INFORMATION POINT SET REGISTRATION FOR SHAPE RECOGNITION

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Introduction

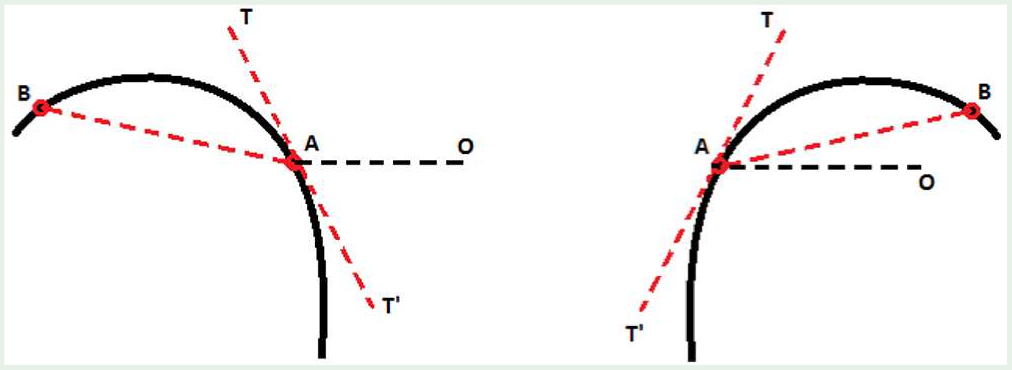
- This paper proposes a way of enhancing shape recognition through point set registration.
- Point correspondences between two shapes are obtained by the flip invariant shape context. Then, the query shape Y is registered to the template shape X using information theoretical learning (ITL) techniques.

Flip Invariant Shape Context

- Shape context (SC) is a well-known descriptor for point sets. Any 2-D point is described by a histogram h binned in distances and angles relative to other points.
- Point correspondences are then found by calculating the matching cost of any two points $\mathbf{x}_i$ and $\mathbf{y}_j$

$$C(\mathbf{x}_i, \mathbf{y}_j) = \sum_{k=1}^{n_d * n_\theta} \frac{[\mathbf{h}_i(k) - \mathbf{h}_j(k)]^2}{\mathbf{h}_i(k) + \mathbf{h}_j(k)} \qquad (1)$$

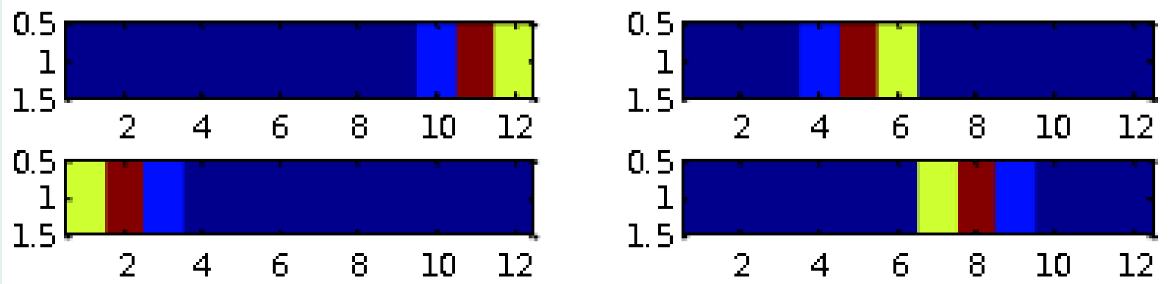
and minimizing the overall cost using Hungarian algorithm.
- SC suffers from not being flip invariant, as well as the ambiguity of the direction of the tangent line. This renders a total of 4 conditions for SC.



$\angle BAO = \beta, \angle TAO = \theta, \angle T'AO = \theta + \pi$ $\quad$ $\angle BAO = \pi - \beta, \angle TAO = \pi - \theta, \angle T'AO = -\theta$

$\angle BAT = \beta - \theta, \angle BAT' = \beta - \theta - \pi$ $\quad$ $\angle BAT = \theta - \beta, \angle BAT' = \theta - \beta + \pi$

- For the query shape, the other 3 SC conditions can be generated from the original one using geometric properties. The best condition is chosen by Hungarian algorithm or greedy search.



