Human Pose Estimation using Motion Priors and Ensemble Models

(Invited Paper)

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Abstract—Human pose estimation in images and videos is one of key technologies for realizing a variety of human activity recognition tasks (e.g., human-computer interaction, gesture recognition, surveillance, and video summarization). This paper presents two types of human pose estimation methodologies; 1) 3D human pose tracking using motion priors and 2) 2D human pose estimation with ensemble modeling.

1. Introduction

Human pose estimation [1, 2] has a large variety of applications such as action recognition [3], and biometrics [4]. Two different levels of human pose estimation problems have been studied in Computer Vision. The first problem is 3D human pose estimation, in which 3D joint positions/angles (e.g., \( x \), \( y \), and \( z \) coordinates of each body joint) are estimated. While the 3D human pose is the complete representation of a 3D human body, the 2D configuration of body joints observed in an image is also useful for understanding human activities. Therefore, 2D human pose estimation, the second problem, is also one of the hot research topics.

3D pose estimation is more difficult than 2D pose estimation. However, several additional cues, such as multi-viewpoint images and temporal smoothness in videos, allow us to resolve this problem. Among these cues, we focus on a motion prior captured in a video. To estimate complex dynamic human poses, the motion prior is widely used for accuracy and robustness. Most recent works obtain it from sample sequences of real human motions. Several kinds of actions, such as walking and running, are recorded in motion datasets that are widely used in Computer Vision [6] and Graphics [7], [5] communities. The motion model of each action can be used for pose tracking in that action.

Unlike 3D human pose tracking in videos, motion priors cannot be employed for 2D human pose estimation in still images. Instead of motion priors, other additional schemes are used for 2D human pose estimation. We focus on a limited variety of possible body poses depending on the scenario (e.g., human activity). In basic methods for pose estimation, the appearance features and body joint distributions of a human body are modeled in a training process. Human pose estimation is challenging due to the wide variety of appearances and joint distributions. One way to alleviate the complexity is to cluster a training dataset so that a set of ensemble models can be learned. Reducing the variation within each subset facilitates learning the ensemble model to accurately estimate the joint locations under a particular pose configuration.

2. 3D Human Pose Tracking using Motion Priors

In 1990s, most human pose estimation methods were based on generative approaches where pose parameters (i.e., joint positions) are optimized so that each body part model overlaps its
image as shown in Figure 1 (a). Recent advances in machine learning allow us to apply discriminative approaches to human pose estimation. While most of our methods are based on a feature-to-pose regression [11], [13], [14], body-part segmentation based on classification [12] can be also useful. In an example shown in Figure 1 (b), a feature vector \( y_F \) is computed from the 3D volume of a target person, and a regression function \( y_P = f_m(y_F) \) is trained to obtain a set of pose parameters \( y_P \).

In generative approaches, most methods assume that the 3D shape of a person is represented as an articulated object consisting of rigid parts. This is because it is difficult to efficiently represent the flexible shape of loose-fitting clothing by 3D model deformation [15]. Feature-to-pose regression approaches, on the other hand, can easily represent such large shape deformation [11].

For successful discriminative approaches, we have to acquire mapping functions between image/shape features and body pose parameters. In order to cope with high dimensionality of the image/shape features, various low dimensional features that are robust to observation noise have been proposed [16]. General dimensionality reduction algorithms are also applicable to this feature extraction; linear algorithms such as PCA, nonlinear algorithms such as Locally Linear Embedding and Isomap, and probabilistic nonlinear embedding methods such as Gaussian Process Latent variable Models, GPLVM [8].

For tracking a complex pose sequence, motion priors are useful. Dynamic and complex human motions can be represented by parametric models and/or instance-based models. In most motion models, the dimension of a feature space is reduced for improving model generalization. In a toy example shown in Figure 2, motion dynamics is modeled in a low-dimensional latent space \( X \) obtained from it original high-dimensional features (i.e., sample pose sequences \( y \)).

### 2.1. Human Pose under Clothing

To estimate complex dynamic poses, pose tracking using motion priors and multiview images is more effective than pose detection from a unidirectional view.

In [17], our goal is 3D body-part segmentation in a reconstructed volume of a human body wearing loose-fitting clothing, as shown in Figure 3. While the similar goal is achieved by frame-wise body-part labeling using a huge number of training data generated by computer graphics in [12], our method uses temporal matching with real-image training data. A set of time-series target volumes, which is acquired by a slow but sophisticated 3D reconstruction algorithm, with body-part labels is learned in advance. The time-series sample volumes are learned using PCA and stored as the manifolds in the eigenspace, as shown in “Voxel latent space” in Figure 4. Each input volume reconstructed online is projected into the eigenspace and compared with the manifolds in order to find similar high-precision samples with body-part labels.
In [11], complex motion priors of a target shape are modeled explicitly with the temporal mapping function defined in a low-dimensional space modeled by probabilistic non-linear embedding, i.e., Gaussian Process Dynamical Models, GPDM [9]. We also obtain the low-dimensional space of a human body pose and train a mapping function from the volume latent space to the pose latent space. Since all of these mapping function are defined by Gaussian process regressions, these functions are generalized in contrast to shape matching/retrieval used in [17]. For further robustness, reconstructed volume tracking is achieved by particle filtering, where the likelihood between the reconstructed volume and each particle in the volume latent space is computed in the volume latent space. The likelihood-weighted mean of all particles is regarded as the target volume at this time step. For the next time step, all particles are shifted using the temporal mapping function defined by GPDM. Finally, the estimated refined volume is mapped to the pose latent space in order to compute the body pose of the target person. As shown in Figure 5, we can estimate the body poses under loose-fitting clothing.

