Binary Symbol Recognition from Local Dissimilarity Map

GREC - 2009

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Goal

- Symbol Recognition using raw pixel information

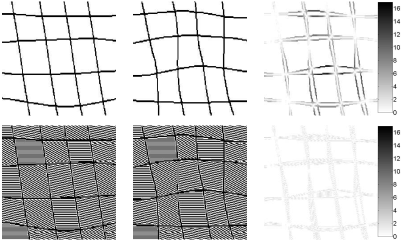
- Not a statistical approach : no learning
- Not a structural approach : no primitive

$\Rightarrow$ **Build a good (di)similarity measure between images**

Local to Global Dissimilarity

- **Local Dissimilarity Map**

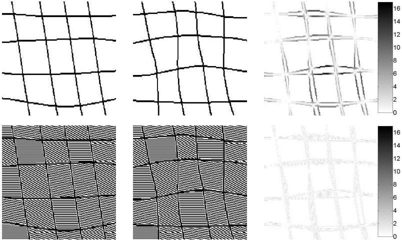
$$\begin{aligned} \mathrm{LDM}_{A,B} &= |A-B| \max(\mathrm{dt}_A, \mathrm{dt}(p)) && (1) \\ &= B\mathrm{dt}_A + A\mathrm{dt}_B. && (2) \end{aligned}$$



Local to Global Dissimilarity

- **Local Dissimilarity Map**

$$\mathrm{LDM}_{A,B} = |A - B| \max(\mathrm{dt}_A, \mathrm{dt}(p)) \quad (1)$$
$$= B\mathrm{dt}_A + A\mathrm{dt}_B. \quad (2)$$



- **Global Dissimilarity Measure : sum the (squared) values** :

$$\mathrm{GDM}(A, B) = \alpha \sum_p B(p)\mathrm{dt}_A^2(p) + \beta \sum_p A(p)\mathrm{dt}_B^2(p). \quad (3)$$

Local to Global Dissimilarity

- Why α and β ?
- Chamfer Matching [Borgefors] : sum of the distances of each translated model's pixel to the nearest images's pixel.
- *GDM* **is a double Chamfer Matching** :

$$\mathrm{GDM}_{A,B} \sim \alpha \mathrm{CS}(A, B) + \beta \mathrm{CS}(B, A) \tag{4}$$

- CS : how is M similar to I ?
- GDM : + how is I similar to M ?
- **symetric or asymetric matching** (links to psychological models of similarity [Tversky]) ?

First Algorithm

1. I contains an unknow symbol.
2. **Foreach model** M :
   - **compute the dissimilarity** $\mathrm{GDM}(I, M)$ between I and M.
3. Keep the model with the **lowest dissimilarity as winner**.

First Algorithm

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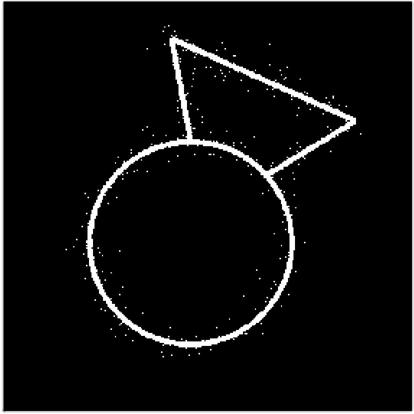
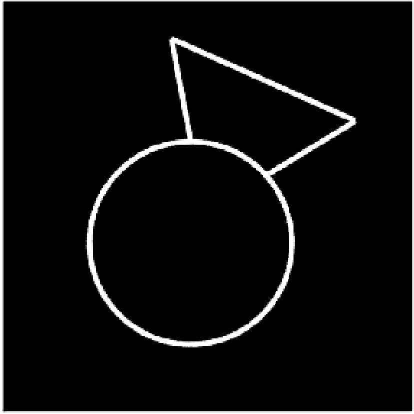
- Tested on the GREC2005 international symbol recognition contest database (electronic and architecture) : six degradations
- 25 symbols to be recognized in 50 images.
- $\alpha = 1$ and $\beta = 0$.

