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Image Retrieval using Autocorrelation Based Chordiogram Image Descriptor and Support Vector Machine

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Abstract*: *Nowadays, evolving systems for indexing and organizing images is more important due to proliferation of images in all domains and it has made content-based image retrieval (CBIR) as significant research area. This paper uses autocorrelation based chordiogram image descriptor (ACID) for effective image representation and Support vector machine (SVM) for effective image classification. The ACID of images is computed from Haar wavelet based multiresolution domain and it exploits shape, texture and geometric details. The proposed combination of ACID and SVM is highly compatible and is comprehensively tested on benchmark datasets namely Gardens Point Walking and St. Lucia and experimental results prove that proposed combination outperforms significantly in terms of precision and recall.

Keywords*: *Chordiogram image descriptor, Autocorrelation, Edgels, Support vector machine.

I. INTRODUCTION

Increasing numbers of image capturing devices has led to the proliferation of images in all domain's day by day. Therefore, developing more efficient image retrieval is needed for effective use and arrangement of images. In CBIR, images are represented using texture, color and shape details. Recently researchers are focusing on combined feature representation instead of using single feature for image retrieval. In addition, researchers also concentrated on resilient behavior of image features against illumination, rotation, scaling, translation, appearance and noise in order to attain better retrieval rate. Apart from the efficiency of feature vector, computational cost of feature vector is also concentrated simultaneously. In the literature, many retrieval systems have been described using various kinds of features. SIFT reported in [1] is a histogram of directions of keypoints and it is invariant illumination and partly invariant to affie distortion. Histogram of directions of gradients is reported in [2] for image retrieval. Later, pyramid form of HOG [3] and co-occurrence of HOG [4] is described for effective representation of image, Jain and Vailya computed edge details using a histogram of edgel orientations [5]. In [5], canny edge operator is employed for edge computation. Later, Sobel operator is employed in [6] for computing the edge details based on its orientation and is used widely. Later on, to improve the discriminative power of edge based features, autocorrelation of edgels based on its orientation is computed [7]. Further to include the color details with edge features, microstructure descriptor is introduced by Liu et al., [8]. Seetharaman and Sathiamoorthy [9, 10] introduced full range Autoregressive model with Bayesian approach-based edge detector to compute the edge details with color details in HSV color space and is enhanced further by incorporating autocorrelation function [11]. Chordiogram image descriptor (CID) is computed in [12] for image retrieval and it performs segmentation operation to exploit the edge details and the edgels used for computing the geometric details like orientations of pair edgels, degree of angle between the line segment connecting the pair of edgels, and length of line segment. Subsequently, Wang et al., [13] addressed the issues with CID like fake edgels and time cost. By computing the edges using the edge detector instead of segmentation process Wang et al., avoids fake edgels. By computing geometric details among every pair of dominant edgels instead of every pair of edgels in the image, Wang et al., decreases the computation cost of CID. Recently, to improve the discriminative power of CID, we computed CID based on autocorrelation function and we termed it as autocorrelation based CID (ACID) [14]. Instead of capturing only geometric details from edgels we also captured texture and spatial structure using edgels and we reported that it outperforms considerably than the CID [14]. Simultaneously, to reduce the computational cost of CID, we proposed it on multiresolution domain and the result of multiresolution domain-based CID [15] is comparable to the CID of [13]. By keeping [14] and [15]in mind, in this paper we introduced ACID in multiresolution domain and for that we employed discrete Haar wavelet [15]. We believed that computing the ACID from pyramid structure wavelet will decreases the computation cost as well maintains the accuracy. Furthermore, we examined the literature and found that SVM performs well for non-linear and non-separable problems because of its generalization capability and resilient to high dimensional data [16].

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Therefore, we used SVM in the classification phase to effectively filter out the images for matching process. The use of SVM in the proposed CBIR considerably decreases the search space and thus the time cost of proposed CBIR is decreased significantly.

In the image matching process, we employed L1 metric owing to its computational efficiency and accuracy [17].

