Lifting from the Deep: Convolutional 3D Pose Estimation from a Single Image

Denis Tomé[1] Chris Russell[2, 3] Lourdes Agapito[1]

[1]University College London [2]University of Surrey [3]Alan Turing Institute

Problem: 3D Human Pose Estimation from a Single Image

INPUT **OUTPUT**

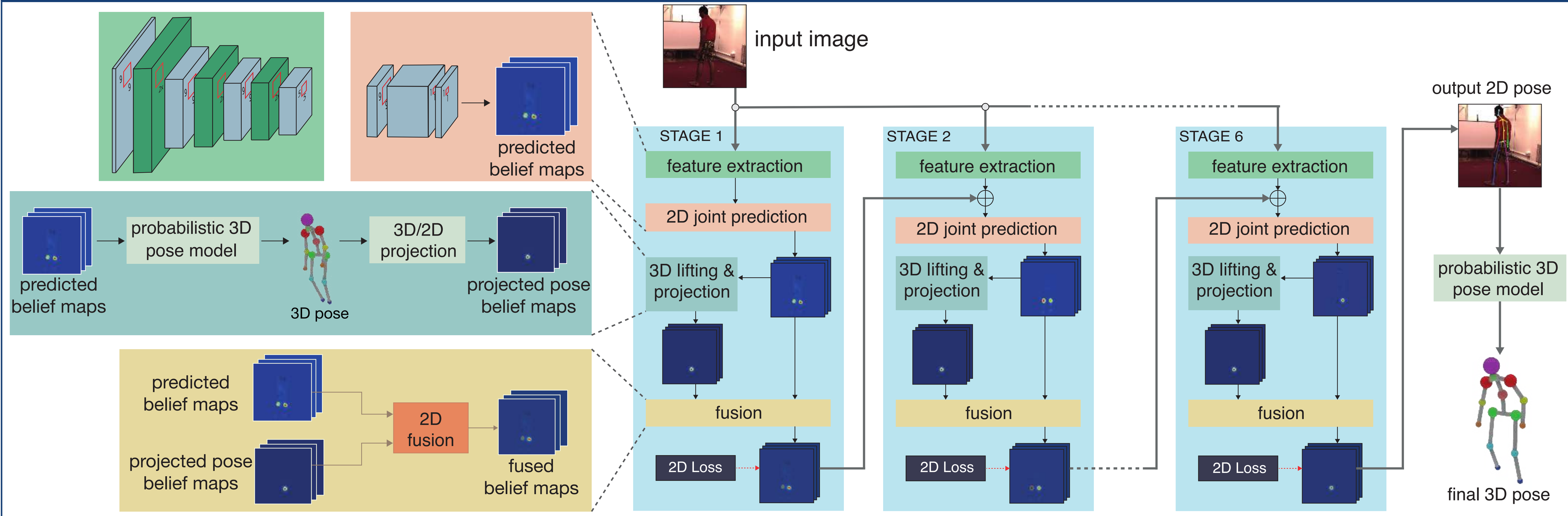
RGB Image 2D pose 3D pose

No temporal information

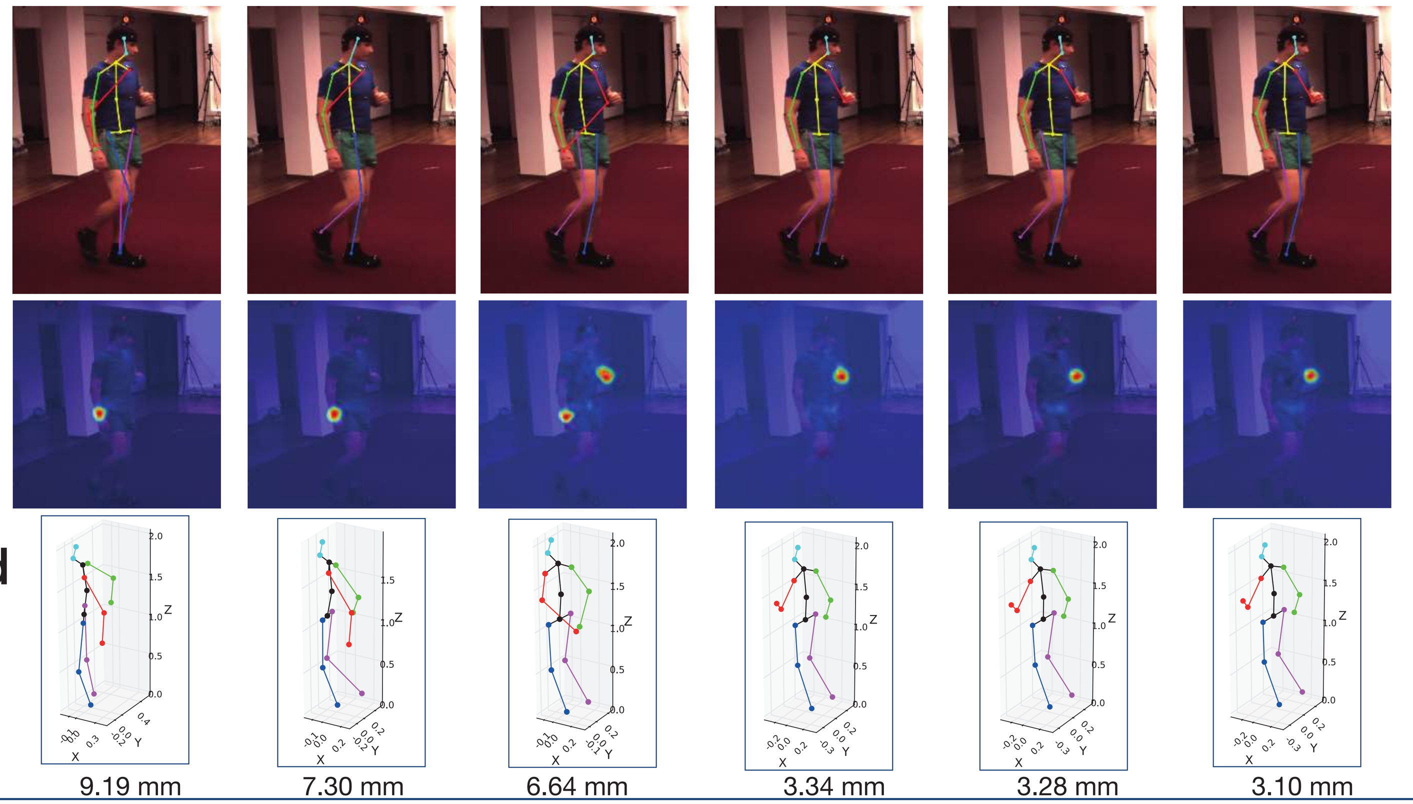
2 **independent** sources of training data

