A Survey on Current Semantic level Algorithms for improving Performance in CBIR

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Abstract - This paper expounds a complete review of recent topical methodological attainments in the investigation region of CBIR. Many decades, Images are being utilized in variety of applications counting with Education, Healthcare, Defense, Engineering and Entertainment etc. Commonly, the amount of images across the world has developed in an enormous way. Consequently, in enormous and wide-ranging group, retrieving images in effective and efficient way is a challenging constraint. To elucidate this situation, diverse practices are implemented. This review comprises numerous publications to pronounce the study features of its region related to extraction of content features in different sized of the vectors, distance matrices, connect bridge between complexities and added with objective of the applications improvement such as precision and recall rate. Moreover, established on the demand of dissimilar applications and recent methodology, limited capable research directions are submitted.

Keywords - CBIR, QBIC, CNN

1. Introduction

Advancement in recent technologies, more images are being processed, stored and utilized in fields such as entertainment, education, defence, pattern recognition, face recognition, computer applications, medical diagnosis and organizations [27]. In recent decades, very large scale of images are being stored and retrieved in conventional way of experiments. Different categories of images are being generated and stored in database by several varieties of systems for example documentary general and special purpose images like urban scene, military photos, medical images like x-ray, ultrasound, microscopy and fingerprint, creative images like painting, computer made ready, and logo images, model images such as chart, map, technically drawn pictures etc. [23]. Multiple systems have been developed in image retrieval by researchers as QBIC, Virage, Chabot, Photobook, Mars, Netra and Informedia [20] [26]. Generally, Text based image retrieval has been encouraged for retrieving particular images as visually satisfying images. But, this method has been providing a usual problem in annotation and identifying the keywords also the manual interpretation is required. Many of its metadata is being required to search and retrieve the datasets in large database collection. So, it is not considered in advance research to search and retrieve the large scale images are being stored.

Moreover, manual interpretation is required in few amount of annotation and assigned metadata’s such as keywords etc. Specifically, a demand of retrieving image in efficient way in large scale database the CBIR techniques are encouraged to overcome the limits of interpretation with automatic way. This concept based retrieval could be developed with different types of queries based
approaches such as query by image example. Many systems has been established to retrieve a relevant images in large scale database especially in CBIR approach its content of the image vectors such as corner details with shape, also in visual details with Colour, and frequency details with texture features.

Conventionally, Images are being retrieved in CBIR [3] approach with their local and global descriptors, edge with point related to individual pixels etc. This approach is described in terms of solving the large scale database, generating comprehensive feature vectors and feature estimation with matching schemes. All hidden level and human identified level features are extracted with hybrid CBIR technology. Relevant images are retrieved using similar images as Query by Visual example, Query by image content or sample query image [25].

Training set is estimated using similar algorithms as applicable to query that converted into feature vectors in specified storage fields. Comparison methodology is varied with feature contents that extracted in both query and data set images in satisfied level which gives the similarity between both competitive feature vectors. In recent eons, advanced algorithms are being practiced in CBIR to retrieve the relevant images for extracting both local and Global level descriptors. However, the emerging technologies invented in such demand areas retrieval is not in satisfied level in such a way it is introducing constraints in accuracy rate and time constraints.

Generally speaking, the CBIR is a technique to retrieve relevant images in large scale database with their contents such colour, texture and shape [29]. Based on the content, conventional ideas classified as colour based, contributed with texture selected retrieval and sketch or shape contributed retrieval. Each approach has its specific method of processing in extracting image features.

![Figure 1. General structure of content oriented Process](image)

Figure 1 represents detailed conventional Content oriented approach which involves Feature extraction, Feature matching with similarity measurements to retrieve required in stored sets

2
comparable to the sample component. Both query and dataset features are extracted which is converted into suitable vectors to match the similarity using distance matrices.

CBIR structures can furthermore make use of relevance feedback, where researcher gradually enhances the results by arranging resultant images with relevant, not as query, and reiterating novel statistics can be explored. The local features and Global features were accumulated to refine the relevant results [1].

In this paper, section II describes about various feature extraction methods are used in general image retrieval using various level features specified in an image for considering the details of the object relation in terms of the neighbour regions. Section III, purely describes the detail information of similarity matching used in different research aspects especially in Content based image retrieval. This paper made an investigation on classification of distance metrics used in different retrieval techniques. Section IV represents the trade-off between conventional and current requirement in emerging retrieval algorithms to fully engage the demand of CBIR in specific methodologies such as machine learning, relevance feedback etc.