Affine and Non-rigid Transformation

- With correspondences available, affine registration becomes a well-defined optimization problem: for point set $\mathbf{X} = \{\mathbf{x}_i\}_{i=1}^N$ and $\mathbf{Y} = \{\mathbf{y}_i\}_{i=1}^N$, find the transformation matrix $\mathbf{A}$:

$$\mathbf{A} = \operatorname{argmax} \sum_{i=1}^{N} G_\sigma(\mathbf{x}_i \mathbf{A}, \mathbf{y}_i) \qquad (2)$$

where $G_\sigma(x,y) = \frac{1}{\sqrt{2\pi}\sigma} exp(-\frac{\|x-y\|^2}{2\sigma^2})$. This is called the maximum correntropy criterion (MCC), which is more robust to outliers than MSE.
- The fixed point solution to (2) is

$$\begin{aligned} \mathbf{D} &= \operatorname{diag}(G_\sigma(f(\mathbf{x}_1), \mathbf{y}_1), \ldots, G_\sigma(f(\mathbf{x}_N), \mathbf{y}_N)) \\ \mathbf{A}_{new} &= (f(\mathbf{X})^T \mathbf{D} f(\mathbf{X}))^{-1} (f(\mathbf{X}) \mathbf{D} \mathbf{Y}) \qquad (3) \\ \mathbf{A}_j &= \mathbf{A}_{j-1} \mathbf{A}_{new}, \quad f(\mathbf{X}) = \mathbf{X} \mathbf{A}_j \end{aligned}$$

Convergence is guaranteed and stopping criterion can be easily set.
- Certain amount of non-rigid transformation is helpful for overcoming intra-class deformation. The Cauchy-Schwarz divergence (D_{CS}) describes two PDFs' similarity. A regularized D_{CS}-based cost function can be written as

$$J = -2\log \sum_{i=1}^N \sum_{j=1}^N G_\sigma(\mathbf{y}_i, \mathbf{t}_j + \mathbf{K}\mathbf{W}_j) + \log \sum_{i=1}^N \sum_{j=1}^N G_\sigma(\mathbf{t}_i + \mathbf{K}\mathbf{W}_i, \mathbf{t}_j + \mathbf{K}\mathbf{W}_j) + \lambda * \operatorname{tr}(\mathbf{W}^T \mathbf{K}\mathbf{W}) \qquad (4)$$

where $\mathbf{T} = \mathbf{X}\mathbf{A}$, $\mathbf{K}$ is the TPS matrix and $\mathbf{W}$ is the transformation matrix to be determined using fixed point solution in a manner similar to (3).

Shape Similarity Criterion

- A correntropy based shape similarity measure is:

$$corr\_cost(\mathbf{X}, \mathbf{Y}) = \sum_{i=1}^{N} G_\sigma(\mathbf{y}_i, f_{nonrigid}(f_{affine}(\mathbf{x}_i))) \qquad (5)$$

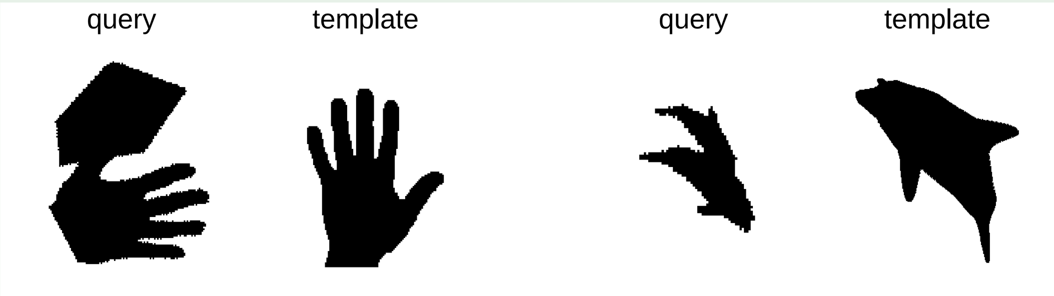
- This measure can be combined with the conventional SC-based similarity measure:

