Texture and Color Features based Color Image Retrieval using Canonical Correlation

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Abstract- This paper proposes a novel technique, based on Canonical correlation analysis, and the Chi-square test is employed to test the significance of the correlation coefficients. If it is significant, then it is concluded that the input query and target images are same or similar; otherwise, it is inferred that the two images are significantly different. In order to experiment the proposed canonical correlation method, a database is designed and constructed with the help of different types of images and their feature vectors. The F_β-measure is applied to evaluate the performance of the proposed method. The obtained results expose that the proposed technique yields better results than the existing.

Keywords: canonical correlation, query images, target images, F-measure, Chi-square test.

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Texture and Color Features based Color Image Retrieval using Canonical Correlation

K. Seetharaman [α] & Bachala Shyam Kumar [σ]

Abstract- This paper proposes a novel technique, based on Canonical correlation analysis, and the Chi-square test is employed to test the significance of the correlation coefficients. If it is significant, then it is concluded that the input query and target images are same or similar; otherwise, it is inferred that the two images are significantly different. In order to experiment the proposed canonical correlation method, a database is designed and constructed with the help of different types of images and their feature vectors. The F_{β}-measure is applied to evaluate the performance of the proposed method. The obtained results expose that the proposed technique yields better results than the existing.

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I. Introduction

The proliferation of digitizing the functions of private and public sectors, governmental organizations impetus to increase the repository capacity of the devices as well as the speed of accessing and retrieving the data through the internet. Owing to awareness and usage of the Internet and World Wide Web (WWW), a number of Internet users increased exponentially. Perhaps, a number of approaches have been developed with a consideration of the internet users and the difficulties in accessing the data available on the Internet and the WWW, they are not completely fulfilling the users' requirements. Specifically, images demand large amount of space and consume more time to retrieve from the image repository.

At the earlier stage, the text annotation based image retrieval method has been developed which is time consuming (Yap and Wu, 2015), and also it is not effective and efficient because it retrieves the images based on the text annotated manually by the user. Then, the content-based image retrieval (CBIR) method has been developed, which attracted a number of researchers. Most of the techniques have been developed based on the contents of the images, namely low-level global visual features, viz. colour properties, shape, texture, spatial orientation, etc., which are used as a query for the retrieval process (Huang et al., 1997; Stricker and Orengo, 1995; Pentland et al., 1994; Fuh et al., 2000). Liu, et. al. (2011) propose micro-structure

descriptor, which extracts and integrates colour, texture, shape and colour layout information for image retrieval. The authors claim that it has only 72 dimensions for full colour image. But this is too large compared to those of the methods proposed by (Seetharaman, 2015; Krishnamoorthi and Sathiya Devi, 2013). The work proposed in (Murala et al., 2012) encodes the relationship between reference pixel and its surrounding neighbors by comparing gray-level values, and it extracts the edge information on local extreme in different angles. Though, a number of works have been developed based on the statistical distributional approaches and parametric tests of hypothesis, most of them are not effective and efficient, since there is no guarantee that all the images are distributed as independent and identical to Gaussian random process. The statistical parametric tests can be applied on an image, if it is distributed to Gaussian process. Otherwise, it does not lead to a good result. Generally, the parametric tests can be used if the data are quantitative and are distributed as independent and identical to Gaussian process. This motivated to develop the proposed method.

This paper adopts the idea of Canonical correlation analysis (CCA) for image retrieval. It is an effective and efficient technique for both textured and structured images, since it does not strictly rely on the distributional process. The Correlation analysis is dependent on the co-ordinate system, in which the variables are described, so even if there is a very strong linear relationship between two sets of multidimensional variables, this relationship might not be visible as a correlation. The CCA seeks a pair of linear transformation for each set of variables such that when the set of variables are transformed, the corresponding co-ordinates are maximally correlated. It is one of the valuable multi-data processing methods (Sun, et al. 1994; Zhang, et al. 1999). In recent years, CCA has been applied to several fields such as signal processing, computer vision, neural network and speech recognition.

