EFFICIENT GROUPWISE NON-RIGID REGISTRATION OF TEXTURED SURFACES

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Introduction

- Groupwise non-rigid registration of 2D images [3, 6] is a powerful technique superior to pairwise methods.
- Video rate textured 3D surface scans are becoming common in computer vision and are a valuable source of data:
 - Appearance modelling in CV, orthodontics, biometrics.
- Here, we generalise our approach (CVPR 09) [6] to register textured 3D surfaces in a principled, groupwise way.

Our Approach

- A novel, fast and reliable, fully unsupervised stochastic algorithm to search for optimal groupwise dense correspondences in ensembles of textured 3D surfaces.
- All the desirable properties of our 2D approach [6] are preserved.

Incrementally learning correspondences

As in [6], we gradually learn the optimal deformations (embeddings) by composing them of simple deformation models:

- This keeps the dimensionality of search constantly low.
- Choosing simple deformation models *randomly* at each iteration serves to explore the space of all possible deformation models, not just parameters of one pre-selected model.

Deformation model

- The deformation model is defined on the original meshes (Fig. 2) and so is explicitly aware of the 3D geometry.
- The correspondences between surfaces are maintained (and textures operated on) in a common flat reference space (Fig. 4) while performing optimisation on the original 3D surfaces.
- This can be regarded as gradually computing the embeddings of the surfaces into a plane such that they also bring all surfaces into alignment simultaneously.

Initial embeddings are computed via bending invariants/MDS, see [1] and Fig. 1.

FIGURE 1: A mesh, its bending invariant, and embedding in $\mathbb{R}^2$.

FIGURE 2: Left: magnitude of influence of several randomly placed individual “deformation disks” (using Eq. 1 with $r = 110$ mm). Right: mixture of their influence.

FIGURE 3: Adaptive, curvature based, farthest-point sampling of “deformation disk” locations. Left: magnitude of the mesh curvature. Right: various number, n , of points seeded using FPS strategy [4, 5].

At each iteration, a new deformation model is chosen by randomly seeding “deformation disks” on the surface (Fig. 2), possibly adaptively (Fig. 3). Bounded ball’s influence [2]:

$$B(\mathcal{M}, \mathbf{v}, \mathbf{c}, r) = \begin{cases} 1 - (d/r)^2 (1 + \log((d/r)^2)), & d < r \\ 0, & d \geq r \end{cases} \quad (1)$$

where $d = \mathcal{G}(\mathcal{M}, \mathbf{v}, \mathbf{c})$ = geodesic distance between points $\mathbf{v}$ and $\mathbf{c}$ on mesh $\mathcal{M}$ (see [4, 5]):

$$\mathcal{G}(\mathcal{M}, \mathbf{v}, \mathbf{c}) = \min_{\gamma} \left(\int_0^1 \|\gamma'(t)\| P(\gamma(t)) dt \right). \quad (2)$$

Using $C(\cdot)$ as a “local” objective function, optimise

$$C_{\text{glob}} = \frac{1}{N} \sum_{i=1}^N C(\mathcal{R}, E_i + D_{i_k}). \quad (3)$$

ALGORITHM 1: Perform non-rigid registration of an ensemble of textured meshes.

Require: Textured meshes $\mathcal{M}_i = \{F_i, V_i, U_i, T_i\}$, their initial embeddings E_i (affinely aligned), depth components of the bending invariants $Z_i, i \in \{1 \dots N\}$

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1: Initialise:  $k \leftarrow 1; D_{i_0} \leftarrow \mathbf{0}, \forall i$ 
2: while not happy do
3:   Randomly permute the order of meshes.
4:    $\mathcal{B}_{\text{sum}} \leftarrow \mathbf{0}_{h \times w \times 4}; \mathcal{M}_{\text{sum}} \leftarrow \mathbf{0}_{h \times w \times 4}$ 
5:   for  $i = 1$  to  $N$  do
6:      $\{\mathcal{B}, \mathcal{M}\} \leftarrow \mathcal{R}(F_i, E_i + D_{i_{k-1}}, U_i, Z_i, T_i)$ 
7:      $\mathcal{B}_{\text{sum}} \leftarrow \mathcal{B}_{\text{sum}} + \mathcal{B}; \mathcal{M}_{\text{sum}} \leftarrow \mathcal{M}_{\text{sum}} + \mathcal{M}$ 
8:   end for
9:   for  $i = 1$  to  $N$  do
10:     $\{\mathcal{B}_{\text{this}}, \mathcal{M}_{\text{this}}\} \leftarrow \mathcal{R}(F_i, E_i + D_{i_{k-1}}, U_i, Z_i, T_i)$ 
11:     $\mathcal{M}_{\mathcal{R}} \leftarrow \mathcal{M}_{\text{sum}} - \mathcal{M}_{\text{this}}$ 
12:     $\mathcal{R}_{i_k} \leftarrow (\mathcal{B}_{\text{sum}} - \mathcal{B}_{\text{this}}) \bullet / \max(1, \mathcal{M}_{\mathcal{R}})$ 
13:     $\mathbf{b}_{n_b \times 1} \leftarrow \text{FPS}(\mathcal{G}(\mathcal{M}_i, \cdot, \cdot), n_b)$ 
14:     $Q \leftarrow \text{influence}(\mathcal{M}_i, \mathbf{b})$ 
15:    Using “local” objective function  $C(\cdot)$  and with
       $H(P) = E_i + D_{i_k} + PQ$ , optimise w.r.t.  $P$  to compute
      the optimal improvement [7]:
       $\Delta D_{i_k} \leftarrow (\arg \min_P C(\mathcal{R}_{i_k}, H(P))) Q$ 
16:     $D_{i_k} \leftarrow D_{i_{k-1}} + \Delta D_{i_k}$ 
17:   end for
18:   Remove embedding bias.
19:   If improvement becomes slow, increase  $n_b$ .
20:    $k \leftarrow k + 1$ 
21: end while
22: return  $(E_i + D_{i_{k-1}})$  — the optimal embedding of  $V_i$  into
 $\mathbb{R}^2$ , that brings all meshes,  $\mathcal{M}_i$ , into alignment.
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FIGURE 4: Correspondences via a flat parametric space.

Results

FIGURE 5: Example meshes from the intra-subject data set.

FIGURE 6: Evolution of the mean surface and texture for the intra-subject data set.

FIGURE 7: The first three modes of variation ($\pm 3\sigma$) of the 3D AAM built from the registered intra-subject data set.

FIGURE 8: Example meshes from the inter-subject data set.

FIGURE 9: Evolution of the texture model in the flat parametric space for the inter-subject data set.

FIGURE 10: Evolution of the mean surface and texture for the inter-subject data set.

FIGURE 11: The first three modes of variation ($\pm 3\sigma$) of the 3D AAM built from the registered inter-subject data set.

FIGURE 12: Progress plots for the experiments: intra-subject (left) and inter-subject (right) data sets.

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