Image Retrieval using Generalized Gaussian Distribution and Score based Support Vector Machine

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Abstract

Objectives: Retrieving images from huge volumes of image database has its application in broad areas like medicine, agriculture, military etc. Annotation based approaches have become obsolete because they are time consuming and cannot describe the image effectively. The rich content in the images can overcome the limitations of annotation based techniques. Texture is the most vital visual cue used to analyze images. Methods: In the proposed technique, the image texture features are statistically represented using Generalized Gaussian Distribution in the wavelet domain. A linear score based Support Vector Machine is incorporated to identify analogous patterns to the query image from the database. Findings: The efficacy of the proposed algorithm is ascertained by conducting extensive experiments. Two texture image database of size 1400 and 1920 is used for our experiment. The proposed algorithm is verified in terms of average recall performance against the standard benchmark algorithms. It is observed that the proposed score based SVM yields higher precision and flexibility in separating the similarity within the classes and dissimilarity across different classes. Improvements/Applications: Compared to the traditional approaches, the retrieval rate of this method is improved by 30% at a considerably low computational complexity.

Keywords: Generalized Gaussian Distribution, Support Vector Machine, Texture Retrieval

1. Introduction

Spatial variation in pixel intensity and orientation called as image texture is often valuable for a variety of applications like classification and recognition of image regions. Textural information is chiefly utilized for texture classification, segmentation and texture synthesis. Texture classification produces a classification map in which textured regions in the input image are recognized with the appropriate category it belongs to. Segmentation of texture is the second category of issue that texture analysis tries to find the solution. Segmentation of textures is used to obtain a boundary map when classification of textured surfaces cannot be carried out. Synthesis of texture is often used for compressing images as well as in graphics to render object surfaces as genuine as possible. The texture features are often distorted by imaging process and the perspective projection. Object’s surface texture is dependent on several factors, like the spatial dependence between the vital textural components, orientation and scale. Spatial and as well as scale texture properties are vital attributes in analyzing remote sensing images, here differences like rock surface, sea-ice surface, sea water surface, foliage, urban areas, etc. can be categorized by distinctive textural features¹. Texture analysis of images may be considered either from statistical point of view solely or from traditional computer-vision approach². Spatial information can be precisely modeled using computer-vision based approaches. In³, the remotely sensed images are analyzed by extracting features using gray level

