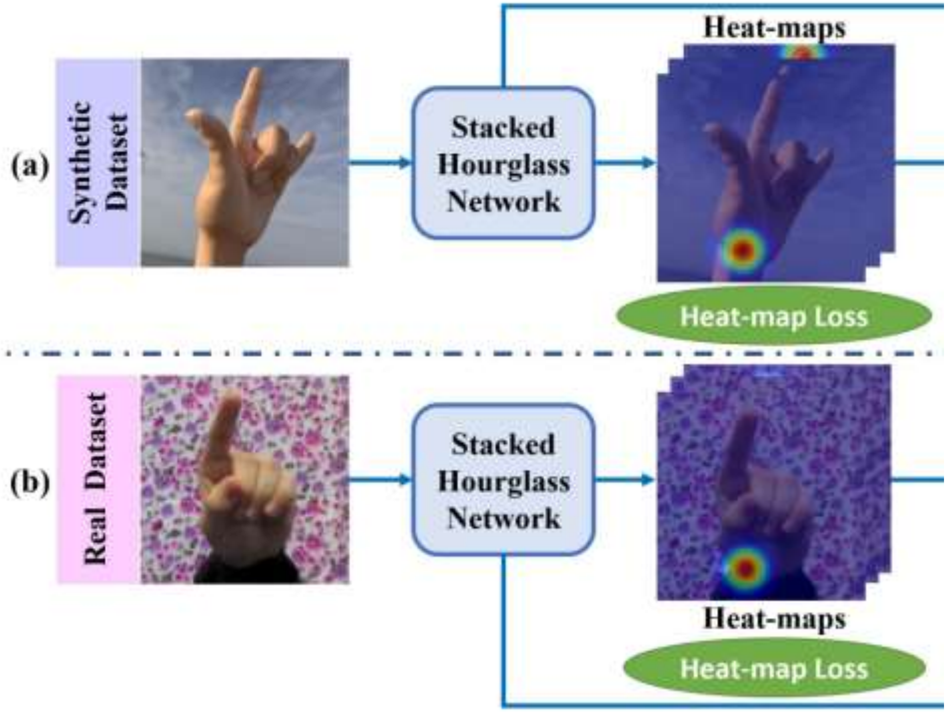
Output



(a) Detections

(b) Confidence Maps

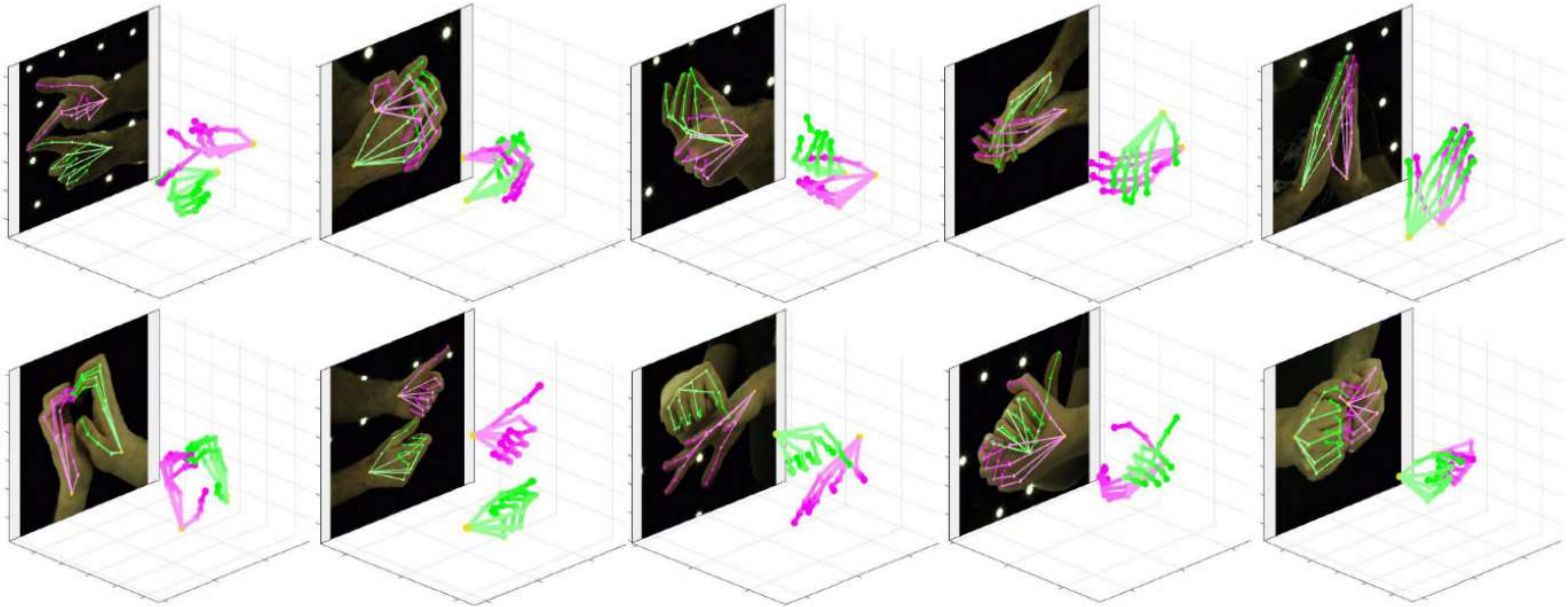
How will you design the network?



$$\mathcal{L}_{\mathcal{H}} = \sum_{j=1}^{J} \left\| \mathcal{H}_j - \hat{\mathcal{H}}_j \right\|_2^2$$

What are 3D Hand Keypoints?

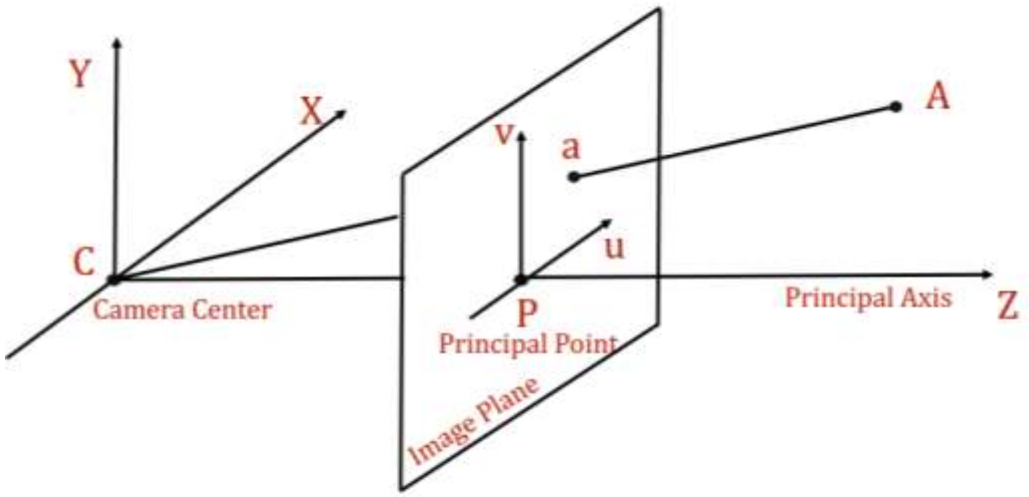
3D Hand Keypoints

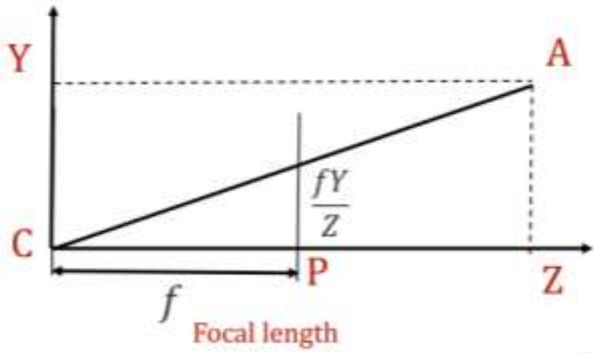


Perspective projection

Assumptions made:

- Principal point **at origin** of image plane
- Camera at center of world coordinates
- Square pixels





$$(X, Y, Z)^T \mapsto (u, v)^T = \left(\frac{fX}{Z}, \frac{fY}{Z}\right)^T$$

Euclidean Coordinates 3D World frame — Euclidean coordinates 2D Image plane

- How to write as linear mapping? (Homogeneous coordinates)

$$\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \mapsto \begin{bmatrix} fX \\ fY \\ Z \end{bmatrix} = \begin{bmatrix} f & & & 0 \\ & f & & 0 \\ & & 1 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

