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COMPARISON STUDY BETWEEN IMAGE RETRIEVAL METHODS

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Abstract- **Searching for a relevant image in an archive is a problematic research issue for the computer vision research community. The majority of search engines retrieve images using traditional text-based approaches that rely on captions and metadata. Extensive research has been reported in the last two decades for content-based image retrieval (CBIR), analysis, and image classification. Content-Based Image Retrieval is a process that provides a framework for image search, and low-level visual features are commonly used to retrieve the images from the image database. The essential requirement in any image retrieval process is to sort the images with a close similarity in terms of visual appearance. The shape, color, and texture are examples of low-level image features. In image classification-based models and CBIR, high-level image visuals are expressed in the form of feature vectors made up of numerical values. The researcher's findings that there is a significant gap between image feature representation and human visual understanding. Due to this reason, the research presented in this area is focused to reduce the semantic gap between the image feature representation and human visual understanding. In this paper, we plan to present a comparison study and a comprehensive overview of the recent developments in the field of CBIR and image representation. We analyzed the main aspects of various image retrieval and image representation models. The important concepts and major research studies based on CBIR and image representation are discussed in detail, and future research directions are concluded to inspire further research in this area.**

keywords: **Image retrieval, CBIR, Curvelet transform, Feature extraction, Fast fourier transform, Gabor filter, Wavelet transformation, Texture feature, Euclidean distance.**

I. INTRODUCTION

Due to the availability of vast storage spaces, a massive amount of images have been produced and stored all over the world. With a huge image database, people want to search it and make use of the images in it, generating a challenge to computer systems for storing, transmission, and indexing such large image data for easy access. Image retrieval (IR) is a method of searching for images in a large database. As a result, one critical issue that must be tackled is the rapid retrieval of images from vast databases. Image retrieval systems attempt to scan a database for images that are identical to a query image. Images can be retrieved in two ways: text-based and content-based or query by example-based. The text-based retrieval method is well-known and commonly used [1] . During this method, users are given a text area in which to enter the keywords that will be used to search for images. It is commonly used in Google's web-based image search technique [2] . Nevertheless, this method takes a long time to annotate each image in a large database and makes the process subjective [3] . And When the database is massive, there is a high likelihood of an error occurring during the image tagging phase [4] . So TBIRS is time-consuming and inefficient [5] . Content-Based Image Retrieval System (CBIRS) has been introduced to overcome the limitations of TBIRS. Image content is the basis of image searching and retrieval in CBIRS. CBIRS has replaced TBIRS in domestic, medical, and industrial applications [6] . CBIR is the process of retrieving the most closely Matched Image to a given Query Image automatically by extracting basic features such as shape, edge, color, and textures from the Query Image and comparing them with the similar features of all the images in the concerned database. The main idea of CBIR is to find the most similar images with the query image from a dataset using distance metrics [7] . It presents a flexible way to index images automatically based on the visual content of images (i.e., color, texture, and shape). Images in the same group might have similar characteristics. As a result, when similarity is measured using image features, the output set achieves a high degree of retrieval accuracy. A typical block diagram for content-based image retrieval is shown in Fig. 1 [8] . The basic objectives of this research study are as follows:

1) How the performance of CBIR can be enhanced by using low-level visual features?
2) How semantic gap between the low-level image representation and high-level image semantics can be reduced?
3) How can improve the performance of CBIR generally?

The remaining parts of this study are organized in the following way: related work in Section II . Features Extraction presented in Section III . Spectral Features PR presented in Section IV . Section V covers similarity measurement. Performance evolution is presented in Section VI . finally, the conclusions are presented in Section VII .