2. Feature Extraction in CBIR

Feature Extraction is the process which involved in extracting visual and text related features. Conventionally, keywords are used as text to extract the text based method. This provides difficulty in annotation and manual interpretation.

2.1 General feature extraction

Generally, this is based on the visual content features which are being utilized in CBIR [5] techniques. Features are classified normally as low level features such colour, shape and textures also with high level feature vectors such as text, tags. The detailed information of low level features are being extracted with different sort of algorithms. Bag of visual words offers opposed to LBP algorithm to provide faithful in low level features [16].

2.1.1 Colour features

For low level feature extraction, visual content of an image is to be processed such as colour pixel intensity component in an object, commonly used DCD, colour layout descriptors, colour edge Histogram Descriptors, hashing and semantic features extraction algorithms [15].

Hassan Farsi and Sajad Mohamadzadeh (2013) proposed a method to extract feature vectors using hadamard matrix in DWT also with RGB plane Hue –M-M-D planes to avoid high computation time and complexity in other levels of colour spaces [29]. Many researchers used RGB, HSV and YCrCb colour space models as low level features [16, 26].

2.1.2 Texture features

Basically, The Texture oriented features are highlighted as (tamura features) coarseness, contrast, directionality and periodicity, regularity features which are being extracted by using DWT [1, 16], Gaussian mixture models [3], Gabor wavelets and curvelet transforms. Haar based features are also extracted to fill the required limitations in conventional ideas. Development with technology in discrete wavelet transform, leads to texture features extraction using Haar and Hadmard algorithms with horizontal and vertical coefficients [29].
Malay Kumar Kundu A et al. (2014) proposed a fortunate way of extracting image features in texture descriptors to find the problem occurred in directionality by Multi Geometrical analysis and Wavelet techniques to find demand in identification of low level features [28]. Mainly, texture descriptors are classified into statistical, model, Structural and signal processing features. DCT, DST and DWT also have been proposed in some research systems to provide higher performance in image retrieval [27]. Even though the intensity has been viewed clearly in colour features, closely connected similar features can be possible in texture extraction based techniques [26].

2.1.3 Shape features
Shape based descriptors are extracted such as polygonal approximations and spatial interrelations by using the semantic edge detection SURF [15], SIFT, SSIM and HOG algorithms in CBIR approaches [14 21]. In recent retrieval techniques, boundary and region based features are being extracted such moment invariants [26].

2.2 High level feature extraction
The pattern recognition, object detection, faces detection and finger print recognition comes into high level features classifications. This locates the features based on the region of interest. Basically, CBIR retrieved images by least after best extraction on the road to fulfil the developed ideas of them. This can be achieved by novel relevance feedback method. Some cases CNN model [3, 11, 12] is combined to extract high level semantic features for effective ideas additionally least oriented features [25].

2.3 Local and Global features
The Edge and points are considered to be a local feature descriptors and Colour, shape and texture information of entire image as global feature descriptors extracted using hybrid methodology [1] such as Grid computing, CNN and colour matrix [15] etc. Usually, local features are related to medical image retrieval applications [8].

2.4 Deep features
Deep features are important to improve promising performance in image retrieval especially in CBIR based applications. The convolution Neural Networks and Diffused block Truncation coding [14] are effectively contributed to retrieve united features in view of adjusting semantic gap.

Mussarat Yasmin et al (2014), proposed a survey on intelligent retrieval system using neural networks provided a favourable results in view of other techniques such as graphical based methods, cognitive related approaches, multi instance model, adaptive learning and 3D model images [22].

Code books and visual dictionaries are created for specific features in an image to improve average recall rate and precision rate. Finding the correlation between details of images such as colour, Shape, intensity and spatial things that can be improved the retrieval performance. The retrieval accuracy can be enhanced by using supervised hashing combined with CNN model [12] is proved. Additionally, CBIR can be secured using hashing methodology in matching similarity between relevant and query image.
2.5 Other features

Conventionally, colour moment features are extracted from an image such as average, smoothness, SD, Kurtosis, Contrast, skewness then GLCM [15] [21] also combined to develop the exactness in the CBIR ideology.