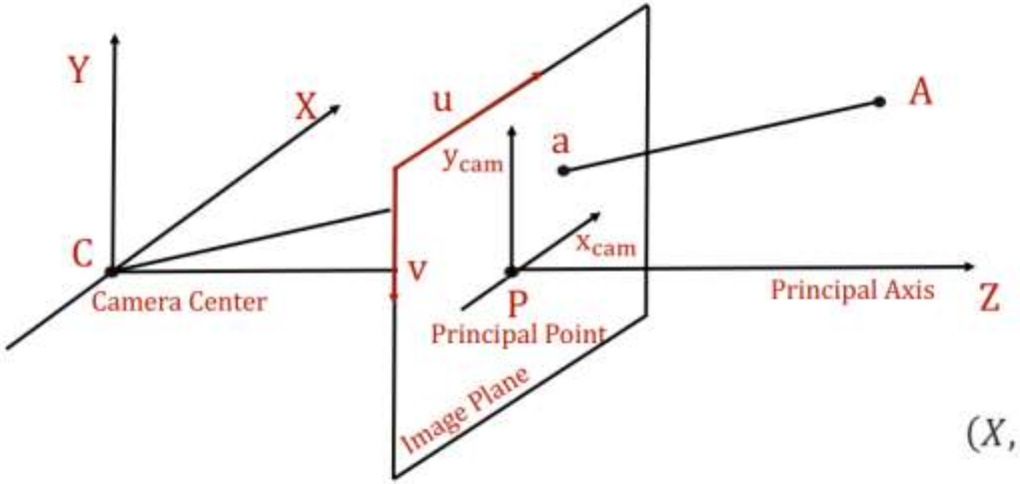
$$a = \mathbf{P}A$$

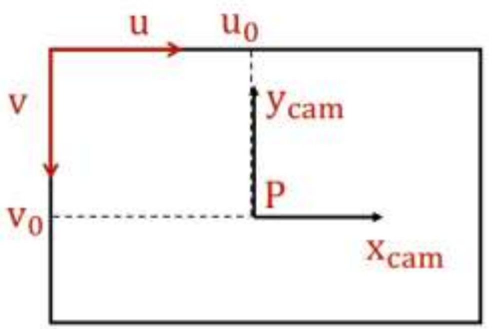
Camera projection matrix

Perspective projection

Assumptions made:

- Principal point at ~~origin~~ (u_0, v_0) of image plane
- Camera at center of world coordinates
- Square pixels





$$(X, Y, Z)^T \mapsto (u, v)^T = \left(\frac{fX}{Z} + u_0, \frac{fY}{Z} + v_0\right)^T$$

Euclidean Coordinates
3D World frame

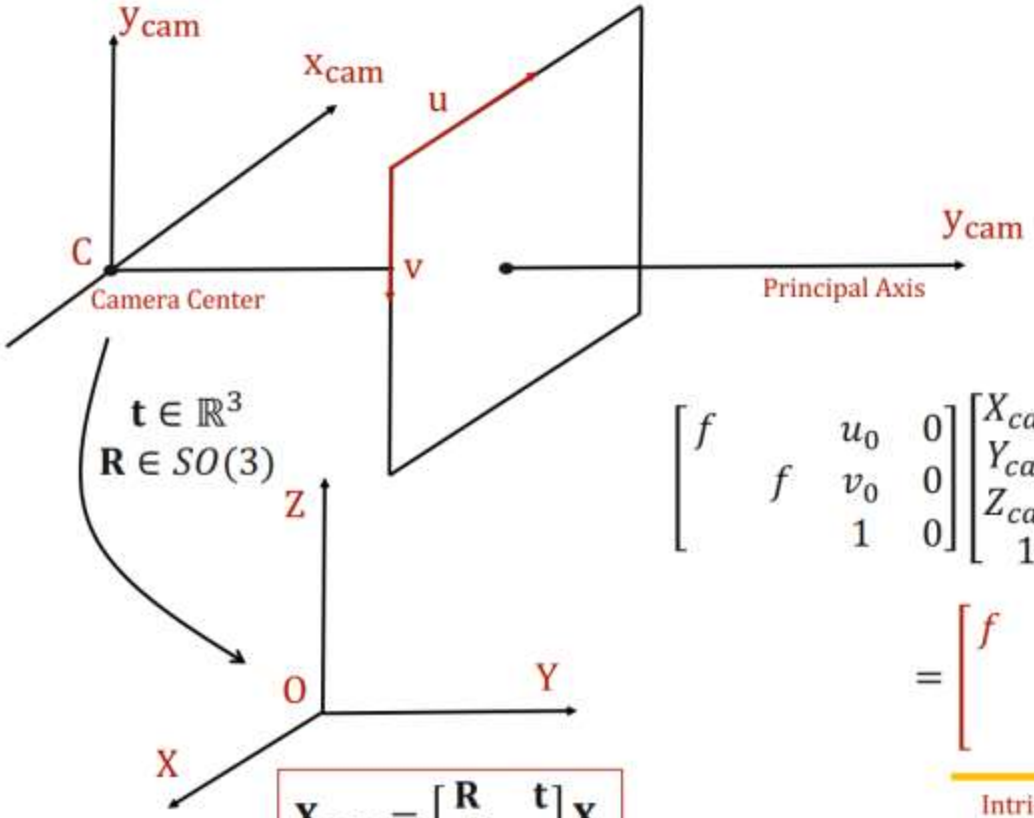
Euclidean coordinates
2D Image plane
(Note nonlinearity)

$$\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \mapsto \begin{bmatrix} fX + Zu_0 \\ fY + Zy_0 \\ Z \end{bmatrix} = \begin{bmatrix} f & & u_0 & 0 \\ & f & v_0 & 0 \\ & & 1 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

Perspective projection

Assumptions made:

- Principal point at ~~origin~~ (u_0, v_0) of image plane
- Camera at ~~center~~ $\mathbf{R}, \mathbf{t}$ of world coordinates
- Square pixels



$$\boxed{\mathbf{X}_{\mathbf{cam}} = \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix} \mathbf{X}}$$

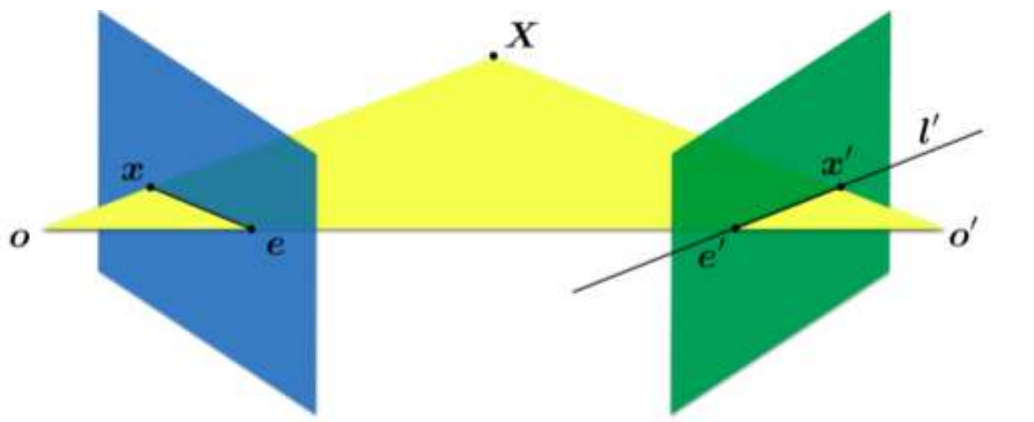
$$\begin{bmatrix} f & & u_0 & 0 \\ & f & v_0 & 0 \\ & & 1 & 0 \end{bmatrix} \begin{bmatrix} X_{cam} \\ Y_{cam} \\ Z_{cam} \\ 1 \end{bmatrix} = \begin{bmatrix} f & & u_0 & 0 \\ & f & v_0 & 0 \\ & & 1 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix} \mathbf{X}$$

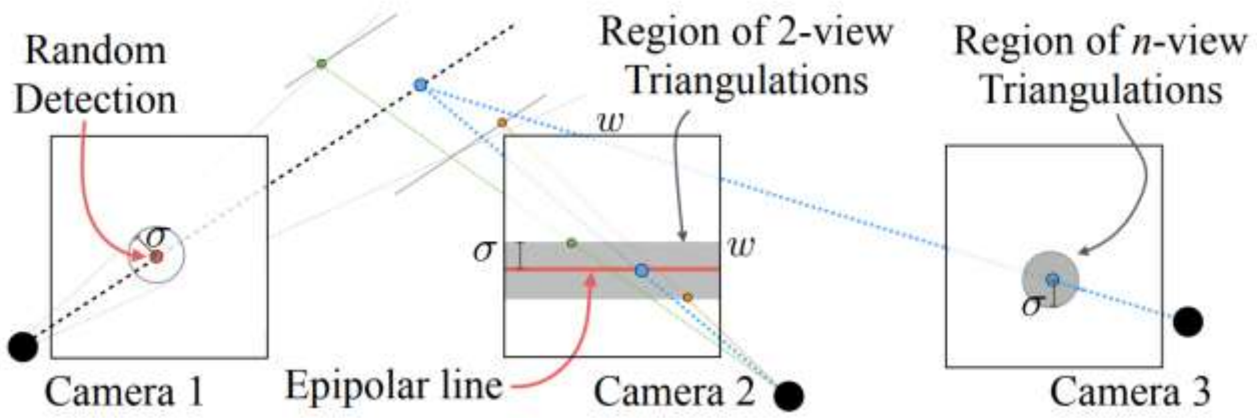
$$= \underbrace{\begin{bmatrix} f & & u_0 \\ & f & v_0 \\ & & 1 \end{bmatrix}}_{\text{Intrinsic matrix}} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \underbrace{\begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix}}_{\text{Extrinsic matrix}} \mathbf{X}$$

How to estimate 3D hand keypoints?

