A Perceptual Model Based on Computational Features for Texture Representation and Retrieval

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Abstract
A new perception model based on image representation and retrieval for a set of computational measures is proposed in this paper. We consider a set of textural features that individuals use to identify and categorize textures having a perceptual meaning and their application to content-based image retrieval. Such features include coarseness, directionality, contrast, and busyness. This paper proposed a new method to calculate a set of perceptual texture features. The perceptual model presented is judged using a psychometric method (based on rank-correlation) and found to represent very well to human judgements. For these measures large database is required. Therefore the Brodatz database and benchmarking based on exploratory results gives exciting performance. This paper proposes to use two representations for better retrieval efficiency: the original image representation and the autocorrelation function representation. In this paper with the help of autocorrelation function related images are presented to the given input image (based on texture and colour). The related images are displayed either the user satisfies or until no change. The compatibility of the preferred computational measures is shown by human judgement. Firstly, based on the spearman rank-correlation coefficient. Second, the proposed computational measures in texture retrieval shows exciting results and their application mostly when using results returned by each of two representations.

Keywords
Multiple Representations, Perceptual Features, Psychometric Evaluation, Texture, Texture Retrieval

I. Introduction

A texture is the visual and especially tactile quality of a surface. Although texture is an important research area in computer vision .There is no precise definition the notion texture some intuitive concept can be defined about texture. Texture refers to a measure of variation f the intensity of a surface, qualifying properties with repetition of small primitives in a random and regular manner in an image. Statistical, structuraland spectral are the three principle approaches which are used to describe texture. Statistical techniques characterise texture by the statistical properties of the grey level of the points comprises a surface. Generally these properties are computed rom the grey level histogram is grey level co-occurrence matrix of the surface.

II. Methodology

A. Existing Method

The human eye can easily identify the difference between textures, but automatic processing of these textures is very complex. According to literature the case for mismatch between computational models and human vision is the fact that almost all computational use mathematical features which have no perceptual meaning for easy understanding of users.

Disadvantages

The majority of existing systems have many drawbacks like statistical methods looks to give better results in micro texture which in case of macro texture structural method gives better results but these are less significant when compared to the computational cost which is more significant.

B. Proposed Method

First user passes query as input then system provides some images in that User can decide the relevant image to further refine the query and this process can be iterated many times until the user find the desired images as he wants.

Advantages

Some features such as coarseness, directionality, contrast and busyness [8], [14] are a set of textural features in the view of computational community that human vision identifies and divide into textures. In such case in order to combine with human vision these perceptual textural features are assigned by computational techniques.

III. Psychometric Method

To evaluate psychometric method we mainly consider three and these are invigorate from [8] and [12] and [14]

- Experimentally the spontaneous definitions of the textural features were subjected to human subjects. The human subjects ranked according to each textural feature. We obtain only one ranking as per human subjects and textural features.
- Human subjects obtain a recognized rank from all the ranks produced by each textural feature. This was accomplished by calculating sum of rank values.
- We calculate the rank correlation between two rankings obtain by human ranking and computational ranking for each textural feature which was based on spearman rank *correlation.*

Calculating Sum of Ranks

We can compute sum of rank values by equation:

$$S_i = \sum_{k=1}^{n} f_{ik} R_k \quad (1)$$

An aggregate S_i means sum of rank values used to calculate the equation.

Where i stand for i^{th} image and varies between 1 and n. k stands for rank set to image i, varies between 1 to n. f_{ik} gives the number of human subject that set rank to image. R_k Denotes the image at top position.

$$R_k = n - k + 1 \quad (2)$$

After calculating sum of rank values of all images the highest value ranked in top position

IV. Computational Measures

The demonstration is reduced when we base the computational features only on autocorrelation function. In case of original images representation we use similar reasoning holds. The replication of human visual perception and computational measures are computed by following steps:

- An image was calculated by autocorrelation function.
- Then calculate the slope of Gaussian function and the vortex of autocorrelation function in a different ways(depending on rows and columns). Then two new functions are obtained (depending on rows and columns).
- The computational measures for each perceptual feature are computed for each of these functions obtained is mentioned below.

A. Coarseness Evaluation

It gives the quality of roughness, comprising with large primitives and having high degree of uniformity of grey-levels.