In recent years, there has been a vast increase in the amount of multimedia content available both in off-line and online, though it is unable to access or make use of this data unless it is organized in such a way as to allow efficient browsing. To enable content based image retrieval with no reference to labeling, this paper attempts to learn the semantic representation of the

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images, and their associated text. This paper presents a general approach using KCCA that can be used for content based (David and John, 2003) as well as region based retrieval (Fyfe and Lai, 2001; David and John, 2003). In both cases, the KCCA approach and the Generalized Vector Space Model (GVSM) are compared, which aims at capturing some term to term correlations by looking at co-occurrence information.

The canonical correlation is the most general multivariate form, because multiple regression, discriminant function analysis and MANOVA are the special cases of the Canonical correlation analysis. Thus, it yields better results. The one more advantage of using canonical correlation is that there is no specific requirement for the data that should follow the normality conditions, if it is a descriptive analysis.

II. Proposed Retrieval Method

Considering a multivariate random vector of the form (x, y). Suppose it is given a sample of instances $S = \left[(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\right]$ of (x, y), Let S_x denote $(x_1, ..., x_n)$, and similarly S_y denote $(y_1, ..., y_n)$. It can be considered for defining a new co-ordinate for 'x' by choosing a direction I_q, and projecting x onto that direction

$$x \to \langle I_q, x \rangle$$

Similarly, by choosing a direction I_t it is obtained a sample of the new 'x' co-ordinate as

$$S_{x, I_q} = \left[\langle I_q, x_1 \rangle, \langle I_q, x_2 \rangle, ..., \langle I_q, x_n \rangle\right]$$

with the corresponding values of the new 'y' co-ordinate being

$$S_{y, I_t} = \left[\langle I_t, y_1 \rangle, \langle I_t, y_2 \rangle, ..., \langle I_t, y_n \rangle\right]$$

The linear combination of the feature vectors x_i of the query image is

$$I_q = f_1 x_1 + f_2 x_2 + ... + f_m x_m \qquad (1)$$

and the linear combination of the feature vectors y_i of the target image is

$$I_t = f_1 y_1 + f_2 y_2 + ... + f_n y_n \qquad (2)$$

The first canonical correlation is the maximum among the correlation coefficients between the variates I_q and I_t that is considered as the canonical correlation coefficient between the query and target images.

The function to be maximized is

$$\rho = \max_{I_q, I_t} corr(S_x I_q, S_y I_t)$$

$$\rho = \max_{I_q, I_t} \frac{\langle S_x I_q, S_y I_t \rangle}{\|S_x I_q\| \|S_y I_t\|}$$

If $E[f(x, y)]$ denote the empirical expectation of the function, $f(x, y)$, then

$$E[f(x, y)] = \frac{1}{N} \sum_{i=1}^{N} f(x_i, y_i)$$

Now, the correlation expression can be rewritten as in equation (3)

$$\rho = \max(I_q, I_t) \frac{\hat{E}\left[\langle I_q, x \rangle \langle I_t, y \rangle\right]}{\sqrt{\hat{E}\left[\langle I_q, x \rangle^2 \hat{E}\langle I_t, y \rangle^2\right]}} \qquad (3)$$

$$\rho = \max(I_q, I_t) \frac{\hat{E}\left[I_q' x y' I_t\right]}{\sqrt{\hat{E}\left[I_q' x x' I_q\right] \hat{E}\left[I_t' y y' I_t\right]}} \qquad (4)$$

Follows that

$$\rho = \max(I_q, I_t) \frac{I_q' \hat{E}[xy'] I_t}{\sqrt{I_q' \hat{E}[xx'] I_q I_t' \hat{E}[yy'] I_t}} \qquad (5)$$

Where, I' represents the transpose of a vector or matrix I. The covariance matrix of (x, y) is

$$C(x, y) = \hat{E}\left[\binom{x}{y}\binom{x}{y}'\right] = \begin{bmatrix} Cxx & Cxy \\ Cyx & Cyy \end{bmatrix} = C \qquad (6)$$

The total covariance matrix C is a block matrix, where the within-sets covariance matrices are C_{xx} and C_{yy}, and the between-sets covariance matrices are

$$C_{xx} = C_{yx}'.$$

Thus, we can rewrite the function, ρ as

$$\rho = \max(I_q, I_t) \frac{I_q' C_{xy} I_t}{\sqrt{I_q' C_{xx} I_q I_t' C_{yy} I_t}} \qquad (7)$$

The maximum canonical correlation is the maximum of ρ with respect to I_q and I_t.

