



National University of Sciences and Technology (NUST)

SEECS

Digital Image Processing

Run Length Smoothing

Algorithm (RLSA)

Run Length Smoothing Algorithm - RLSA

- Change runs of white pixels of length below a threshold to black
- Black pixels remain unchanged
- Example: $C=4$

$X = 0\ 0\ 0\ 1\ 1\ 1\ 0\ 0\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ 1\ 1\ 1\ 0$

$Y = 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0$



Object Type	Resolution Test	Result Type
	1. Location	
	2. Relative Size	
	3. Rotational	
	4. Average Transparency	
	5. Solid Region	
	6. One Object Property	
	7. Most Object Property	
	8. Second Size	
	9. Number	
	10. Transparency Size	
	11. Shape Transparency	

Chemical Species	
CO (projected)	77.09
CO (observed)	95.19
CO (Projected & Observed)	86.11

Thermodynamic-based Species	
P1 (Projected)	56.59
P1 (Observed & Observed)	85.59

Petroleum Species	
B1 (Est. 20)	19.87
B1 (Est. 12)	19.48
B2 (Est. 55)	16.70
B4 (Est. 35)	17.40
B1 (Keros. 10)	17.5
B1 (Keros. 25)	17.1

Table 10. Homologation rates on possible dates of the CHLAE database.

Also, The qualification factor p is related to the participation degree by:

[illegible]

In short, the particularized-based recognition is characterized by the following parameters:

$\mathcal{P}(x, y)$ where $(x, y) = \mathcal{P}(x', y'; t; \mathbf{M})$. For each perturbation type i , the localization depends on an empirically determined value M_i , which represents the maximum extent of that perturbation. The function, the resulting angle of the first perturbation type ($i = 1$) is defined by $\theta = i - M_i$. (i.e., the resultant angle for $i = 1$ takes the value of the perturbation degree $i = 1$, since all perturbations type I have the identity transformation, i.e., $(x, y) = (x', y')$).

In order to match the time point-to-point prediction of f , we may try to answer the parameter question (δ, f) by sampling δ to be always (exactly) with a small sampling interval Δ , i.e., $\delta = \Delta, 2\Delta, 3\Delta, \dots, N\Delta$, $N\Delta \leq \Delta t$. However, this approach is only valid assuming that the such additional value of δ , $T = 1$ is always lower to be added to the options. Simultaneously, we decided to test a bid strategy range sampling interval ($\Delta t = 0.2$) and to learn the range of values for δ to $\delta = \Delta, 2\Delta, 3\Delta, \dots$ resulting in an actual range of $(-0.6, 0.6)$ for δ . This means that we do not intend to detect the best point-to-point prediction but simply verify the input (range) above or one of its specified limits.

X_i : numbers of each of perturbations type i
 $i = 1, \dots, 17$

- Δ : sampling interval for $\theta, \Delta = 0.1$
- \tilde{X} : stochastic perturbations degree, $\tilde{X} = 1$
- m : number of iterations, $m = 1000$

(continued)

Taking into account the middle channel of Fig. 4 ($M = 0$), the total number of channels is $2M \cdot T + 1$.

3.1.4. Experiments. We have not yet had a problem on the open data as in Section 3.1. As "Classical Recursion" (see Fig. 6) we considered three potential systems, namely, the two parallel and the combination based one, all mentioned in Section 3.1. They will be called respectively, C1, C2 and C3 in the following.

In order to test the proposed protection-based method, we built two systems, which will be called *P1* and *P2*, respectively. *P1* - which is the system tested among *C1*, *C2*, and *C3* - was adopted as "chemical program" in *P1*, while *C2* - the strongest method among *C1*, *C2*, and *C3* - was used in *P2*. In both *P1* and *P2*,

Symbol	Permutation Type	Symbol/Type
	1. Identity	
	2. Horizontal Shift	
	3. Vertical Shift	
	4. Horizontal/Vertical Shift	
	5. Horizontal/Vertical Shift	
	6. Horizontal/Vertical Shift	
	7. Horizontal/Vertical Shift	
	8. Horizontal/Vertical Shift	
	9. Horizontal/Vertical Shift	
	10. Horizontal/Vertical Shift	
	11. Horizontal/Vertical Shift	

Figure 1: Permutations.