- When depth map is available as input

- When depth map is not available as input during inference
  - Depth map is accessible in the training data
  - Multi-view images with relative poses are available





What is Hand Mesh?

Hand Models

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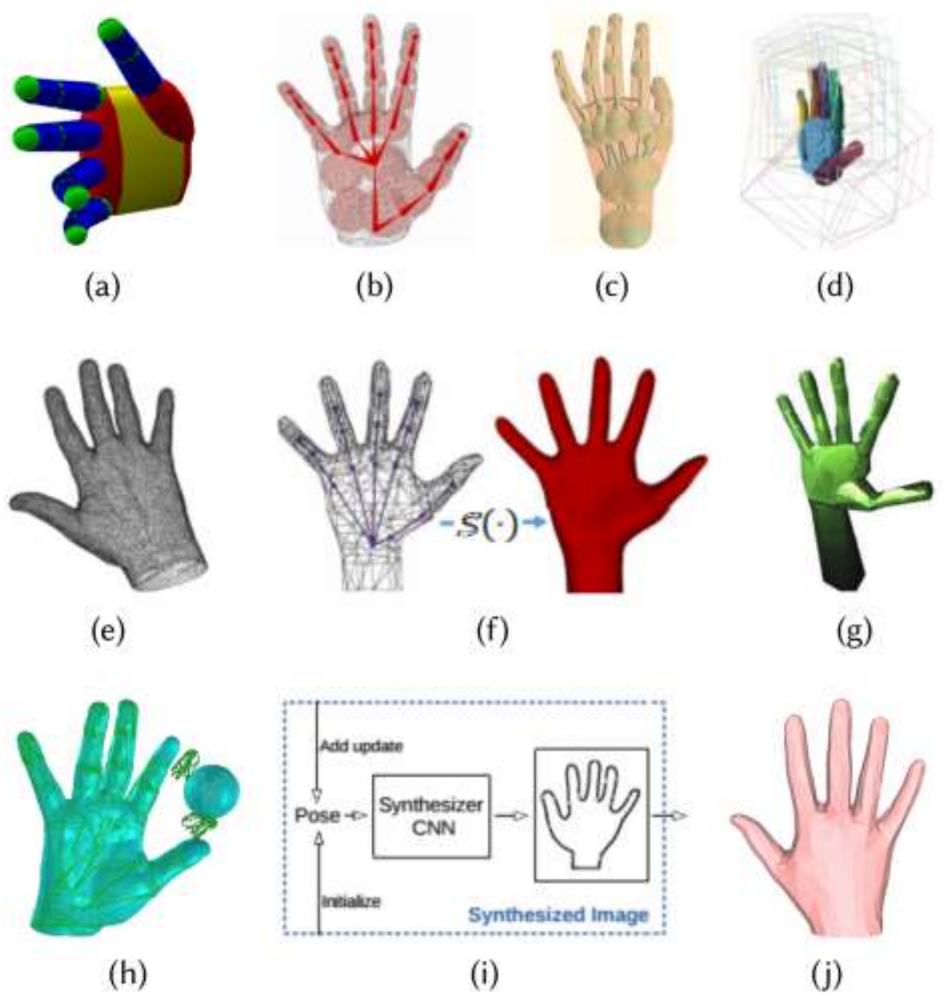

(a) Primitives approximation [Oikonomidis et al. 2011a]
(b) Sum-of-Gaussians model [Sridhar et al. 2013],
(c) Sphere-Meshes [Tkach et al. 2016] can be thought of as a generalization of the previous models,
(d) Articulated TSDF for a voxelized shape-primitive hand model [Schmidt et al. 2014]
(e) Triangular Mesh [Ballan et al. 2012; Tzionas et al. 2016]
(f) Loop Subdivision Surface of a triangular control mesh [Khamis et al. 2015]
(g) Convex Bodies for tracking [Melax et al. 2013]
(h) Convex Parts of a triangular mesh for contact point detection [Tzionas et al. 2016]
(i) Learned Model using a CNN to synthesize images of a given hand pose [Oberweger et al. 2015]
(j) MANO model.

Hand mano model

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Mano Model

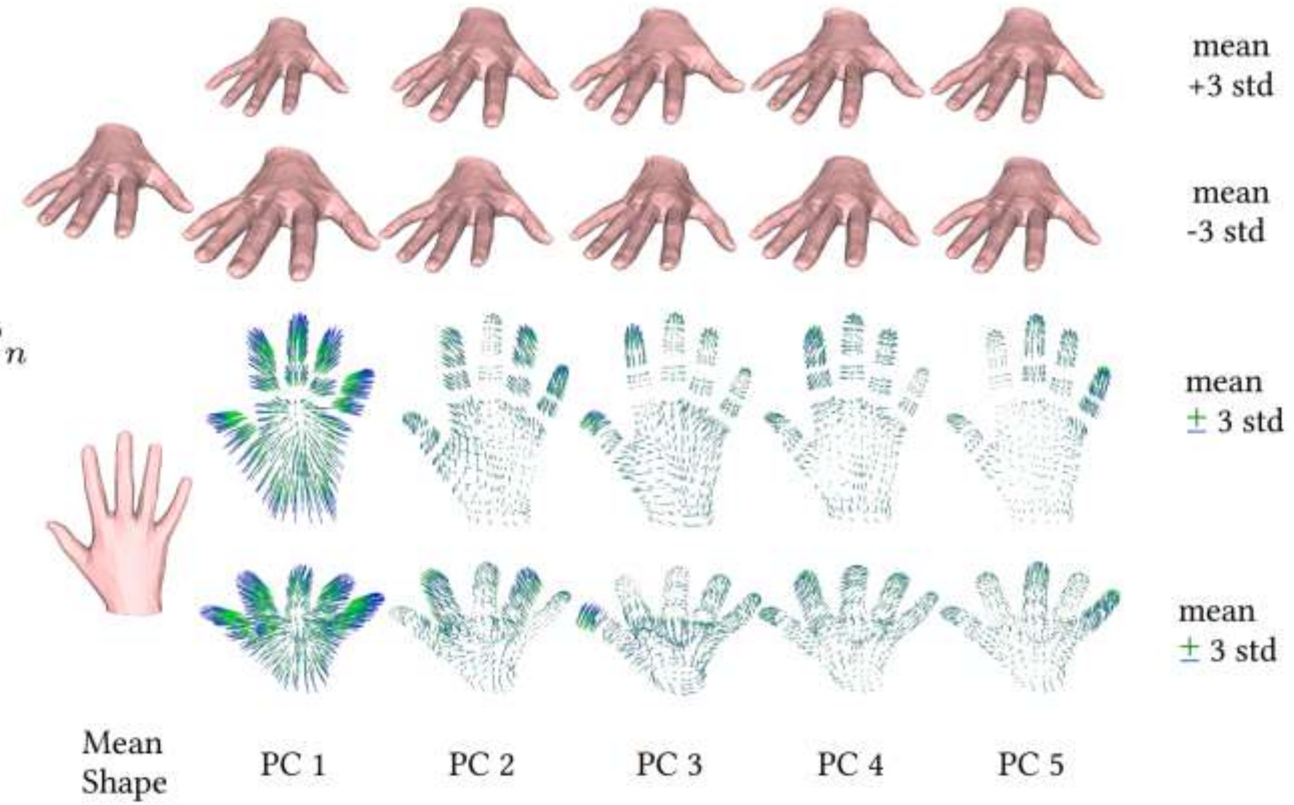
$$M(\boldsymbol{\beta}, \boldsymbol{\theta}) = W(T(\boldsymbol{\beta}, \boldsymbol{\theta}), J(\boldsymbol{\beta}), \boldsymbol{\theta}, \mathcal{W})$$

$$T(\boldsymbol{\beta}, \boldsymbol{\theta}) = \bar{\mathbf{T}} + \sum_{n=1}^{|\boldsymbol{\beta}|} \beta_n \mathbf{S}_n + \sum_{n=1}^{9K} (R_n(\boldsymbol{\theta}) - R_n(\boldsymbol{\theta}^*))\mathbf{P}_n$$

$$\boldsymbol{V}_h, \boldsymbol{P}_h = \mathcal{M}(\boldsymbol{\theta}, \boldsymbol{\beta}) + \boldsymbol{P}_{h,0}$$

