Optimizing Over a Set of Manifolds*

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Abstract. We give a comprehensive description of the algorithm proposed in "2D Action Recognition Serves 3D Human Pose Estimation" [1].

1 Preliminaries

Having a skeleton and a surface model of the human, the human pose is represented by a vector in a bounded, high-dimensional state space $\mathbb{E} \subset \mathbb{R}^{D+6}$. While $\Theta = \theta_1, \cdots, \theta_D \in \mathbb{E}_\Theta$ denotes the joint angles, the global orientation and position are encoded by the 6D vector (r, t). An element of the search space is given by $x = (r, t, \Theta)$. We formulate pose estimation as an optimization problem over $\mathbb{E}$ for a given positive energy function V, i.e. $\min_{x \in \mathbb{E}} V(x)$. The energy function measures the consistency between the image and the projected surface of the human for a given pose x.

2 Baseline

As a baseline, we implemented the particle-based annealing optimization scheme ISA over $\mathbb{E}$ (Algorithm 1), which has been used in the multi-layer framework [2]. The optimization scheme, based on the theory of Feynman-Kac models [3], iterates over a selection and mutation step, and is also the underlying principle of the annealed particle filter [4]. In our experiments, we use the polynomial annealing scheme:

$$\beta_k = (k+1)^b \tag{1}$$

with $b = 0.7$. The mutation step is implemented with the scaling factor $\alpha_\Sigma = 0.4$ and the positive constant $\rho = 0.0001$. The set of particles is denoted by $\mathcal{S}$. An estimate of the pose is given by the weighted mean of the particles after the last iteration, i.e. $\hat{x} = \sum_{s^i \in \mathcal{S}} (w^i \cdot x^i)$. For r^i, the mean is computed in the space of rotations. The uniform distribution and the normal distribution are denoted by $\mathcal{U}[0,1]$ and $\mathcal{N}(\mu, \Sigma)$, respectively.

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Algorithm 1 Interacting Simulated Annealing over $\mathbb{E}$

For $k = 1, \ldots, It$

- *Selection*
  - $\forall s^i \in \mathcal{S}_{k-1}$: $w^i = \exp\left(-\beta_k \cdot V\left(r^i, t^i, \Theta^i\right)\right)$
  - $\forall s^i \in \mathcal{S}_{k-1}$: $w^i = w^i / \sum_{s^j \in \mathcal{S}_{k-1}} w^j$
  - $\mathcal{S}_k = \emptyset$; $\forall s^i \in \mathcal{S}_{k-1}$ draw u from $\mathcal{U}[0,1]$:

    If $u \leq w^i / \max_{s^j \in \mathcal{S}_{k-1}} w^j$ then
      - $\mathcal{S}_k = \mathcal{S}_k \cup \{s^i\}$

    Otherwise
      - $\mathcal{S}_k = \mathcal{S}_k \cup \{s^j\}$, where s^j is selected with probability w^j
- *Mutation*
  - $\mu = \frac{1}{|\mathcal{S}_k|} \sum_{s^j \in \mathcal{S}_k} (r^j, t^j, \Theta^j)$

    $\Sigma = \frac{\alpha \Sigma}{|\mathcal{S}_k| - 1} \left(\rho I + \sum_{s^j \in \mathcal{S}_k} \left((r^j, t^j, \Theta^j) - \mu\right) \left((r^j, t^j, \Theta^j) - \mu\right)^T\right)$
  - $\forall s^i \in \mathcal{S}_k$ sample (r^i, t^i, Θ^i) from $\mathcal{N}((r^i, t^i, \Theta^i), \Sigma)$