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co-occurrence matrix. The Gray Level Co-Occurrence Matrices (GLCM) are computed for unit distance in one of these standard orientations (0°, 45°, 90°, and 135°). Approximately, 80% classification accuracy is obtained using texture features, for a 7-class classification problem. In4, semi-variogram functions are compared to GLCM features for classifying the image texture. The accuracy of this algorithm is accessed using two terrestrial images. Semi-variogram relates the variance of pixels with the spatial location and designates the scale and patterns of spatial variability. For optical images, GLCM provide enhanced classification accurateness, whereas semi-variogram is preferred for microwave images. Hence, no universal agreement can be made on the overall superlative investigation technique for different stages like classification, segmentation and retrieval. In4 Gabor filters together with Markov Random Fields (MRF) are utilized. Based on the classification and significance level testing, it has been shown that co-occurrence probabilities followed by Gabor filters can be utilized to classify with high accuracy. It is demonstrated that improved classification performance compared to GLCM can be achieved when co-occurrence and features extracted using MRF can be fused5. In investigated the measures that evaluate texture such as histogram, semivariograms, lacunarity, energy of wavelet sub bands and fractal dimension by utilizing separability metrics that are non-parametric and few classification techniques. It is concluded that measures like mean intensity, variance, lacunarity, weighted-rank fill ratio14, and semi-variogram improve the texture classification accuracy. In14, a perception based approach for CBIR is proposed, which estimates a collection of non-cognitive textural features like contrast, roughness, directionality and busyness. Calculation of similarity measures using perceptual features demand human interaction to determine the Spearman rank correlation coefficient. Based on the statistical occupancy model of similarity evaluation, the patch based reoccurrences is presented for texture analysis. The approximate textural features using reoccurrences are extracted for two widespread techniques available for textural analysis, the GLCM and Gabor wavelets. This method thereby reduces the high computational cost involved in image texture analysis14. In14, the influence of numerous statistical measures are analyzed for their discriminative capability to identify land cover types like water, urban, and vegetation areas. In gray level difference between the pixel of reference and its neighboring pixels are used to define the Local Ternary Pattern (LTP). The computation process involves first-order derivatives in the horizontal as well as the vertical direction. LTP features achieve 3% to 6% increase in average precision, compared to the standard local binary pattern. The performance of an image retrieval system is hugely dependent on the representation of the image with an effective feature vector14. Homogeneous or textural features are utilized to differentiate images from different categories. Statistical model based texture analysis targets at seizing natural characteristics of texture images using few and compact set of parameters. In the last two decades, multi-scale wavelet transform is one of the most widespread and prevailing tools used for texture analysis and representation14,24. Texture classification and retrieval algorithms using multi-scale wavelet transform generally employ statistical models that represent the coefficients in the wavelet transformed domain. Also, for extracting wavelet-based texture measures it is required to consider filters that are orthogonal, numerically stable and has good approximation quality. A research on psychological human discernment of texture recommends that two identically textured regions are tough to differentiate because they yield comparable marginal density functional response to filter banks. The statistical models used in wavelet based algorithms include Generalized Gaussian Density (GGD), generalized Gamma density generalized Gaussian Mixture Model (GMM), refined histogram and bit plane probability model. In, the wavelet coefficients in each scale are modeled using refined histogram is proposed. The refined histogram exploits a step function with exponentially accumulative interval to model the histogram of the detailed sub-bands. A lifting wavelet based on color histogram for image retrieval is proposed. The translation and rotation invariant color features are employed. Lifting technique utilized for the wavelet transformation reduces the computational time and edge structures from various directions of the image can be extracted efficiently. In, bitplane signature obtained using Bernoulli distribution is utilized to characterize the wavelet sub-bands for texture retrieval and classification applications. The supremacy in utilizing GGD signature over the custom energy dependent methods for textural discernment and retrieval is demonstrated. A joint modeling and classification algorithm where the wavelet coefficients are represented using
GGD marginal distribution and distance is computed using Kullback-Leibler metric is employed to measure the likeness between the two GGDs. This method provides greater accurateness and tractability in apprehending the texture information. In, it is shown, that the flexibility to regulate the profile of the statistical model, which is the key characteristic for any application based on histogram, can be provided by utilizing generalized Gamma distribution. In, generalized GMM based feature extraction in the wavelet domain is employed to construct a dense feature space. The parameters of generalized GMM are derived using Expectation-Maximization algorithm (EM). However, generalized GMM and EM algorithms are computationally complex processes. Recently, a 2D spectrum estimator which is built on the statistical properties of the wavelet packet coefficients of the random processes is derived. From the literature, it can be understood that the performance of the statistical model based texture retrieval algorithms rely on the approximation of the statistical model to the actual image texture and on the capability of the statistical similarity measure to differentiate interclass textures. Whereas, the efficiency of the computer vision based techniques are based on the performance of the machine learning algorithm chosen for classification process. Support Vector Machine (SVM) is a non-linear, non-parametric classification technique that has gained momentum in the recent times and is proved to demonstrate noteworthy results in the field of medical diagnosis, optical character recognition, electric load forecasting etc. In texture retrieval, SVM with relevance feedback is often incorporated to bridge the semantic gap by allowing the users to specify positive and negative feedback for refining the results. According to our knowledge, SVM based texture retrieval algorithms generally exploit user interactive relevance feedback techniques to retrieve identically textured images. In this paper, a hybrid approach for the texture retrieval problem is introduced, which has a tradeoff between vision based and statistical model based texture retrieval algorithms. In this paper, the images are modeled using GGD and the parameters of the GGD are utilized to designate the texture. These parameters used as features, are then trained using computer vision based SVM. Here, user intervention is eliminated by utilizing an automatic score based SVM technique for texture retrieval. The outline of the paper is as Section 2 covers the modeling aspect of the images in the wavelet domain and the estimation of the texture parameters. In the Section 3, a brief introduction to binary SVM classifier is produced, followed by the proposed score based SVM. Section 4 verifies the proposed technique.