2D pose annotations 3D mocap

End-to-end Architecture



The accuracy of both 2D and 3D landmark locations improves progressively through the stages.



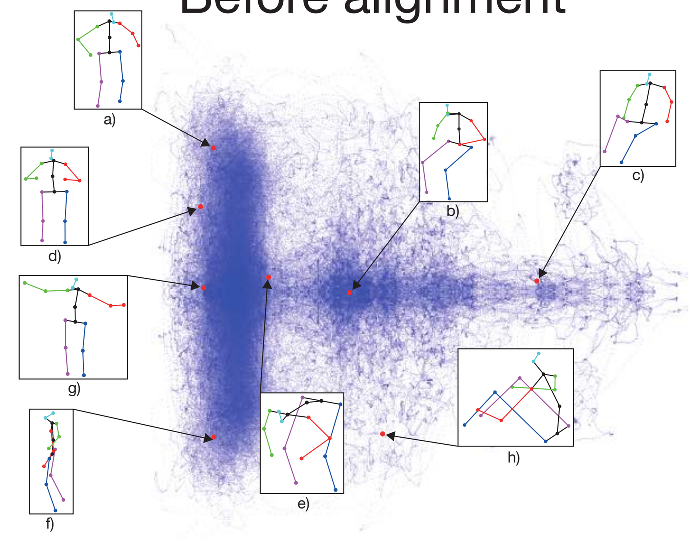
Training the Probabilistic 3D Human Pose Model

First step: aligning the data

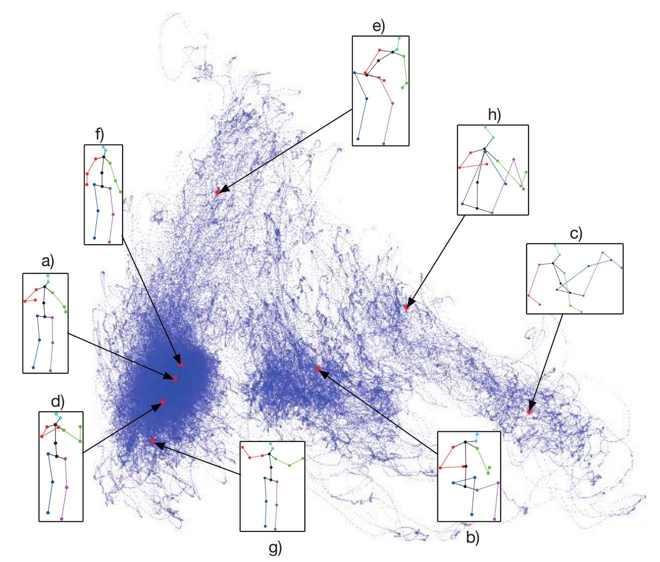
We seek the optimal rotations for each pose such that after rotating the poses they are closely approximated by a low-rank compact Gaussian distribution.