$$\boldsymbol{P}_h \in \mathbb{R}^{21\times 3} \quad \boldsymbol{V}_h \in \mathbb{R}^{778\times 3}$$

$$\boldsymbol{P}_{h,0} \in \mathbb{R}^3$$

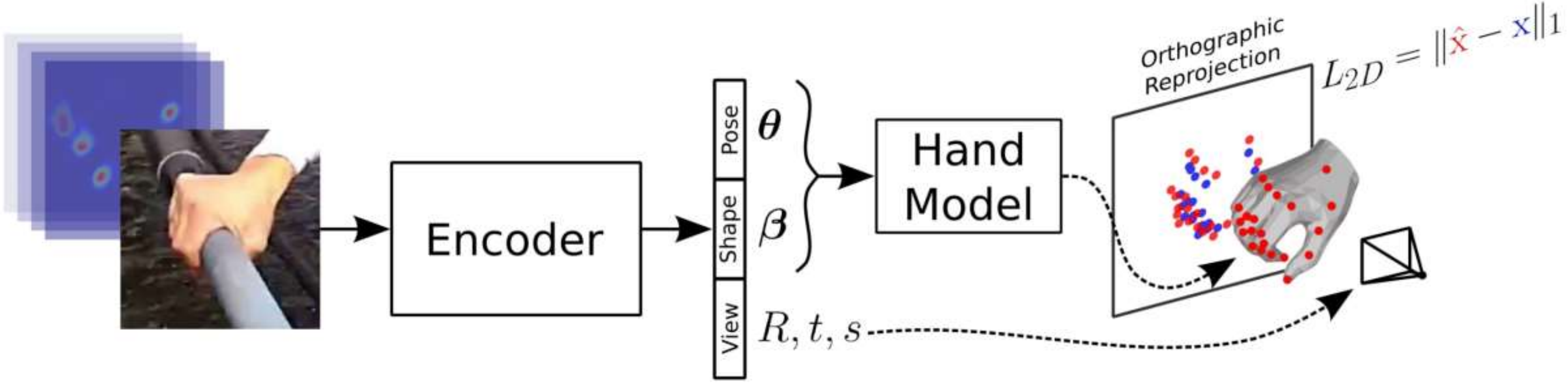


Mano Parameters

$$\boldsymbol{\beta} \in \mathbb{R}^{10} \quad \boldsymbol{\theta} \in \mathbb{R}^{16\times 3}$$

How to Estimate Hand Mesh?

3D Hand Shape and Pose from Images in the Wild , CVPR 2019



$$\hat{\mathrm{x}} = s\Pi(RJ(\boldsymbol{\beta}, \boldsymbol{\theta})) + t,$$
$$\hat{\mathrm{y}} = s\Pi(RM(\boldsymbol{\beta}, \boldsymbol{\theta})) + t$$

Supervision

$$L = L_{2D} + \alpha_{3D} L_{3D} + \alpha_{mask} L_{mask} + \alpha_{reg} L_{reg}$$

No GT
Mano Pose

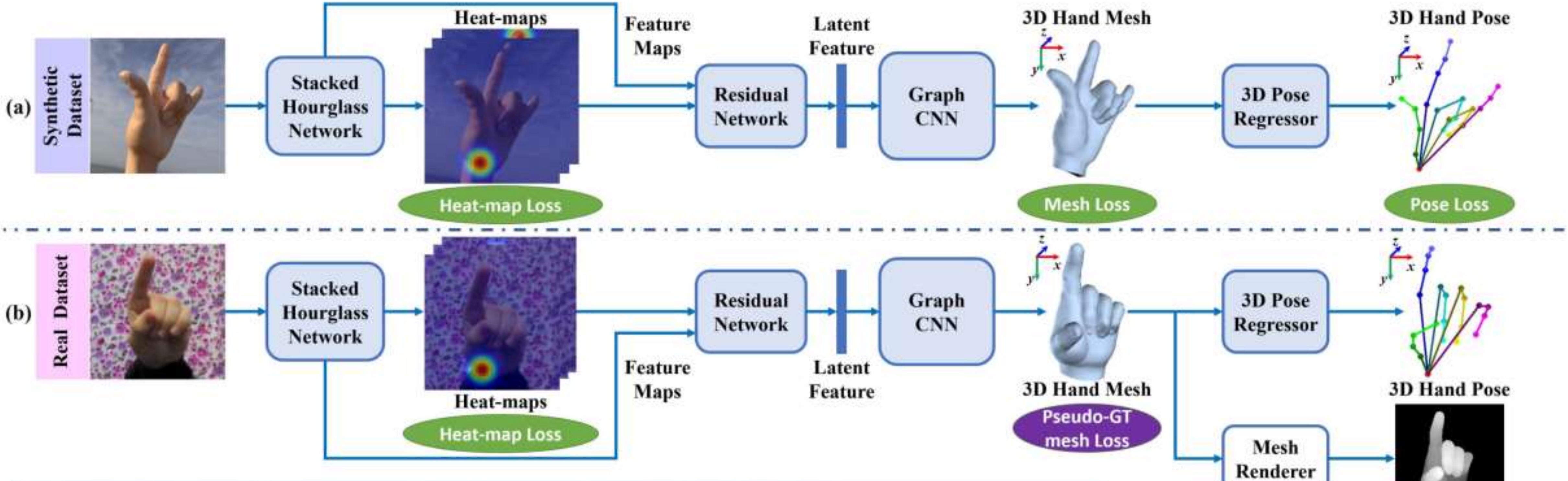
$$L_{2D} = \|\hat{\mathrm{x}} - \mathrm{x}\|_1,$$

$$L_{3D} = \|RJ(\boldsymbol{\beta}, \boldsymbol{\theta}) - \mathrm{x}_{3D}\|_2^2$$

$$L_{mask} = 1 - \frac{1}{N} \sum_i H(\hat{\mathrm{y}}_i)$$

$$L_{reg} = \|\boldsymbol{\theta}\|_2^2 + \alpha_{\beta} \|\boldsymbol{\beta}\|_2^2$$

3D Hand Shape and Pose Estimation from a Single RGB Image, CVPR 2019



(a) On synthetic dataset: (fully-supervised)	Loss = heat-map loss + mesh loss + pose loss
(b) On real dataset: (weakly-supervised)	Loss = heat-map loss + depth map loss + pseudo-ground truth mesh loss

Supervision-Synthetic Data

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$$\mathcal{L}_{fully} = \lambda_{\mathcal{H}}\mathcal{L}_{\mathcal{H}} + \lambda_{\mathcal{M}}\mathcal{L}_{\mathcal{M}} + \lambda_{\mathcal{J}}\mathcal{L}_{\mathcal{J}}$$

Heat map loss: $\mathcal{L}_{\mathcal{H}} = \sum_{j=1}^{J} \left\| \mathcal{H}_j - \hat{\mathcal{H}}_j \right\|_2^2$

Mesh loss: $\mathcal{L}_{\mathcal{M}} = \lambda_v \mathcal{L}_v + \lambda_n \mathcal{L}_n + \lambda_e \mathcal{L}_e + \lambda_l \mathcal{L}_l$

$$\mathcal{L}_v = \sum_{i=1}^{N} \left\| \boldsymbol{v}_i^{3D} - \hat{\boldsymbol{v}}_i^{3D} \right\|_2^2 + \left\| \boldsymbol{v}_i^{2D} - \hat{\boldsymbol{v}}_i^{2D} \right\|_2^2$$

Vertices loss

$$\mathcal{L}_n = \sum_t \sum_{(i,j)\in t} \left\| \langle \hat{\boldsymbol{v}}_i^{3D} - \hat{\boldsymbol{v}}_j^{3D}, \boldsymbol{n}_t \rangle \right\|_2^2$$

Normal loss

$$\mathcal{L}_e = \sum_{i=1}^{E} \left(\|\boldsymbol{e}_i\|_2^2 - \|\hat{\boldsymbol{e}}_i\|_2^2 \right)^2$$