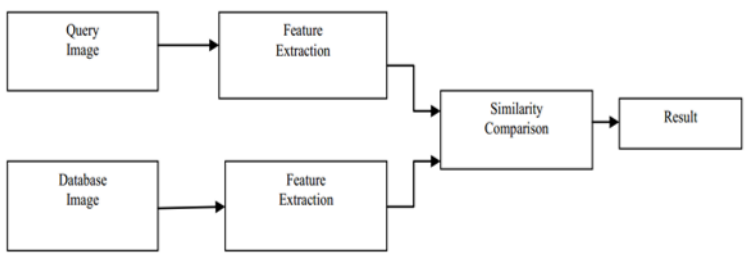

Figure 1: Content-based Image Retrieval (CBIR) system

II. Related work

Shao et al. [9] presented a novel approach for CBIR based on the MPEG-7 descriptor. Eight dominant colors from each image are selected, features are calculated by the histogram intersection algorithm, the dominant color descriptor (DCD) is used to reduce the complexity of the similarity computation. A small amount of representing colors can replace the image's overall color information. DCD has been taken as one of the MPEG-7 color descriptors that use an effective, intuitive, and compact format to narrate the indicative color distribution and feature. According to Duanmu [10] , traditional techniques can retrieve images by using their labels and annotations, which are insufficient to meet customers' needs; thus, the researchers concentrated on another method of retrieving images, which is retrieving images based on their material. The proposed method employs a small image descriptor that can be changed based on the image's meaning by a clustering two-stage technique. The experiments were carried out using COIL-100 images. The results of the experiments demonstrated that the proposed approach is efficient. In Baharudin et al. [11] have proposed a system using the query sub-blocks and database images, the adjacency matrix of a bipartite graph is formed. Extraction of statistical textural features from the quantized histograms in the discrete cosine transform employing only the DC coefficient and three AC coefficients for effective image retrieval. Papakostas et al. [12] performed their experiments on four datasets to show the discrimination power of the wavelet moments. The proposed model wavelet moments (WMs) is evaluated using two different wavelet configurations, WMS-1 and WMs-2, where the former uses cubic B-spline and the latter uses Mexican hat mother wavelets.

By retaining only effective characteristics in the feature selection strategy, the wavelet moments' classification capabilities are greatly improved. The proposed model's efficiency is compared with pseudo-Zernike, Zernike, Legendre, and Fourier-Mellin and two others using 75, 100, 50, and 25 percent of the entire datasets. Classification efficiency of the moment descriptors yields the better results of the proposed model (moment invariants and wavelet Moments). An Enhanced Gabor wavelet correlogram is presented for the retrieval performance in Moghaddam and Dehaji [13] . Gabor wavelet function is used to divide the input image based on various scales, orientations and then correlogram descriptors are extracted. In Krishnamoorthy and Devi [14] , shape features based on the edge were extracted by using morphological operations and an orthogonal polynomial model. To enhance the retrieval rate, global shape feature extraction based on the invariant pseudo-Zernike moment is performed. Iqbal el. [15] have proposed a CBIR method based on the Haar wavelet transform and color moments. The Haar wavelet transform has been used to extract texture features, and for color feature extraction, we use color moments. The distance between the query image features and the database images' features is computed using Canberra distance. The results of the experiments show that this approach outperforms the other methods in terms of retrieval accuracy. Guo et al. [16] suggested a novel approach to image indexing based on features derived from error diffusion block truncation coding (EDBTC). To generate an image feature descriptor, EDBTC processes a bitmap image and two color quantizers using vector quantization (VQ). To evaluate the similarity between a query image and the image in the database, Bit Pattern Histogram Feature (BHF) and two features Color Histogram Feature (CHF) are introduced. The BHF and CHF are calculated from the VQ-indexed color quantizer and VQ-indexed bitmap image, respectively. The distance calculated from BHF and CHF can be used to compare the likeliness of the two images. The experimental results indicate that the proposed system outperforms previous BTC-based image indexing and other current image retrieval schemes. The EDBTC has well capable of image compression as well as indexing images for CBIR. Jiexian et al. [17] have presented a multiscale distance coherence vector (MDCV) for CBIR. The reason for this is that different shapes may have the same descriptor, and the distance coherence vector algorithm may not fully remove noise. The proposed technique begins by developing the image contour curve with the Gaussian function. The proposed technique is invariant to various operations such as rotation, translation, and scaling transformation. Wang et al. [18] suggested a color-based approach for retrieving images based on image content, which is based on the consolidation of color and texture features. It provides an effective and flexible estimation of how early humans can process visual content. The combination of color and texture features provides a robust feature set for color image retrieval methods. The results of the experiment show that the proposed method retrieves images more effectively than the other traditional methods. However, the feature dimensions are not larger than other methods, and the computational cost is substantial. A pairwise comparison of both low-level features is used to determine the similarity measure, which can be a bottleneck. Guo et al. [19] have developed a hybrid retrieval system that uses a Local binary pattern (LBP) as a texture extraction technique. Here, the LBP calculation is based on the different scales, which capture more prominent features of an image as compared to single-scale LBP. Lastly, the Gray level co-occurrence matrix (GLCM) has been used efficiently to compute feature vectors. Mistry et al. [20] conducted a study on CBIR using hybrid features and various distance metrics. In this paper, the hybrid features combine different feature descriptors, which consist of spatial features, frequency, edge directivity descriptors (CEDD), binarized statistical image