$f(x, y)$ where $(x, y) = f(x', y') \in [0, 255]$. For each permutation type i , the transformation f depends on an empirically determined value θ_i , which represents the rotation angle of that permutation. The function, the rotation angle of the first permutation type ($i = 1$) is defined by $\theta = \theta_1 \cdot \theta_i$, i.e., θ_i is the rotation angle for $i = 1$. Note that θ is the permutation degree $\theta = 0$, from all permutation types, because the identity transformation, i.e., $(x, y) = (x', y')$.

In order to match the two permutation parameters θ , we may use the parameter space (θ, i) by sampling i to be already discrete with a small sampling interval Δ , i.e., $i = 1, 2, 3, \dots, \Delta, \dots, \theta/\Delta$, $\Delta \leq 1$. However, this approach is very slow concerning about the each additional value of i , $\theta = 1$ elements have to be added to the system. Alternatively, we decided to use a relatively large sampling interval ($\Delta = 0.2$) and to limit the range of values for i to $i = 1, 2, 3$, resulting in an actual range of $[0, 0.6]$ for θ . This means that we do not attempt to detect the low perturbation permutations but simply restrict the input images those to one of the restricted forms, i.e.,

Classical Systems	
C1 (Projected)	97.69
C2 (Filtered)	98.19
C3 (Projected & Contrary)	98.71
Permutation-based Systems	
P1 (Projected)	98.59
P2 (Projected & Contrary)	98.79
Hybrid Systems	
H1 (C1 & P1)	98.87
H2 (C2 & P2)	98.88
H3 (C3 & P3)	98.91
H4 (C1 & P2)	98.85
H5 (C2 & P1)	97.8
H6 (C3 & P2)	97.1

Table 1: Recognizing rate on possible data of the CIFAR-10 database.

Also, the permutation factor p is related to the permutation degree by:

$$p = (2\pi)^{-\theta} \quad (p > 1) \quad (1)$$

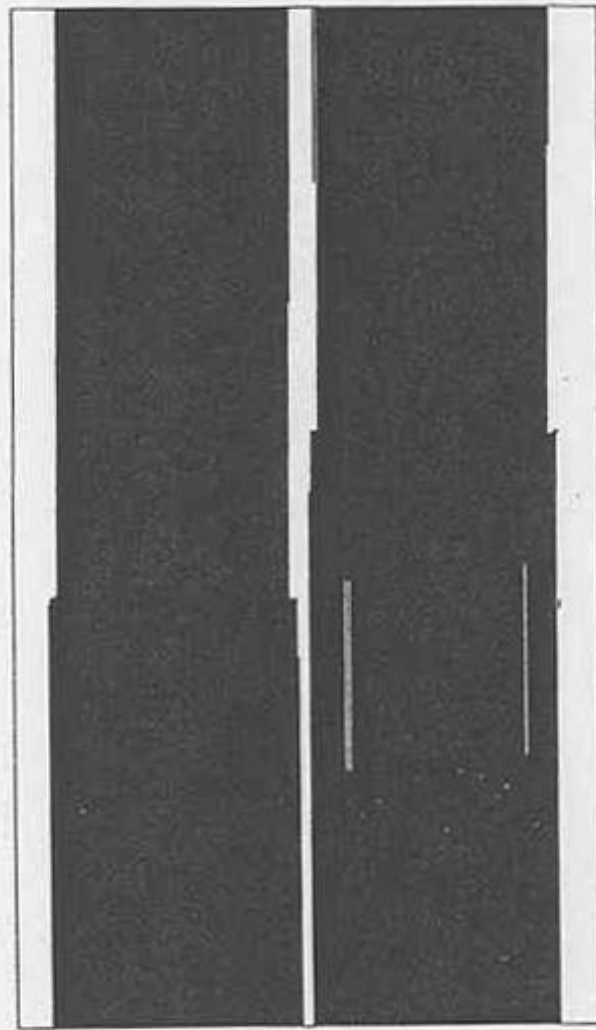
In short, the permutation-based recognition is characterized by the following parameters:

- θ : maximum value of permutation type i , $i = 1, \dots, \theta/\Delta$, $\Delta = 0.2$.
- Δ : sampling interval for θ , $\Delta = 0.2$.
- θ : maximum permutation degree $\theta = 1$.
- p : permutation factor $p = (2\pi)^{-\theta}$.

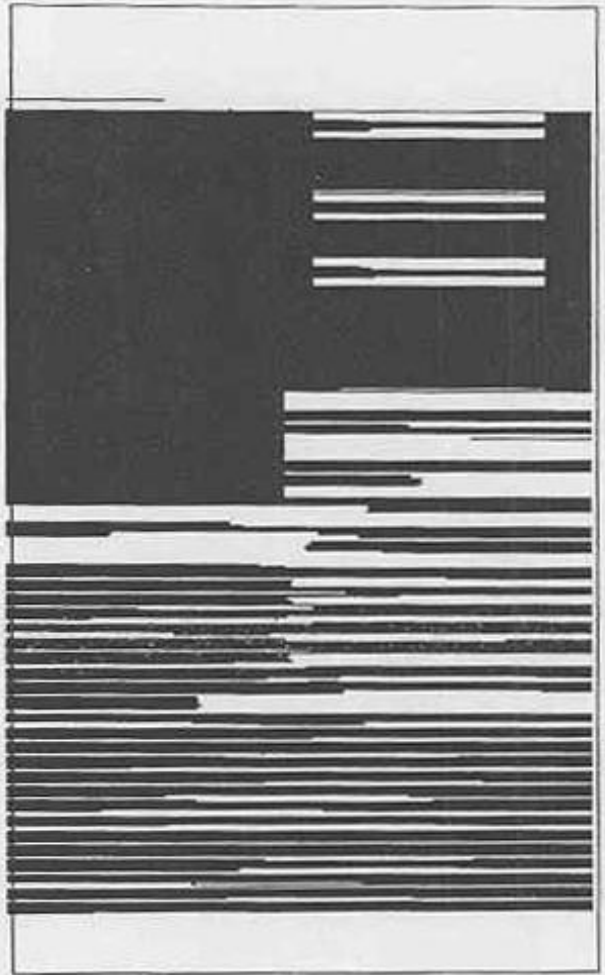
Table 1 shows the results of Fig. 4 ($\theta = 0$), the total number of elements is $16 \cdot \theta + 1$.

3.1.4. Experiments. We tested our test algorithm on the given data as in Section 3.1. As "Classical Recognition" (see Fig. 4) we considered three potential systems, namely, the two statistical and the combination-based ones, all mentioned in Section 3.1. They will be called respectively, C1, C2 and C3 in the following.