2.2. Pose Tracking in Multiple Actions

Motion priors can be modeled and applicable to pose tracking as described in Section 2.1. Training data of motion priors can be obtained from various motion datasets [6], [7], [5]. Different kinds of actions (e.g. walking, jogging, dance) are recorded independently in these datasets. The motion model of each action can be leveraged for analyzing that action. Different actions are smoothly transited from one to another (e.g. from walking to jogging) in a natural scenario, while they are recorded independently in motion datasets. For efficiently using motion priors of multiple actions in such natural scenarios, we proposed two kinds of motion modeling schemes where different training sequences are connected via transitions paths. While motion transitions among training sequences have been proposed for graphics animations [18], [19], we optimize the transition paths for vision-based tracking problems.

Unified model: The motions of all actions are modeled in a unified latent model [20]. In order
to optimize the latent model with kinematically-realistic transitions between different actions, topologically-constrained modeling [10] is used with constraints such that each transition path connects two different action sequences as smooth and short as possible, as shown in Figure 6. Then these two different sequences are connected via synthesized paths for smooth action transitions. With this model, error in 3D body-joint localization during action transitions decreases 49% on average in contrast to a latent model produced by GPDM with no transition paths.

Separate models: The motion of each action is modeled in its independent latent model [21]. Such independent modeling of action-specific motions allows us 1) to optimize each model in accordance with only its respective motion and 2) to improve the scalability of the models. For robust tracking with the multiple models, particle filtering is employed so that particles are distributed simultaneously in the models. Efficient use of the particles can be achieved by locating many particles in the model corresponding to an action that is currently observed. For transferring the particles among the models in quick response to changes in the action, transition paths are synthesized between the different models. The effectiveness of the proposed models is validated with several datasets. Figure 7 shows tracking results in an image sequence including six gait actions; only four of them are shown in this example. Compared with independent models with no transition paths, error in body-joint localization decreases 20% on average in our proposed models.

3. 2D Human Pose Estimation with Ensemble Modeling

Pictorial structure models (PSMs) [22] have been extensively applied to 2D human pose estimation because of their ability for efficient and global optimization. PSMs can be augmented by discriminative training [23], [24]. Several extensions have been proposed to improve PSMs, including coarse-to-fine modeling [25], appearance modeling using region segmentation [28], occlusion-robust modeling [29], and appearance learning between parts [26], [27]. While global optimality of the PSM is attractive, its ability to represent complex relations among joint locations is limited compared to deep neural networks.

Convolutional neural networks (ConvNets) have recently been applied to pose estimation. A ConvNet can directly estimate the joint locations [30] or estimate the pixel-wise likelihood of each joint location as a heatmap [31]. Recent approaches explore sequential structured estimation to iteratively estimate the part locations [32], [33].

3.1. Action-specific Pose Models

We can roughly understand a human activity from a human pose. That is, human pose and action are mutually related to each other. Based on this idea, action classification has been achieved by pose matching (e.g. 2D pose-based matching [34] in videos and view-invariant 3D pose matching in videos [35]). In an opposite manner,
for pose tracking in videos, action-specific model selection has been also achieved (e.g., efficient particle distribution in pose models [21] and unified multi-action modeling [20]).

With the aforementioned mutual augmentation, in [36], we proposed an iterative scheme between action classification and pose estimation in still images, as shown in Figure 8. Initial action classification is achieved only by global image features that consist of the responses of various object filters. The classification likelihood of each action (“Probability estimates” in the figure) weights human poses estimated by the pose models of multiple action classes (“Model” in the figure). Such action-specific pose models allow us to robustly identify a human pose under the assumption that similar poses are observed in each action. From the estimated pose (“Best pose” in the figure), pose features are extracted and used with global image features for re-classification. With this scheme, pose accuracy increases 11.3% compared with the base model [27].

The aforementioned action-specific pose models can be employed for weakly-supervised learning. Assume that most training images have only the action label of a person of interest (i.e., “Weakly-supervised training set” in Figure 9), while some training images have also a human pose annotation (i.e., “Fully-supervised training set” in the figure). By utilizing the fact that the pose features of the same action make clusters, we estimate a human pose in each weakly-supervised image and classify whether or not the estimated pose is correct. The correctly-estimated pose is employed with its image for re-training the pose model of its corresponding action. The detail of this work will be introduced in the talk.

3.2. Pose Modeling with Pose Similarity

Unlike action-specific models, pose models can be clustered also depending on pose similarity independently of human actions. Figure 10 shows the basic scheme in pose inference in this approach. Before this inference, heterogeneous pose estimation models (“PM model” in the figure) are trained from the full set of training images. In the inference, all pose estimation models estimate their own outputs independently. Then all the pose outputs are merged in order to obtain the final output (“Estimated joint locations” in the figure). This pose mergence is achieved by a huge deep neural network for capturing complex interdependency among noisy and ambiguous output poses. This is a major difference from pose selection from multiple candidates [37]. The detail of this work will be also introduced in the talk.

4. Conclusion

All pose estimation models presented in this paper utilize motion priors or ensemble modeling for improving the performance. For future work, complex and huge data representation using neural networks and semi/weakly-supervised approaches should be important in order to represent a huge variety of human activities.
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