IN-BED PRESSURE-BASED POSE ESTIMATION USING IMAGE SPACE REPRESENTATION LEARNING

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ABSTRACT

Recent advances in deep pose estimation models have proven to be effective in a wide range of applications such as health monitoring, sports, animations, and robotics. However, pose estimation models fail to generalize when facing images acquired from in-bed pressure sensing systems. In this paper, we address this challenge by presenting a novel end-to-end framework capable of accurately locating body parts from vague pressure data. Our method exploits the idea of equipping an off-the-shelf pose estimator with a deep trainable neural network, which pre-processes and prepares the pressure data for subsequent pose estimation. Our model transforms the ambiguous pressure maps to images containing shapes and structures similar to the common input domain of the pre-existing pose estimation methods. As a result, we show that our model is able to reconstruct unclear body parts, which in turn enables pose estimators to accurately and robustly estimate the pose. We train and test our method on a manually annotated public pressure map dataset using a combination of loss functions. Results confirm the effectiveness of our method by the high visual quality in the generated images and the high pose estimation rates achieved.

Index Terms— In-Bed Pose Estimation, Smart Beds, Pre-processing, Deep learning

1. INTRODUCTION

Sleeping makes up a third of human’s life-span. As a result of recent advances in science, sleep studies, especially data-driven techniques, have attracted many researchers to the field. Moreover, low-cost processing and monitoring systems have enabled the utilization of sleep-related technologies in smart homes and clinics, paving the way for considerable impacts on health and quality of life.

Generally, sleep-related research includes the study of complications in the respiratory system, insomnia, and movement-related disorders [1]. Furthermore, it is shown that movement and posture during sleep have critical impacts on disorders such as sleep apnea [2] and pressure ulcers [3,4]. As a result, monitoring posture in smart home and clinical settings is of great importance in order to identify or prevent the occurrence of such disorders.

Sleep monitoring technologies, such as textile-based pressure recording systems, have enabled ubiquitous and automated monitoring of movement, allowing for their use in both clinical health-care and research [5,6]. However, most of the studies using such systems are limited to coarse pose identification [6–10], namely left, supine, and right postures. However, in clinics, it is critical to obtain information about specific pressure points and the relative pose of the limbs with respect to the body [11–13]. Consequently, in-bed body part localization and pose estimation has recently attracted researchers [14]. Nonetheless, such related works are very scarce and very little work has been performed in this area.

With the recent advances in deep learning, a number of data-driven methods have been developed for pose estimation using natural camera-based images for a wide range of applications such as animation, robotics, sports, and human tracking [15–19]. Although these models are capable of achieving strong body pose recognition, they perform poorly when used on matrices acquired through in-bed pressure-mapping systems, mostly due to the difference in postures and low-pressure points such as the head, knees, and hands. In this paper, we address this issue by proposing a learnable pre-processing block that enables off-the-shelf pose estimation models to generalize to pressure maps as well.
Our pipeline consists of two blocks: (1) PolishNet which filters the pressure maps (2) A pre-trained pose estimation network that generates a heatmap for every body part that corresponds to their location. As illustrated in Figure 2 PolishNet utilizes a combination of loss functions, namely the pixel mean-squared error of an image space between input and the PolishNet output, a heatmap loss corresponding to the body part positions, and a Part Affinity Fields (PAF) loss for body part identification. By training the pipeline using the mentioned loss functions, we ensure the generation of polished images consistent with the pose estimation networks’ input data manifold while keeping the general properties of the input image.

Architecture and Loss: Let $I \in \mathbb{R}^{W \times H \times 3}$ be the input pressure data. Pre-processing the input is then performed by a variant of an hourglass network $P$ called PolishNet. Our proposed network (see Figure 2) contains three encoder blocks of Conv-Conv-BatchNorm-LeakyReLU and three blocks of DeConv-DeConv-BatchNorm-LeakyReLU on the decoder side. By utilizing the encoder-decoder blocks, we enable the network to capture the properties of the pressure data and incorporate pose and shape information in the latent space to generate the desired image in the polished data space $I'$, which is compatible with the pose estimation module. Accordingly, $I' = P(I; \theta_P)$, $I' \in \mathbb{R}^{W' \times H' \times 3}$ is the output of PolishNet, where $\theta_P$ are the network’s trainable parameters.