Coarseness of a texture can be determined number of granules in autocorrelation function (either maximum or minimum). To evaluate coarseness we use the following equation then two functions C_x (i, j) ET C_y(i, j) are obtained

$$\begin{cases} C_x(i,j) = f(i,j) - f(i+1,j) \\ C_y(i,j) = f(i,j) - f(i,j+1) \end{cases} \quad (3)$$

We calculate the first derivatives of the obtained functions C_{xx} two functions (i, j) ET C_{yy} (i, j) are obtained

$$\begin{cases} C_{xx}(i,j) = C_x(i,j) - C_x(i+1,j) \\ C_{yy}(i,j) = C_y(i,j) - C_y(i,j+1) \end{cases} \quad (4)$$

For maxima

$$\begin{cases} C_x(i,j) = 0 \\ C_{xx(i,j)} < 0 \end{cases} \quad (5)$$

$$\begin{cases} C_y(i,j) = 0 \\ C_{yy}(i,j) < 0 \end{cases} \quad (6)$$

Coarseness (C_s) is evaluated by average number of maximum in the auto correlation function. Coarseness can be expressed as follow.

$$C_s = \frac{1}{1/2 \times \frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1} Max_x(i,j)}{n} + \frac{\sum_{j=0}^{m-1}\sum_{i=0}^{n-1} Max_y(i,j)}{m}} \quad (7)$$

B. Contrast Evaluation

It measures the degree of clarity with which one can clearly differentiate between primitives in a texture. Depending on the lines and columns we can say that the amplitude of the slope of autocorrelation function can be used to calculate contrast

The two main parameters related to are:

- By considering only pixels with significant amplitude.
- We also consider the number of pixels that have significant amplitude.

The number of pixels (i, j) that have a significant amplitude

$$\begin{cases} C_x = f * G_x \\ C_y = f * G_y \end{cases} \quad (8)$$

$$M = \sqrt{C_x^2 + C_y^2} \quad (9)$$

G_x, G_y Are the partial derivatives of the Gaussian according to rows and columns? Let N_t the number of pixels having an amplitude superior to threshold t

$$N_t = \sum_{l=0}^{n-1}\sum_{j=0}^{m-1} \delta_t(i,\ j) \quad (10)$$

The average amplitude M_a is given by

$$M_a = \frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1} M(i,j) \times t(i,j)}{N_t} \quad (11)$$

To evaluate contrast C_t we use equation:

$$C_t = \frac{M_a \times N_t \times C_s^{\frac{1}{\alpha}}}{n \times m} \quad (12)$$

Where M_a represents average amplitude $\frac{N_t}{(n\times m)}$, denotes percentage of pixels having amplitude more than threshold t. C_s measures the coarseness. 1/α Is a parameter for C_s.

C. Directionality Evaluation

It is a spatial property which is related occupying space in an image. It measures the degree of visible dominant orientation of primitives in an image also said to be isotropic which can have one or several arrangements or not at all.

Concerned to directionality we need to determine the two parameters which are dominant orientation and degree of directionalities.

The degree of directionality is corresponded to visibility of the influencing positions in an image.

In this we consider mainly two evaluations

1. Orient Estimation: it was calculated by the following equation:

$$\theta = arctan\frac{C_y}{C_x} \quad (13)$$

2. Directionality Estimation: The degree of directionality can be expressed as follow:

$$N_{\theta_d} = \frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1} \theta_{d(i,j)}}{(n-m) - N_{\theta_d}} \quad (14)$$

D. Busyness Evaluation

It can be defined as change of intensity from a pixel to its proximity. it is related to spatial frequency of intensity changes in image. Busyness is associated with coarseness is in counter direction. As this feature has not much impact in texture retrieval as its calculation based on coarseness this was used as textural features is due to the view point of users it is very useful for easy understanding and unlike from coarseness.

It can be evaluated as follow:

$$B_s = 1 - C_s^{\frac{1}{\alpha}} \quad (15)$$

C_s Denotes the computational measure of coarseness, 1/α is amount used to make C_s as significant against 1. Alpha sets to number of experiments.