2. Statistical Modeling of Images in Wavelet Domain

Let the input image is denoted as X. J Level Discrete Wavelet Transform (DWT) of the two-dimensional image X, yields an approximation low frequency sub-band and three directional detailed sub-bands at each level. These sub-bands are strongly directed towards 0°, 45°, and 90°, angles. The low frequency portions of the image are comprised in the approximation sub-bands and features particular to the texture are pre-dominant in the three directional sub-bands. After applying DWT on X, we obtain \( \chi^j(p,q) \), \( d = 0°, 45°, 90° \), where \( \chi^j(p,q) \) denote the \((p,q)\)th DWT coefficient of the image X at level j with orientation d. We will omit d and \((p,q)\) for minimalism. Statistical model based texture retrieval algorithms necessitate that the wavelet coefficients of the input image are represented with an appropriate probability density function as a prior model. It is studied that the marginal distribution used to describe the wavelet image coefficients is symmetric, severely peaked around zero, non-Gaussian, and heavy tailed. Experiments illustrate that GGD can yield equivalent approximation to the symmetric, non-Gaussian and heavy tailed properties. The symmetric GGD function can be represented using two parameters, \( \alpha \) and \( \beta \). These parameters can be efficiently estimated even when less number of samples is available. The GGD of X with \( N \) dimension is given by,

\[
p(x; \alpha, \beta) = \frac{\beta}{2\alpha \Gamma\left(\frac{1}{\beta}\right)} x^{-(\alpha+1)\beta} e^{-\frac{x}{\beta}} \tag{1}
\]

Where \( \Gamma(L) = \int_0^\infty t^{L-1} e^{-t} dt \) denotes the Gamma function, \( \alpha \) and \( \beta \) represent the scale parameter and shape parameter respectively. The peak decreases at a rate inversely proportional to the shape parameter. The mentioned parameters can be estimated using several techniques, like maximum likelihood or ‘method of moments’. In this paper, the method of moments is incorporated to estimate the GGD parameters \( \alpha \) and \( \beta \) using the first order and second order moments with respect to the origin.
The parameters are computed for the three directional sub-bands at all the $J$ levels. Since three directional sub-bands for $J$ levels are utilized for computing the principal texture features, the parameters are estimated from the set of $N$ wavelet coefficients from the $i^{th}$ wavelet detailed sub-band
\[
x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,N}) \quad \text{for } 1 \leq i \leq 3J.
\]
The GGD model parameters can be estimated from the first and second order moment, $m_i^1$ and $m_i^2$ with respect to the origin. These moments can be computed empirically from the $i^{th}$ sub-band as
\[
m_i^1 = \frac{1}{N} \sum_{j=1}^{X} |x_{i,j}| \quad \text{and} \quad m_i^2 = \frac{1}{N} \sum_{j=1}^{X} x_{i,j}^2 \quad \text{respectively.}
\]
The scale and the shape parameters $a$ and $\beta$ of the GGD model can be computed using the first and second order empirical moments $m_i^1$ and $m_i^2$ as, as given,
\[
a_i = m_i^1 \left( \frac{\Gamma(1/\beta)}{\Gamma(2/\beta)} \right) \quad \text{for } 1 \leq i \leq 3J \tag{2}
\]
\[
\beta_i = F^{-1} \left( \left( \frac{m_i^1}{m_i^2} \right)^{2/(2/\beta)} \right) \quad \text{for } 1 \leq i \leq 3J \tag{3}
\]
Where $F(x) = \frac{\Gamma^2(2/x)}{\Gamma(3/x)\Gamma(1/x)}$

For every training image $X$, the feature vector is constructed using the shape and scale parameter at every sub-band as,
\[
z = [a_1, \beta_1, a_2, \beta_2, \ldots, a_{3J}, \beta_{3J}] \tag{4}
\]

In general for a $J$-level DWT decomposition, the individual feature in $z$ is denoted as $z_f \in z$, for $0 < f < 2 \times 3J$.

\section*{3. Texture Retrieval using Score based SVM}

The feature vector is constructed for every image in training dataset and testing dataset. The texture features of the images in the training dataset are trained using a multi-class SVM. SVM is a promising and successful machine learning algorithm that is often employed in the classification of images. Initially, SVM is employed in binary classification problems, where an optimal hyper-plane is computed in a high dimensional space\textsuperscript{31,32}. The two class SVM can be extended into a multiclass problem using a number of methods. Two kinds of methods are commonly used: All-Verses-All (AVA) and One-Verses-All (OVA) approach. In the first case, $m$-classifiers are trained; each classifier separates a pair of classes. In the latter case, the multi-class problem is solved by resolving it into multiple binary class problems and by joining the predictions by assigning a confidence or probability score. The score embodies the weightage of a label or class with respect to the overall description and the final decision corresponds to the class with highest confidence. In spite of its wide acceptance, the complexity of a non-linear SVM is $O(n^2 \cdot n^3)$ during the training phase and $O(n)$ during the testing phase, here $n$ denotes the size of the training set. Hence using it for algorithms handling thousands of training images is non-trivial. A brief introduction about the binary SVM classifier is discussed in this section, which is then followed by the proposed texture retrieval using the linear multi-class SVM. SVM has $O(n)$ complexity in training the linear multiple classes and testing requires constant time.