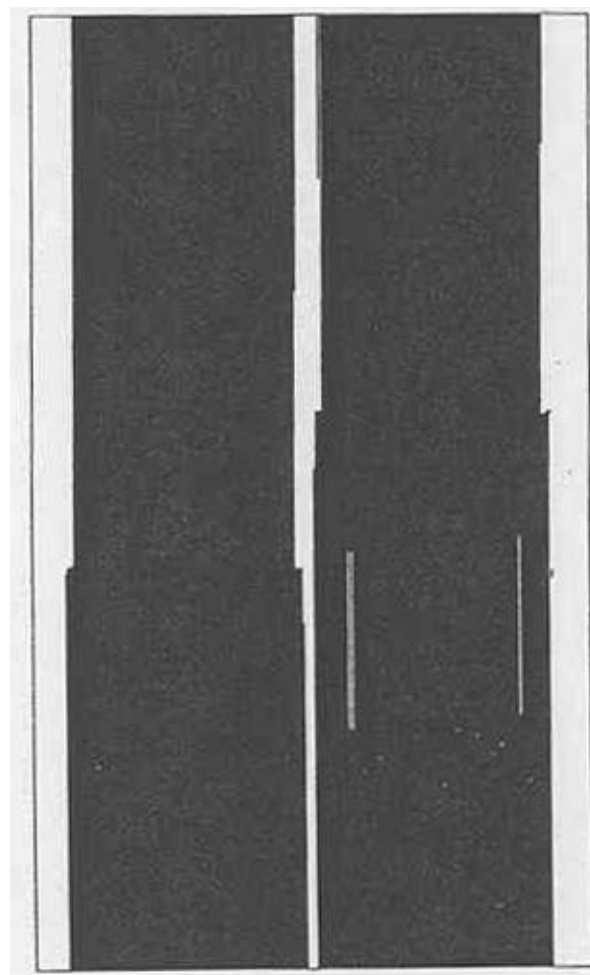
In order to test the proposed permutation-based method, we built two systems, which will be called P1 and P2, respectively. C1 - which is the system method among C1, C2 and C3 - was adopted as "classical recognition" in P1, while C2 - the strongest method among C1, C2 and C3 - was used in P2. In both P1 and P2,



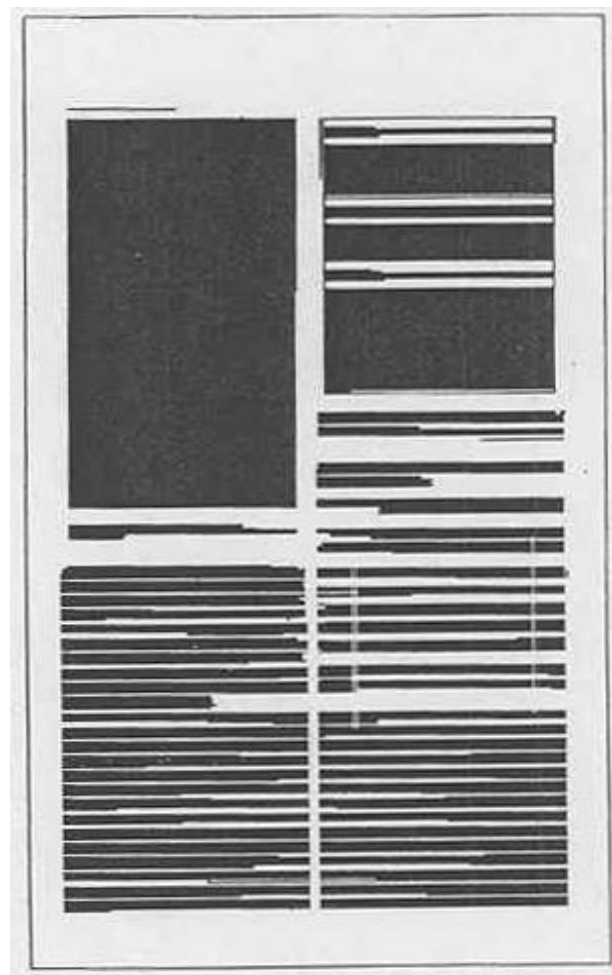
Vertical RLSA



Horizontal RLSA



Vertical RLSA



Combined

Line Extraction?

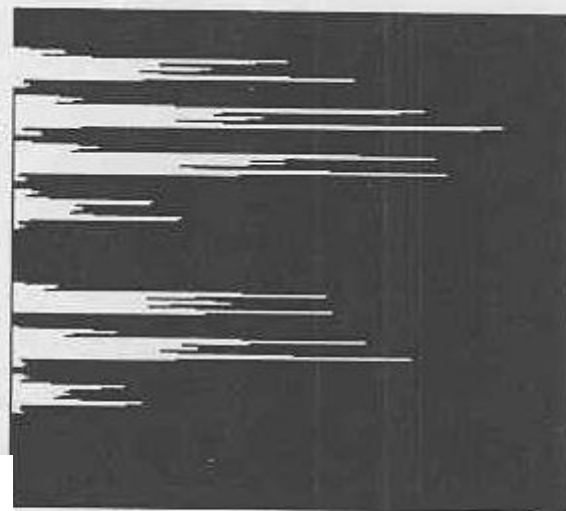
This is a text example,
used to illustrate the principle
of the X-Y-tree decomposition
algorithm.