E. Threshold and Normalization

A Threshold's' is used for calculate different measures of textural features. Severalfeatures are tested and we take threshold that consists of average number of oriented pixels across all orientations is the best one. Different measures are normalized to this between 0 and 1. It is known as range normalization. This was achieved by two ways

- Compute and divide the range values for each feature
- The value of each feature divided by maximum highest value obtained over the whole data set of the each feature.

V. Spearman Rank Correlation Coefficient

It is one of the most known methods to calculate rank-correlation, between the two ranked variables. It determines the relationship between two variables can be described using monotonic function.

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The consolidated ranking of each textural features obtained by human ranking and computational ranking are considered and calculate the rank-correlation between two rankings. By this we can estimate the correspondence between the two variables by using the method spearman rank correlation.
It can be calculate by using below equation

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \qquad (16)$$

Where d=difference between the two number s in each pair of ranks.
Interpretation of result (vary between -1 and 1). When correlation close to -1 it represents negative correlation, if it is 0 it represents no linear correlation and it represents positive if it is 1.

VI. Autocorrelation Function

The main aim of autocorrelation function is to retrieve relevant images which are similar to the original image by using content of images (such as colour and texture).For images with high degree of coarseness the autocorrelation function decreases slowly and gives few variations. For images with a fine degree of coarseness it decreases quickly and gives a lot of variations.
We calculate autocorrelation function, denoted $f(\delta_i, \delta_j)$ for an $n \times m$ image I by using the below equation [13]

$$f(\delta_i, \delta_j) = \frac{1}{(n-\delta_i)(m-\delta_j)} \times \sum_{i=0}^{n-\delta_i-1} \sum_{j=0}^{m-\delta_j-1} I(i,j) I(i+\delta_i, j+\delta_j) \qquad (17)$$

Where $0 \le \delta_i \le$ n-1 and $0 \le \delta_j \le$ m-1. δ_i, δ_j Represents shift on rows and columns

VII. Psychometric and Computation Estimation

In order to examine the assessments of computational results and evaluations which are obtained by human analysis some psychological experimentations are conducted with human subjects

Tabel 1:

Rank(k)	C_s	$N_{\theta d}$	C_t	B_S
1	K	G	J	I
2	H	C	B	B
3	D	B	F	E
4	C	A	A	F
5	L,G	J	L	J
6	-	L	I	A
7	A	D	G	G,L
8	F,J	F	E	-
9	-	E	C	C
10	E	I	D	D
11	B	K,H	H	H
12	I	-	K	K

Computational ranking for textural features

Table 2:

Rank(k)	Coars.	Cont.	Direct.	Bus.
1	K	F	C	F
2	L	J	B	E
3	H	A	A	A
4	D	L	J	B
5	G	B	G	I
6	C	D	L	D
7	F	C	E	J
8	J	E	I	L
9	A	G	F	G
10	E	K	D,H,K	C
11	B	I	-	K
12	I	H	-	H

Human ranking for textural features

Table 3:

r_s	Coars.	Direct.	Cont.	Bus.
C_S	0.913	-0.388	-0.290	-0.748
$N_{\theta d}$	-0.201	0.841	0.435	0.082
C_t	-0.587	0.573	0.755	0.601
B_S	-0.904	0.390	0.299	0.774

Spearman rank correlation coefficient between computational rank and human ranking:

According to the result every computational measures is correlated with the related textural feature
The relation between consolidated human ranking and computational measures, computed using (17) as stated below
For coarseness the relation is good (r_S:0.913) the difference between two ranks set to image L: (k=5) for computational ranking and (k=2) for human ranking. Now the difference d_i=3. other differences are less than 1 so we can ignore that.
For contrast the relation is satisfactory (r_s=0.755) the difference between two rankings of images I (d_i =5), D (d_i =4) and F (d_i = 2).
For directionality relation is better (r_s=0.841) the main difference is between image. G (d_i=4) and E (d_i=5).
For busyness, the relation is favourable (r_s=0.774) the difference for imageI (d_i=4) and D (d_i=4).

VIII. Experimental Results

A. Comparison

In this we can compare the obtained results with the related works.