\subsection*{3.1 Binary Classifier}

Let the projected Eigen space for training the N dimensional data and their respective labels be denoted as $(z_1, z_2, \ldots, z_N)$, $z_i \in \mathbb{R}^m$ and $(y_1, y_2, \ldots, y_N)$,
\[
y_i \in (+1, -1)^n \quad \text{respectively. In the Eigen space, let the linear binary classification function be represented in the standard form as}
\]
\[
g(z) = w.z + b \tag{5}
\]

Let the hyper-plane that separates the two class is denoted by $w.z + b = 0$, here the vectors $z$ and $w$ represents the input in the Eigen space and weight respectively. Let $b$ signifies the bias. For the best possible hyperplane SVM tries to determine the parameters $w$ and $b$. The geometric margin between the hyper-planes are maximized by optimizing the equation given\textsuperscript{31},
\[
\min_{w,b} \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \tag{6}
\]
subject to the constraints,
\[ y_i \left( w^T \phi(z_i) + b \right) \geq 1 - \xi_i \]
And \[ \xi_i \geq 0 \quad \text{for } 0 < i \leq N \]
The slack variables \( \xi_1, \xi_2, \ldots, \xi_N \) are introduced while the data cannot be linearly separable. \( \xi_i \) is used to all misclassified point. The number of training errors has an upper bound and is indicated by,
\[ \sum_{i=1}^{N} \xi_i . \]
Here, \( C \) corresponds to the penalty term for misclassification. In general, the dimension of the texture image is large (\( \geq 1000 \)) and number of images used in training is also sufficiently large. This indicates that we can separate the training data linearly. Subsequently, the significance of \( C \) and \( \xi_i \) has a little influence on the performance. The optimization problem in (6) and the following inner product can be used to yield the solution.
\[ f(z) = \text{sign} \left( \sum_{i=1}^{N} y_i K(z_i, z) + b \right) \tag{7} \]

3.2 Texture Retrieval using Multi-Class SVM

In the proposed work, the multi-class linear SVM proposed in \( \text{(ii)} \) is extended to make it suitable for the image retrieval problem using a score based approach. In \( \text{(iii)} \), a linear SVM is devised to train from \( L \) linear functions \( \{w_c^T z | c \in Y\} \) provided \( \{(z_i, y_i)\}^N_{i=1}, y_i \in Y = \{1, \ldots, L\} \), denote the training data. Prediction for the class label for a test datum \( z \) is given by
\[ y = \max_{c \in Y} w_c^T z \tag{8} \]

The class label is obtained after re-parameterizing \( w^T \leftarrow [w^T, b] \) and \( z^T \leftarrow [z^T, 1] \). The two class L linear SVM can be trained using the OVA strategy and the objective of each binary SVM is to solve the following unconstraint convex optimization problem,
\[
\min_{w_i} \left\{ J(w_i) = \|w_i\|^2 + C \sum_{i=1}^{N} l(w_i; y_i^c, z_i) \right\} 
\]
Where \( y_i^c = \begin{cases} 1 & \text{if } y_i = c \\ -1 & \text{otherwise} \end{cases} \)
And \( l(w_i; y_i^c, z_i) = \left[ \max(0, w_i^T z: y_i^c - 1) \right]^2 \)
is the quadratic hinge loss function.

The gradient-based optimization technique devised by in with limited memory is utilized for training the multi-class SVM. Prime objective of the multi-class SVM is to identify the best values for the parameters \( w \) and \( b \) during the training stage. The score is computed by weighting the feature vector with \( w \) and adding the bias \( b \). The score is given by,
\[ s = w^T z + b \tag{10} \]

SVM is commonly utilized for classification problems and relevance feedback based SVM are popularly used for retrieval problem. The proposed technique, utilizes an unsupervised score based SVM for texture retrieval. Using Equation (4), compute the scores of the training and query feature vectors \( s_{tr}, s_q \) for \( 0 < tr < TR \) and \( s_q \) for \( 0 < q < Q \) respectively. Here \( TR \), and \( Q \) denote the number of images in training and testing datasets. Determine the \( f^\text{th} \) feature that yields maximum score \( s_{qf} \) for the query image and is denoted by \( q_f \),
\[ q_f = \arg \max_{f} \left\{ s_{qf} \right\} \quad \text{for } 0 < f < 2 * 3J \]

The training features are sorted based on the descending order of the feature \( q_f \). The top \( R \) images are retrieved from the sorted training feature set.