3 Proposed Algorithm

We modify the baseline algorithm to optimize over a set of manifolds instead of a single state space. To this end, we consider a set of action classes $\mathcal{A} = \{a_1, \cdots, a_{|\mathcal{A}|}\}$, where we learn for each class an action-specific low-dimensional manifold $\mathbb{M}_a \subset \mathbb{R}^{d_a}$ with $d_a \ll D$. We assume that the following mappings are available:

$$f_a : \mathbb{E}_\Theta \mapsto \mathbb{M}_a, \quad g_a : \mathbb{M}_a \mapsto \mathbb{E}_\Theta, \quad h_a : \mathbb{M}_a \mapsto \mathbb{M}_a, \tag{2}$$

where f_a denotes the mapping from the state space to the low-dimensional manifolds, g_a the projection back to the state space, and h_a the prediction within an action-specific manifold. Since the manifolds encode only the space of joint angles, a low-dimensional representation of the full pose is denoted by $y_a = (r, t, \Theta_a)$ with $\Theta_a = f_a(\Theta)$. A particle $s^i = (y^i_a, a^i)$ stores the corresponding manifold label a^i in addition to the vector $y^i_a = (r^i, t^i, \Theta^i_a)$. While *Select* p_1 is outlined in Algorithm 2, *Optimization A*, *Select* p_2, and *Optimization B* are described in Algorithm 3. The particles in the manifolds $\mathbb{M}_a$ after *Optimization A* are denoted by $\mathcal{S}^{\mathbb{M}}_{It_A}$ and the particles in the state space after *Optimization B* are denoted by $\mathcal{S}^{\mathbb{E}}_{It_B}$. The probability of an action class a for a given frame t is denoted by $p(A = a \,|\, T = t, \mathcal{I})$ and the estimated joint angles of the previous frame are denoted by $\hat{\Theta}_{t-1}$.

Algorithm 2 *Select* p_1

- $\mathcal{S}^{\mathbb{M}} = \emptyset$; $\forall s^i \in \mathcal{S}^{\mathbb{M}}_{It_A}$ draw u from $\mathcal{U}[0,1]$:

  If $u < p_1$ then
  - $\mathcal{S}^{\mathbb{M}} = \mathcal{S}^{\mathbb{M}} \cup \{s^i\}$

  Otherwise
  - $\mathcal{S}^{\mathbb{M}} = \mathcal{S}^{\mathbb{M}} \cup \left\{\left(r^j, t^j, f_{a^j}(\Theta^j), a^j\right)\right\}$, where $(r^j, t^j, \Theta^j) \in \mathcal{S}^{\mathbb{E}}_{It_B}$ and a^j is selected with probability $p(A \,|\, T = t, \mathcal{I})$

References

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Algorithm 3 Optimizing over $\mathbb{M}_a$

Optimization A:

For $k = 1, \ldots, It_A$
- *Selection*
  - $\forall s^i \in \mathcal{S}^{\mathbb{M}}_{k-1}$: $w^i = \exp\left(-\beta_k \cdot V\left(r^i, t^i, g_{a^i}(\Theta^i_a)\right)\right)$
  - $\forall s^i \in \mathcal{S}^{\mathbb{M}}_{k-1}$: $w^i = w^i / \sum_{s^j \in \mathcal{S}^{\mathbb{M}}_{k-1}} w^j$
  - $\mathcal{S}^{\mathbb{M}}_k = \emptyset$; $\forall s^i \in \mathcal{S}^{\mathbb{M}}_{k-1}$ draw u from $\mathcal{U}[0, 1]$:
    If $u \leq w^i / \max_{s^j \in \mathcal{S}^{\mathbb{M}}_{k-1}} w^j$ then
    - $\mathcal{S}^{\mathbb{M}}_k = \mathcal{S}^{\mathbb{M}}_k \cup \{s^i\}$

    Otherwise
    - $\mathcal{S}^{\mathbb{M}}_k = \mathcal{S}^{\mathbb{M}}_k \cup \{s^j\}$, where s^j is selected with probability w^j
- *Mutation*
  - $\forall a \in \mathcal{A}$: $\mu_a = \frac{1}{|\mathcal{S}_a|} \sum_{s^j \in \mathcal{S}_a} \Theta^j_a$ with $\mathcal{S}_a = \{s^i \in \mathcal{S}^{\mathbb{M}}_k : a^i = a\}$
    $\forall a \in \mathcal{A}$: $\Sigma_a = \frac{\alpha_\Sigma}{|\mathcal{S}_a|-1} \left(\rho\, I + \sum_{s^j \in \mathcal{S}_a} (\Theta^j_a - \mu_a)\,(\Theta^j_a - \mu_a)^T\right)$
    $\mu_0 = \frac{1}{|\mathcal{S}^{\mathbb{M}}_k|} \sum_{s^j \in \mathcal{S}^{\mathbb{M}}_k} (r^j, t^j)$
    $\Sigma_0 = \frac{\alpha_\Sigma}{|\mathcal{S}^{\mathbb{M}}_k|-1} \left(\rho\, I + \sum_{s^j \in \mathcal{S}^{\mathbb{M}}_k} \left((r^j, t^j) - \mu_0\right) \left((r^j, t^j) - \mu_0\right)^T\right)$
  - $\forall s^i \in \mathcal{S}^{\mathbb{M}}_k$ sample Θ^i_a from $\mathcal{N}(\Theta^i_a, \Sigma_{a^i})$ and (r^i, t^i) from $\mathcal{N}((r^i, t^i), \Sigma_0)$