Table 4:

	Our model	Tamura's model	Amadasun model
Coarseness	0.913	0.831	0.856
Contrast	0.755	0.904	0.685
Directionality	0.841	0.823	-
Busyness	0.774	-	0.782

Comparison with other work

We can compare our results with other works known as Tamura et al. work [14] and Amadasun et al. work [8].that [14] did not consider busyness in his work and [8] did not consider directionality in his work. By observing the table 4 it is clear that Comparing with Tamura's model our obtained results are better in all features except contrast. When compare with Amadasun's model we have better results obtained by all features.

B. Result Merging

The experimental results mainly concentrate on the ranks obtained by spearman rank-correlation method which calculates both the consolidated ranks of textural features for human subjects and computational measures. Finally we can combine all the obtained results by using result fusion. We use the model FusCL to merge two ranks thus the final result was obtained. The result fusion can be defined by below equation

$$FusCL_{ij} = \frac{\sum_{k=1}^{k} GS_{M_{ij}^{k}}}{k} \quad (18)$$

M^k Means model/view point k and K used number of models/ view points, i represent a given query.

IX. Conclusion

The automatic process based on perceptual texture features for searching relevant images.

In this we mainly consider two representations:

1. Original image representation
2. The autocorrelation image representation

The computational measures propose for each feature were evaluated and also

Psychometric based on sum of rank values and spearman coefficient of rank correlation evaluated

Now compared two results with related works and to store these results we use large database known as Brodatz database

The results obtained by two representations are merged by using result fusion

References

[1] N. Abbadeni,"Information retrieval from visual databases using multiple representations and multiple queries", in Proc. ACM Symp. Appl. Compute., 2009, pp. 1523–1527.

[2] N. Abbadeni,"Perceptual image retrieval", In Proc. Int. Conf. Vis. Inf. Syst., Amsterdam, Netherlands, 2005, pp. 259–268.

[3] N. Abbadeni, "Multiple representations, similarity matching, and results fusion for content-based image retrieval," Multimedia Syst. J., vol. 10, no. 5, pp. 444–456, 2005.

[4] N. Abbadeni,"Content representation and similarity matching for texture- based image retrieval", In Proc. 5th ACM Int. Workshop Multimedia Inf. Retrieval, Berkeley, CA, 2003, pp. 63–70.

[5] N. Abbadeni,"A new similarity matching measure: Application to texture- based image retrieval", In Proc. 3rd Int. Workshop Texture Anal. Synth., Nice, France, 2003, pp. 1–6.

[6] N. Abbadeni, D. Ziou, S. Wang,"Computational measures corresponding to perceptual textural features", In Proc. 7th IEEE Int. Conf. Image Process., Vancouver, Canada, 2000, Vol. 3, pp. 897–900.

[7] N. Abbadeni, D. Ziou, S.Wang,"Auto covariance-based perceptual textural features corresponding to human visual perception", In Proc. 15th IAPR/IEEE Int. Conf. Pattern Recognit., Barcelona, Spain, Sep. 3–8, 2000, Vol. 3, pp. 901–904.

[8] M. Amadasun, R. King,"Textural features corresponding to textural properties", IEEE Trans. Syst., Man Cybern., Vol. 19, No. 5, pp. 1264–1274, Sep.-Oct. 1989.

[9] J. Ashley, R. Barber, M. Flickner, J. Hafner, D. Lee, W. Niblack, D. Petkovic,"Automatic and semi-automatic methods for image annotation and retrieval in QBIC", In Proc. SPIE Conf. Storage Retrieval for Image and Video Databases, 1995, Vol. 2420, pp. 24–35.

[10] J. R. Bergen, E. H. Adelson,"Early vision and texture perception", Nature, Vol. 333, No. 6171, pp. 363–364, May 1988.

[11] J. C. Gower,"A general coefficient of similarity and some of its properties", Biometrics J., Vol. 27, pp. 857–874, 1971.

[12] J. P. Guildford,"Psychometric Methods", New York: McGraw-Hill, 1954.

[13] R. Jain, R. Kasturi, B. G. Schunck,"Machine Vision", New York: McGraw-Hill, 1995H. Tamura, S. Mori, and T. Yamawaki, "Textural features corresponding

[14] H. Tamura, S. Mori, T. Yamawaki,"Textural features correspondingto visual perception", IEEE Trans. Syst., Man Cybern., Vol. 8, No. 6, pp. 460–472, Jun. 1978.

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