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SEMANTIC PATENT EXTENDED BASED ON CONCEPTUAL COMPARABILITY OF TEXT WITH UTILIZING HISTOGRAM ARITHMETIC FOR ILLUSTRATIONS TO MINIMIZE TRADE MARK

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Abstract:
A trademark distinguishes your business's goods or services from others'. Symbols, logos, titles, etc. can be trademarks, so they must be protected. This research deciphers trademark hypotheses when two or more have the same semantic implant. State-of-the-art semantic algorithm to similitude trademarks in hypothetic parallelism. Search and indexing established similarity distance utilizing data similarity. The proposed reflow technique is confirmed using a trademark database and a corporate names database. The conceptual comparison of written works that share a comparable domain, use similar concepts, or communicate similar ideas has been explored extensively. Existing trademark search engines are generally text-based. Measure the algorithm's accuracy in different domains. Your business can distinguish its products and services with a trademark. Therefore they need protection. When multiple trademarks are conceptually similar trademarks are valuable phrases and images used in applications that need infringement protection. Until infringement cases, trademark features, hypothetic, and phonetic similarities are evaluated. This research proposes a conceptual similarity of trademarks for distance computation and input retrieval. Similarity distance is used to search and index using similarity trademark offer a semantics-based computational approach to recommend trademarks for conceptual similarity and reduce future infringement protection costs. A trademark retrieval system processes a huge number of semantic trademarks with conceptual similarity.

Keywords: Feature Extraction, Text, Image Retrieval, Histogram, Framework Design Analysis

I. INTRODUCTION

In common parlance, a trademark is synonymous with a brand or a logo. Obtaining trademark registration for a business name that features unusual catch phrases, tag lines, or captions is also possible. If it is used and promoted effectively, a business's trademark has the potential to become its most valuable asset. Both the origin of the items and their quality can be deduced from trademarks such as Coca-Cola, HP, Canon, Nike, Adidas, and Puma, amongst many others. Trademarks also serve as an indication of quality. Obtaining trademark registration for the company name or trade name in accordance with the trademarks laws is also something that is absolutely necessary. The registration of a company or business name under the companies act does not, on its own, confer any protection against third parties who may start using marks that are identical or similar to those registered. A unique statement that is connected to a product or service and serves to differentiate it from others is considered to be a trademark. A trademark is a visual symbol that may be a word, a name, a device, a label, or numerals used by a business to differentiate its goods from those of other businesses' goods. This visual symbol may also be called a logo. The system will be able to scale across a number of different platforms and will offer increased reliability as a result of its high level of efficiency and robustness. In the early days of trademarks, anyone who created a new one had to first obtain a patent for it before they could even check to see if it was already in use. This was the case even if the new trademark was an improvement on an existing one. Understanding the issue in the earliest feasible stage proved to be exceedingly challenging for the inventors. Because of this issue, a significant amount of time is lost while going to get the patent, and the number of instances of identical trademarks also rose. Hence, in order to get around these obstacles Semantic retrieval by data similarity of trademarks system is proposed.

Digitized images are retrieved. Sorting a huge image database; digitized images are retrieved. Large databases sort images by text, color, and shape. Combining CBIR features produces relevant visuals. A typical CBIR system extracts and displays pictures as m-dimensional feature vectors. This vector database comprises database images. Most desired systems employ color and form to match photos to collection and test dataset elements. We introduce HSV color space and form coupling using through wavelet methods.

Multimedia uses visuals. Information systems help entertainment, creativity, business, engineering, and science. Relevant themes have photo libraries and image searches. Bi-dimensional images; Preset rectangular arrays hold pixels. Each photo pixel has lighting and color information. Photos depict the viewpoint of surfaces. Phone cameras, scanners, digital cameras, mobile cameras, and internet multimedia are increasing photo collections. This requires searching and retrieval.

II. FEATURE EXTRACTION

High-level and low-level picture characteristics are distinguished. Color and shape features make a database. Databases are used to measure similarity. CBIR Systems includes:

Acquisition- Acquire images using digital devices and standard datasets to construct image database.

Preprocessing- Before retrieving photos, they must be improved.

Extraction- Required features are removed.

Similarity and Matching- To calculate the query image's similarity to database images

Output- The final outcome after the process is validated for accuracy and recall. Image visuals are extracted. It's usually about the image. Color and form are low-level properties. Global and local characteristics examine if the entire image should be considered or just regions. Image color is crucial. Image color extraction techniques abound. Color histogram, color correlogram, color coherence vector, and color moments are color-based retrieval approaches. Contour-based and region-based features characterize the shape. Contour feature describes picture border, while region-based feature considers complete image.

Following steps illustrate the picture retrieval algorithm.

- Load database pictures into Software by specifying the dataset's directory.
- Convert all database photos to HSV using formula.
- Histograms for hue, saturation, and value are then generated and quantized.
- File is created to store database image values.
- Load the Query picture.
- To find HSV values in Query image, repeat steps 2 and 3.
- As values are obtained, calculate the distance between them and the trained dataset query image.
- Sort distances to assess image relevancy.
- GUI display of output images

For both query and database photos, we extract features by generating histograms for hue, saturation, and value. This section described histograms.

