Combining Features and Intensity for Wide-Baseline Non-Rigid Surface Registration

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Non rigid surface registration consists in estimating the deformation of a known surface between two images, usually by fitting a warp such as a Thin-Plate Spline or a Free-Form Deformation. Common techniques are split in two categories: *feature-based surface detection* i.e. estimation of a potentially important deformation from an image and a flat source template, and *pixel-based surface tracking* where important deformations can be estimated over a video sequence as long as the frame to frame steps are small. Our contribution consists in bridging the two worlds by introducing a new data term robustly merging feature and pixel-based costs in a pyramidal variational approach. By using a robust estimator we achieve an implicit optimal filtering of features and automatic balancing between the two terms.

Our goal is to directly estimate a deformation between an image $\mathcal{I}$ and a given flat template $\mathcal{I}_0$. This deformation is parametrized by the displacements $\mathbf{u}$ of the control points of a Free-Form Deformation warp [4]. The image in $\mathcal{I}$ of the point $\mathbf{q}$ from $\mathcal{I}_0$ is $\mathcal{W}(\mathbf{q},\mathbf{u})$. For the sake of clarity and to allow easier comparison with feature-based methods, we adopt a feature-filtering model for our cost function:

$$\varepsilon(\mathbf{u},\mathcal{F},\mathcal{I},\mathcal{I}_0) = \underbrace{\varepsilon_f(\mathbf{u},\mathcal{F})}_{\text{features cost}} + \underbrace{\varepsilon_b(\mathbf{u}) + \varepsilon_s(\mathbf{u}) + \varepsilon_d(\mathbf{u},\mathcal{I},\mathcal{I}_0)}_{\text{priors}} \tag{1}$$

where $\mathcal{F}$ is the set of feature matches provided as input. This function is optimized over all control points using a Gauss-Newton approximation embedded in a coarse-to-fine framework.

The feature-based cost function is similar to the ones used in [5] and [1]:

$$\varepsilon_f(\mathbf{u},\mathcal{F}) = \lambda_f \sum_{(\mathbf{f}_0,\mathbf{f})\in\mathcal{F}} \iint_\Omega \omega(\mathbf{q},\mathbf{f}_0)\Psi_\sigma\left(\|\mathbf{u}-(\mathbf{f}-\mathbf{f}_0)\|_2\right)\mathrm{d}\mathbf{q} \tag{2}$$

where ω is a weight function based on the distance to feature only, and $\Psi_\sigma(x) = \frac{x^2}{\sigma+x^2}$ is the Geman McClure estimator, providing an implicit filtering of outliers. By avoiding any assumption on the feature used (such as the availability of a confidence measure), we leave open the possibility of using any current and future feature matchers.

We use three priors to constrain and regularize the warp produced by the feature matches. First the bending energy regularizer

$$\varepsilon_b(\mathbf{u}) = \lambda_b \iint_\Omega \left(\frac{\partial\mathcal{W}(\mathbf{q};\mathbf{u})^2}{\partial^2 q_x}\right) + \left(\frac{\partial\mathcal{W}(\mathbf{q};\mathbf{u})^2}{\partial q_x \partial q_y}\right) + \left(\frac{\partial\mathcal{W}(\mathbf{q};\mathbf{u})^2}{\partial^2 q_y}\right)\mathrm{d}\mathbf{q} \tag{3}$$

that enforces a smooth displacement field. Then a *shrinker* term [3] preventing the warp from folding in self-occluded areas:

$$\begin{aligned}\varepsilon_s(\mathbf{u}) &= \lambda_s \sum_{\mathbf{q}\in\Omega}\sum_{\mathbf{d}\in\mathcal{D}}\sum_{c\in\{x,y\}} \gamma\left\{\left(D_{\mathbf{d}}^{(l)}(\mathbf{q};\mathbf{u})\right)_c \left(D_{\mathbf{d}}^{(r)}(\mathbf{q};\mathbf{u})\right)_c\right\} \\ \gamma(x) &= 0 \text{ if } x \geq 0 \text{ and } x^2 \text{ otherwise}\end{aligned} \tag{4}$$

where $\mathcal{D}$ is a discretized set of directions and the function γ penalizes points whose right and left derivatives have opposite signs.

The flexible robust-estimator-based framework allows us to use the brightness constancy assumption (common in dense optical flow estimation) as an additional prior to fully take advantage of all the available data:

$$\varepsilon_d(\mathbf{u},\mathcal{I},\mathcal{I}_0) = \lambda_d \sum_{\mathbf{q}\in\Omega}(1-\mathcal{P}_{\mathrm{SO}})(\mathcal{I}_0(\mathbf{q}) - \mathcal{I}(\mathcal{W}(\mathbf{q};\mathbf{u})))^2 \tag{5}$$

where $\mathcal{P}_{\mathrm{SO}}$ is the self-occlusion probability. It is computed by noticing that on self-occluded areas, the derivative of the warp vanishes in one direction.

Figure 1: Qualitative results on [7, 8]. First row: templates, second row: deformed surface with estimated deformation.

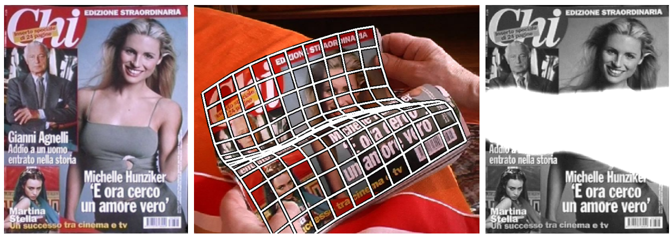

Figure 2: Challenging case from [2]. From left to right: template, estimated deformation and estimated self-occlusions (in white).

Most state of the art methods [6, 9] for wide-baseline surface registration without tracking operate in separate steps: feature filtering, warp fitting using features and optional refining using a pixel-wise data term. We demonstrate that our joint warp estimation and implicit feature filtering using the brightness constancy prior outperforms methods based on separate steps. Qualitative and quantitative evaluations using different priors on synthetic data and public datasets validate this claim and are available in the full paper.

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