Exhaustive experiments are done using the benchmark datasets and it is seen obviously from the outputs that proposed combination of techniques performs better. The rest of the manuscript discusses the following: wavelet-based ACID computation is explained in Section 2. SVM is discussed in Section 3. Section 4 describes experimental results and performance and matching measures. Conclusion is discussed finally in Section 5.

II. WAVELET BASED ACID

The geometric details of edgels together with autocorrelation function are introduced by us in [14]. The ACID computes geometric details as well as texture and spatial structure of edgels more effectively. Since CID is not sensitive to edges, any of the edge operator available in the literature is used to identify the edgels. In our case, we used Sobel operator for edge computation than identified edgels are quantized uniformly. Subsequently, image is partitioned into number of 3×3 sub images and we moved through each 3×3 image and for each quantized edgel value. For each move, we look for the matching of center edgel with its neighbour edgels. If matching is found, we computed the correlation between the center and its neighbours and computed the geometric details like orientations(θ_1 and θ_2), angle of deviation of line connecting the pair of edgels and horizontal axis (ϕ) between every pair of center and its identical neighbours. For example, computation of geometric details is illustrated in Fig.1

The computed ACID features are characterized in table format. The table consists of 2 columns and number of rows equal to number of quantization level of edgels. The first column corresponds to quantized edgel values and the second column corresponds to distance that is distance between center edgel and its neighbours. The rows in the table specify the output of autocorrelation function for each quantized edgel. For example, autocorrelation table is illustrated in Table I. The ACID is computed as follows:

Let I be n x n image, an edgels in I are $e_1, e_2, \ldots, e_m$. For an edgel $E = (x, y) \in I$, let $I(E)$ represent its edge value. Let $I_e \overset{\Delta}{=} \{E | I(E) = e\}$. Hence, the notation $E \in I_e$ is synonymous with $E \in I, I(E) = e$. For convenience, [33] use L_∞ norm to assess distance among edgels i.e., for edgels $E_1 = (x_1, y_1), E_2 = (x_2, y_2)$, [33] define $|E_1 - E_2| \overset{\Delta}{=} \max\{|x_1 - x_2|, |y_1 - y_2|\}$. [33] denote the set $\{1,2,\ldots,n\}$ by $|n|$.

Definitions. The histogram h of I is expressed for $i \in |m|$ by

$$h_{e_i}(I) \overset{\Delta}{=} n^2 \Pr_{E \in I} \left| E \in I_{e_i} \right| \tag{1}$$

For any edgel in the image, $h_{e_i}(I)/n^2$ presents probability that value of edgel is e_i. Let a distance $d \in |n|$ be fixed a priori. Then, correlation of I is expressed for $i, j \in |m|, k \in |d|$ as

$$\gamma^{(k)}_{e_i,e_j} \overset{\Delta}{=} \Pr_{E_1 \in I_{e_i}, E_2 \in I} [E_2 \in I_{e_j} \; \| E_1 - E_2 | = k] \tag{2}$$

Given any edgel of value e_i in image, $\gamma^{(k)}_{e_i,e_j}(I)$ presents probability that edgel at distance k away from given edgel is of value e_j. The autocorrelation of I exploits spatial correlation with identical edgels only.

TABLE. I. Autocorrelation of identical edgels at distance 1 for quantized edgel value

Distance (d) / Edgel Value	d=1
255	0.016
250	0.025
243	0.110
.	.
.	.
.	.
.	.

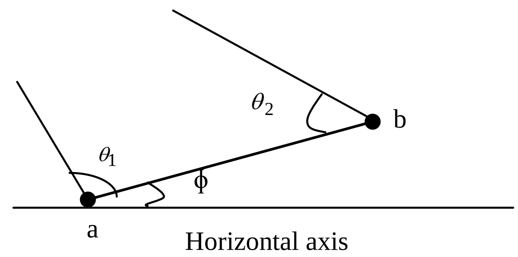

Fig.1 Computation of orientation of edgels a, b and angle of deviation between horizontal axis and line connecting edgels a and b

Like CID, ACID is also 4 dimensional one i.e., instead of length of line between pair of edgels in CID, ACID incorporates autocorrelation details which effectively characterizes the textures and spatial details [14].

