Digital Image Processing Introduction

Histogram based methods

Histogram equalization

- Histogram equalization is a common technique for image enhancement
- Histogram equalization involves finding a grey scale transformation function that creates an output image with a uniform histogram (or nearly so).
- We must find a transformation T that maps grey values r in the input image F to grey values s = T(r) in the transformed image.
- It is assumed that
 - T is single valued and monotonically increasing, and
 - \bullet 0 <= T(r) <= 1 for 0 <= r <= 1

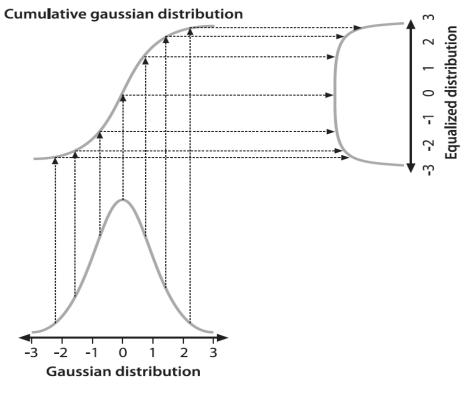


Histogram equalization

the transformation – remapping function should be the cumulative distribution function.



a gaussian distribution



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Example of Histogram equalisation

5000

original

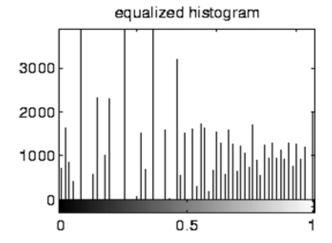


4000 3000 2000 1000 0 0.5

histogram

equalized image





Comparing Two Histograms

- the ability to compare two histograms in terms of some specific criteria for similarity.
 - (first introduced by Swain and Ballard [Swain91] and further generalized by Schiele and Crowley [Schiele96])
- distance metric:
 - Correlation

$$d_{\text{correl}}(H_1, H_2) = \frac{\sum_{i} H_1'(i) \cdot H_2'(i)}{\sqrt{\sum_{i} H_1'^2(i) \cdot H_2'^2(i)}}$$

where $H'_k(i) = H_k(i) - (1/N) \left(\sum_j H_k(j) \right)$ and N equals the number of bins in the histogram.

For correlation, a high score represents a better match than a low score. A perfect match is 1 and a maximal mismatch is –1; a value of 0 indicates no correlation (random association).



Comparing Two Histograms

Chi-square

$$d_{\text{chi-square}}(H_1, H_2) = \sum_{i} \frac{(H_1(i) - H_2(i))^2}{H_1(i) + H_2(i)}$$

For *chi-square*, a low score represents a better match than a high score. A perfect match is 0 and a total mismatch is unbounded (depending on the size of the histogram).

Intersection

$$d_{\text{intersection}}(H_1, H_2) = \sum_{i} \min(H_1(i), H_2(i))$$

For *histogram intersection*, high scores indicate good matches and low scores indicate bad matches. If both histograms are normalized to 1, then a perfect match is 1 and a total mismatch is 0.

Comparing Two Histograms

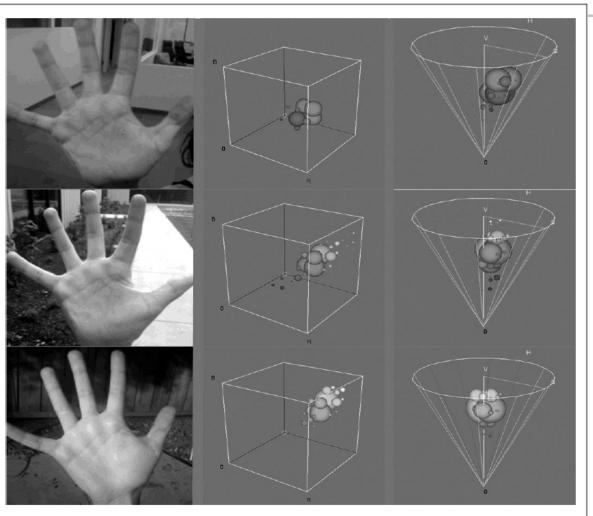
Bhattacharyya distance

$$d_{\text{Bhattacharyya}}(H_1, H_2) = \sqrt{1 - \sum_{i} \frac{\sqrt{H_1(i) \cdot H_2(i)}}{\sqrt{\sum_{i} H_1(i) \cdot \sum_{i} H_2(i)}}}$$

For *Bhattacharyya matching*, low scores indicate good matches and high scores indicate bad matches. A perfect match is 0 and a total mismatch is a 1.

