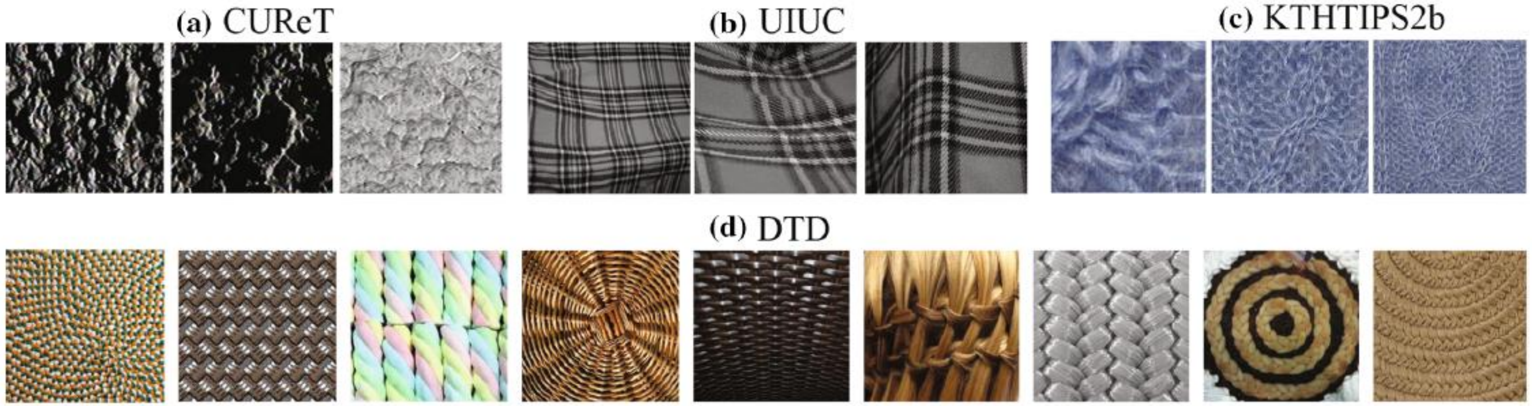
Texture features

- Visual characteristics and appearance of objects
- Powerful discriminating feature for identifying visual patterns
- Properties of structural homogeneity beyond colour or intensity
- Especially used for texture classification



https://arxiv.org/abs/1801.10324

Haralick texture features

- Array of statistical descriptors of image patterns
- Capture spatial relationship between neighbouring pixels
- Step 1: Construct the gray-level co-occurrence matrix (GLCM) – representing the frequency of pixel intensity pairs occurring at a specific offset and direction
- Step 2: Compute the Haralick feature descriptors from the GLCM – that summarises texture information (how pixel intensities are spatially related)

https://doi.org/10.1109/TSMC.1973.4309314

Haralick texture features

- Step 1: Construct the GLCMs
  - Given distance d and orientation angle a
  - Compute co-occurrence count $p_{(d,a)}(i_1, i_2)$ of going from gray level i_1 to i_2 at d and a
  - Construct matrix $\mathbf{P}_{(d,a)}(i_1, i_2)$ with elements (i_1, i_2) being $p_{(d,a)}(i_1, i_2)$
  - If an image has L distinct gray levels, the matrix size is $L \times L$

Example image:

$L = 4$

0	0	0	0	1	1	1	2
0	0	0	1	1	2	2	3
0	0	1	1	2	2	3	3
0	2	2	3	3	2	2	1
2	2	3	3	3	2	1	1
2	3	3	3	2	2	1	0
3	3	2	2	1	1	0	0
3	2	2	1	1	0	0	0

$p_{(d=1,a=0)}(i_1 = 0, i_2 = 0)$

$$\mathbf{P}_{(1,0°)} = \begin{bmatrix} 18 & 6 & 1 & 0 \\ 6 & 14 & 8 & 0 \\ 1 & 8 & 16 & 10 \\ 0 & 0 & 10 & 14 \end{bmatrix}$$