Results (no deformation)

Degradation 1

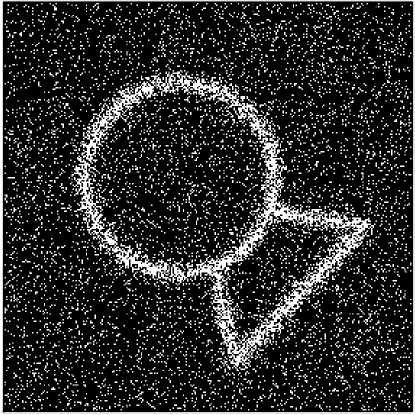


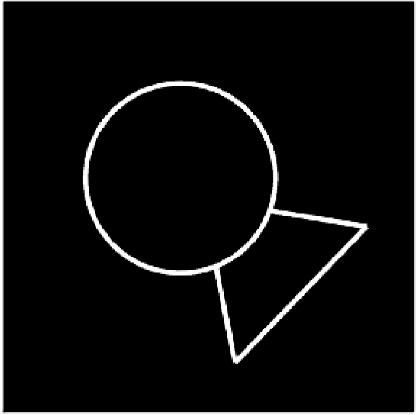


100 %

Results (no deformation)

Degradation 2

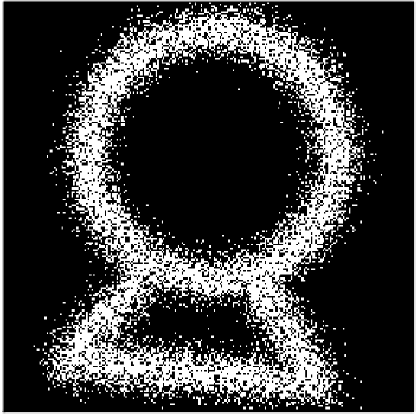


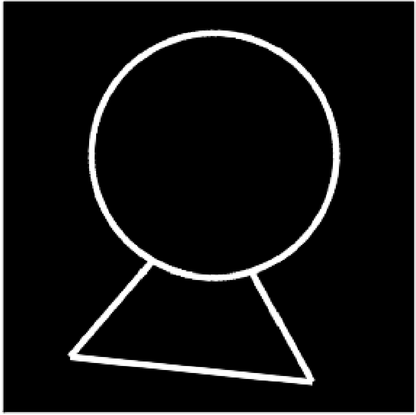


100 %

Results (no deformation)

Degradation 3

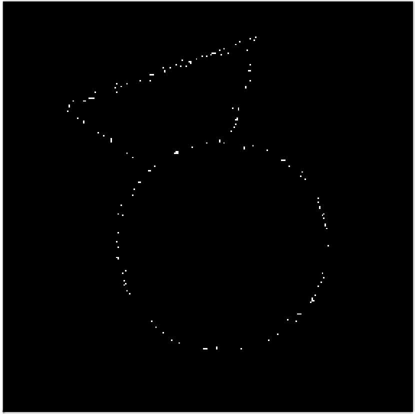


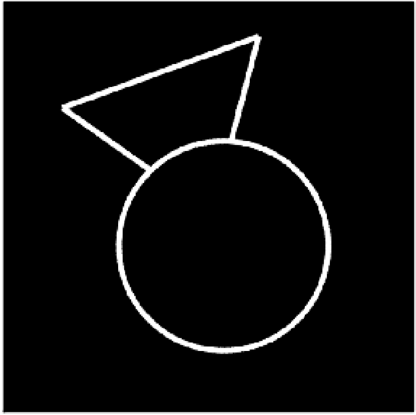


100 %

Results (no deformation)