To estimate the body pose and train PolishNet, we utilize OpenPose [18], a fast and reliable pose estimation network $(Q)$ capable of accurately detecting different body joints known as keypoints. The output of OpenPose includes several heatmaps $(H)$ and PAF $(F)$ for each keypoint and its connections. Each heatmap is a 2D distribution of the belief that a keypoint is located on each pixel, while the PAF is defined as a 2D vector field connecting two limbs, encoding both position and the orientation of the connection. For our purposes, we only utilize the visible keypoints of the head, neck, shoulders, elbows, wrists, ankles, knees, and the hip, for a total of $h = 14$ heatmaps and $f = 28$ PAF for their connections. Accordingly, we define $H', F' = Q(I'; \theta_Q)$, where $\theta_Q$ is a set of trainable parameters, and $H' \in \mathbb{R}^{W_h \times H_h \times 14}$ and $F' \in \mathbb{R}^{W_h \times H_h \times 28}$ are the estimates of the ground-truth heatmaps and PAF respectively.

Next, we define an objective function with a heatmap term $E_{heatmap}$, a PAF term $E_{PAF}$, and a pixel loss term $E_{pixel}$ for training PolishNet as follows:

$$E_{heatmap} = \sum_{k=1}^{h} \sum_{i=1}^{H_h} \sum_{j=1}^{W_h} \|H_k - H'_k\|_2^2,$$

$$E_{PAF} = \sum_{k=1}^{f} \sum_{i=1}^{H_h} \sum_{j=1}^{W_h} \|F_k - F'_k\|_2^2,$$

$$E_{pixel} = \sum_{i=1}^{H} \sum_{j=1}^{W} \|I - I'\|_2^2.$$

2. PROPOSED METHOD

Overview: Our goal is to learn a pre-processing step that receives the pressure data as inputs and synthesizes images such that a pre-trained pose estimation module shows stable and accurate performance. In other words, the output data from the learner should lie on the data manifold used by the pose estimation module. Therefore, this learnable pre-processing step, which we call PolishNet, converts the pressure data to polished images that better resemble human figures as expected by the commonly available pose estimation models.
The final objective function is then defined by:

\[ E(\theta_p) = \lambda_{heatmap} E_{heatmap} + \lambda_{PAF} E_{PAF} + \lambda_{pixel} E_{pixel}, \]

where the first two terms force PolishNet to synthesize images containing the correct pose, and the last term helps PolishNet to maintain the original pressure image’s shape information.

**Implementation Details:** We implement the pipeline using TensorFlow on an NVIDIA Titan XP GPU. The convolution kernels of the PolishNet module were 3 × 3 with a stride of 2, and the LeakyReLU use a negative activation coefficient of 0.1. Bigger kernel sizes interpolate the body shapes better at the cost of losing input-output image similarity. We use an Adam optimizer to train the pipeline for 50 epochs with a batch size of 16. We use a learning rate of $10^{-4}$, which we decay with a rate of 0.95 for every 100 update iterations. Finally, $\lambda_{PAF}$ and $\lambda_{heatmap}$ are both set to 1, while $\lambda_{pixel}$ is empirically set to 0.2 to allow PolishNet to focus more on reconstructing the vague pressure points of the body.

### 3. EXPERIMENT SETUP AND RESULTS

#### 3.1. Data Preparation

We used the PmatData dataset \[6, 22\] to train and test our pressure-based pose estimation approach. The pressure data have been recorded by the Force Sensitive Application (FSA) pressure mapping mattress. The mattress was equipped with 32 × 64 sensors, 1 inch apart from each other. The recording was performed with a frequency of 1 Hz for a pressure range of 0-100 mmHg. 13 subjects, with a height range of 169-186 cm, a weight range of 63-100 Kg, and an age range of 19-34 years participated in the experiment of sleeping on the mattress in a total of 17 unique poses.

The PmatData dataset does not contain the ground-truth join labels needed for training and evaluation purposes. Therefore, we developed and utilized a tool in MATLAB for annotating the body part locations, and subsequently labeled 1000 pressure maps. We then implemented an annotation tool that automatically annotated the rest of the pressure maps for each subject and each posture using similarity in the image space based on the sum of squared errors. This was possible since each subject appears to be in a very similar (almost identical) posture with small variances in terms of general position during the majority of recording sessions given posture class.