3. Feature Matching

In recent way of feature matching process, the similarity of the individual sample and individual dataset is identified established on some distance matrices. This similarity measurement checks the closeness of both features which was stored in feature database. Actually, most of the researchers used Euclidean distance [1 3] to measure similar and dissimilar images to provide promising performance outperforming to other conventional methods.

In literature, different distance measures have been applied to find combined performance in similarity matching for colour features and texture features as DCD and wavelet and curvelet features by centric PSO algorithms and it has been improved demand in low level feature matching schemes [27]. Some cases, the other sort of similarity matching techniques are also being combined with Euclidean such as Bray, Canbraa, Chebychev, Cosine, Manhattan distance, Hamming distance, Bhattacharya and Jaccard [6, 16, 17, 20]. Specifically, histogram related features have been measured using city block distance and Minkowski distance.

Minkowski Distance can be represented as,

\[ D(P, Q) = \left( \sum_{i=1}^{n} \left| p_i - q_i \right|^r \right)^{1/r} \] (1)

Minkowski distance, normally represented with ‘r’, if r=1 then it is represented the Manhattan distance.

Manhattan distance:

\[ D(Z, K) = \sum_{i=1}^{l} |z_i - k_i| \] (2)

If r=2 in eqn.1, then it is represented as the Euclidean distance.

Euclidean distance:

\[ D(K, J) = \left( \sum_{i=1}^{m} |k_i - j_i|^2 \right)^{1/2} \] (3)

4. Semantic Gap Identification

4.1 Machine Learning

In recent periods, advancement in machine learning is accomplished demand in searching requirements and it is being an emerging identified technology over the decades to improve retrieval performance in an automatic way of pre-processing and other aspects of image processing.

The recently deeply developed learning is a part of this approach that provides depth information about feature vectors. The supervised and unsupervised model is being introduced in fast and semantic image retrieval especially in medical image processing [11]. Some of the identified supervised learnings are neural networks, support vector machines and decision tree supervised learning models [21]. K means clustering, fuzzy means clustering and ncut clustering have been contributed in
unsupervised learning to extract unpredicted details in an image with cluster model engaging with distance metrics [17, 21].

This approach also provides an improvement in ARR, APR and time constraints of image retrieval. Different sort of classifiers are used to train the data set using deep learning that improves sufficient level of performance metrics [27].

4.2 Relevance Feedback

In this retrieval research, most of the systems and users are interacted to interpret the relevant and query image matching in form perception as well as relevant. Widely, the relevance feedback is encouraged to improve performance for sketch and colour based image features [24]. This process checks the user feedback till user gets satisfied with retrieved results [8]. In many research papers, the relevance feedback have been contributed to define the feedback matches with user perceptions [21].

5. Performance Analysis

5.1 Database Images

Most of the methods have been developed an available to measure metrics of Content oriented techniques. Depends upon the algorithm which is used to process the images in database and query, the measurement metrics are varied. Most of the techniques used to find performance by precision and recall rate of image retrieval. Corel 1k, 10k images are being tested with rank and average rank rate in measurement of retrieval performance. It is often called Average precision rate and average recall rate related to accuracy of the system performance. Computation time also has been maintained in terms of speed improvement as a part of performance valuation with different classes of database.

The large scale database is consisting of different dimensions of images with different grouping of classes such as Corel1k, Corel10K, UK benchmarks, Holidays, Oliva dataset and self-oriented images [15, 28, and 29] with different intensities based on the user requirements. Usually, colour conversion has been initiated in all retrieval ideas to find better objects irrelevant with applications. The clustered images by contents are likely to be stored as a set of categories in database with so many orientations and dimensions. These categories have been normally selected as Natural scenes, Elephants, Dinosaurs, Horses, Buildings, Beaches, Flowers, vehicles, Computer drawings, Manmade pictures, clinical images, satellite images and map images etc [21].

Yong and Thomas authors who (1999) suggested a promising review of CBIR with three acceptable techniques as visual features selection, MD indexing and contribution in system design which can be explored a past and current methods have been followed in CBIR retrieval [20]. Multi-dimensional feature indexing has been practiced in future development retrieval systems [19].