Significance of the canonical correlation coefficient, ρ, is examined by employing the Chi-squared test expressed in equation (8).

Statistical hypothesis:

$$H_o : \rho(I_q, I_t) = O$$

$$H_\alpha : \rho(I_q, I_t) \neq O$$

$$\chi 2 = -\left(p - 1 - \frac{1}{2}(m + n + 1)\right) ln \prod_{j=1}^{min(m,n)} (1 - \hat{\rho}_j^2) \quad (8)$$

Which is asymptotically distributed as a Chi-squared with $(m - i + 1)(n - i + 1)$ degrees freedom for large sample size, N. If $\rho(I_q, I_t) < \chi_\alpha^2$, then the two images belong to the same class; otherwise, the two images are different, where α is the level of significance (Kanti et al., 1979).

III. Image and Feature Databases Settings

To experiment the proposed CCA method, an image database is constructed using 1, 27,167 images, which have been collected from different sources, and that are subjected to experiments. Among them, 1932 colour images of size 512×512 pixels have been collected from various sources such as 4676 images from CalTech image database (Coral database); 695 images from Corel image database; 3336 images from INRIA Holidays image database (CalTech Holiday Database); 682 images from VisTex image database; 558 images with size 128×128 that are photographed by a digital camera; 537 images with size 128×128 that have been downloaded from various websites. The texture images collected from Corel and VisTex image databases are divided into 16 non-overlapping sub-images of size 128×128. To evaluate the proposed method is invariant for rotation and noise, the images are rotated through 90°, 180° and 270° degrees. In addition to that 524 multi-spectral satellite images such as tropical depression and cyclone images, and wetland images are incorporated in the image database. Therefore, totally there are [1932 (actual image) + ((16 × (695+682)) + (4676 + 3336 + 558 + 537)) × 3 (rotated through 90°, 180° and 270°) +30,289 (scaled) + 626 (satellite)] = 1, 28, 482 images. Based on these image collections, an image database and FV database are constructed.

IV. Measure of Performance

In order to measure the performance of the proposed method, the F_β-measure is adopted, which is a harmonic mean of precision (P) and recall (R) values, and that are given in equations (9), (10) and (11). The F_β, measures the effectiveness of retrieval with respect to a user who attaches β times as much importance to recall as precision (Van Rijsbergen, 1979). The β value is decided with respect to weight which is given to the P and R. In the context of the proposed research work, the

β is considered as 0.5, since more weight is given to the precision. Thus, equation (9) is rewritten as in equation (12).

$$F_\beta \text{ measure} = (1 + \beta^2) \times \frac{(P) \cdot (R)}{(\beta^2 \times P) + (R)} \quad (9)$$

Where,

$$P = \frac{\left|\{Relevant\ Images\} \cap \{Retrieved\ Images\}\right|}{\left|Retrieved\ Images\right|} \quad (10)$$

$$R = \frac{\left|\{Relevant\ Images\} \cap \{Retrieved\ Images\}\right|}{\left|Relevant\ Images\right|} \quad (11)$$

In the context of the proposed research, the β is considered as 0.5 since more weight is given to the precision. Thus, equation (9) can be written as in equation (12).

$$F_{0.5} \text{ measure} = (1 + 0.5^2) \times \frac{(P) \cdot (R)}{(0.5^2 \times P) + (R)} \quad (12)$$