In [15], we reported that Haar wavelet-based CID preserves the accuracy and reduces the computational cost. Accordingly in this paper, we computed ACID from Haar wavelet domain in which image is decomposed in the form of pyramid structure by calculating the approximations and

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details and decomposition is continued till reaching the optimum level and we determined the level of optimum experimentally as in our previous work [15]. The multi-resolution pyramid image is obtained as follows [15]

Where $I_{0,}, I_1, ..., I_k$ - input images and have k coefficients which have k/2 approximations and k/2 wavelet coefficients and are kept in upper $[a_{0,}, a_1, .a_3]$ and lower $[w_{0,}, w_1, .w_3]$ arrays respectively.

This decomposition procedure is performed again and again until we get the fine level and in the proposed CBIR, the optimum level is 3 in accordance with [15].

$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ w_0 \\ w_1 \\ w_2 \\ w_3 \end{bmatrix} \Leftarrow \begin{bmatrix} a_0 \\ w_0 \\ a_1 \\ w_1 \\ a_2 \\ w_2 \\ a_3 \\ w_3 \end{bmatrix} = \begin{bmatrix} 0.5 & 0.5 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.5 & 0.5 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.5 & 0.5 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.5 & 0.5 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.5 & 0.5 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.5 & 0.5 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.5 & 0.5 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.5 & 0.5 \end{bmatrix} \cdot \begin{bmatrix} I_0 \\ I_1 \\ I_2 \\ I_3 \\ I_4 \\ I_5 \\ I_6 \\ I_7 \end{bmatrix} \quad (3)$$

III. CLASSIFICATION

A. SVM

SVM introduced by Vapnik [16] drawn more attention in image retrieval and classification problems because it provides better classification rate than the classical classification approaches. First SVM maps input feature points into high dimensional feature space then finds separate hyperplane using dot product functions in feature vector space and are known as kernals. The result of optimal hyperplane is combination of few input points and is known as support vectors. Later, it maximizes the margin among hyperplane and data in order to minimizes the generalization error. That is the basic idea behind SVM is structural risk minimization. Due to the promising results of SVM, it is widely used many applications including fingerprint identification, face recognition, image retrieval and credit analysis [16]. Theory of SVM is described as follows

Consider the training sample T = $\{(x_i, y_i)\}_{i=1}^{n}$, where $x_i \in \Re^d$ - i th input pattern, d – dimension off training sample and x_i' is feature vector and y_i is class label which is a binary value, -1 or +1. If the training sample is linearly separable, the hyperplane is defined ass $w^T x_i + b = 0$, which satisfies that $y_i(w^T x_i + b) \geq 0$, where w is the weight vector orthogonal to the hyperplane, b is an offset term and x_i is the attributes. The training must minimize sum of errors and maximize classification hyperplane. Thus, the problem for the linearly separable case could be formulated as (4) [16].

$$\min_{w,b} \frac{1}{2} w^T w \quad (4)$$

Subject to $y_i(w^T x_i + b) \geq 0$

In case the data are non-linearly separable in the input space, the previous analysis can be generalized by introducing a slack variable ξ_i to x_i, which transfers the optimal hyperplane problem into (5) [16]

$$\min \frac{1}{2} w^T w + C\sum_{i=1}^{n} \xi_i \quad (5)$$

Subject to $y_i(w^T x_i + b) \geq 1 - \xi_i$

and $\xi_i \geq 0, i = 1,...n$

where the parameter C can be regarded as a regulation parameter that imposes a balance between the minimization of the error function and the maximization of the margin of the optimal hyperplane. Slack variable is used to measure the error in the SVM classifier. The optimization problem (5) can be solved by introducing a Lagrange multiplier α_i to x_i and then based on the Karush–Kuuhn–Tucker theorem, and the dual form of (6) could be formulated as in[16]

$$\max_{\alpha} w(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} y_i y_j \alpha_i \alpha_j k(x_i, x_j)$$

$$\text{Subject to } \sum_{i=1}^{n} y_i \alpha_i = 0, 0 \leq \alpha_i \leq C, i = 1,...,n \quad (6)$$