Select p_2:

- $\hat{a} = \text{argmin}_{a \in \mathcal{A}} \left\| \hat{\Theta}_{t-1} - g_a(f_a(\hat{\Theta}_{t-1})) \right\|$, $\quad (\Sigma_{\hat{a}})_{ii} = \frac{|\hat{\Theta}_{t-1} - g_{\hat{a}}(f_{\hat{a}}(\hat{\Theta}_{t-1}))|_i}{3}$
- $\mathcal{S}^{\mathbb{E}}_{It_A} = \emptyset$; $\forall s^i \in \mathcal{S}^{\mathbb{M}}_{It_A}$ draw u from $\mathcal{U}[0, 1]$:
  If $u < p_2$ then
  - $\mathcal{S}^{\mathbb{E}}_{It_A} = \mathcal{S}^{\mathbb{E}}_{It_A} \cup \left\{\left(r^i, t^i, g_{a^i}(\Theta^i_a)\right)\right\}$

  Otherwise
  - $\mathcal{S}^{\mathbb{E}}_{It_A} = \mathcal{S}^{\mathbb{E}}_{It_A} \cup \left\{(r^i, t^i, \hat{\Theta})\right\}$, where $\hat{\Theta}$ is sampled from $\mathcal{N}(\hat{\Theta}_{t-1}, \Sigma_{\hat{a}})$

Optimization B:

For $k = It_A + 1, \ldots, It_B$
- *Selection*
  - $\forall s^i \in \mathcal{S}^{\mathbb{E}}_{k-1}$: $w^i = \exp\left(-\beta_k \cdot V\left(r^i, t^i, \Theta^i\right)\right)$
  - $\forall s^i \in \mathcal{S}^{\mathbb{E}}_{k-1}$: $w^i = w^i / \sum_{s^j \in \mathcal{S}^{\mathbb{E}}_{k-1}} w^j$
  - $\mathcal{S}^{\mathbb{E}}_k = \emptyset$; $\forall s^i \in \mathcal{S}^{\mathbb{E}}_{k-1}$ draw u from $\mathcal{U}[0, 1]$:
    If $u \leq w^i / \max_{s^j \in \mathcal{S}^{\mathbb{E}}_{k-1}} w^j$ then
    - $\mathcal{S}^{\mathbb{E}}_k = \mathcal{S}^{\mathbb{E}}_k \cup \{s^i\}$

    Otherwise
    - $\mathcal{S}^{\mathbb{E}}_k = \mathcal{S}^{\mathbb{E}}_k \cup \{s^j\}$, where s^j is selected with probability w^j
- *Mutation*
  - $\mu = \frac{1}{|\mathcal{S}^{\mathbb{E}}_k|} \sum_{s^j \in \mathcal{S}^{\mathbb{E}}_k} (r^j, t^j, \Theta^j)$
    $\Sigma = \frac{\alpha_\Sigma}{|\mathcal{S}^{\mathbb{E}}_k|-1} \left(\rho\, I + \sum_{s^j \in \mathcal{S}^{\mathbb{E}}_k} \left((r^j, t^j, \Theta^j) - \mu\right) \left((r^j, t^j, \Theta^j) - \mu\right)^T\right)$
  - $\forall s^i \in \mathcal{S}^{\mathbb{E}}_k$ sample (r^i, t^i, Θ^i) from $\mathcal{N}((r^i, t^i, \Theta^i), \Sigma)$