The text was scanned at
the resolution of 300 dpi (dot
per inch).

Line Extraction?

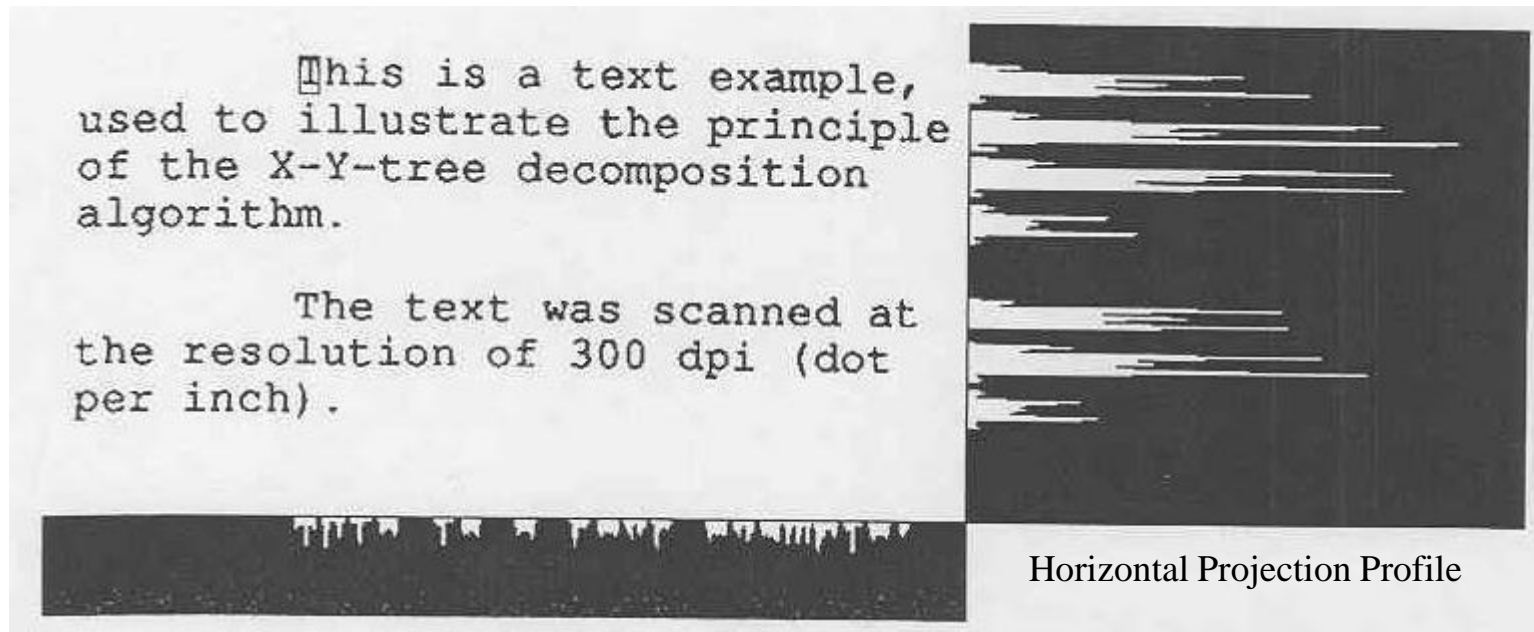
This is a text example,
used to illustrate the principle
of the X-Y-tree decomposition
algorithm.

The text was scanned at
the resolution of 300 dpi (dot
per inch).



Horizontal Projection Profile

Projection Profiles



Word Extraction using RLSA

l'expérimentation physiologique

~~l'expérimentation~~ ~~physiologique~~

End
RLSA