V. Experiments and Results

A colour image is given as input key image to the system, and the shapes in the image are segmented; the segmented image is modelled to HSV colour space. The texture features are extracted from the V component of the HSV colour space. The colour features, such as H, S and V, and the texture feature are considered as observation and used in the CCA method expressed in equation (7). For a sample, due to space constraints, a shape segmented colour image is presented in Fig.1.
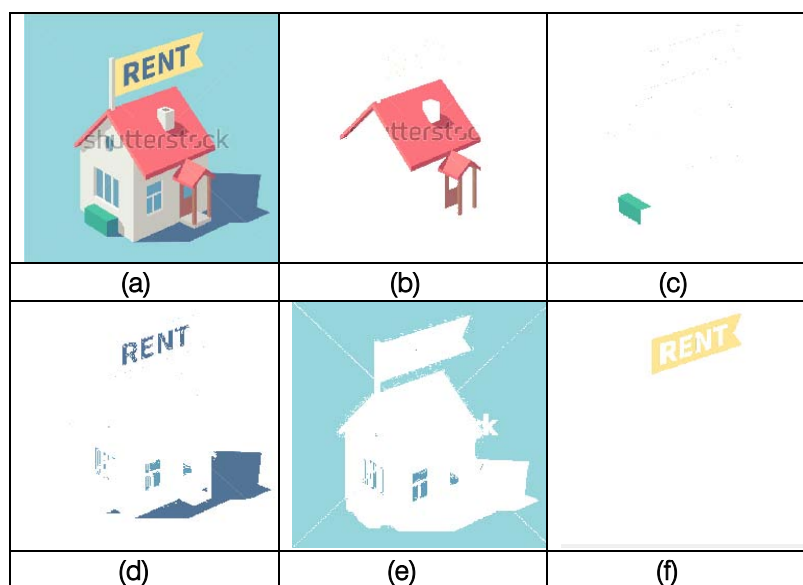
Figure 1: Segmented Shapes: (a): actual image; (b): red component shape; (c): green component shape; (d): blue component shape; (e): combination of green and blue; (f): combination of red and green.

In order to experiment the CCA method discussed in section 2, the expression in equation (7) is implemented with the image and their feature databases constructed and discussed in section 4 that measures the correlation between both query and target images. Due to space constraints, for a sample, some of the images considered from the image database are presented in this paper that have been included during the experiments.

The target images are identified and marked in the image database, based on the results obtained by experiments. According to the users' requirements, the user can fix the level of significance of the tests by which the user can retrieve a number of same or similar images. The proposed system matches and retrieves the same image (target and query images are the same) from the image feature database at the level of significance 0% or 0.001 (100% accuracy – same images); almost the same images for 1% to 2% (99% to 98% accuracy) level of significance; similar images for the level of significance from 3% to 5%; related images for the level of significance from 6% to 8%. The selected images are indexed (ranked) from lowest to highest, i.e. in an ascending order based on the test statistic values obtained. The image which corresponds to the first value in the indexed list is marked as target image and it is retrieved from the image database.

The canonical correlation coefficient ρ is computed, based on the equation (8), on the input query image. The query and target images are considered in various combinations, and the computed ρ values are tested using the Chi-squared test statistic given in equation (9) of the section 2.

In order to validate the proposed system, the image in column 1 of Figure 1(a) is given as input query image, for which the system retrieves the images in row against them. The retrieved output images show that the proposed CCA method is robust for scaling and rotation for both textured and structured images. Since the proposed system serves same as the distributional approach, the proposed system acts as invariant for rotation and noise.

The experiment is conducted at various levels of significance on the input query Wall Street Bull image given in Figure 2(a). The images in column 2 of the Figure 2(b) are retrieved at 2% level of significance; images in columns 3, 2 and 1 are retrieved at 5% level of significance; at 8% and 12% level of significance, the system retrieves the images in columns 4, 3, 2, 1 and 7 respectively; at 15% level of significance, all the images presented in Figure 2(b) are retrieved. The number of shapes in both query and target images are compared, if it matches, then it is emphasized that both the images are same or similar.
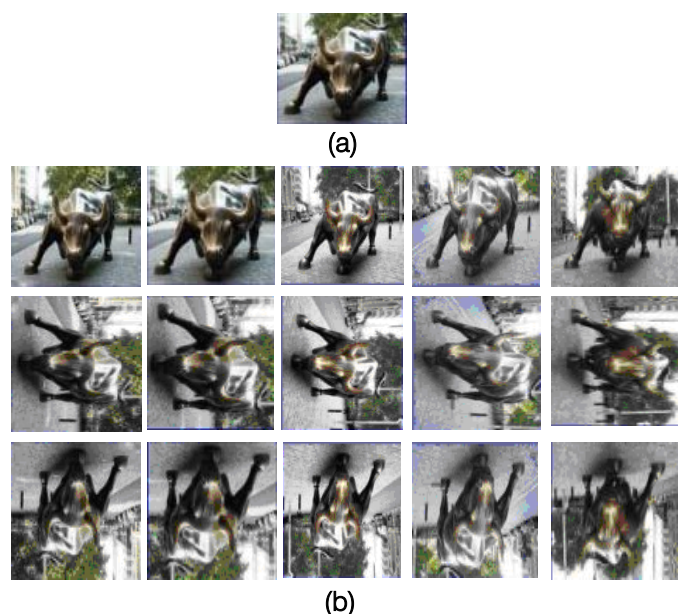
(a)