$p_{(d=1,a=90)}(i_1 = 0, i_2 = 2)$

$$\mathbf{P}_{(1,90°)} = \begin{bmatrix} 18 & 5 & 2 & 0 \\ 5 & 10 & 8 & 2 \\ 2 & 8 & 14 & 11 \\ 0 & 2 & 11 & 14 \end{bmatrix}$$

$(i_1 = 3, i_2 = 3)$

Haralick texture features

- Step 1: Construct the GLCMs
  - For computational efficiency L can be reduced by binning (similar to histogram binning) Example: $L = 256/n$ for a constant factor n
  - Different co-occurrence matrices can be constructed by using various combinations of distance d and angular orientation a
  - On their own these co-occurrence matrices do not provide any measure of texture that can be easily used as texture descriptors
  - The information in the co-occurrence matrices needs to be further extracted as a set of feature values such as the Haralick descriptors

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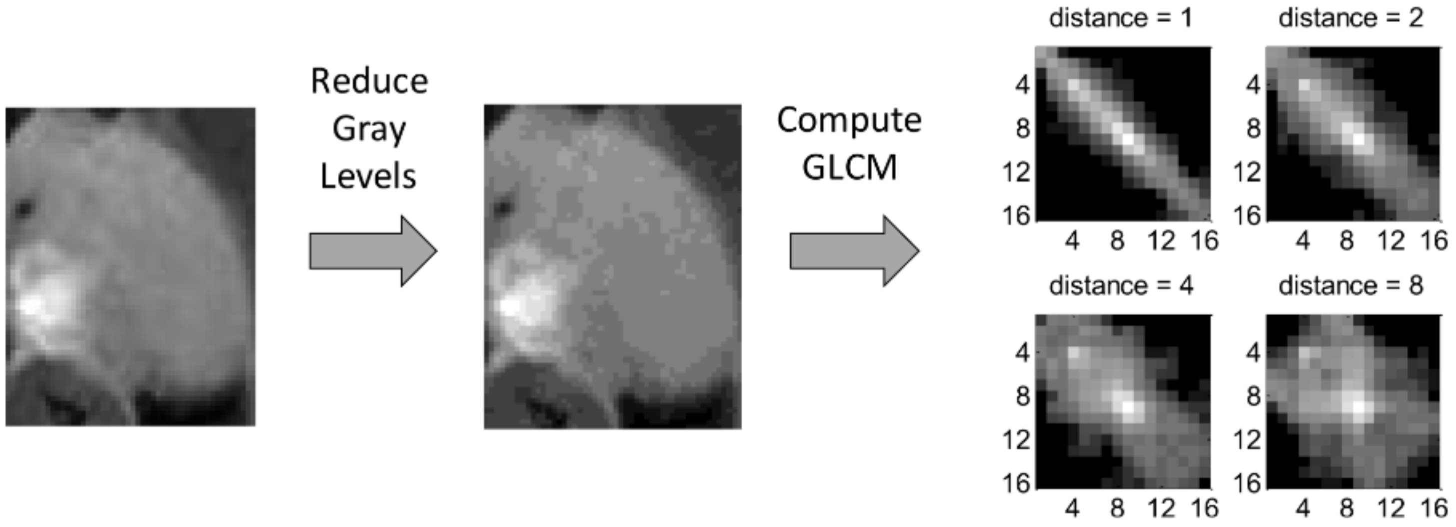
Haralick texture features

- Step 2: Compute the Haralick descriptors from the GLCMs
  - One set of Haralick descriptors for each GLCM for a given d and a