Edge loss

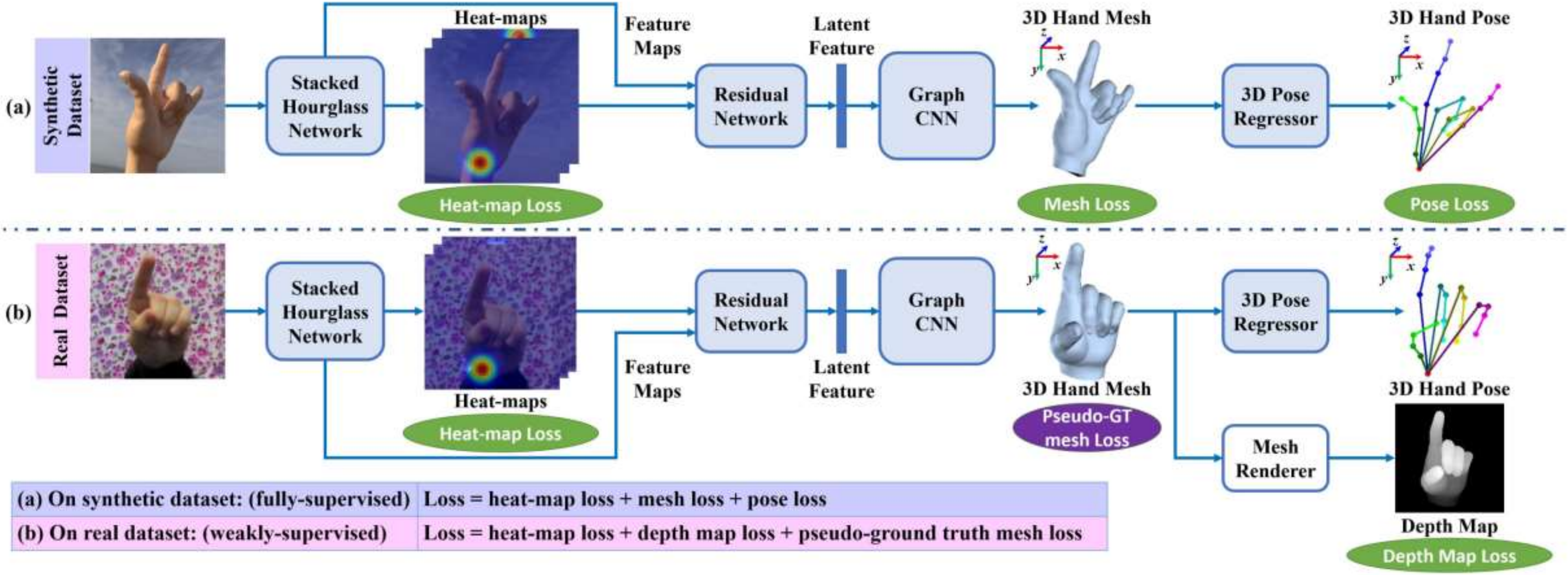
$$\mathcal{L}_l = \sum_{i=1}^{N} \left\| \boldsymbol{\delta}_i - \sum_{\boldsymbol{v}_k \in \mathcal{N}(\boldsymbol{v}_i)} \boldsymbol{\delta}_k \Big/ B_i \right\|_2^2$$

prevents the neighboring vertices from having opposite offsets

3D Pose loss: $\mathcal{L}_{\mathcal{J}} = \sum_{j=1}^{J} \left\| \phi_j^{3D} - \hat{\phi}_j^{3D} \right\|_2^2$

Joint Locations

3D Hand Shape and Pose Estimation from a Single RGB Image, CVPR 2019



(a) On synthetic dataset: (fully-supervised)	Loss = heat-map loss + mesh loss + pose loss
(b) On real dataset: (weakly-supervised)	Loss = heat-map loss + depth map loss + pseudo-ground truth mesh loss

Supervision - Real Data

$$\mathcal{L}_{fully} = \lambda_{\mathcal{H}}\mathcal{L}_{\mathcal{H}} + \lambda_{\mathcal{M}}\mathcal{L}_{\mathcal{M}} + \lambda_{\mathcal{J}}\mathcal{L}_{\mathcal{J}}$$

Heat map loss: $\mathcal{L}_{\mathcal{H}} = \sum_{j=1}^{J} \left\| \mathcal{H}_j - \hat{\mathcal{H}}_j \right\|_2^2$

Pseudo-GT Mesh loss: $\mathcal{L}_{\mathcal{M}} = \cancel{\lambda_v\mathcal{L}_v + \lambda_n\mathcal{L}_n} + \lambda_e\mathcal{L}_e + \lambda_l\mathcal{L}_l$

$$\cancel{\mathcal{L}_v = \sum_{i=1}^{N} \left\| \boldsymbol{v}_i^{3D} - \hat{\boldsymbol{v}}_i^{3D} \right\|_2^2 + \left\| \boldsymbol{v}_i^{2D} - \hat{\boldsymbol{v}}_i^{2D} \right\|_2^2}$$

Vertices loss

$$\cancel{\mathcal{L}_n = \sum_t \sum_{(i,j)\in t} \left\| \langle \hat{\boldsymbol{v}}_i^{3D} - \hat{\boldsymbol{v}}_j^{3D}, \boldsymbol{n}_t \rangle \right\|_2^2}$$

Normal loss

$$\mathcal{L}_e = \sum_{i=1}^{E} \left(\|\mathbf{e}_i\|_2^2 - \|\hat{\mathbf{e}}_i\|_2^2 \right)^2$$

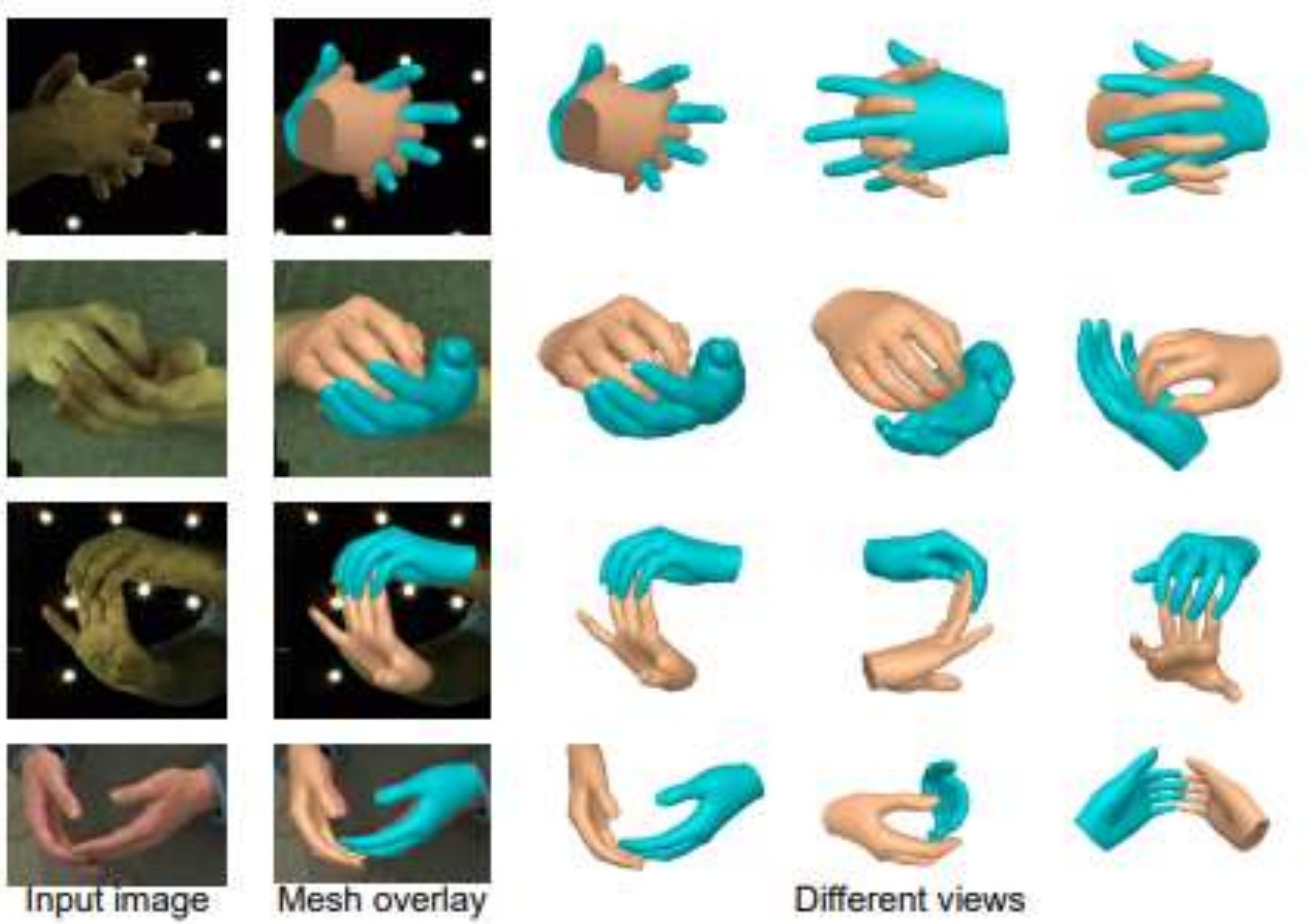
Edge loss

$$\mathcal{L}_l = \sum_{i=1}^{N} \left\| \boldsymbol{\delta}_i - \sum_{\boldsymbol{v}_k \in \mathcal{N}(\boldsymbol{v}_i)} \boldsymbol{\delta}_k \Big/ B_i \right\|_2^2$$

prevents the neighboring vertices from having opposite offsets

Depth Map loss: $\mathcal{L}_{\mathcal{D}} = smooth_{L1}\left(\mathcal{D}, \hat{\mathcal{D}}\right), \ \hat{\mathcal{D}} = \mathcal{R}\left(\hat{\mathcal{M}}\right)$