(b)

Figure 2 : Wall Street Bull – (a): actual image with size 75 × 100; row 2 of (b): actual image with size 96 × 128; row 3 of (b): images in row 2 are rotated clockwise through 90 degrees; row 4 of (b): images in row 2 are rotated clockwise through 180 degrees.

The obtained output of the experiments, based on the canonical correlation, is tabulated in Table 1; it can be observed from the output that the proposed CCA yields 0.9982 for the images Wall Street Bull-1 versus Wall Street Bull -1, i.e. the query and target images are same. Similarly, the canonical correlation coefficients are obtained for different combinations of the Bull images are presented in Table 1. The computed canonical correlation coefficient matrix is a symmetric. The main advantage of the proposed system is that it facilitates the user to retrieve only the required number of images by fixing the level of significance, whereas the existing methods retrieve a number of similar images. Thus, in the existing methods, the user has to expend time to select the required image from the set of retrieved same or similar images. In addition to that the proposed system retrieves a set of similar images by fixing the level of significance at a desired level.

Table 1: Canonical Correlation Coefficient for Wall Street Bull images

Vs.	Bull-1	Bull-2	Bull-3	Bull-4	Bull-5
Bull-1	0.9999	0.9881	0.7506	0.7457	0.6152
Bull-2	0.9881	0.9998	0.7561	0.7389	0.5896
Bull-3	0.7506	0.7561	0.9999	0.7931	0.6856
Bull-4	0.7457	0.7389	0.7931	0.9998	0.7953
Bull-5	0.6152	0.5896	0.6856	0.7953	1.0000

Furthermore, to prove the efficacy of the proposed method, a number of structured images are considered for the experiment. For a sample, a few of them are presented in Figure 3. The image given in Figure 3(a) is fed as input query to the system, and the level of significance is fixed at 0.08 (i.e. 8 percent); for which the system retrieves the images presented in row 1. The images in row 2 are retrieved, while the level of significance is fixed at 0.12 or lesser (i.e. 12 percent or lesser), whereas it retrieves the images in rows 3 and 4 at the level of significance 0.15

Figure 3 : Structure images downloaded from Internet – (a): input key image; (b): retrieved output images

Moreover, to emphasis that the system works well for the textured or semi-structured images, a number of images are considered from the Corel-10K and 5K image databases; and the obtained retrieved images are present in Figure 4. The system retrieves the images in columns 2-6 for the input key images in column 1. Images in in column 2 are retrieved at the level of significance 0.01 (i.e. 1%); the images in column 3 are retrieved while the level of significance is fixed at 0.08 or lesser (8% or lesser); while the level of significance is at 0.15 or lesser (i.e. 15% or lesser), the images in columns 4 and 5 are retrieved; images in column 7 are retrieved at the level of significance, 0.18 (i.e. 18% or lesser).

Figure 4 : Corel 5K and 10K images – Texture or Semi-structured images.

Column 1: input query images; columns 2-5: retrieved output images

A comparative study is performed to measure the efficiency of the proposed method with the existing methods: Orthogonal Polynomial (OP) (Krishnamoorthi and Sathiya Devi, 2013), Bhattacharyya distance (BD) (Yang and Newsam, 2013), and Mahalanobis distance (MD) (Hoi, et al., 2010) in terms of average of the precision and recall values of the retrieved results. The average of the precision and recall values are obtained at the level of significance (α) 0.12 percent and above.

The obtained results reveal that the proposed method outperforms the existing systems. But, this paper takes account of texture and structure images. Averages of the precision and recall values are calculated for various methods: OP, BD and MD measures, and the results are presented in Table 2. Bar chart is plotted for the observed results, and is presented in Figures 5.