$$\arg\min_{\mathbf{R},\mu,a,\mathbf{e},\sigma} \sum_{i=1}^{N} \left(\|\mathbf{P_i} - \mathbf{R_i}\left(\mu + a_i \cdot \mathbf{e}\right)\|_2^2 + \sum_{j=1}^{J} (a_{i,j} \cdot \sigma_j)^2 + \ln \sum_{j=1}^{J} \sigma_j^2 \right)$$

Before alignment



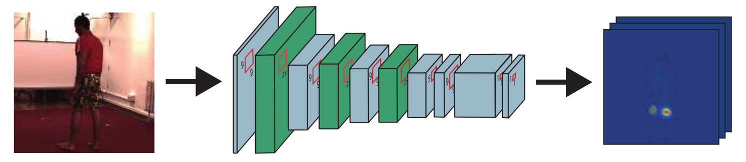
After alignment



Second step: train a mixture of PPCA models

Architecture of Each Stage

1. From image to belief maps



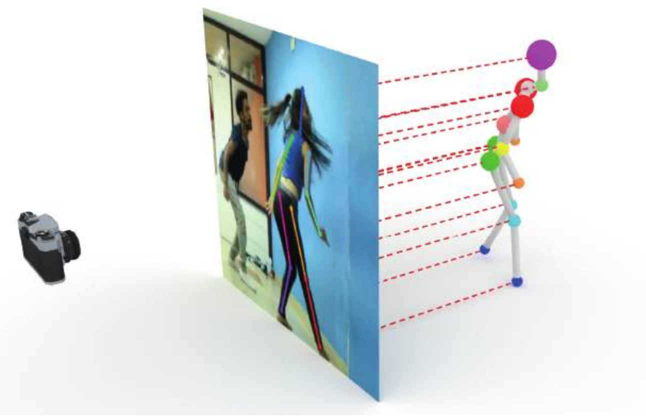
2. From belief maps to 2D pose

$$Y_p = \arg\max_{(u,v)} b_p[u,v]$$

3. From 2D to 3D pose

$$\arg\min_{R,a} \|Y - s\Pi E R(\mu + a \cdot \mathbf{e})\|_2^2$$

$$+ \|\sigma \cdot a\|_2^2$$



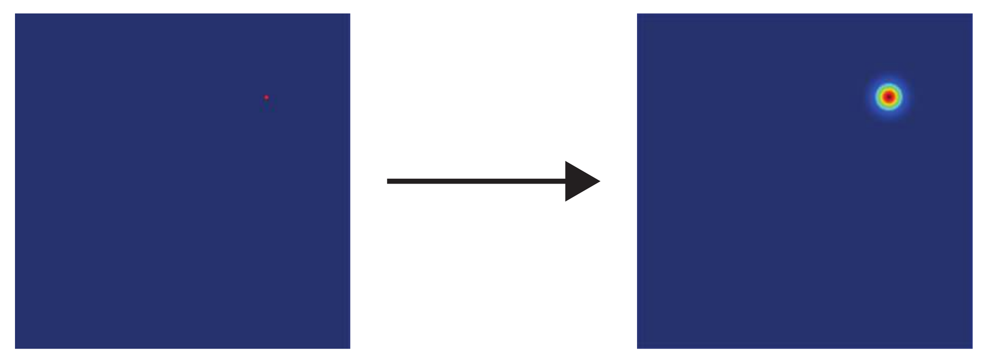
4. From 3D back to 2D

$$\hat{Y} = s\Pi E R(\mu + a \cdot \mathbf{e})$$

5. Generate projected belief maps

$$\hat{b}_{i,j}^p = \begin{cases} 1 & \text{if}(i,j) = \hat{Y}_p \\ 0 & \text{otherwise.} \end{cases}$$