Finally, decision function *h(x)* off SVM classifier can be expressed as

$$f(x) = sign(h(x)) = sign(\sum_{i=1}^{n} \alpha_i y_i k(x, x_i) + b) \quad (7)$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Datasets

We evaluated the proposed CBIR system using the benchmark datasets namely Gardens Point Walking [13] and St. Lucia [13] and the outputs are compared with CID, wavelet-based CID, ACID and proposed wavelet-based ACID with SVM in classification stage.

The Gardens Point Walking dataset have images captured in the day with the camera fixed in right- and left-hand sides of a moving vehicle and images captured in the night time with the camera fixed in right-hand side of a vehicle and each category has 200 images of dimension 960×540.

St. Lucia dataset have images which are captured at early morning and late afternoon of a day and a day after two weeks. For sample, some images from benchmark datasets are shown in Fig.2.

B. Similarity Measurementt

The similarity matching operation between input and dataset images is done using L1 metric which is also named as Manhattan metric and it utilizes sum of absolute variances of variable [17] to computed the similarity among two pixels in Euclidean space. The Manhattan metric between two images is given as $S(I^q, I^t) = \sum_{i=1}^{k} (I_i^q - I_i^t)$

(8)

where, I_i^q and I_i^t - query and target image feature vectors respectively and k-dimension of the combined feature vector.

C. Evaluation measures

We evaluated the proposed CBIR using precision (P), average retrieval precision(ARP), recall(R) and average retrieval rate (ARR) [14] and are given as follow for a query image I_q.

$$Precision: P(I_q) = \frac{\text{No.of relevant images retrieved}}{\text{Total No.of images retrieved}} \tag{9}$$

$$Recall: R(I_q) = \frac{\text{No.of releveant images retrieved}}{\text{Total No.of releveant images in database}} \tag{10}$$

$$ARP = \frac{1}{|DB|}\sum_{k=1}^{|DB|} P(I_k) \,\Big|\, n \le 10 \tag{11}$$

$$ARR = \frac{1}{|DB|}\sum_{k=1}^{|DB|} R(I_k) \,\Big|\, n \ge 10 \tag{12}$$

Where DB - total no. of images in each class.

D. Results and Discussion

As discussed in Section 2, we computed the wavelet based ACID and existing techniques namely CID [13], WCID [15] and ACID [14] for all the images in the benchmark datasets and are stored separately in feature dataset. We selected the query image randomly from both datasets and we designed the proposed system such that all the images in the benchmark datasets takes part in training and testing. In order to achieve that we implemented the 5-fold cross validation approach in which each dataset is randomly grouped into 5 and each group takes part in testing and training such that when one group is used for training, all the remaining groups are participated in testing.

When the input image is submitted to the proposed CBIR, first it performs decomposition operation up to level 3 then it computes ACID and it becomes an input for SVM to determine the class label. Once the class label of input image is identified, similarity matching process is performed within that corresponding class using the L1 metric. After computing the similarity values between input and all the images in the corresponding class, the similarity values are sorted in ascending manner and the user can retrieve top N images from the sorted output.

Fig.3 and Fig.4 illustrates the plots of precision(P) versus recall(R) for proposed and existing approaches namely CID, WCID and ACID for Gardens Point Walking and St.Lusia datasets respectively. It is seen obviously from Fig.3 and Fig.4 that the proposed approach is superior to CID and WCID and the difference between the performance of proposed WACID and ACID is very moderate. Similarly, the difference between the performance of CID and WCID is also moderate. But the computation cost of WACID is too less then ACID. Further, combining SVM with WACID improves the performance considerably and also it reduces the search space more effectively by filtering out the unrelated images from the search space and thus the computational cost is further reduced. In addition to that instead of Pearson's correlation coefficient [14], we incorporated L1 metric which is very easy to compute and thus it also reduces the computation cost further. Therefore, it is proved obviously that proposed integration of WACID with SVM and L1 similarity metric outperforms significantly than the existing state-of-art-approaches.