Table 2 : Performance of the Proposed System with Other Existing Methods
(Average values of the Precision and Recall)

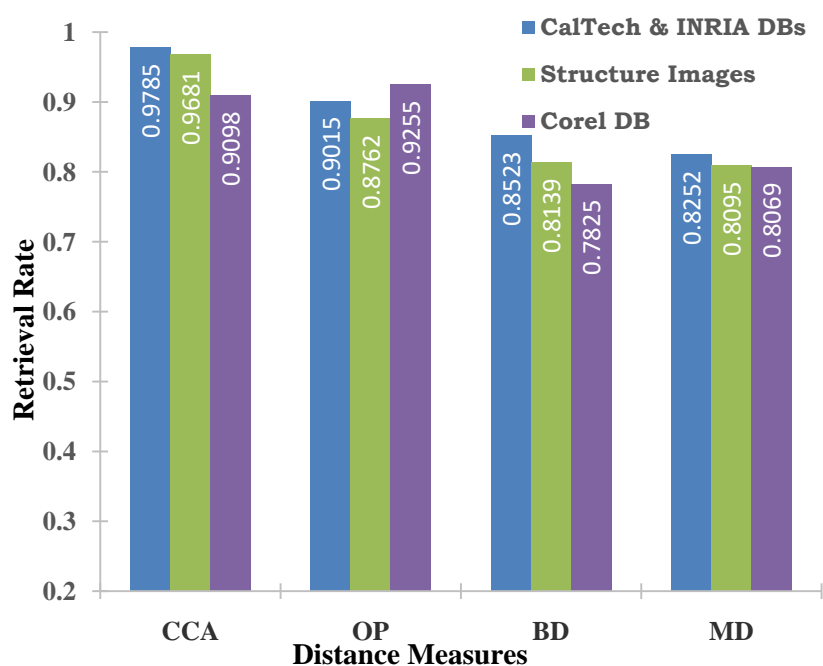| Image Database	Proposed system (α is at 0.12 and above)			OP			BD			MD		
	R	P	$F_{0.5}$	R	P	$F_{0.5}$	R	P	$F_{0.5}$	R	P	$F_{0.5}$
CalTech	0.9585	0.7952	0.8233	0.9015	0.7631	0.7873	0.8523	0.6937	0.7205	0.8252	0.6817	0.7063
Corel	0.9098	0.8585	0.8683	0.9255	0.8039	0.8256	0.7829	0.7736	0.7754	0.8095	0.6912	0.7120
Structure Images	0.9681	0.7852	0.8160	0.8762	0.7729	0.7916	0.8139	0.6483	0.6758	0.8069	0.6275	0.6567

Figure 5 : Bar Chart: Comparison of Retrieval Rates of Different Methods

Time Complexity

The performance of the proposed system is compared with the existing systems: OP method, BD and MD distance measures in terms of computational time complexity. The system is implemented using Java SE 7 compiler with the system specification, Intel Core i5-4440 processor based PC with 4GB DDR3 RAM. The time consumed by the proposed system for feature extraction, matching and retrieving the images is measured in terms of seconds after a rigorous experimentation, and the obtained results are presented in Table 3. The proposed system demands lesser time compared to that of the existing systems, and also the proposed system yields better retrieval results.

Table 3 : Comparison of Computational Time Complexities

Time Consumption	Proposed System	OP	BD	MD
Feature extraction time	0.485 sec	0.798 sec	0.975 sec	0.852 sec
Searching time	0.0581 sec	0.072 sec	0.070 sec	0.069 sec

VI. Conclusion

In this paper a novel technique, Canonical correlation analysis and the Chi-square test are employed. The Chi-square test tests the correlation coefficient between the query and target images that whether it is significant or not. The canonical correlation coefficient extracts the spatial relationship among the pixels in the image, by which the spatial orientation of the texture properties are extracted; and the properties between the query and target images are tested. If it is significant, then it is concluded that the input query and target images are same or similar; otherwise, it is inferred that the two images differ significantly. It is observed from the results that the proposed technique yields better results than the existing techniques

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