! normalize histograms before comparing

Example -Histogram comparison



Histogram of fl esh colors under indoor (upper left),

shaded outdoor (middle left),

and outdoor (lower left) lighting conditions;

the middle and right-hand columns display the associated BGR and HSV histograms, respectively

Example -Histogram comparison

 Histogram comparison, via four matching methods, of palmflesh colors in upper half of indoor palm with listed variant palm-flesh color

Comparison	CORREL	CHISQR	INTERSECT	BHATTACHARYYA	
Indoor lower half	0.96	0.14	0.82	0.2	
Outdoor shade	0.09	1.57	0.13	0.8	
Outdoor sun	-0.0	1.98	0.01	0.99	

What vs. Where Problem

Identification (,,What``)

- is a is the approximate location of the object in the image is known. This object is then for example compared with a database to identify it.
 - Swain and Ballard : Histogram Intersection Algorithm

Object detection (`` Where ``)

- a known object will be found at an unknown background,
 - modification of the histogram backprojection algorithm.

Color indexing

- Swain and Ballard introduced (1991) :
- Colour can be a useful feature for rapid detection
- Concept of color histograms for indexing objects in image databases
- Robust in position, translation, rotation changes
- This method does not address the issue of varying illumination,
- illumination invariant features / methods
 - Funt (1995) uses ratios of colors from neighboring locations, so as to extend Swain's method to be insensitive to illumination changes.



Histogram Intersection

- Approximate location of an object in the picture is known
- Color histogram of the object is calculated, including its surrounding background, which has only a relatively small effect on the object comparison
- The color histograms can then be compared with the color histograms stored in a database of known objects. The degree of compliance is ensured through the following intersection measure V:

$$V(H_I, H_M) = \frac{\sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \sum_{k=1}^{n_3} \min(H_i(i, j, k), H_M(i, j, k))}{\sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \sum_{k=1}^{n_3} H_M(i, j, k)}$$

where Hi, Hm are the normalized histograms and n1, n2 and n3 are number of bins in the histograms.

Histogram Intersection

- Changes as resolution or orientation => the change of V is small.
 - ...it is possible full description of a three-dimensional object with a small number (about 6) of histograms from different viewing points
- Changes of the lighting, => V is changing significantly and the probability of successful identification decreases significantly.
- Works very well in case of objects with colour texture.
- All color indexing method fail in the case of homogeneous objects and backkground with the same color

Color constancy algorithm

- Color indexing fails, however, when the incident illumination varies either spatially or spectrally. Although this limitation might be overcome by
 - preprocessing with a color constancy algorithm
 - Color reference
 - derived from known lightness
 - color references calibration

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Color constant color indexing

Funt, B.V. Finlayson, G.D. (1995)

- To improve the behavior of the original color indexing algorithm with respect to lighting changes, developed in 1995 Brian V. Funt and Graham D. Finlayson, an advanced algorithm [FF95], the Color Constant Color Indexing, which should be lightness invariant.
 - propose histogramming color ratios.
 - the ratios of color RGB triples from neighboring locations are relatively insensitive to changes in the incident illumination,

Color constant color indexing

For each pixel with its surrounding pixels results in the secondary characteristics d_k (x, y) as follows:

$$d_k(x,y) = \nabla^2 \ln(\rho_k(x,y)), \quad k = 1...3$$

Laplace-Filtration of 3x3 pixel array around the element (x, y) k is the number of color channal ... like intersection algorithm

Improved lightness-invariance comparing with intersection algorithm, ~ not robust solution