Interacting Two-Hand 3D Pose and Shape Reconstruction from Single Color Image



ICCV 2021

Two hand relationship

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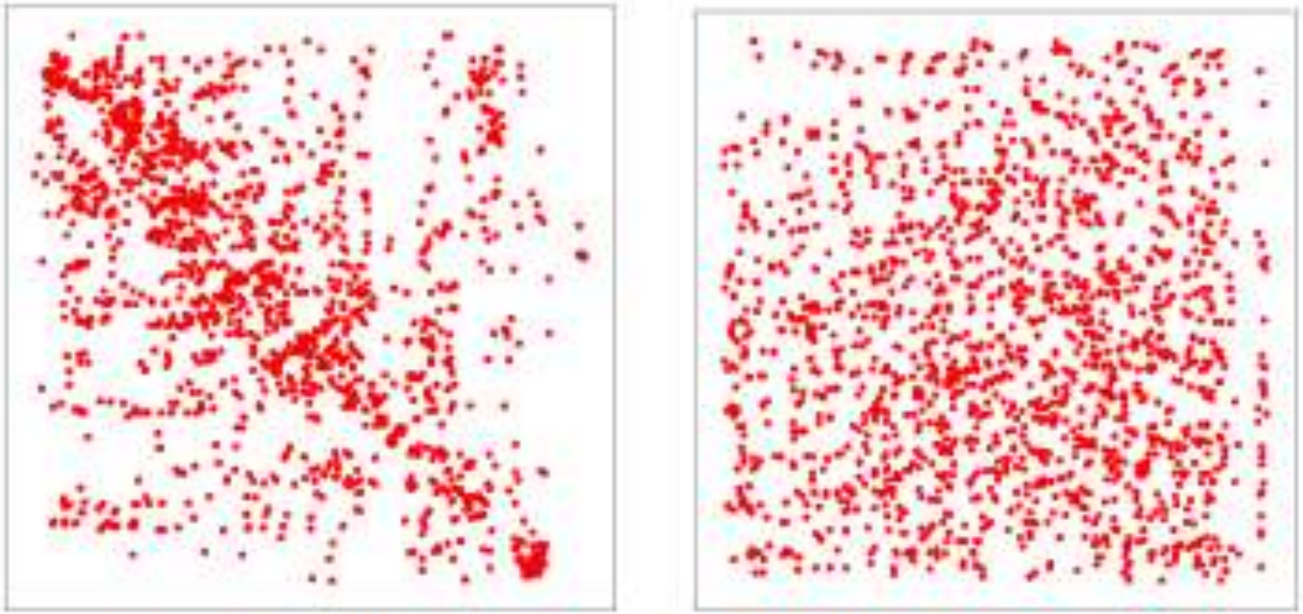

(a) Paired hand poses (b) Unpaired hand poses

Inspired by [26], we use 2D manifold representation, where the hand pose (without root rotation) of each hand is projected to 1D manifold by t-SNE [34] and used as x, y coordinates, respectively. We find that the paired hand poses show clear correlation in 2D space, but the distribution of unpaired hand poses is almost random.

Overall Framework

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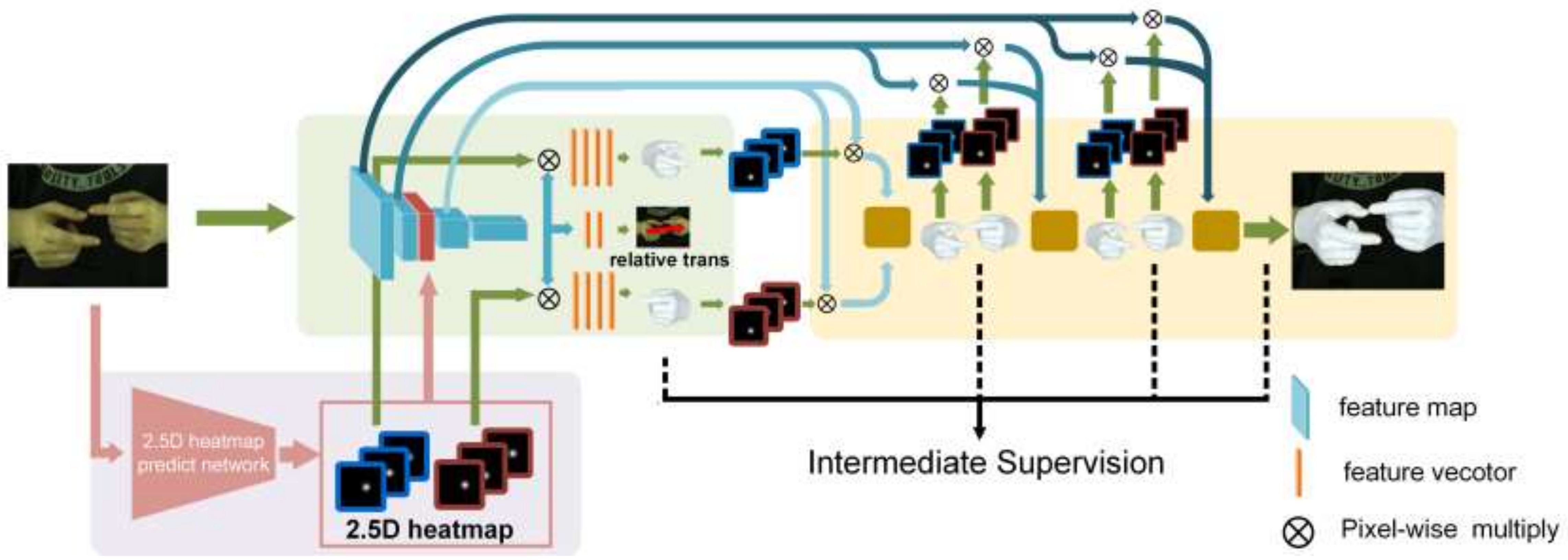
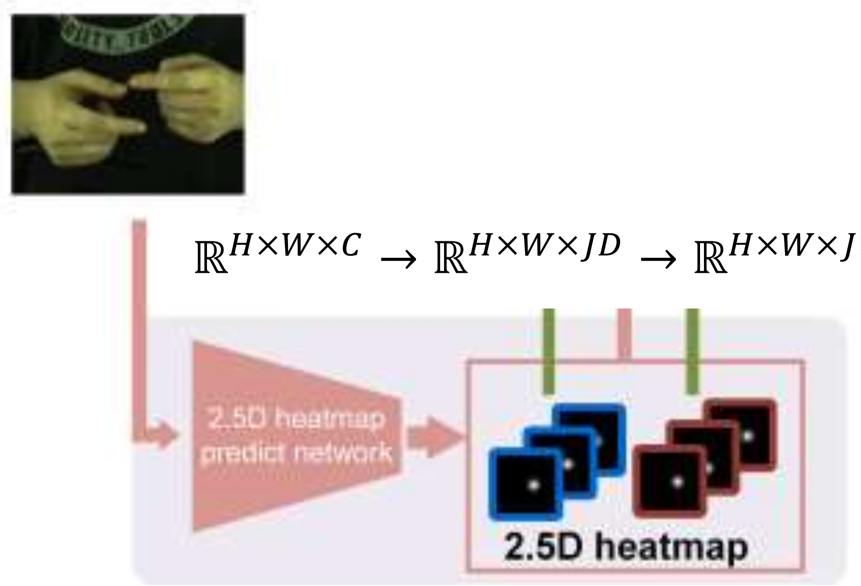
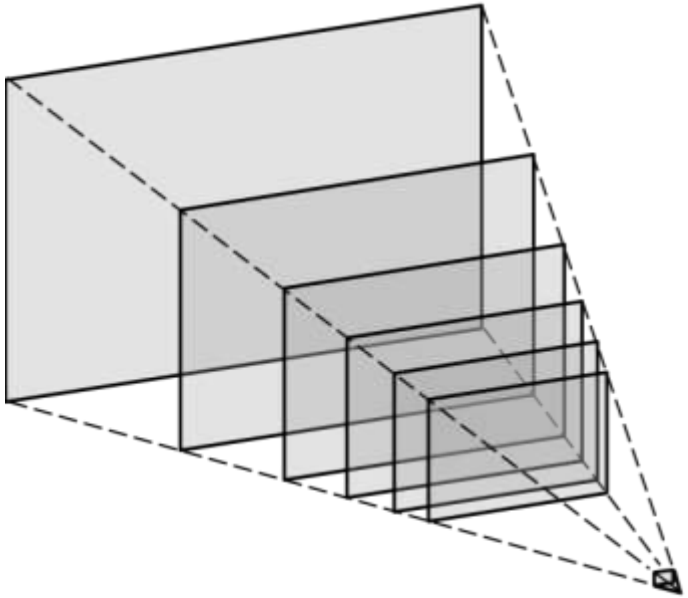