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features (BSIF), and color. The features are extracted using CEDD, HSV, color histogram, BSIF, and color moment. Color quantization, color space conversion, and histogram calculation are among the features derived using the HSV histogram. Using the BSIF to remove features entails converting an RGB image to a grayscale image and selecting a patch from the grayscale image. It also includes subtracting the mean value from the variable. The CEDD method involves an HSV color two-stage fuzzy linking mechanism for feature extraction. Using the color moment method, features are extracted by first converting the RGB into its constituents and then calculating each variable's mean and standard deviation. After that, the stored features are compared to a query image feature vector. The comparison is performed using the minimum distance classifiers, and the picture is then retrieved. Several tests are run on that approach, and the findings show that it outperforms the current methods significantly. Liu et al. [21] proposed a method for classifying and searching an image by fusing the color information feature (CIF) and local base pattern (LBP). The LBP extracts the textural attribute to derive the image descriptor. However, the LBP does not do well in terms of color attribute descriptors. Both the color feature and the textural feature are used to efficiently retrieve a color image from a large database. In this proposed approach, a new color feature CIF combined with an LBP-based feature is used for both image retrieval and classification. Both LBP and CIF represent an image's color and textural detail. Several experiments are carried out using a broad database collection, and the results show that this approach performs well for image retrieval and classification. Fadaei et al. [22] conducted content-based image retrieval experiments on the Brodatz and Vistex datasets, which included 112 grayscale and 54 color images, respectively. The distance between a query image and the dataset image is determined, images with the shortest distance are retrieved, and the precision and recall rates are computed. The proposed models' effects are compared to other prior approaches. Brodatz's retrieval time is longer than Vistex's because Brodatz has more images than Vistex and needs more time for feature matching and processing. Even though the feature vector dimension is high, the proposed model's retrieval time is slower in feature matching and faster in feature extraction. The comparison and results show that the proposed model (local directional relation pattern (LDRP)) has better performance and average precision rates, as well as being faster in feature extraction and slower in feature matching. Chandan Singh et al. [23] have been described a CBIR system where the Color histogram is utilized as a color descriptor. A Color histogram is a graphical characterization of pixels in an image. In addition to the color histogram, Block variation of local correlation coefficients (BVLC) and Block difference of Inverse Probabilities (BDIP) are adopted for texture extraction. Amita et al. in 2017 [24] proposed a method for fast discrete curvelet transform-based anisotropic feature extraction in biomedical image indexing and retrieval. The curvelet transform is implemented in the image. The feature vector is determined using the directional energies of the curvelet coefficients, resulting in more directional information extracted at each scale. The efficacy of the suggested methodology is tested in three landmark biomedical databases. The results revealed a significant improvement in performance and computation time compared to other methods. Ahmed et al. [25] used image attribute information fusion to perform a study on CBIR. This technique combines extracted spatial color features with extracted shape features and object recognition. Colors used in conjunction with shape can help to discern an object more accurately. The spatial color feature in the feature vector improves the retrieval of the image. In the proposed method, RGB color is used to extract the color feature, while the gray level images are used to extract the object edges and corners in the formation of shape. The detection of corners and

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edges from the shape creates a more powerful descriptor. Shape detection conforms to a better understanding of an object or image. Shape image detection based on edges and corner formation combined with the color produces more accurate results for retrieval or image detection. For picking the high variance component, the dimension reduction takes place on the feature vector. The results of the experiment based on this methodology demonstrate that it outperforms the current CBIR technique. Anan Banharnsakun, in 2019 [26] , has suggested a new efficient approach for content-based image retrieval based on the combination of the gray-level co-occurrence matrix (GLCM) and the ABC, called "GLCM-ABC" (CBIR). The experimental results show that the proposed method is effective for CBIR and can distinguish particular types of material surfaces in images with a reasonable degree of accuracy. Ibtihaal and Sadiq in 2021 [27] presented an efficient multistage CBIR method to retrieve images based on low-level features. the focus was to reduce images passed from the first stage to the second one by depending on the use of Squared Krawtchouk Tchebichef polynomials (SKTP) and then calculating the mean and standard deviation of the image. Then, LBP and Canny edge detection methods are utilized for extracting the texture and shape features respectively. Manhattan distance is used as a similarity measure. The proposed system has been tested using Wang's dataset. The improvement ratio in terms of computation time achieves 73.99%, which is considered a promising result.