Next, we applied a 3 × 3 × 3 spatio-temporal median filter on the input data to remove the noise generated from occasional sensor values measuring unexpected values. We also removed 6 frames recorded at the time of transition between sleeping poses, since in some cases, they did not show a clear image of the body.

### 3.2. Performance Evaluation

To evaluate the performance of our pipeline on the annotated data, we used the probability of correct keypoint (PCK) evaluation metric, which is a measure of joint localization accuracy \[23\]. Accordingly, we measure the distance between the detected and ground-truth keypoints, and if this distance is below a certain threshold, the keypoint in question is considered as true-positive. The threshold is defined as a fraction of the person’s size, where the size is defined as the distance between the person’s left shoulder and right hip \[24\]. To perform a thorough evaluation of our method, we use a leave-one-subject-out cross-validation, where we leave 2 subjects out for validation and use the remaining subjects for training.

We evaluate our method by comparing the performance of OpenPose on colorized pressure maps vs. the proposed pipeline, including PolishNet. The area under the PCK curves are presented in Table 1 demonstrating that for all the body parts, our proposed pipeline considerably outperforms the use of only OpenPose on the colorized pressure maps. Low standard deviations in our test results indicate the consistency our model. It is observed from the table that for challenging body
Table 1. The area under the PCK curves and their standard deviations are presented for our proposed method and OpenPose only.

| Model                  | Head & Neck | R Shoulder | R Elbow | R Wrist | R Hip | R Knee | R Ankle |
|------------------------|-------------|------------|---------|---------|-------|--------|---------|
| Pre-trained PolishNet  | 94.9 ± 18.1 | 73.6 ± 21.9 | 57.4 ± 20.1 | 30.1 ± 17.7 | 4.5 ± 7.4 | 55.4 ± 30.9 | 39.6 ± 21.0 |
| PolishNet + OpenPose   | 95.5 ± 3.0  | 73.0 ± 19.1 | 55.6 ± 15.4 | 28.1 ± 14.4 | 67.2 ± 25.5 | 56.4 ± 30.9 | 37.8 ± 20.3 |
| OpenPose only          | 79.2 ± 18.8 | 73.6 ± 21.9 | 57.4 ± 20.1 | 30.1 ± 17.7 | 4.5 ± 7.4 | 55.4 ± 30.9 | 39.6 ± 21.0 |
| Proposed Method        | 94.9 ± 18.1 | 73.6 ± 21.9 | 57.4 ± 20.1 | 30.1 ± 17.7 | 4.5 ± 7.4 | 55.4 ± 30.9 | 39.6 ± 21.0 |

Table 2. Quantitative evaluation of different models is presented. OpenPose and DeeperCut are tested with and without a PolishNet that has been pre-trained for OpenPose. For both OpenPose and DeeperCut, the original and frozen versions are used.

| Model                          | Average Detection Rate |
|--------------------------------|------------------------|
| OpenPose only                  | 47.7 ± 10.8            |
| PolishNet + OpenPose           | 95.5 ± 0.3             |
| DeeperCut only                 | 54.1 ± 1.3             |
| Pre-trained PolishNet + DeeperCut | 80.9 ± 2.4         |

Some examples depicting the performance of our method are presented in Figure 4. It is seen that in most cases, OpenPose alone is not able to correctly identify poses without PolishNet, if at all. Moreover, we observe that our proposed PolishNet + OpenPose pipeline accurately identifies the poses for vague input pressure maps. Since PolishNet is trained to synthesize images compatible with the image space by which OpenPose was trained, the polished outputs show a higher resemblance to common standing human poses. In Figure 4, we notice that PolishNet reconstructs and connects the limbs and weak pressure areas that are not clearly visible in the pressure maps. We have highlighted some of these reconstructed regions in Figure 4. Moreover, in some instances, PolishNet even attempts to interestingly synthesize outfits for the subjects to make the output images look more natural and consistent with the input image space of the pose estimator. See Figure 4, row 3, columns 3, 4, 8, 10, and 11 for the synthesized outfit-like patches, especially around the hip and torso areas.