4. Experimental Results

Extensive experiments on the standard texture databases are performed to verify the efficiency of the proposed score based SVM technique. Figure 1 shows the thumbnail of the images in the seven classes of the texture album used for our first experiment. Each image is of size 512x512, which is further partitioned into four 128x128 non-overlapping sub-images, thus creating a database of 1400 texture images with 200 images in each class. The test set contains 14 images in each class, which is parti-
tioned into four 128x128 sub-images. Hence the test set consists of 392 images. The test results are averaged to compute the overall performance. Table 1 portrays the average retrieval performance of the proposed algorithm with GGD texture features with score based SVM. The retrieval efficiency of the proposed algorithm is compared against the algorithms with GLCM features and Euclidean distance, scale and rotation invariant Steerable features with Euclidean distance, and GGD texture features and Kullback - Leibler distance. From Table 1, it can be inferred that the efficiency of the benchmark techniques are not consistent for every class, whereas the proposed algorithm could effectively discriminate the interclass features and could retrieve images with similar textures. The maximum recall performance in each class are highlighted in the Table 1, one can observe that the proposed score based SVM algorithm produces high recall performance in retrieving test images in five out of the seven classes. In the second experiment, the retrieval performance is verified on an intricate Outex database. The database considered in the experiment has twelve image classes and each class is said to contain 160 images each. Figure 2 shows thumbnails of the twelve texture classes of the Outex database. From Figure 2, it can be seen that the texture patterns possesses similarity across different classes, thereby it demands an algorithm robust to discriminate features. The average retrieval performance on the Outex database is tabulated in Table 2. Table 2 confirms the effectiveness of the proposed technique and it provides supreme recall performance for ten out of the twelve classes in the Outex database. In, GGD with KLD texture retrieval method, the similarity measure is computed between the entire feature vector for the query and training images, whereas in the proposed score-based SVM technique, the images on retrieved based on the dominant feature in the query image and hence GGD with KLD outperform the proposed algorithm for certain classes of texture images. The top 20 images retrieved using the score based SVM retrieval technique is shown in Figure 3. For the given query image, the number of related images in the considered database is 160, and the number of true positives for GLCM features and Euclidean distance, scale and rotation invariant Steerable features with Euclidean distance, GGD texture features and Kullback - Leibler distance, Zernike moments with Euclidean distance and the proposed algorithm are 71, 95, 122, 86, and 157 respectively. In summary, their average retrieval performance are 41%, 52%, 67%, 47% and 87% for the first experiment and 52%, 60%, 69%, 57% and 88% for the second experiment.

Figure 1. Thumbnail of seven texture classes.

Figure 2. Thumbnail of twelve texture classes from outex database.

Figure 3. Top 20 retrieved images using GGD texture features and score based SVM.

4.1 Statistical Significance Test

Table 1 and Table 2 show the average retrieval performance of the benchmark techniques as well as that of the proposed algorithm and it can be observed that the retrieval efficiency of the proposed score based SVM technique outpaces others. Friedman test is employed to verify the statistical significance of the results obtained. This is a non-parametric test which does not make hypothesis about the data distribution. Friedman test is experimented on $n = 7$ and $n = 12$ classes in Table 1 and Table 2 respectively. $k = 5$ can be used to ascertain whether the proposed technique outdoes the state of the art algorithms. The null hypothesis can be accepted or rejected.
based on the relevant $P$-value obtained using the $\chi^2$ distribution for large values of $k$, i.e., $k > 4$. When the average accuracy of the benchmark algorithms is equal to the average accuracy of the proposed algorithm, then it is called as the null hypothesis. When $P < 0.05$, the hypothesis can be discarded. The average retrieval performance in terms of Friedman test is tabulated in Table 1 and Table 2 utilizing $\chi^2$ distribution and $(k - 1)$ degrees of freedom yield 0.0004 and 0.0008 as its respective $P$-value. Friedman’s ANOVA test for Table 1 and Table 2 are portrayed in Figure 4 and Figure 5 correspondingly. The significance level is set as 0.05 and the $P$-values are observed to be lesser than the set level. Thus, it can be verified from the null hypothesis that the proposed score based SVM image retrieval algorithm is comparable to the state of the art techniques is discarded.