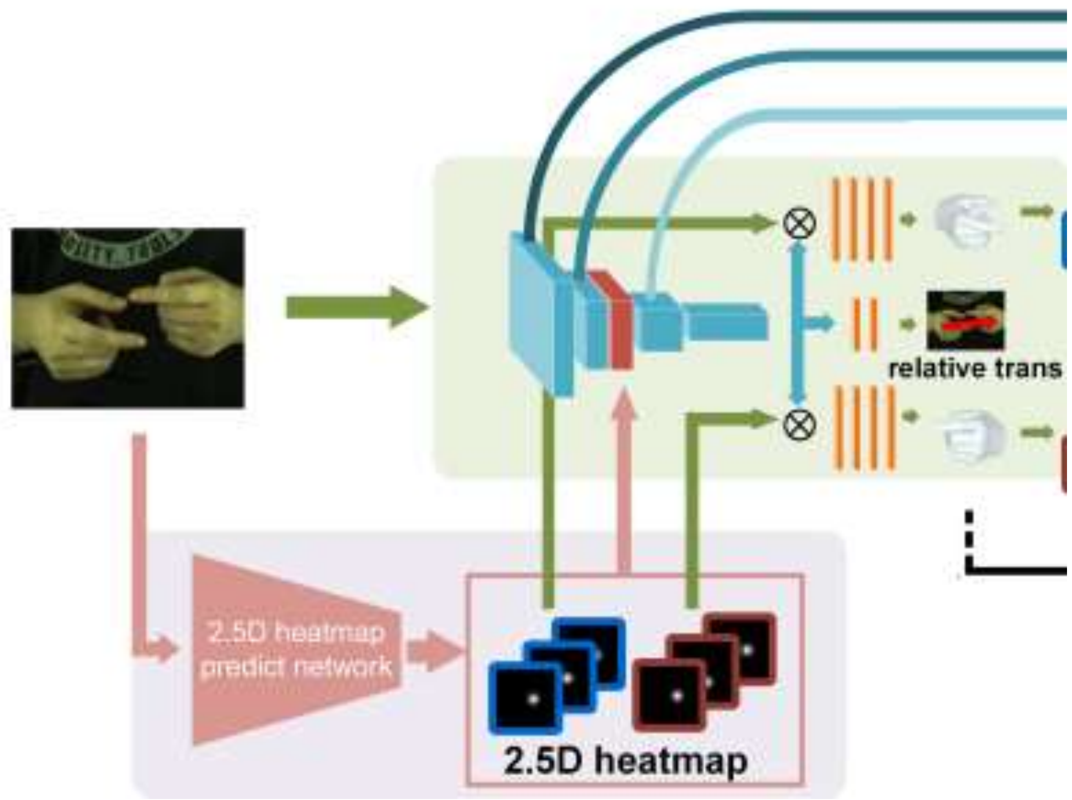
2.5D Joint keypoints heatmap estimation

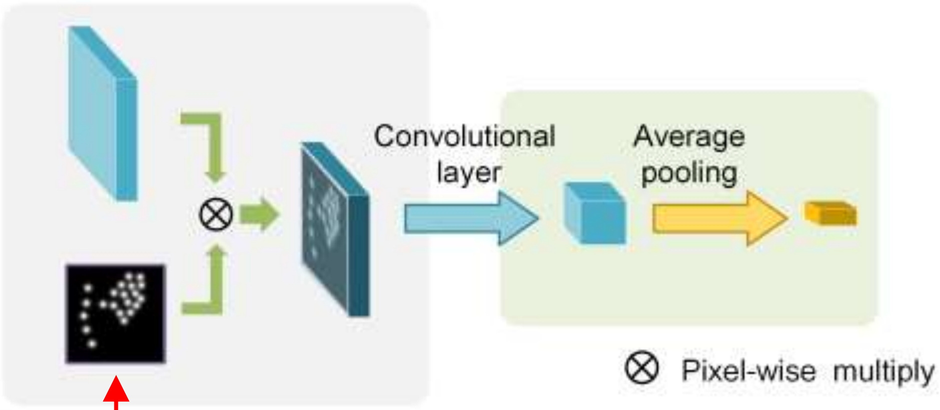


$\mathbb{R}^{H\times W\times C} \rightarrow \mathbb{R}^{H\times W\times JD} \rightarrow \mathbb{R}^{H\times W\times J\times D}$



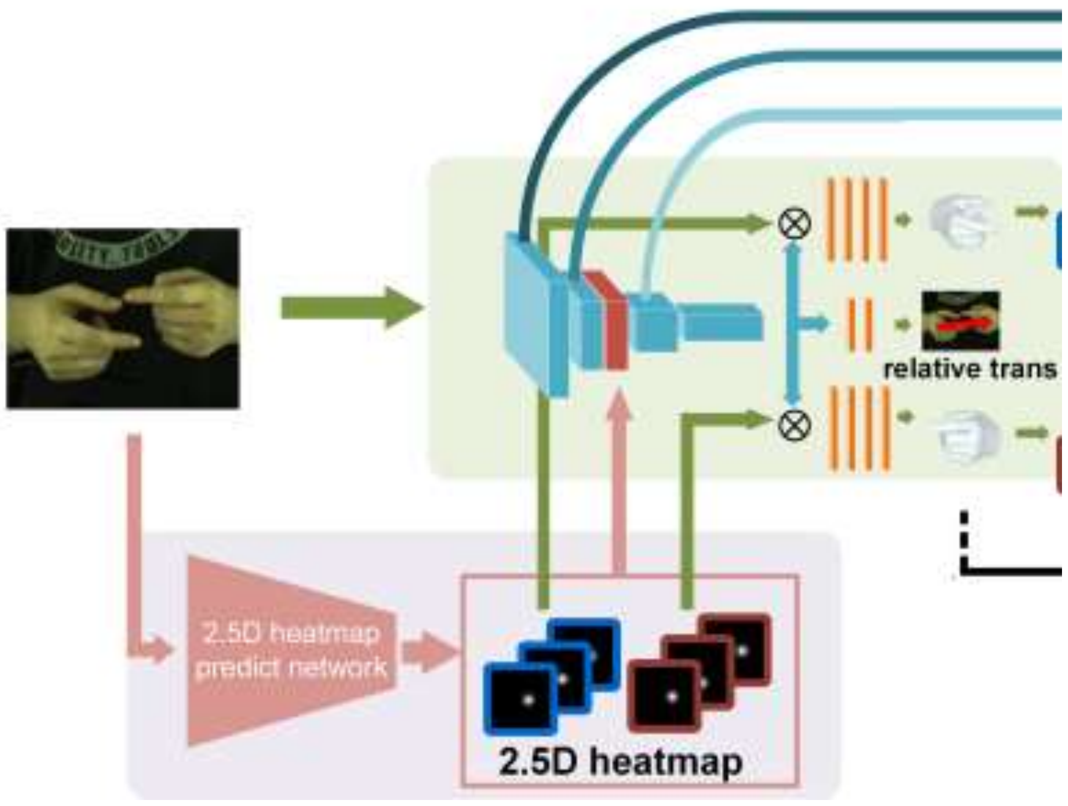
Feature Extraction with Keypoints Attention





$$\mathbf{A}_h = 1 - \prod_{i=1}^{K}(1-\mathcal{H}_{h_i}), \quad h \in \{right, left\},$$