Degradation 4

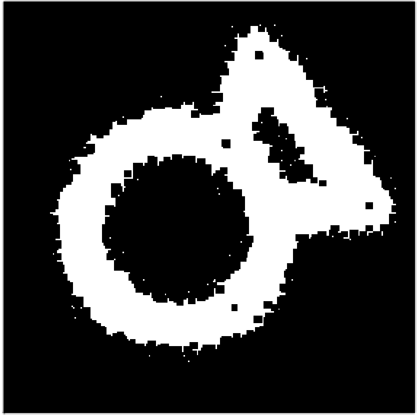


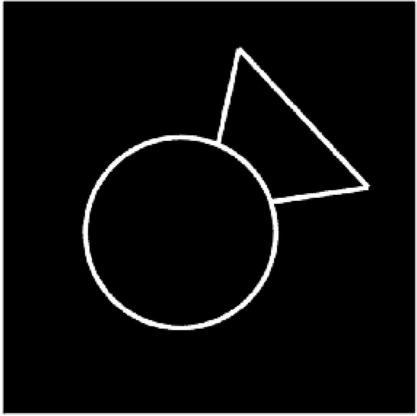


100 %

Results (no deformation)

Degradation 5

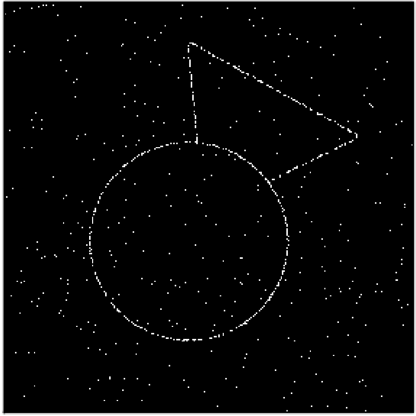


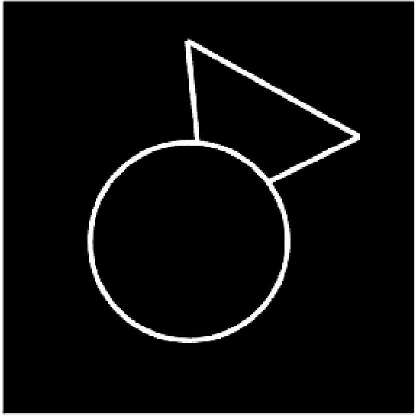


100 %

Results (no deformation)

Degradation 6





54 % (but best is 59.81 %)

And with deformations ?

- Transform **rotation and scale into translations**
  $\Rightarrow$ log-polar transform

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- Transform **rotation and scale into translations**
  $\Rightarrow$ log-polar transform
- Given two images I and M to be registrated :
  - **Compute** I_{lp} **and** M_{lp}
  - **Which translation produces the most similar images ?**
    $\Rightarrow$ compute the global dississimilarity between I_{lp} and each translation of M_{lp}.
  - Very fast with cross-correlations (in Fourier Domain) :

$$\mathrm{Loc}_{I,M} = \alpha \mathrm{dt}_I^2 \star M + \beta I \star \mathrm{dt}_M^2. \quad (5)$$

  - **Find the minimum** of $\mathrm{Loc}_{I,M}$ and find the rotation and scale parameters from its position.

Complete Algorithm

1. Compute I_{lp}, **log-polar representation of** I.
2. Foreach model M :
   1. compute M_{lp}, **log-polar representation of** M
   2. find the **global minimum** of $\mathrm{Loc}_{I_{lp},M_{lp}}$ (fast computation)
   3. find (σ, θ) the scaling and rotation parameters of M.
   4. compute $M_{\mathrm{corrected}}$ from (ρ, θ), by **applying reverse scale and rotation**.
   5. compute the dissimilarity $\mathrm{GDM}(I, M_{\mathrm{corrected}})$ between $M_{\mathrm{corrected}}$ and I.
3. Keep the model with the **lowest dissimilarity as winner**.

Advantages and Drawbacks

rot/scale	m1	m2	m3	m4	m5	m6
without	100%	100%	100%	100%	100%	54%
with	96%	40%	94%	70%	42%	12%

- **Quite good performances** (lowered by 5%-10% with 100 images/150 symbols)
- **without any a-priori knowledge, pre-processing, nor primitive extraction**
- **Fast but still needs parameters estimations**
- Next :
  - Gray level images $\Rightarrow$ Localization with rotation/scale variations.
  - Balance the asymetry, e.g. $\alpha = 0.9$ and $\beta = 0.1$ (take into account noise)
  - Direct measure in log-polar domain.
  - Apply preprocessing to boost performances.