followed by convolution with Gaussian filter



6. Fusion

$$f_t^p = w_t * b_t^p + (1 - w_t) * \hat{b}_t^p$$

weights learned in the end-to-end learning

Quantitative Results on Human3.6M Dataset

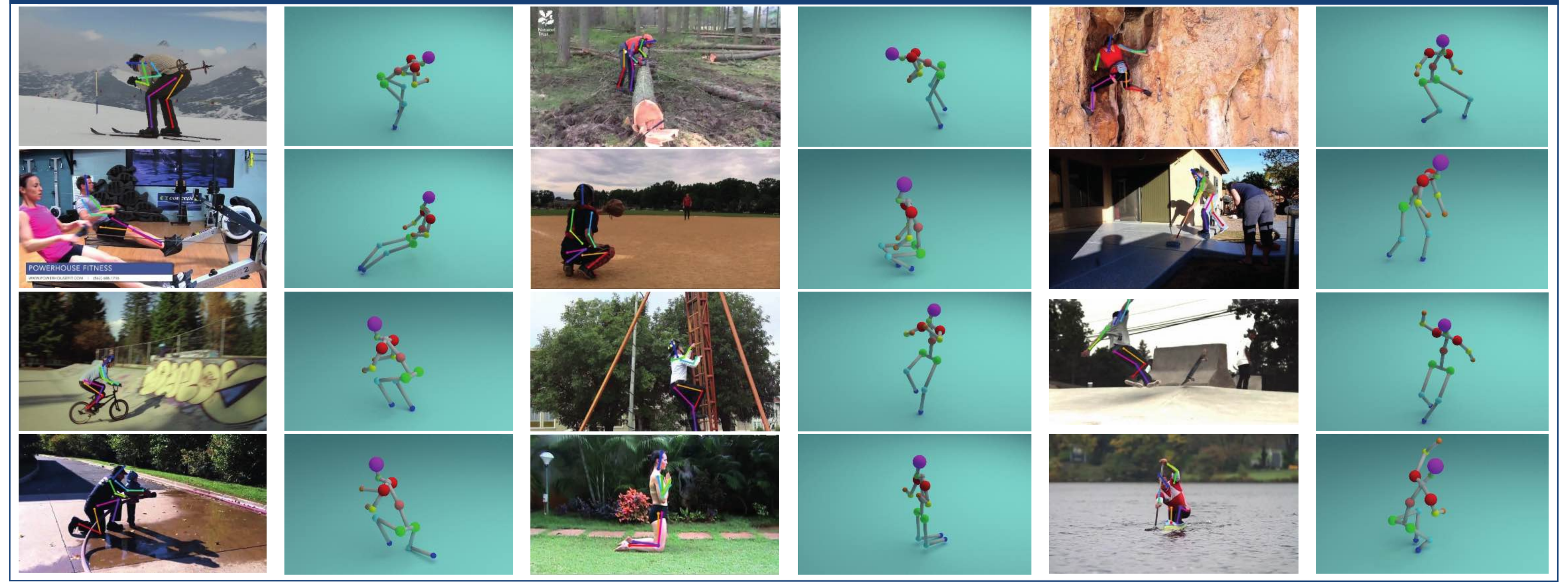
	Directions	Discussion	Eating	Greeting	Phoning	Photo	Posing	Purchases
Tekin *et al.* [2]	85.03	108.79	84.38	98.94	119.39	**95.65**	98.49	93.77
Zhou *et al.* [3]	87.36	109.31	87.05	103.16	116.18	143.32	106.88	99.78
Sanzari *et al.* [4]	**48.82**	**56.31**	95.98	**84.78**	96.47	105.58	**66.30**	107.41
Ours - Single PPCA Model	68.55	78.27	77.22	89.05	91.63	110.05	74.92	83.71
Ours - Mixture PPCA Model	64.98	73.47	**76.82**	86.43	**86.28**	110.67	68.93	**74.79**
	Sitting	Sitting Down	Smoking	Waiting	Walk Dog	Walking	Walk Together	Average
Tekin *et al.* [2]	**73.76**	170.4	85.08	116.91	113.72	**62.08**	94.83	100.08
Zhou *et al.* [3]	124.52	199.23	107.42	118.09	114.23	79.39	97.70	113.01
Sanzari *et al.* [4]	116.89	**129.63**	97.84	**65.94**	130.46	92.58	102.21	93.15
Ours - Single PPCA Model	115.94	185.72	88.25	88.73	92.37	76.48	77.95	92.96
Ours - Mixture PPCA Model	110.19	173.91	**84.95**	85.78	**86.26**	71.36	**73.14**	**88.39**

3D error (mm)	Protocol #2
Yasin *et al.* [5]	108.3
Rogez *et al.* [6]	88.1
Ours	**70.7**

3D error (mm)	Protocol #3
Bogo *et al.* [7]	82.3
Ours	**79.6**

2D pixel error	
Zhou *et al.* [3]	10.85
Trained CPM [1] architecture	10.04
Ours using 3D refinement	**9.47**

Qualitative Results on MPII Dataset



References

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Acknowledgements

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