III. FEATURES EXTRACTION IN CBIR

In a CBIR method, feature extraction is a fundamental step that depends on how the scholar describes the visual content or visual signature. Extraction of features is the method of converting the input data into a collection of features that can represent the input data very well. Extraction of features is performed on the pre-processed image, and Image attributes are determined according to the requirements. These features can be derived either in the spatial domain or in the spectral domain. Image retrieval feature extraction is performed to achieve better efficiency, extracting the most famous signatures. This special signature is often referred to as the feature vector of the image. Based on the pixel values, these features are extracted. These extracted features define the image content, such as shape, color, and texture, etc. [28]. As shown in this Fig. 2.

Image features can be categorized as either local or global [29] . A local feature describes the visual content of a group of pixels, while a global feature describes the visual content of the entire image. Global features based CBIRS is fast but has the disadvantage of failure to identify critical visual characteristics [30] . Local features based CBIRS is better and more effective than global features based CBIRS [31] . This is because the former represents an image with multiple points in a feature space, whereas the latter represents an image with a single point.

A. Color Feature

The color feature of the image is the most popular, and it is one of the most widely used visual content for image retrieval [4] . The selection of color features depends primarily on the color model used by the system. More discriminating information about the image can obtain by three-dimensional color models. There are different models of color, like are RGB, HSV, HSL, CIE-LUV, etc. [28] . It is possible to transform one color mode into another, although there is no agreement the superiority of one color model over another model yet, each color model has its specific characteristic like

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HSV color model is more accessible to the human visual system, and RGB is richer between all color models in terms of chrominance power. This low level feature can be extracted by different existing color descriptors. The Color Histogram is the most commonly used color descriptor. It extracts the global distribution of the color among the pixels. This descriptor, however, ignores the spatial relationship between pixels of the same color. To provide improved computational efficiency and decreased histogram size, the use of color quantization is further implemented. Other descriptors used to define the color characteristics of the image are: color correlogram, Color coherent vector (CCV), color moment, color histogram, joint histogram, MPEG-7, color descriptor, and dominant color descriptor are other descriptors used for describing the color features of the image [4] .

TABLE I
Review of Related Works for CBIR

Author	Dataset	Method	Precision
Shao et al. [9]	Corel	MPEG-7 dominant color descriptor	0.8964
Duanmu [10]	COIL-100	Color moment invariant	0.985
Baharudin et al. [11]	Coral	DCT	0.81
Papakostas et al. [12]	COIL, ORL, JAFFE, TRIESCH I	Wavelet moments and moment invariants	0.3083, 0.1784 , 0.2425, and 0.1500.
Moghaddam and Dehaji [13]	Brodatz texture Coral	Gabor transform	0.1 0.4166
Krishnamoorthy and Devi [14]	Yale face MPEG-7	DWT	0.82, 0.85 0.839
Iqbal H. Sarker [15]	Wang	Haar wavelet transform, Color moment	Recall is 0.88
Guo et al. [16]	Corel	Error diffusion block truncation coding features	0.797
Jiexian et al. [17]	MPEG-7 image database	Multiscale distance coherence vector algorithm	0.97
Wang et al. [18]	Corel	Integrated color and texture features	0.613
Guo et al. [19]	Corel-1K	Local binary pattern	77.3
Mistry et al. [20]	Wang	Hybrid features and various distance met	0.875
Liu et al. [21]	Brodatz, Vistex	Fusion of color histogram and LBP-based features	0.841 and 0.952
Fadaei et al. [22]	Brodatz and Vistex	LDRP	0.8081 and 0.911
Srivastava et al. [23]	GHIM-10	Color histogram	76.99
Amita et al. [24]	MRI dataset	Curvelet transform	51.55
Ahmed et al. [25]	Corel- 1000	Image features information fusion	0.90
Banharnsakun [26]	Flickr Material Database	GLCM-ABC	0.76
Ibtihaal and sadiq [27]	Wang	Squared Krawtchouk Tchebichef polynomials	0.826