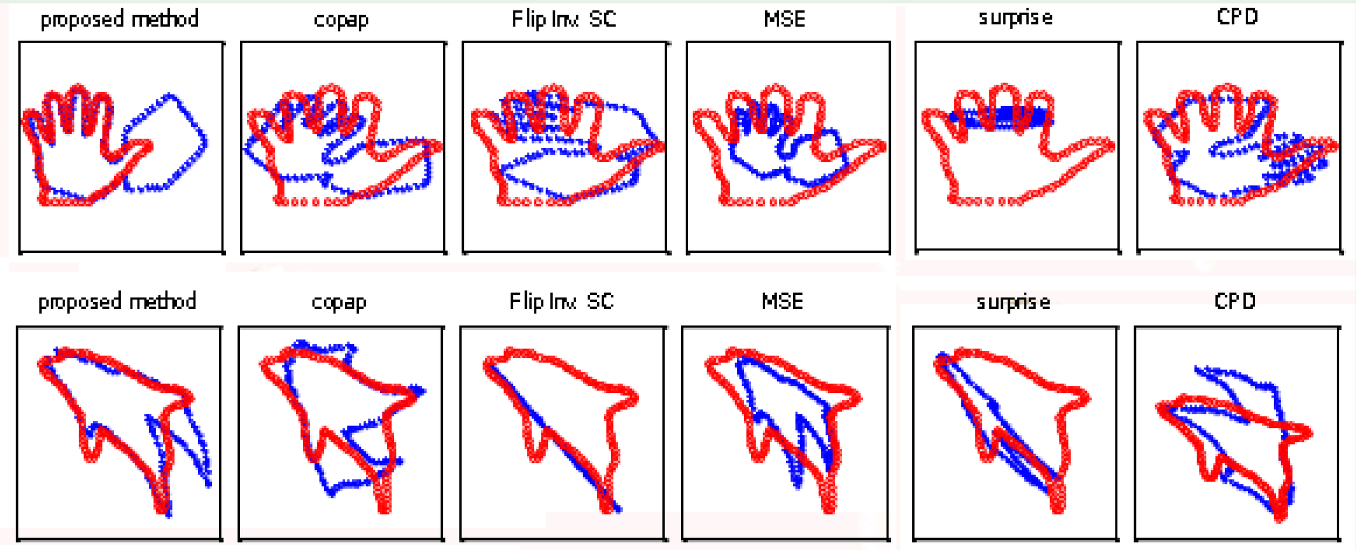
$$new\_cost(\mathbf{X}, \mathbf{Y}) = \frac{corr\_cost(\mathbf{X}, \mathbf{Y})}{SC\_cost(\mathbf{X}, \mathbf{Y})} \qquad (6)$$

The correntropy cost is able to suppress bad SC matches such that their effects are nearly negligible.

Experimental Results

- Shape registration: the query shape is registered to the template shape.

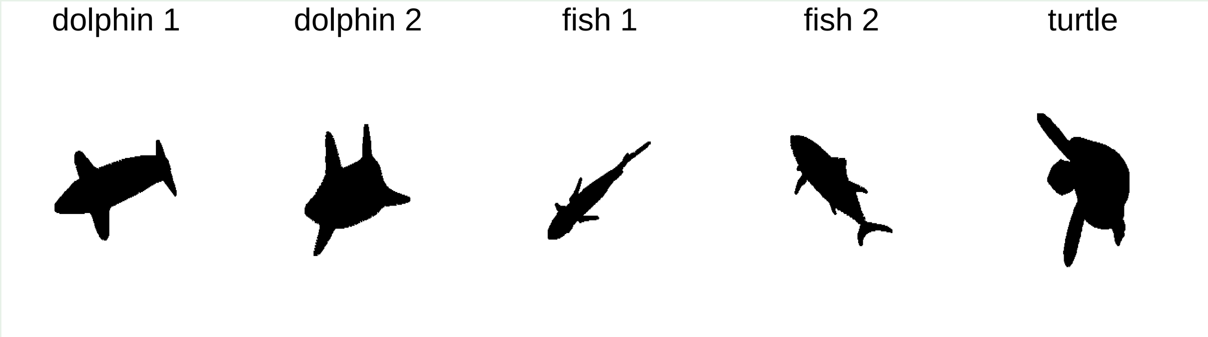




- Shape retrieval (Kimia-99 dataset): shown in the table are the "bull's eye" score.

Method	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
SC cost	99	97	97	97	96	94	94	88	84	81
Corr. (affine only)	99	98	98	98	98	98	97	96	91	75
SC+Corr.	**99**	**99**	**98**	**98**	**98**	**98**	**98**	**95**	**94**	**81**
SC cost	97	91	88	85	84	77	75	66	56	37
Shock Edit	99	99	99	98	98	97	96	95	93	82
IDSC+DP	99	99	99	98	98	97	97	98	94	79

- Marine animal classification: 5 instances shown are "templates". A "query" is classified as the specie of the template that produces highest matching score.



Method	Accuracy(%)
SC cost	94.37
Corr. (affine only)	97.00
SC+Corr.	**97.43**
IDSC+DP	95.77

- Both registration and recognition results outperform or matches up with state-of-the-art algorithms.