To further evaluate our method, we freeze PolishNet after training with OpenPose as the pose estimation module, then swap OpenPose with another popular pose estimation model, in this case, DeeperCut [20, 21]. We then test the pipeline with pressure maps. The average area under the PCK curves for all the body parts and respective standard deviations are provided for each architecture in Table 3. As expected, PolishNet + OpenPose achieves the highest average detection rate since PolishNet is trained in a pipeline where OpenPose is used as the pose identification module. Interestingly, the pre-trained PolishNet followed by DeeperCut outperforms pose estimation with DeeperCut alone, improving the average detection rate by 26.8%. This further demonstrates that the images synthesized by PolishNet lie on, or close to, the manifolds with which most pose estimation models are trained. This allows us to use the pre-trained PolishNet as a learned pre-processor for enhancing ambiguous pressure maps, followed by any pre-trained pose identification block that may be selected based on available resources, constraints, and other properties.

4. CONCLUSIONS

Deep pose estimators are capable of detecting users’ pose from natural images, while failing on data acquired from other devices such as pressure mapping systems, which are gaining popularity for health- and sleep-related research. In this paper, we addressed this issue by presenting a novel framework for in-bed pose estimation using an off-the-shelf pose estimation network, OpenPose, equipped with a learnable pre-processing block, called PolishNet. Using this design, our end-to-end model not only allows for pose estimation models to detect body parts with high accuracy, but also uses PolishNet to reconstruct vague and ambiguous body parts, such as wrists and knees. Furthermore, PolishNet results in synthesized images that can be used by other pose estimators as well. Our evaluation on a public dataset, PmatData, showed a 95.8% detection rate with a leave-one-subject-out strategy, and 80.9% when tested with another pose estimation network, namely DeeperCut. Finally, our proposed model can be effectively implemented for smart homes and clinical settings for ubiquitous and unobtrusive sleep monitoring.

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6. REFERENCES

[1] James A Douglas, Ching Li Chai-Coetzer, David McEvoy, Matthew T Naughton, Alistair M Neill, Peter Rochford, John Wheatley, and Christopher Worsnop, “Guidelines for sleep studies in adults—a position statement of the australasian sleep association,” *Sleep Med*, vol. 36, no. Suppl 1, pp. S2–S22, 2017.

[2] Chul H Lee, Dong K Kim, So Y Kim, Chae-Seo Rhee, and Tae-Bin Won, “Changes in site of obstruction in obstructive sleep apnea patients according to sleep position: a disc study,” *The Laryngoscope*, vol. 125, no. 1, pp. 248–254, 2015.

[3] Joyce Black, Mona Mylene Baharestani, Janet Cuddigan, Becky Dorner, Laura Edsberg, Diane Langemo, Mary Ellen Posthauer, Catherine Ratliff, George Taler, et al., “National pressure ulcer advisory panel’s updated pressure ulcer staging system,” *Advances in Skin & Wound Care*, vol. 20, no. 5, pp. 269–274, 2007.

[4] Jason J Liu, Ming-Chun Huang, Wenyao Xu, and Majid Sarrafzadeh, “Bodypart localization for pressure ulcer prevention,” in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2014, pp. 766–769.

[5] Abdul Q Javaid, Rishabh Gupta, Alex Mihalidis, and S Ali Etemad, “Balance-based time-frequency features for discrimination of young and elderly subjects using unsupervised methods,” in *IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, 2017, pp. 453–456.

[6] Sarah Ostadabbas, Maziyar Baran Pouyan, Mehrdad Nourani, and Nasser Kehtarnavaz, “In-bed posture classification and limb identification,” in *IEEE Biomedical Circuits and Systems Conference*, 2014, pp. 133–136.

[7] Aite Zhao, Junyu Dong, and Huiyu Zhou, “Self-supervised learning from multi-sensor data for sleep recognition,” *IEEE Access*, 2020.

[8] Rasoul Yousefi, Sarah Ostadabbas, Miad Faezipour, Masoud Farshbaf, Mehrdad Nourani, Lakshman Tamil, and Matthew Pompeo, “Bed posture classification for pressure ulcer prevention,” in *IEEE Engineering in Medicine and Biology Society, 2011*, pp. 7175–7178.