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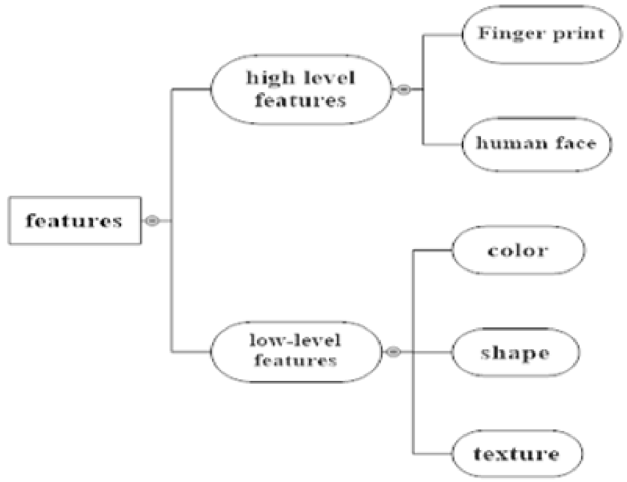

Figure 2: Classification of features extraction used in the retrieval CBIR System

B. Shape Features

The shape of the image is also an important visual content of the image. Shape feature extraction is performed based on the region or object of the image, and different methods based on region-based shape features have been proposed. The two classifications of shape features are boundary-based and region-based. Image segmentation is the first step in the shape feature extraction process. Segmented image regions are distinguished solely by the characteristics of shape features, where their solid and well-organized acting plays a significant role in image retrieval. For feature extraction, color and texture features need not be segmented, whereas shape feature extraction methods require robust segmentation methods to divide the image into meaningful regions or objects. Shape transforms domains, and scale-space approaches, Polygonal approximation, spatial interrelation feature moments are the different approaches for calculating the shape features [32] . The shape of the image can also be described numerically by calculating the different aspects such as circularity ratio, convexity, hole area ratio, elliptic variance, solidity, eccentricity, Euler number, the center of gravity, etc. These aspects are also called shape parameters. Shape feature descriptors are of two types, namely boundary-based and region-based descriptors. Boundary descriptors are also known as an external descriptor, includes the application of finite element models, Fourier shape descriptors, polygonal approximation, and rectilinear shapes. Region descriptors are also called internal descriptor, includes moment invariants to translation, rotation, and scale [4] . Methods [33] , [34] are used for shape feature extraction for retrieving the images based on shape.

C. Texture Feature

The texture is an essential and prominent visual characteristic of an image that is used to partition and classify images into fields of interest. It offers data in the color or intensity spatial structure of an image [35] . Low-level texture features play an important role in CBIR and texture classification. This feature can be calculated in the spatial and spectral domain and shown in Fig. 3 [36] .

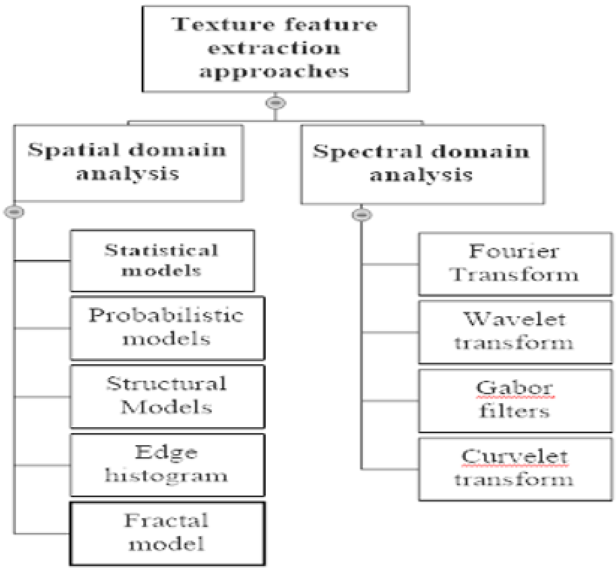

Figure 3: Classification of texture features extraction [36]

In the spectral domain, there are different methods presented by researchers. Wavelet and its variants are commonly used for extracting spectral texture properties. One of the primary benefits of extracting texture features in the spectral domain is that derived texture features are less susceptible to noise. In the spatial domain, local binary patterns and their variants are widely used by various researchers. In the spatial domain, for calculating the binary pattern [4] , the relationship of neighboring pixels with the central pixel is calculated. Due to their reliance on central pixels, these methods are more vulnerable to noise. When comparing the same image with and without noise, the values of their texture features differ significantly. As a consequence, identical but noisy images can be missed by a CBIR system that uses spatial features. The main attributes of texture are randomness, regularity, and directionality. These attributes can be used to determine differences in the surface between two objects [37] . The intensity of grayscale image pixels in a cross-diagonal position and the intensity of pixels in an axis-ordinate position are used to determine regularity and randomness.