Table 1. Retrieval evaluation using average recall

| Class of the Test Image (ref. Fig. 1.) | GGD Texture Features & Score based SVM | GLCM Features & Euclidean Distance | Steerable Features & Euclidean Distance | GGD Texture Features & Kullback – Leibler Distance | Zernike Moments & Euclidean Distance |
|--------------------------------------|----------------------------------------|-----------------------------------|----------------------------------------|-----------------------------------------------|-----------------------------------|
| 1                                    | 0.92                                   | 0.70                              | 0.37                                   | 0.78                                          | 0.68                              |
| 2                                    | 0.95                                   | 0.60                              | 0.78                                   | 1                                             | 0.62                              |
| 3                                    | 0.81                                   | 0.33                              | 0.69                                   | 0.56                                          | 0.51                              |
| 4                                    | 0.76                                   | 0.20                              | 0.47                                   | 0.56                                          | 0.35                              |
| 5                                    | 0.92                                   | 0.60                              | 0.75                                   | 1                                             | 0.63                              |
| 6                                    | 0.86                                   | 0.18                              | 0.20                                   | 0.52                                          | 0.19                              |
| 7                                    | 0.85                                   | 0.27                              | 0.36                                   | 0.28                                          | 0.32                              |

Table 2. Retrieval evaluation using average recall

| Class of the Test Image (ref. Fig. 2.) | GGD Texture Features & Score based SVM | GLCM Features & Euclidean Distance | Steerable Features & Euclidean Distance | GGD Texture Features & Kullback – Leibler Distance | Zernike Moments & Euclidean Distance |
|--------------------------------------|----------------------------------------|-----------------------------------|----------------------------------------|-----------------------------------------------|-----------------------------------|
| 1                                    | 0.68                                   | 0.54                              | 0.67                                   | 0.67                                          | 0.62                              |
| 2                                    | 0.98                                   | 0.58                              | 0.67                                   | 0.72                                          | 0.64                              |
| 3                                    | 0.78                                   | 0.45                              | 0.69                                   | 0.86                                          | 0.54                              |
| 4                                    | 0.78                                   | 0.71                              | 0.72                                   | 0.60                                          | 0.65                              |
| 5                                    | 0.95                                   | 0.57                              | 0.47                                   | 0.60                                          | 0.58                              |
| 6                                    | 1                                      | 0.55                              | 0.57                                   | 0.46                                          | 0.57                              |
| 7                                    | 0.54                                   | 0.79                              | 0.44                                   | 0.66                                          | 0.67                              |
| 8                                    | 0.89                                   | 0.41                              | 0.68                                   | 0.76                                          | 0.59                              |
| 9                                    | 0.99                                   | 0.44                              | 0.67                                   | 0.53                                          | 0.55                              |
| 10                                   | 1                                      | 0.22                              | 0.70                                   | 0.91                                          | 0.43                              |
| 11                                   | 1                                      | 0.71                              | 0.59                                   | 0.5                                           | 0.66                              |
| 12                                   | 1                                      | 0.32                              | 0.28                                   | 1                                             | 0.35                              |

Figure 4. Friedman’s test for Table 1.
4.2 Time Analysis

The retrieval speed of the proposed score based technique is faster when equated to any of the benchmark methods, because the proposed algorithm retrieves images using an unique feature that yields maximum score. On a contrary, the distance based algorithms computes the overall distance between the query and image database, by summing the distance between the individual features in the feature vector. The time required to retrieve 160 images after comparing the 1920 (160 x 12) images for the various algorithms are tabulated in Table 3.

Table 3. Time complexity.

| Algorithm                              | Time in seconds |
|----------------------------------------|-----------------|
| GLCM Features & Euclidean Distance     | 35.58           |
| Steerable Features & Euclidean Distance| 36.42           |
| Zernike Moments & Euclidean Distance   | 36.12           |
| GGD Texture Features & Kullback – Leibler Distance | 35.81 |
| GGD Texture Features & Score based SVM | 1.94            |

5. Conclusion

This paper, thus presents a score based SVM for retrieving images based on their texture. The images are transformed into the wavelet domain and the parameters of the GGD are used to model the texture characteristics. The score based SVM replaced the traditional interactive relevance feedback mechanism used for image retrieval problems. Also, a single feature contributing towards the SVM classifier is identified based on the maximum score for the features of the query image. The proposed technique thereby dramatically improves the retrieval speed as well as accuracy. Our experiments on a variety of image textures demonstrate the effectiveness of the proposed approach.

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