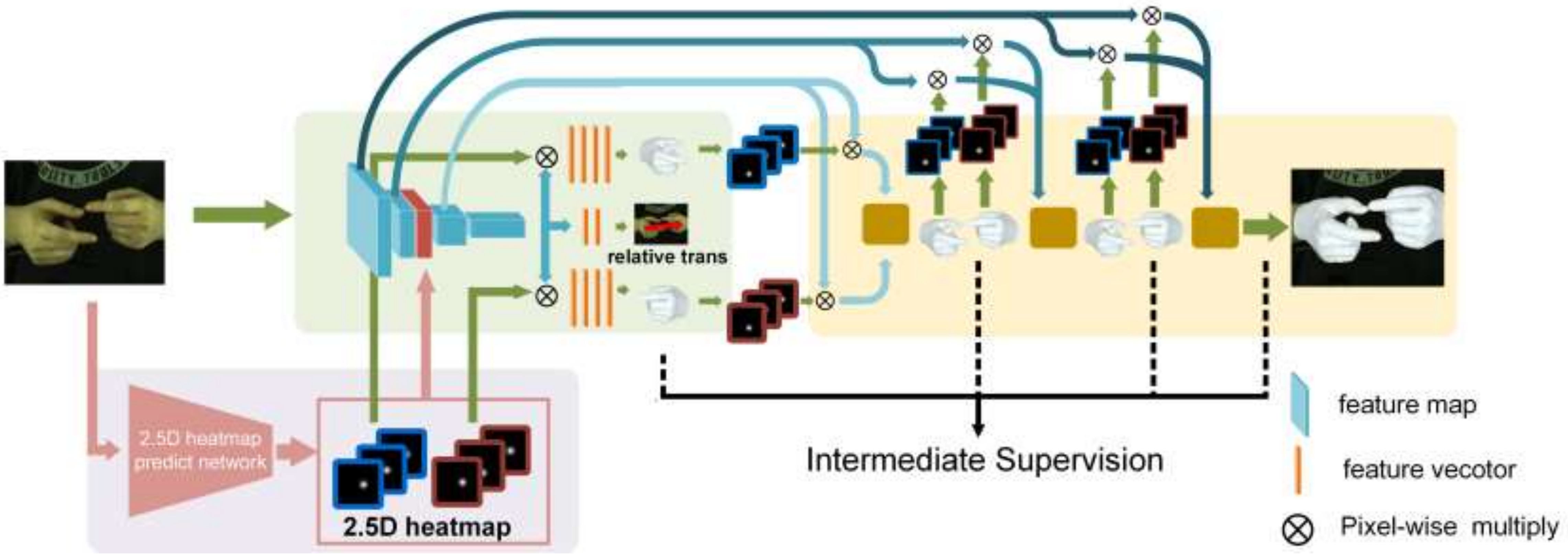
Relative Transformation



$$\mathbf{J}_{left,i}^{right} = s(\mathbf{J}_{left,i}^{left} + \Delta)$$

where $\mathbf{J}_{left,i}^{right}$ and $\mathbf{J}_{left,i}^{left}$ are the left hand joints in the right hand coordinate system and the left hand joints in the left hand coordinate system, respectively.

Overall Framework



Supervision

- Two hand loss
  - Joint offset loss $L_o = \sum_{i=1}^{K} ||(\mathbf{J}_{right,i} - \mathbf{J}_{left,i}) - (\mathbf{J}^*_{right,i} - \mathbf{J}^*_{left,i})||_2^2$
  - Shape consistence loss $L_c = ||\beta_{right} - \beta_{left}||_2^2$
- Single hand loss
  - Joint loss $L_J = \sum_{h\in\{left,right\}} \sum_{i=1}^{K} ||\mathbf{J}_{h,i} - \mathbf{J}^*_{h,i}||_1$
  - Bone length loss $L_l = \sum_{h\in\{left,right\}} \sum_{b} ||\frac{l^*_{h,b}}{l^*_{h,ref}} - l_{h,b}||_2^2$
  - Shape loss $L_M = \sum_{h\in\{left,right\}} \mathbf{1}||\beta_{\mathbf{h}} - \beta^*_{\mathbf{h}}||_{\mathbf{2}}^{\mathbf{2}}$
  - Regularizer loss $L_{reg} = \sum_{h\in\{left,right\}} \lambda_\beta ||\beta_h||_2^2 + ||\theta_h||_2^2$

Supervision

$$\begin{aligned} L_{total} = &\lambda_o L_o + \lambda_c L_c + \lambda_J L_J \\ &+ \lambda_l L_l + \lambda_M L_M + \lambda_{reg} L_{reg} \end{aligned} \tag{10}$$

where $\lambda_o, \lambda_c, \lambda_J, \lambda_l, \lambda_M, \lambda_{reg}$ are the loss weights, and they are set to 1, 0.01, 10, 100, 0.1, and 0.05, respectively.

References

- Boukhayma, Adnane, Rodrigo de Bem, and Philip HS Torr. "3d hand shape and pose from images in the wild." *CVPR* 2019.
- Zhang, Baowen, et al. "Interacting two-hand 3d pose and shape reconstruction from single color image." ICCV 2021.
- https://github.com/iscas3dv/Two-Hand-Shape-Pose_v2
- Li, Mengcheng, et al. "Interacting attention graph for single image two-hand reconstruction." CVPR 2022
- https://mediapipe.readthedocs.io/en/latest/solutions/hands.html
- https://medium.com/@turgay2317/hand-detection-and-finger-counting-in-python-40f21719f1b6

Project Requirement (Basics)

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- Take pictures (20 images) of your own or your friends’ hands, with diverse perspective/viewpoint/background
  - Evaluate the trained model of [Zhang et al. ICCV 2021] on your newly collected hand images;
  - Visualize the estimated 2D & 3D keypoints, and mesh models (overlayed with the original image);
  - Analyze the performance, especially on failure scenarios.

```python
def register_heatmap(self,xyc:torch.Tensor,J:torch.Tensor,origin_size:int,output_size:int):
    '''
    xyc: shape of [B, N, 3];  N -- Joint Number; 3 -- [u,v,confidence]
    J: shape of [B, N, 3]; 3D joints coordinates
    '''
    device_run=xyc.device
    batch_size=xyc.shape[0]
    M=torch.cat([J[:,:,:2,None],torch.eye(2,device=device_run)[None,None,:,:].repeat(batch_size,J.shape[1],1,1)],dim=-1)
    wM=xyc[:,:,2,None,None]*M
    wB=xyc[:,:,2,None,None]*xyc[:,:,:2,None]
    wM=wM.reshape(batch_size,-1,3)
    wB=wB.reshape(batch_size,-1,1)
    MTM=torch.bmm(wM.transpose(2,1),wM)
    MTB=torch.bmm(wM.transpose(2,1),wB)
    sT=torch.bmm(torch.inverse(MTM),MTB)[:,:,0].detach()
    ratio=output_size/origin_size
    projected_xy=(J[:,:,:2]*sT[:,None,0,None]+sT[:,None,1:])*ratio
    #sigma = cfg.sigma * 2 * max(ratio, 0.25)
    heatmap=self.generate_batch_heatmap(projected_xy,output_size, sigma: 3)
    output_heatmap=1-torch.prod(1-heatmap,dim=1)
    return output_heatmap
```

Least Square Method

$$Ax = b$$

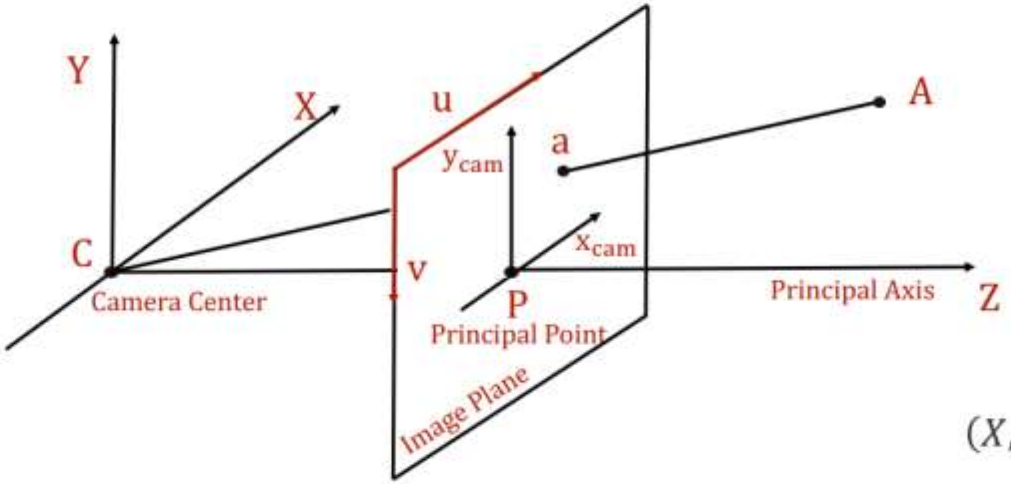
$$x = (A^T A)^{-1} A^T b$$

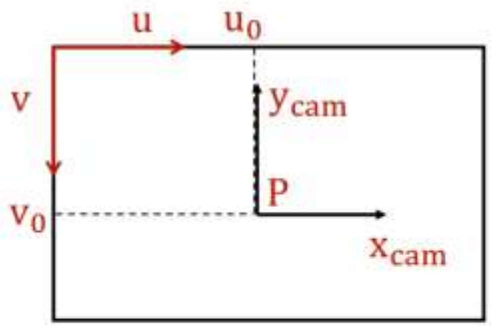
Perspective Projection

Perspective projection

Assumptions made:

- Principal point at ~~origin~~ (u_0, v_0) of image plane
- Camera at center of world coordinates
- Square pixels





$$(X, Y, Z)^T \mapsto (u, v)^T = \left(\frac{fX}{Z} + u_0, \frac{fY}{Z} + v_0\right)^T$$

Euclidean Coordinates
3D World frame

Euclidean coordinates
2D Image plane
(Note nonlinearity)

Call for Presentations!

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- Project-5
  - Multi-view Stereo for view synthesis
  - NeRF
  - 3DGS
  - Other view synthesis variants.

- Project-6
  - Latent Diffusion
  - LoRA
  - ControlNet
  - Other diffusion variants.