IV. Spectral Features

We have been clarified some spectral approaches that have already been used in texture feature extraction for content-based image retrieval. A human can tell the difference between two images at a glance, but when a machine attempts to perform the same task, a large amount of discriminatory image information must be pre-processed and stored to make the system automated. Using the mathematical transforms used in various spectral methods, the popular texture characteristics of an image can be discovered. The effectiveness of several well-known transforms in representing image texture characteristics, as well as their acceptance in CBIR techniques, are discussed further below:

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A. Filter Transformation

Gabor filters transform a suitable multiresolution approach that effectively represents the edges of the image using different orientations and scales, a short-term Fourier transformation for evaluation in the temporal domain with the Gaussian window. The content-adaptive image steganography distortion data requires the texture data of the image. Incorporating in an image creates an anomaly in the texture [38]. Gabor filter is an excellent band-pass filter and is used to utilize representation of images, texture segmentation, edge detection, and image coding [39]. The Gabor filters transform can be described as [40] :

$$G_{m,n}(x,y) = \sum_{s}\sum_{t} f(x_1,y_1) * g_{m,n}(x-x_1, y-y_1) \tag{1}$$

where t and s are the size variables for the filter mask, $x_1 = x - s$ and $y_1 = y - t$, (m & n) represent the scale and orientation of a Gabor wavelet. Gabor filters use multiple window sizes at varying levels of resolution. From a recent literature study, we find that Gabor filters have been widely used in texture representation. Manjunath and Ma [41] presented a comparison of the performance of image retrieval with Gabor filters, Pyramid Structured Wavelet Transform (PWT), Tree-Structured Wavelet Transform (TWT), and Multiresolution Simultaneous Auto-Regressive (MR-SAR) model where Gabor filters texture features are found to be the most promising and robust. The Gabor filters have been widely used in segmentation and texture classification [42], fingerprint analysis [43] , and medical image classification [44] , [45]. Image retrieval performance several various spectral approaches have been demonstrated in [46] where Gabor filters outperform other Wavelet transforms, including the biorthogonal Wavelet (BWT), orthogonal Wavelet (OWT), and TWT at the cost of high computational expense. Texture features of Gabor filters are useful in CBIR of biomedical images such as cervicographic images for cancer detection [44]. It distinguishes strongly ordered textures well, while MR-SAR texture features are only useful for retrieving weakly ordered or random textures. While Gabor filters texture features are the best overall, they do have some drawbacks because they use wavelets as a filter bank. Wavelets are not effective at representing image edge discontinuities [39]. Furthermore, Gabor spectral coverage is not complete to avoid spectral-domain overlap. In the frequency domain, Gabor filters only use half-peak magnitudes. As a result, information loss occurs in the spectral domain. The tiling of Gabor filters is seen in (Fig. 4), where only half of the peak-magnitude filters meet each other. As a result, the high-frequency components, which are thought to be the most important for characterizing image textures, are ineffectively captured.

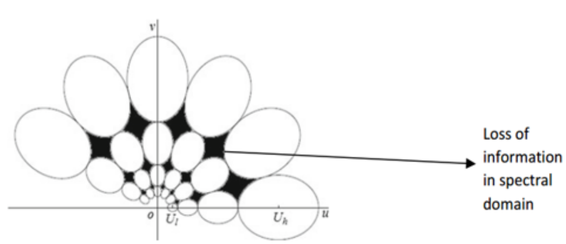

Figure 4: Frequency tiling of half frequency plan by Gabor filters [44]

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B. Wavelet Transform

Wavelet transform has an excellent time and frequency domain location characteristic. It proved to be a promising means for analyzing operations such as compression [47] , reducing noise in each image. The wavelet domain offers the best result for functions with multiple discontinuities and differing sharp spikes [48] . Using Discrete Wavelet Transform (DWT), both high and low pass filters can be implemented along with horizontal and vertical directions of the selected image [49] . Discrete Wavelet [50] is a function that is used to transform the pixel of an image into the frequency domain and is used to modify images from the spatial domain to the domain of frequency [8]. Discrete Wavelet transforms one of the most promising multiresolution methods used in CBIR. The continuous wavelet transform of an image $f(x, y)$ is given by [51] :

$$WT_{\Psi}(a_1, a_2, b_1, b_2) = \int_R \int_R f(X, Y) \Psi_{a_1,a_2,b_1,b_2}(X, Y) d_x d_y \tag{2}$$

where a wavelet with scale parameter a_1, a_2 and position parameter b_1, b_2 can be described as follows:

$$\Psi_{a_1,a_2,b_1,b_2}(x, y) = a_1^{-1/2} a_2^{-1/2} \Psi(\frac{x - b_1}{a_1}) \Psi(\frac{x - b_2}{a_2}) \tag{3}$$