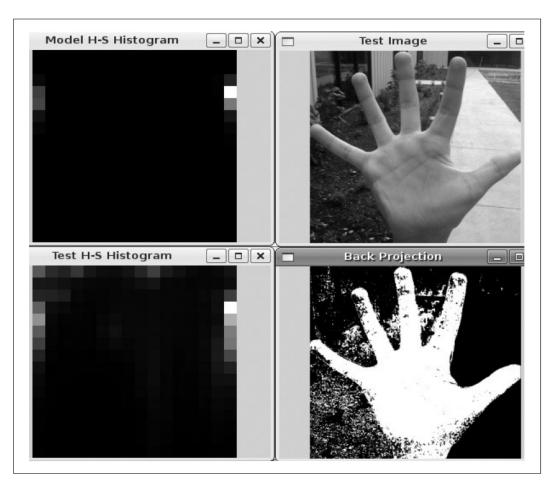
Histogram Backprojection

- The histogram backprojection algorithm is used for the detection of known objects.
- 1) color histogram Hr as a ratio of a color histogram of the desired object Hm and of a color histogram of the image HI is calculated.

$$\forall i \in [0, n_1] \ \forall j \in [0, n_2] \ \forall k \in [0, n_3]: \ H_R(i, j, k) = \min \left(\frac{H_M(i, j, k)}{H_I(i, j, k)}, 1 \right)$$

• 2) Finally, a backprojection of the histogram Hr (i, j, k) in the image is calculated. In the resulting image, only the object colors are available.

- Back projection of histogram values onto each pixel based on its color: the HSV flesh color
- histogram (upper left) is used to convert the hand image (upper right) into the fl esh-color
- probability image (lower right); the lower left panel is the histogram of the hand image

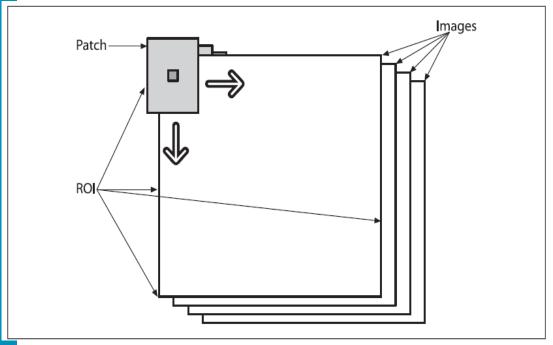


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Comparing Backprojection/ Intersection algorithms

- The same advantages
 - (~ in case of changes as resolution or orientation)
- & disadvantage
 - (~ in case of changes of the lighting)
- …like intersection algorithms

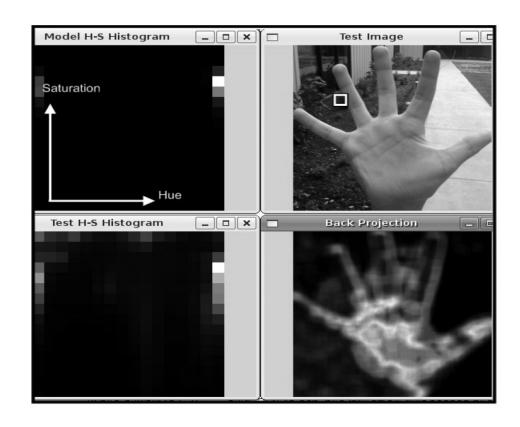
consider subregions of an image and the feature (e.g., color) histogram of that subregion and to ask whether the histogram of features for the subregion matches the model histogram sliding window over the entire input image



Back projection: a sliding patch over the input image planes is used to set the corresponding pixel (at the center of the patch) in the destination image; for normalized histogram models, the resulting image can be interpreted as a probability map indicating the possible presence of the object

When the window size is roughly the same size as the objects we are hoping to find in an image, the whole object "lights up" in the back projection image. Finding peaks in the back projection image then corresponds to finding the location of objects that we are looking for.

Back projection used for histogram object model of flesh tone where the window (small white box in upper right frame) is much smaller than the hand; here, the histogram model was of palm-color distribution and the peak locations tend to be at the center of the hand



Using cvCalcBackProjectPatch() to locate an object (here, a coff ee cup) whose size approximately matches the patch size (white box in upper right panel): the sought object is modeled by a hue-saturation histogram (upper left), which can be compared with an HS histogram for the image as a whole (lower left); the result of cvCalcBackProjectPatch() (lower right) is that the object is easily picked out from the scene by virtue of its color