No	Features	Formula
1	Angular Second Moment	$\Sigma i\, \Sigma j\; p(i,j)^2$
2	Contrast	$\Sigma_{n=0}^{Ng-1} n^2\{\Sigma_{i=1}^{Ng} \Sigma_{j=1}^{Ng} p(i,j)\}, \lvert i-j \rvert = n$
3	Correlation	$\dfrac{\Sigma i \Sigma j (ij) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$
4	Sum of Squares: Variance	$\Sigma_i \Sigma_j (i-\mu)^2 p(i,j)$
5	Inverse Difference Moment	$\Sigma_i \Sigma_j \dfrac{1}{1+(i-j)^2} p(i,j)$
6	Sum Average	$\Sigma_{i=2}^{2N_g} i p_{x+y}(i)$
7	Sum Variance	$\Sigma_{i=2}^{2N_g} (i - f_{8)}{}^2 p_{x+y}(i)$
8	Sum Entropy	$-\Sigma_{i=2}^{2N_g} p_{x+y}(i) \log\{p_{x+y}(i)\} = f_8$
9	Entropy	$-\Sigma_i \Sigma_j\, p(i,j) \log(p(i,j))$
10	Difference Variance	$\Sigma_{n=0}^{Ng-1} i^2 p_{x-y}(i)$
11	Difference Entropy	$-\Sigma_{n=0}^{Ng-1} p_{x-y}(i) \log\{p_{x-y}(i)\}$
12	Info. Measure of Collection 1	$\dfrac{\mathrm{HXY} - \mathrm{HXY1}}{\max\{HX, HY\}}$
13	Info. Measure of Collection 2	$(1 - \exp[-2(HXY2 - HXY)])^{\frac{1}{2}}$
14	Max. Correlation Coefficient	*The square root of the second largest eigenvalue of Q, where* $Q(i,j) = \Sigma_k \frac{p(i,k)p(j,k)}{p_x(i)p_y(k)}$

Haralick texture features

- Example:
  - Often used in medical imaging studies due to their simplicity and interpretability



1. Preprocess the MRI images
2. Extract Haralick, run-length, and histogram features
3. Apply feature selection
4. Classify using machine learning algorithms

Yang et al., Evaluation of tumor-derived MRI-texture features for discrimination of molecular subtypes and prediction of 12-month survival status in glioblastoma, Medical Physics, 2015.

Local binary patterns

- Describe the spatial structure of local image texture
  - Divide the image into cells of $N \times N$ pixels (for example $N = 16$ or 32)
  - Compare each pixel in a given cell to each of its 8 neighbouring pixels
  - If the centre pixel value is greater than the neighbour value, write 0, otherwise write 1
  - This gives an 8-digit binary pattern per pixel, representing a value in the range 0…255

Example:

0	0	0	0	1	1	1	2
0	0	0	1	1	2	2	3
0	0	1	1	2	2	3	3
0	2	2	3	3	2	2	1
2	2	3	3	3	2	1	1
2	3	3	3	2	2	1	0
3	3	2	2	1	1	0	0
3	2	2	1	1	0	0	0

→ 1 1 1 1 0 0 0 0 → 240

Local binary patterns

- Describe the spatial structure of local image texture
  - Count the number of times each 8-digit binary number occurs in the cell
  - This gives a 256-bin histogram (also known as the LBP feature vector)
  - Combine the histograms of all cells of the given image
  - This gives the image-level LBP feature descriptor

Example:

0	0	0	0	1	1	1	2
0	0	0	1	1	2	2	3
0	0	1	1	2	2	3	3
0	2	2	3	3	2	2	1
2	2	3	3	3	2	1	1
2	3	3	3	2	2	1	0
3	3	2	2	1	1	0	0
3	2	2	1	1	0	0	0

→

1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1
1 1 1 1 0 0 0 1
1 1 1 1 1 0 1 1
…

