Animation character identification from color images

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October 8, 2013

Animation character identification

- ▶ (Semi) supervised classification of animation character images.
- ▶ Dealing with variations in character posture, occlusion, drawing style, exaggerations.
- Application domain: web artist communities such as Pixiv, deviantArt.



Figure: Images illustrating variations for a single character.

- Animation character identification
 - Preprocessing: removing outlines, switching color space.
 - ► Segmentation to isolate parts of interest hair, clothes, face...
 - ▶ Classification by comparing segmentation against training set.

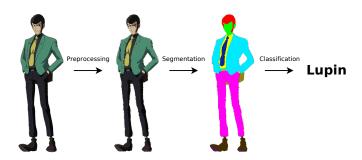


Figure: Diagram depicting how preprocessing, segmentation and classification interact.

- ► Consider 4 square windows around the pixel to filter.
- Compute mean color and variance in lightness (L in HSL) for each window.
- Assign mean corresponding to smallest variance.



Figure: Results of Kuwahara filtering with varying window size.

Felzenszwalb' segmentation [1]

- Graph method based on Kruskal's algorithm.
- ▶ Efficient: $O(n \log(n))$ time with 4-connected neighborhood.
- ▶ Accurate: neither too "coarse" nor too "fine".
- ▶ But depends on a scale parameter *k* which controls the size of segments.



(a) Original image

(b) k = 100.

(c) k = 1000.

- ► Compute 4/8-connected graph on the pixels of the image.
- Edges weighted by euclid distance in color space:

$$w(u_1, u_2) = ||(I_1, a_1, b_1) - (I_2, a_2, b_2)||$$

- Consider edges in ascending weight order.
- ▶ Fuse segments C_1 , C_2 related by edge (u_1, u_2) if $w(u_1, u_2) \leq MInt(C_1, C_2)$.

$$MInt(C_1, C_2) = \min(Int(C_1) + \tau(C_1), Int(C_2) + \tau(C_2))$$

Where $Int(C) = \max_{\{u,v\} \in MST(C,E)} w(u,v)$, and $\tau(C) = \frac{k}{\sum_{v \in C} d_v}$.

- Post processing by merging segments with close hue.
- Allows varying segment sizes and non locally connected segments.



(a) Original image.

(b) Before merging.

(c) After merging.

Spectral classification method

- ▶ For segmentation S consider features $(f_i : S \to \mathbb{R}^q_i)_{1 \le i \le m}$. (average color, gravity center, size...)
- For each feature f_i , compute K-nearest neighbor graph G_i on S with weights $w(u,v)=e^{-\frac{||f_i(S_u)-f_i(S_v)||^2}{\sigma_i^2}}$ and Laplacian L_i .
- Classifying images according to the eigenvectors of the Laplacians.



$$L_i(u,v) = \begin{cases} \sum_{u' \text{ adjacent to } u} w(u,u') & \text{if } u = v \\ -w(u,v) & \text{if } u \text{ and } v \text{ are adjacent} \\ 0 & \text{otherwise} \end{cases}$$

(b) Laplacian matrix definition.

(a) Example of graph

Method from Wilson, Hancock, Luo [2], with some changes:

- ▶ Compute k eigenvectors corresponding to smallest non zero eigenvalues of Laplacian $L_i \in \mathbb{R}^{n \times n}$.
- Invariance by vertex permutation using symmetric polynomials $P = (P_1, ..., P_n)$.
- Difference in number of vertices by padding with zeros.
- ▶ Classifying concatenated vectors E_i with SVM.

$$\Phi = \left(\sqrt{\lambda_1}e_1...\sqrt{\lambda_k}e_k\right) \in \mathbb{R}^{n \times k} \quad E_j = \begin{pmatrix} signum(P_1(\Phi_j))\ln(1+|P_1(\Phi_j)|) \\ ... \\ signum(P_n(\Phi_j))\ln(1+|P_n(\Phi_j)|) \end{pmatrix}$$
 (a) e_j is eigenvector of L_i corresponding to λ_j (b) Where Φ_j denotes the j^{th} column of Φ

Results and analysis

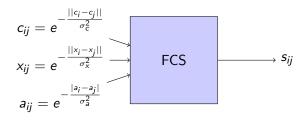
- Low recognition rate (close to random).
- Graphs do not encode enough information about individual segments.
- Deals poorly with different number of segments.
- Could be salvaged with dimensionality reduction?

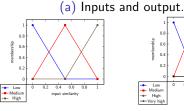
Segment matching classification

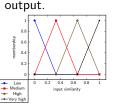
- Consider 3 features for each segment: average L*a*b* color, gravity center, and area.
- Measure similarity between segments using a fuzzy system.
- ► Find a one to one relation between similar segments of 2 images.



Figure: Original images (left) and corresponding relation (right). Segments with the same color are matched together.





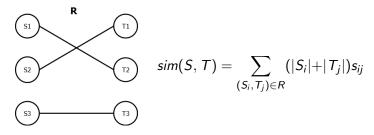


(b) Inputs membership functions.

(c) Output membership functions.

Figure: Segment similarity fuzzy control system.

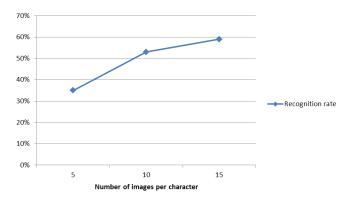
- Measure overall similarity sim(S, T) between segmentation S and T by sum of matching segments similarity weighted by segment areas.
- Classify by nearest neighbor.



Where s_{ij} denotes the similarity between segments S_i and T_j computed by the fuzzy control system.

Results and analysis

- ▶ 59% recognition rate for dataset with 12 characters and 15 images per character for a total of 180 images.
- Recognition rate scales well with size of dataset.
- Has trouble with characters sharing similar color palette.



Possible extensions:

- ► Color palette issues: determining a (possibly non-linear, or high-dimensional) color space ideally separating training data, with some (semi) supervised embedding method [3] ?
- ▶ Background extraction: detecting important character features (face, hair, clothes) using method inspired by the face detection algorithm from Viola and Jones [4] ?
- ► Also using segmentation graph, as in works from Bach and Harchaoui [5] ?

References



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