Table. II and III symbolizes the precision(P)% and recall(R)% respectively for proposed and existing CID, WCID and ACID approaches for Gardens Point Walking and St. Lucia Datasets. Example input image and its top 5 matching is depicted in Fig.6. It is obviously understood from Fig.6 that the result of proposed system is invariant to illumination.

Fig-2.Example images from experimental databases

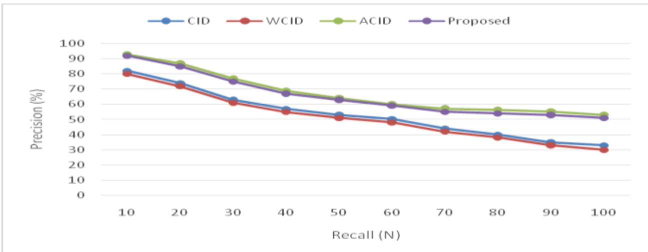

Fig.3.Precision(P) Vs Recall(R) for proposed and existing approaches for Gardens Point Walking Dataset

Table. III. Precision(P) for proposed and existing approaches

Datasets	CID	WCID	ACID	Proposed
Gardens Point Walking	56.23	55.36	61.34	61.23
St. Lucia	54.37	54.01	58.61	58.39

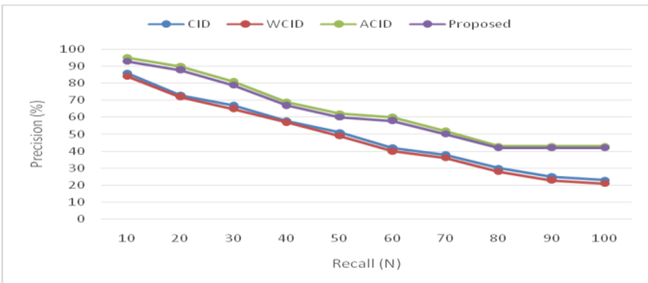

Fig.4.Precision(P) Vs Recall(R) for proposed and existing approaches for St. Lucia Dataset

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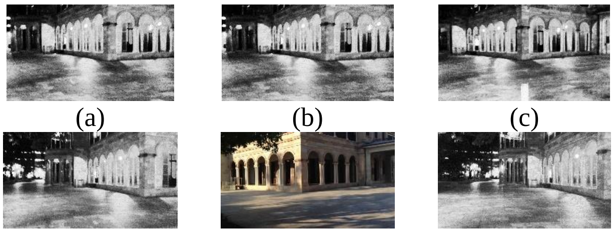

Fig.5 (a). Example input image; (b)-(f).Top 5 retrieval results using proposed approach

Table. IV. Recall(R) for proposed and existing approaches

Datasets	CID	WCID	ACID	Proposed
Gardens Point Walking	8.01	8.24	7.45	7.56
St. Lucia	9.32	9.39	6.46	6.52

V. CONCLUSION

In this paper, we presented multiresolution pyramid approach to autocorrelation based chordiogram image descriptor (ACID) for place recognition with illumination invariant. The multiresolution pyramid structure is exploited through the use of Haar wavelet. The proposed WACID is combined with SVM which reduces the search space in feature vector space by filtering out the unrelated feature vectors. Very simple L1 metric is used for performing similarity matching process. The results shown obviously that proposed combination of techniques outperforms significantly than existing CID, WCID approaches and attains almost equal performance with ACID. It is also noticeable that computation cost of proposed approach is too less. In future, we intended to decrease the computation cost of ACID.

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