The Wavelet Transform manipulates wavelets for analyzing the signal as they have energy concentrated in time series [52]. When the WT is applied to an image, the window size varies at each resolution level. Though the wavelet transform is commonly used, it has many flaws that result in poor results for content-based image retrieval. Since wavelets are ineffective at representing line singularities, they cannot effectively capture highly anisotropic elements such as image curves in 2-D space. Images with a dense composition of highly anisotropic elements such as curves may not be well represented using wavelet texture representation [53] . Furthermore, the discrete wavelet transform only uses three directional wavelets to capture image texture information: horizontal, vertical, and diagonal. Because of the above-mentioned shortcomings of the discrete wavelet transform, images with a high degree of directionality will not be well interpreted by the wavelet spectral domain.

C. Curvelet Transform

A new multiresolution transform is known as Curvelet Transform developed by Candes and Donoho, which shows an advancement to overcome the limitations of wavelet and Gabor filters [54] . Curvelet transform has been developed to achieve complete coverage of the spectral domain and capture more orientation information. The first generation of curvelets was based on Ridgelets transform [55] , which is a combination of the Radon transform, and the Wavelet transform. In this curvelet approach, an input image is decomposed into a set of subbands. Each of which is then partitioned into many blocks for ridgelet analysis then a ridgelet transform is performed. One of the processes involved in the ridgelet transform is spatial partitioning, which requires the overlapping of windows to prevent blocking effects. As a consequence, there is much redundancy. Furthermore, this approach is time-consuming, making it less feasible to analyze texture features in a vast database [56]. It was discarded in the second generation of curvelets [57] in which Candes et al. proposed two new approaches of curvelet transform based on different Fourier sample processes [54] , namely, wrapping-based fast curvelet transform and unequally-spaced fast Fourier transform (USFFT). Wrapping-based curvelet transform is faster in

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computation time and more robust than ridgelet and USFFT based curvelet transform [58]. FDCT based on the wrapping of Fourier samples has less computational complexity as it uses fast Fourier transform instead of complex ridgelet transform. The curvelet transform, which is based on the wrapping of Fourier sampling, takes a 2-D image in the form of a Cartesian array $f[m, n]$ such that $0 < n \leq N - 1$, $0 \leq m < M - 1$ as an input and generates several curvelet coefficients. Discrete curvelet coefficients can be defined by [59] :

$$C_{j,\theta}(k, l) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} f(x, y)\Psi_{j,\theta,k,l}(m, n) \tag{4}$$

where $\Psi_j, \theta, k, l(m, n)$ is a discrete curvelet, j and θ are the scale and orientation respectively, k and l are the spatial location parameters. A wedge is a curvelet's frequency response, and the curvelet tiling of the frequency plane that covers the entire image in the spectral domain is shown in Fig. 5.

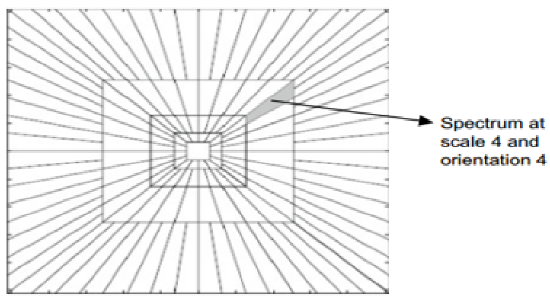

Figure 5: Curvelet tiling of frequency plane with 5 level curvelets [45]

Curvelet transform is applied in the frequency domain to achieve a higher level of efficiency and effectiveness. The image and the curvelet are both transformed and multiplied in the Fourier frequency domain. The result is then inverse Fourier transformed to obtain the curvelet coefficients. The process can be summarized as follows:

$$Curvelet\,Transform\,(Image) = FFT - 1(FFT(Curvelet) \times FFT(Image)) \tag{5}$$

However, the product from the multiplication is a wedge. As for the properties of the curvelet can be summarized as follows [60]:

1) The transform curvelet is based on a modern type of pyramid filter structure.
2) The frame elements of the curvelet include new scaling rules.
3) Curvelet provides an adequate representation of images with edges that curvelet can provide.