[9] Vandad Davoodnia, Monet Slinowsky, and Ali Etemad, “Deep multitask learning for pervasive bmi estimation and identity recognition in smart beds,” *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–15, 2020.

[10] Vandad Davoodnia and Ali Etemad, “Identity and posture recognition in smart beds with deep multitask learning,” in *IEEE International Conference on Systems, Man and Cybernetics (SMC)*, 2019, pp. 3054–3059.

[11] João Paulo Silva Cunha, Hugo Miguel Pereira Choupina, Ana Patrícia Rocha, José Maria Fernandes, Felix Achilles, Anna Mira Loesch, Christian Vollmar, Elisabeth Hartl, and Soheyl Noachtar, “Neurokinect: a novel low-cost 3d video-eeg system for epileptic seizure motion quantification,” *PLoS One*, vol. 11, no. 1, pp. e0145669, 2016.

[12] Matthew J Peterson, Wilhelm Schwab, Johannes H Van Oostrom, Nikolaus Gravenstein, and Lawrence J Caruso, “Effects of turning on skin-bed interface pressures in healthy adults,” *Journal of Advanced Nursing*, vol. 66, no. 7, pp. 1556–1564, 2010.

[13] Patina S Walton-Geer, “Prevention of pressure ulcers in the surgical patient,” *AORN Journal*, vol. 89, no. 3, pp. 538–552, 2009.

[14] Henry M Clever, Zackory Erickson, Ariel Kapusta, Greg Turk, Karen Liu, and Charles C Kemp, “Bodies at rest: 3d human pose and shape estimation from a pressure image using synthetic data,” in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 6215–6224.

[15] Wei Tang, Pei Yu, and Ying Wu, “Deeply learned compositional models for human pose estimation,” in *European Conference on Computer Vision (ECCV)*, 2018, pp. 190–206.

[16] Lipeng Ke, Ming-Ching Chang, Honggang Qi, and Siwei Lyu, “Multi-scale structure-aware network for human pose estimation,” *arXiv preprint arXiv:1803.09894*, 2018.

[17] Wei Yang, Shuang Li, Wanli Ouyang, Hongsheng Li, and Xiaogang Wang, “Learning feature pyramids for human pose estimation,” in *IEEE International Conference on Computer Vision (ICCV)*, 2017, pp. 1290–1299.

[18] Zhe Cao, Tomas Simon, Shih-En Wei, and Yaser Sheikh, “Realtime multi-person 2d pose estimation using part affinity fields,” *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1302–1310, 2017.

[19] Yilun Chen, Zhicheng Wang, Yuxiang Peng, Zhiqiang Zhang, Gang Yu, and Jian Sun, “Casced pyramid network for multi-person pose estimation,” in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018, pp. 7103–7112.

[20] Eldar Insafutdinov, Leonid Pishchulin, Bjørn Andres, Mykhaylo Andriluka, and Bernt Schiele, “Deepercut: A deeper, stronger, and faster multi-person pose estimation model,” in *European Conference on Computer Vision (ECCV)*. Springer, 2016, pp. 34–50.

[21] Eldar Insafutdinov, Mykhaylo Andriluka, Leonid Pishchulin, Siyu Tang, Evgeny Levinkov, Bjørn Andres, and Bernt Schiele, “Artrack: articulated multi-person tracking in the wild,” in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 1293–1301.

[22] Ary L. Goldberger, Luis A. N. Amaral, Leon Glass, Jeffrey M. Hausdorff, Plamen Ch. Ivanov, Roger G. Mark, Joseph E. Mietus, George B. Moody, Chung-Kang Peng, and H. Eugene Stanley, “PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals,” *Circulation*, vol. 101, no. 23, pp. e215–e220, June 2000.

[23] Yi Yang and Deva Ramanan, “Articulated human detection with flexible mixtures of parts,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 12, pp. 2878–2890, 2013.

[24] Mykhaylo Andriluka, Leonid Pishchulin, Peter Gehler, and Bernt Schiele, “2d human pose estimation: New benchmark and state of the art analysis,” in *IEEE Conference on computer Vision and Pattern Recognition (CVPR)*, 2014, pp. 3686–3693.