5.2 Precision Rate

Precision rate (APR) is the demarcated as relation between numbers of related images retrieved and training set total cost [6] [7] [9]. This performance matric has been analysed in most of the research papers in image retrieval.

\[
\text{Precision Rate} = \frac{\text{Retrieval total of relevant images (Nr)}}{\text{No of Stored images in Training set(Nt)}}
\] (4)
In this measure, the relevant images are matched with entire data images for considering retrieval performance.

5.3 Recall Rate
Recall Rate (ARR) is well-defined with the total relevant images retrieved with available total relevant sets in storage database [6] [7] [9].

\[
\text{Recall Rate} = \frac{\text{Retrieval total of relevant images}(Nr)}{\text{Total relevant images in Training Set}(Ntr)} \tag{5}
\]

The relevant images in database are to be considered for measuring recall rate performance of retrieval.

| Table 1. Sample Precision and Recall rate |
|-----------------------------------------|
| **Dataset** | **Precision** | **Recall** |
| Dinosaur  | 1.00 | 0.100 |
| Mountain  | 0.76 | 0.076 |
| Rose      | 0.81 | 0.081 |
| building  | 0.87 | 0.087 |
| Elephants | 0.83 | 0.083 |

Table 1 represents the Precision and Recall rate of the corel1k database images using conventional methods. This measure has been considered for class of images such as dinosaur, mountain, rose, building and elephants etc [1].

| Table 2. Comparison of various methods of CBIR models |
|-----------------------------------------------|
| **Ref .** | **Data set** | **Feature Extraction** | **Feature evaluation** | **Similarity Matching** | **Performance** |
| 1       | Corel Dataset | DCD, Wavelet, Curvelet | Colour, Shape, Texture | QSM, MPHS M | Precision and Recall rate |
| 2       | Corel Dataset | GLCM, CNN, BTLHF, BTLHCF | Code BOOK | Euclidean | Average Precision rate |
| 3       | Flicker 15k  | Loss function, Transfer learning | Feature Pooling | Euclidean | Average Precision rate |
| 4       | Natural      | Correlation | SURF, MSER | Euclidean | Precision rate |
| 5       | Flicker 15K  | KM, HKM, Spectral Clustering | Low level local features & Global Features, Visual Dictionary, SURF, SIFT, MSER | Euclidean distance | Precision rate |
| 6       | Holiday, Benchmark | CNN, Colour matrix | Image local features and deep features | Euclidean | Precision, Accuracy, Hamming Loss and Time |
| 7       | Whole Slide Images*(WSI), Cancer Images | Scale invariant Feature Transform[SIFT] | DCNN, DFDL, LDA | Euclidean | Sensitivity, Specificity and Accuracy |
| Page | Dataset | Description | Methods Used | Evaluation Metrics |
|------|---------|-------------|--------------|--------------------|
| 8    | DLp, DRM, Normal Caecum, Normal Pylorus | Deep learning, GCLM, mean, SD, skewness, smoothness | different methods used | Precision and Recall Rate |
| 9    | Decoded JPEG 2000 | DWT | Grid computing, Gabour, Curvelet, wavelet, GCLM, LBP | Pyramid Match Kernal, Precision |
| 10   | CE-MRI Dataset | Deep CNN, Distance Matric Learning, Transfer Learning and Fine Tuning | Aspects in CBIR flow in clear | Squared Mahalanobis Distance, mAP, AP |
| 11   | Oxford Buildings 5k, UKB | FCN segmentation, CNN and Fusion | SURF | Semantic matching, mAP, AP |
| 12   | TCIA CT, ELCAP Lung, Pancreas CT, neurological | Hash mapping, new loss function | Spectral, minimized, supervised Hashing with kernels, Deep hashing | Hamming, Average Precision rate |
| 13   | Oxford, Paris, Uk bench, Holiday datasets | BoW | SF, SIE, SRE, SRR used | saliency filter intensity embedding, representation embedding, Representation re ranking, Effectiveness Test, Scalability Test |
| 14   | 3D images | CNN, siamese learning, loss function, Whitening and dimensionality reduction, Single scale and Multi scale evaluation | Euclidean distance | Precision Rate |
| 15   | MRI, NEMA CT, TCIA CT, EXACT09 CT | COLOR SHAPE statistical approach, HCSC coefficients, directional wavelet transform | Histogram combined scattering coefficients, codebook | Euclidean distance, Average Precision rate |
| 16   | Corel Dataset | Ontology, ML for low level features, ST, Fusing | - | Angular, Canberra, one to one match, many to many match |
| 17   | Corel Dataset | Clustering(Statistical), Kmeans, Fuzzy clustering | Multidimensional scaling | Minkowski, angular and Canberra distance, one to one match, many to many match |
| 18   | Corel Dataset | Classification | dimensionality reduction | Euclidean distance, Relevance feedback |
| 19   | Corel Dataset | All features colour histogram, coocurrence matrix, spatial gray level dependencies, random field modelling, segmentation, boundary, region based | Multi-dimensional indexing | Euclidean distance, Accuracy |
|   | Corel Dataset | Colour Shape Texture all are considered | Multi indexing, SVD, KLT | Non-euclidean distance | Different resolutions and memory size |
|---|---|---|---|---|---|
| 20 | Corel Dataset | colour Histogram, Colour Moments other methods, machine learning, SVM, SVM BDT, Semantic features Relevance feedback | - | Euclidean and minskowski | Precision and Recall rate based on relevance feedback |
| 21 | Corel Dataset | Neural networks | Supervised and unsupervised learning | Euclidean and minskowski | Precision rate |
| 22 | Corel Dataset | Neural networks | - | Euclidean distance | Precision rate |
| 24 | Images variety | Contrast, Light dark contrast, Warm cold contrast, Simultaneous contrast | Low level features into high semantic features | Relevance feedback | Euclidean and minskowski |
| 25 | Corel Dataset | Colour Histogram Wavelet (Statistics and transforms) Moment invariant (boundary and region based) | Machine learning and web retrieval | City block, minskowski, Euclidean | Precision rate |
| 26 | Corel Dataset | Colour Histogram Wavelet (Statistics and transforms) Moment invariant (boundary and region based) | Machine learning and web retrieval | City block, minskowski, Euclidean | Precision rate |
| 27 | 1k-Corel and 10k, Caltech scaled 1k-Corel, Illuminated 1k-Corel 1k | Multi geometrical Analysis WT Relevance Feedback | Rotation and scale invariant Different weights are assigned | Euclidean distance Center dominant distance DCD similarity Wavelet Similarity curve let similarity | Precision rate: DCD - 67.85 to 71.05 Wavelet - 58.90 to 65.43% Curve let - 53.18 to 56.00% |
| 28 | SIMPLICITY Oliva Dataset Caltech 256 Dataset | Multi geometrical Analysis WT Relevance Feedback | Least square SVM | Euclidean distance | Precision and Recall Rate |
| 29 | Corel 1k | DWT HMMD | - | Euclidean distance | Rank average rank |