V. Similarity Measurement

The approach to choosing a similarity measure affects the image retrieval system performance and is measured when the features are extracted from all database images and the query image. The process of finding the similarity between

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the database images and the query image using its features is similarity measurement. The main objective of distance measurement is to find the target images with the least associated error and optimum image similarity. There are many methods of calculating this distance, for example, the Minkowski-Form distance, quadratic form distance, Kullback-Leibler divergence [61] , etc. The Euclidean distance [62] , also known as L2 distance, is one type of the Minkowski Form distance [61] , an appropriate and efficient approach that is commonly used in the field of image retrieval. The Euclidean distance method is the distance between two points that can be measured and produced based on two vectors. Based on the two vectors, the distance between the two vectors can be determined using the following equation [63] :

$$ED(Q,T) = \sum_{i=1}^{2n} (Q_i - T_i)^{1/2} \tag{6}$$

Here: $Q = Q_1, Q_2, ..., Q_{2n}$ is the feature vector of the query image, and $T = T_1, T_2, ..., T_{2n}$ is the feature vector of the target image in the database.

VI. Performance Evaluation

Precision and recall rates have been used to evaluate the efficiency and effectiveness of the suggested CBIR method [64]. Precision measures the CBIR system's ability to obtain only similar images to the query image [65] . In this respect, the recall rate is the actual positive rate. It is used to assess the CBIR system's ability to measure the number of relevant images retrieved compared to all related images in the database. Precision (P) is defined as the ratio between the number of relevant images retrieved and the total number of images retrieved, P = r/n [61] . Precision measures the retrieval's accuracy. As for recall (R), it is concerned with the ratio of the number of relevant images retrieved to the total number of relevant images in the whole database, R= r/m [61] . Recall measures the retrieval robustness.

$$P = \frac{Number\,of\,relevant\,images\,retrieved}{Total\,number\,of\,images\,retrieved} = \frac{r}{n} \tag{7}$$

$$R = \frac{Number\,of\,relevant\,images\,retrieved}{Total\,number\,of\,relevant\,images\,in\,DB} = \frac{r}{m} \tag{8}$$

In general, with improvements in recall values, precision values drop. A retrieval system can be considered 'ideal' when both the precision and recall values stay high.

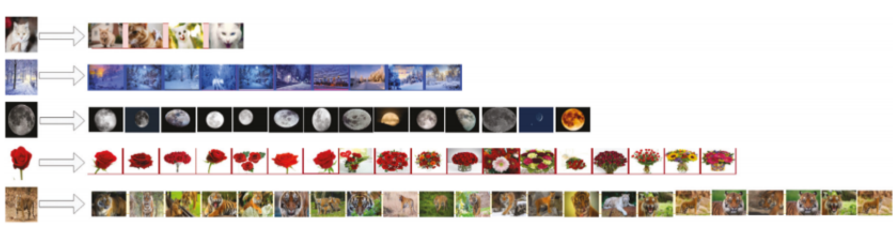

Figure 6: Example of image retrieval results based on search by query image

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VII. Conclusion

We presented a systematic literature review on various CBIR and image representation techniques. The primary goal of this research is to provide an overview of various techniques that have been used in various research models over the last 10-15 years. Following this analysis, it is concluded that image feature representation is accomplished by using low-level visual features such as shape, color, texture, and spatial layout. Color is usually represented by the color correlogram, color coherence vector, color histogram, and color moment under a specific color space. Texture can be represented by Tamura feature, SAR model, Wold decomposition, Wavelet, and Gabor filter transformation. The shape can be represented by turning angles, Fourier descriptors, moment invariants, circularity, eccentricity, and major axis orientation, and radon transform. The spatial relationship between regions or objects is usually represented by a 2D string. In addition, the general visual features on each pixel can be used to segment each image into homogenous regions or objects. Local features of these regions or objects can be extracted to facilitate region-based image retrieval. The semantic gap can be minimized by using different local features, which reflect the image in the form of patches, and performance is improved by using local features. One of the future research in this field direction is the combination of local and global features.

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