→

255
255
241
251
…

→ histogram

Local binary patterns

- Describe the spatial structure of local image texture
  - Count the number of times each 8-digit binary number occurs in the cell
  - This gives a 256-bin histogram (also known as the LBP feature vector)
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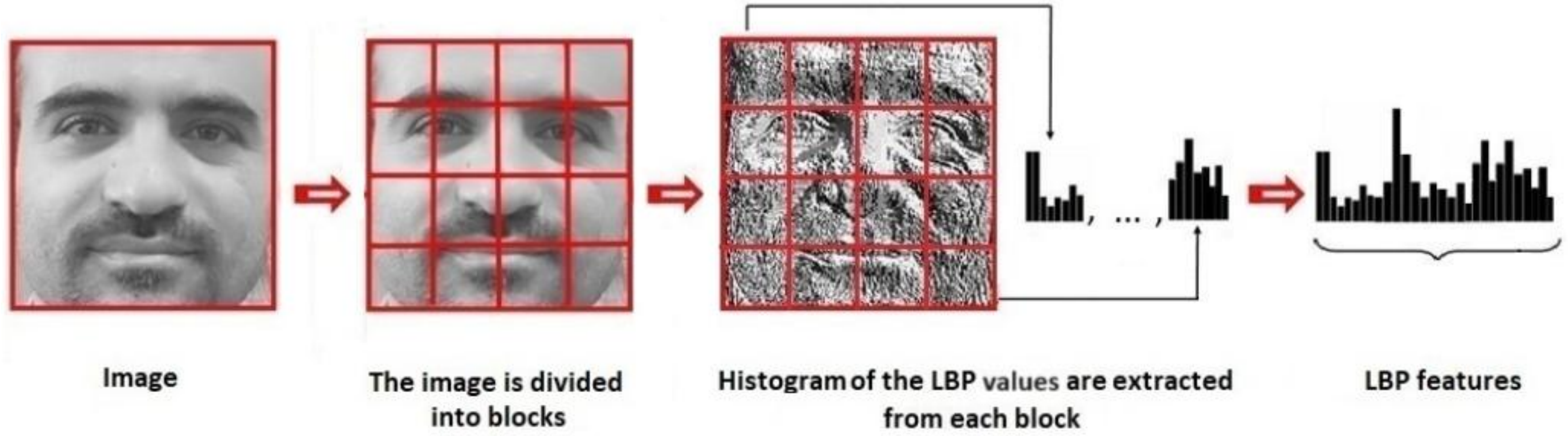
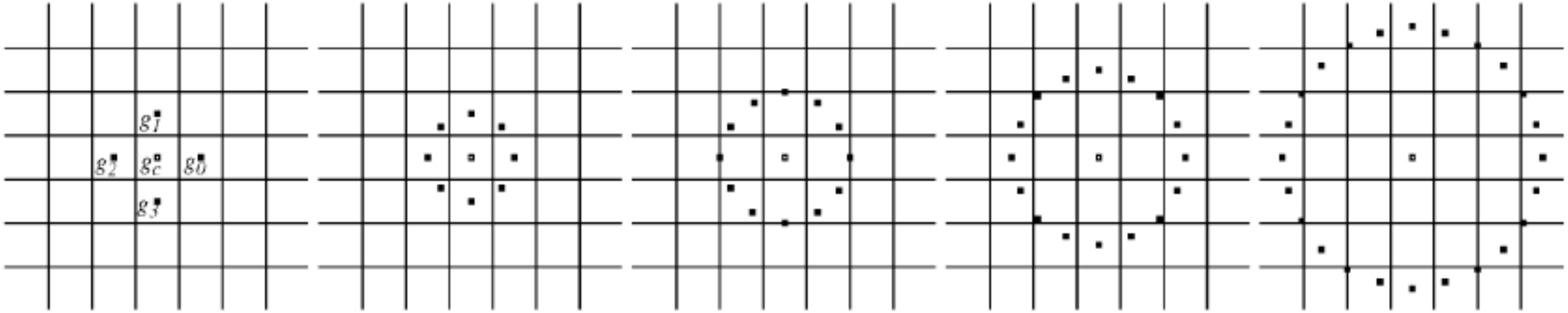
  - This gives the image-level LBP feature descriptor



Local binary patterns

- LBP can be multiresolution and rotation-invariant
  - Multiresolution: vary the distance between the centre pixel and neighbouring pixels and vary the number of neighbouring pixels



(P=4,R=1.0) (P=8,R=1.0) (P=12,R=1.5) (P=16,R=2.0) (P=24,R=3.0)

T. Ojala, M. Pietikainen, T. Maenpaa (2002) https://doi.org/10.1109/TPAMI.2002.1017623
Multiresolution gray-scale and rotation invariant texture classification with local binary patterns
IEEE Transactions on Pattern Analysis and Machine Intelligence 24(7):971-987

