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Computer Vision - Exercise 8 Shape Context

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Shape Context Descriptors and Shape Matching

How can we enable a computer to recognize shapes the way that a human observer does? Looking at two handwritten letters, they appear very similar as images but will be very different if one compares the pixel intensity values. This exercise will introduce a feature descriptor called *shape context* [1] and explore their use in matching two shapes. You will then explore the use of shape contexts for shape classification.

8.1 Shape Matching (100%)

Your task is to implement a shape matching algorithm using MATLAB. We will make use of a descriptor called the *shape context descriptor*, described in detail in [1], which is available in the released files as *BelongiePAMI02.pdf*.

Suppose we are given a set of points from a template contour for which we want to match to a set of points on a target contour. One possible algorithm to achieve this is:

- **a)** Compute shape context descriptors for the points from both sets, the template and the target contour.
- **b)** Estimate the cost matrix between the two sets of descriptors.
- c) Use the cost matrix to solve the correspondence problem between the two sets of descriptors, finding the one-to-one matching that minimizes the total cost (e.g. with the provided Hungarian algorithm).
- **d)** Use the solution of the correspondence problem to estimate a transformation from template to target points (e.g. with Thin Plate Splines) and perform this transformation on the template points.
- e) Iterate steps (a-d).

We provide parts of the algorithm in shape_matching.m. Your task is to provide the missing code marked in shape_matching.m by comments. The MATLAB functions to be written are described below.

a) Shape Context Descriptors (40%)

Write a function which computes the shape context descriptors for a set of points. Your function should have the following form:

```
d = sc_compute(X, nbBins_theta, nbBins_r, smallest_r, biggest_r)
```

with the output d containing the shape context descriptors for all input points, and the inputs given by:

- set of points, X
- number of bins in the angular dimension, nbBins_theta
- number of bins in the radial dimension, nbBins_r
- the length of the smallest radius, smallest_r
- the length of the biggest radius, biggest_r

Hint: The shape context descriptor is described in detail in [1] in pages 511-513. For increased robustness, implement the normalization of all radial distances by the mean distance of the distances between all point pairs in the shape.

b) Cost Matrix (20%)

Write a function which computes a cost matrix between two sets of shape context descriptors. The cost matrix should be an $n \times m$ matrix giving the cost of matching two sets of points based on their shape context descriptors. One possibility is to use the χ^2 test statistic:

$$C_{gh} = \frac{1}{2} \sum_{k=1}^{K} \frac{\left[g(k) - h(k)\right]^2}{g(k) + h(k)}$$
(1)

where C_{gh} is the shape matching costs between two points with shape context descriptors g and h, each made up of $K = nbBins_theta \times nbBins_r$ bins.

The function should have the following form:

```
C = chi2\_cost(s1, s2)
```

where the output C is the cost matrix for matching two sets of shape context descriptors s1 and s2.

c) Hungarian Algorithm

We provide the code for the Hungarian algorithm which performs a one-to-one matching of the points based on the cost matrix, minimizing the total cost. This code is provided in the released file:

hungarian.m

d) Thin Plate Splines (40%)

From the point correspondences, we can estimate a plane transformation $T: \mathbb{R}^2 \to \mathbb{R}^2$ that maps any point (not only those originally sampled) from one shape to the other. We will use a thin plate spline (TPS) model:

$$f(x,y) = a_1 + a_x x + a_y y + \sum_{i=1}^{n} \omega_i U(\| (x_i, y_i) - (x, y) \|)$$
 (2)

where $U(t) = t^2 log(t^2)$ and U(0) = 0 and it holds that $\sum_{i=1}^n \omega_i = \sum_{i=1}^n \omega_i x_i = \sum_{i=1}^n \omega_i y_i = 0$.

This model gives a 1D output. Since we are interested in a 2D warping, we will use **two independent TPS models**, which we call f_x and f_y , to model the x and y coordinate transformations respectively. These combine to give the full transformation T:

$$T(x,y) = (f_x(x,y), f_y(x,y))$$
(3)

For both of these models, (x_i, y_i) are given by the points coordinates in the **original** template shape, and the appropriate coordinates of the corresponding points on the target shape give the values v_i used to solve for the TPS model.

For each TPS model, you will have to solve a system of the form

$$\begin{pmatrix} K + \lambda I & P \\ P^T & 0 \end{pmatrix} \begin{pmatrix} \omega \\ a \end{pmatrix} = \begin{pmatrix} v \\ 0 \end{pmatrix} \tag{4}$$

where $K_{ij} = U(\parallel (x_i, y_i) - (x_j, y_j) \parallel)$, the *i*-th row of *P* is $(1, x_i, y_i)$, ω and *v* are column vectors formed from ω_i and v_i , respectively, *a* is the column vector with elements a_1 , a_x , a_y , and λ is a regularizer (see [1] for details).

Solving this system allows not only the transformation to be determined, but the bending energy of the transformation to be computed. This bending energy can be used as a measure of the cost of the shape matching. It is given by:

$$E = \omega^T K \omega \tag{5}$$

Your task is to implement a MATLAB function that computes the weights ω_i and a_1 , a_x , a_y for both f_x and f_y . The function should have the following form:

$$[w_x w_y E] = tps_model(X,Y,lambda)$$

where the outputs w_x and w_y are the parameters (ω_i and a_i) in the two TPS models, E is the total bending energy and the inputs are as following:

- points in the template shape, X
- corresponding points in the target shape, Y
- regularization parameter, lambda

You can use a MATLAB solver for the linear system (if you have to find x, in Ax = b, you can find the solution in MATLAB with $x = A \setminus b$). Having w_-x and w_-y you are now able to perform the transformation (warping) on the template points.

Hint: For regularization, set *lambda* to the square of the mean distance between two target points.

8.2 Hand In

Write up a short report explaining the main steps of your implementation and discussing the results of the methods. Make sure to include answers to the following questions:

• Is the shape context descriptor scale-invariant? Explain why or why not.

Send the report together with the source code for your implementation (including the following functions shape_matching, sc_compute, chi2_cost, tps_model) to the Moodle exercise page. If you have any questions about this exercise, please email to yawei.li@vision.ee.ethz.ch.

References

[1] Belongie, S., Malik, J. and Puzicha, J., 2002, 'Shape Matching and Object Recognition Using Shape Contexts', IEEE Trans. PAMI