This above table represents the comparison of various CBIR retrieval algorithms with datasets, Feature extraction similarity matching and performance metrics.
6. Research Facets

Many research aspects have to be identified in this survey. Actually, the annotation needs latest approach to be practiced for providing reduction in semantic gap. Most of the systems have been exploited the challenges in combining features in reduction of demanded ideas which can be explored in terms of combined results in both systems. Many aspects have been measured in originating the CBIR model with high level performance. Such a challenge has been contributed to innovate a novel technology in general image retrieval applications [17].

Specifically, the new methodology needs to be incorporated in application and domain oriented CBIR techniques. User interaction associated with relevance feedback is being used to get accurate results in reduction multi-disciplinary problems in image retrieval [18].

Classification has been made through relevance feedback provided by user interaction to extract corrective actions in further processing of the entire setup such as matching and to meet suitable retrieval. Identification of similarity has to be contributed relevant to the human perceptions [17, 18].

7. Conclusions

In this detailed survey, conventional and latest technologies of selected areas are reviewed. Approaches used in this concept are so far unsuitable for certain applications. Many technologies are being used with different levels of processing to improve achievable performance in retrieval.

This paper explores the detailed survey of semantic gap, similarity matching, feature extraction algorithms and performance improvement in these techniques with different classes of images with numerous dimensions added with independent orientations.

To provide speed and accurate retrieval using Content based image retrieval can be promising by combined dissimilar methodology in hybrid way. Thus the combination of emerging new invention of Convolution Neural Networks model [3] [11] [12] and Discrete Wavelet Transform methods [1] also with various level of processing in combination further will be improved the accuracy, APR, ARR and Time consumption as expected with new technology in different classification of Large scale database. Inference based on the survey, the integration of different feature extraction and artificial knowledge also is needed in improving better performance.

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