Local binary patterns

- LBP can be multiresolution and rotation-invariant
  - Rotation-invariant: vary the way of constructing the 8-digit binary number by performing bitwise shift to derive the smallest number

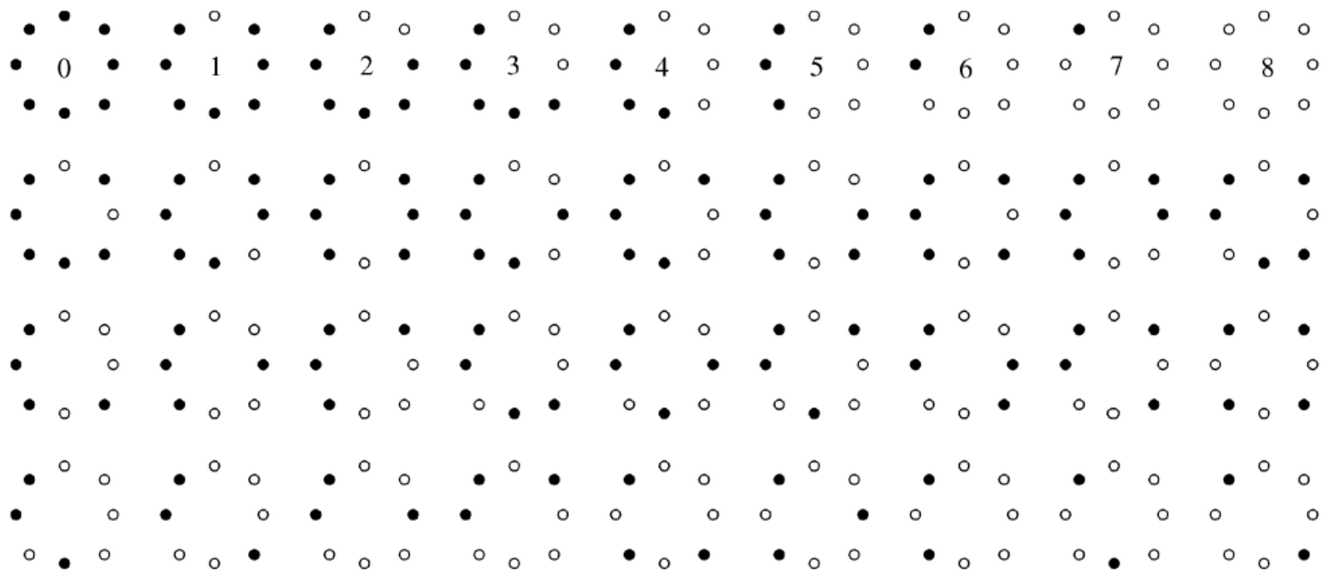
Example:

$$\left.\begin{array}{lcr}
1\,1\,1\,1\,0\,0\,0\,0 & = & 240 \\
1\,1\,1\,0\,0\,0\,0\,1 & = & 225 \\
1\,1\,0\,0\,0\,0\,1\,1 & = & 195 \\
1\,0\,0\,0\,0\,1\,1\,1 & = & 135 \\
0\,0\,0\,0\,1\,1\,1\,1 & = & 15 \\
0\,0\,0\,1\,1\,1\,1\,0 & = & 30 \\
0\,0\,1\,1\,1\,1\,0\,0 & = & 60 \\
0\,1\,1\,1\,1\,0\,0\,0 & = & 120
\end{array}\right\} \quad 15$$

Note: not all patterns have 8 shifted variants (e.g. 11001100 has only 4)

Local binary patterns

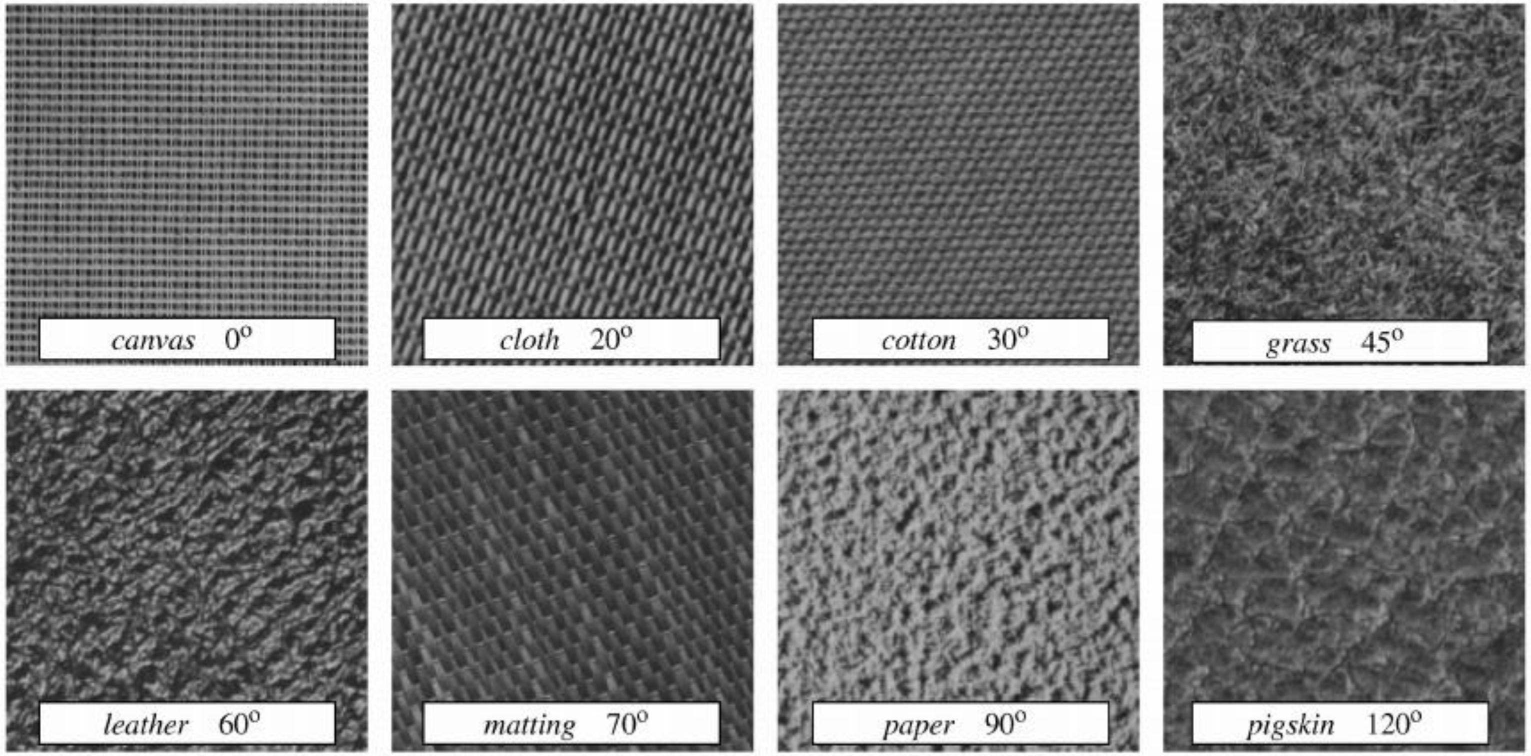
- LBP can be multiresolution and rotation-invariant
  - Rotation-invariant: vary the way of constructing the 8-digit binary number by performing bitwise shift to derive the smallest number



This reduces the LBP feature dimension from 256 to 36

Example application of LBP

- Texture classification



P,R	$LBP_{P,R}$	
	BINS	RESULT
8,1	10	88.2
16,2	18	98.5
24,3	26	99.1
8,1+16,2	10+18	99.0
8,1+24,3	10+26	99.6
16,2+24,3	18+26	99.0
8,1+16,2+24,3	10+18+26	99.1

https://doi.org/10.1109/TPAMI.2002.1017623