Fundamental of content based image retrieval

Image retrieval involves finding digital images in a large database. An effective image retrieval system may retrieve relevant images based on a query image that conforms to human perception. Text-based and visual-based viewpoints exist in database management and computer vision. Language-based image retrieval uses text to explain image content, while content-based uses image visual attributes.

Conventional or text based image retrieval

Conventional picture retrieval is a keyword-based method. Words-based image retrieval strategies employ text to describe image content, which is ambiguous and insufficient for image database search and query processing. Text-based image retrieval has trouble specifying exact keywords for visual material. Language-based textual annotations influence retrieval results.

Content or visual based Image Retrieval

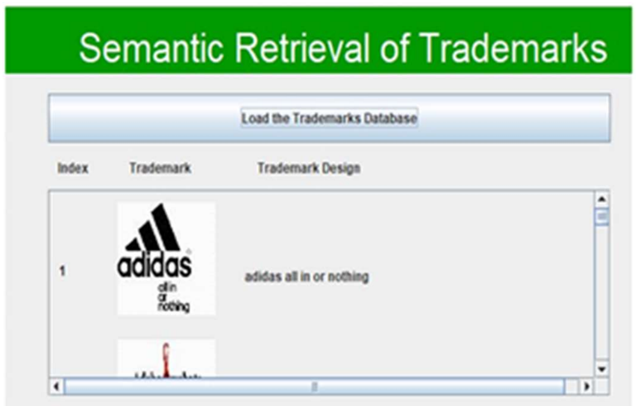
Visual Image Retrieval uses visual properties such as color, texture, shape, and spatial relations to retrieve images.

Image features

There are many ways to extract features for image analysis and understanding. Color histograms and MPEG7 features have been proposed for scene-wide characterization. Imaging has examined global characteristics like textures and down-scale representations. Global image description eliminates the need to model image objects and regions. Global characteristics depict the image as a whole.

Histopathology images may have substantial visual variabilities and various feature sets, hence we treated them as global histogram features. The NPC pattern, emphasized in green dotted lines, combines nodule textures, cleft edges, and palisading cell density. Seven feature spaces describe histopathological patterns visually: gray scale, invariant feature, local binary patterns, RGB color, and bag of SIFT features, Sobel, and Tamura texture histograms.

Since they compute histograms differently, these seven low-level characteristics measure image pixels in complimentary ways. However, Tamura texture and local binary patterns, which characterize texture patterns using statistical and deterministic methods, assess similar visual qualities on images. The invariant feature histogram and SIFT features indicate rotation- and translation-invariant traits. The invariant feature histogram is integral and adds globally over rotation and translation. However, the bag of SIFT features uses a learned dictionary of rotation-invariant visual patterns to count them in each image to create a histogram of frequencies.



Block color histograms divide images into n×n chunks. Too large blocks have less meaning, while too small blocks increase retrieval process computation. Based on our comparison, a two-dimensional space partitioned into 3 × 3 is more effective.

Each block undergoes color space conversion and quantization. Calculate each block's normalized color characteristics.

Each block receives a weight coefficient to highlight its weight. Middle blocks weigh more.

Feature extraction

The initial challenge in CBIR is to extract the features of the picture in an effective manner and then to represent those features in a specific way so that they can be utilized in an efficient manner in the process of image matching. It has been found that the statistical texture features can be helpful in the categorization and retrieval of images that are quite similar. These elements of the image's texture provide information about the attributes of the intensity level distribution in the image, such as the image's uniformity, smoothness, flatness, contrast, and brightness. The proposed method is responsible for the extraction of the statistical texture features. The proposed texture features, such as mean, standard deviation, skewness, kurtosis, energy, entropy, and smoothness, are computed with the help of the probability distribution of intensity levels in the histogram bins of the histograms of DC, AC1, AC2 and AC3 coefficients. Other terms used in the calculation include smoothness, energy, and entropy.

If we define P(b) as the probability distribution of bin b in each of the four histograms of the coefficients with L bins, then we can compute it using the following formula:

$$P(b) = \frac{H(b)}{M}$$

Where M represents the total number of blocks contained inside the image I.

The average of the intensity levels found across all four bins of the quantized histograms constitutes the mean. It is a measurement that may be used to describe how bright the image is and can be computed as follows:

$$\text{Mean} = \sum_{b=1}^{L} bP(b)$$

The distribution of intensity values relative to the mean is what the standard deviation attempts to quantify across all blocks of the histogram. The calculated value of standard deviation reveals if an image's histogram has a low or high contrast based on whether the image has low or high values overall.

$$std = \sqrt{\sum_{b=1}^{L} (b - mean)^2 P(b)}$$

The skewness is a measurement that determines how unequally the intensity values of all blocks of histograms are distributed in relation to the mean value. The fact that the skewness has a negative value indicates that the majority of the intensity value distribution will be on the right side of the mean, while the tail of the distribution of intensity values will be longer and more skewed on the left side of the mean.

$$SKEW = \frac{1}{(std)^3} \sum_{b=1}^{L} (b - mean)^3 P(b)$$

The positive value indicates that the intensity value distribution will be highest on the right side of the mean value in comparison to the left side, and that the values on the left side will be skewed with a longer tail on the left side of the mean value.

When it has a value of zero, the skewness parameter indicates that there is a balanced distribution of intensity values on both sides of the mean. Calculations can be done to determine the skewness using

$$kurtosis = \frac{1}{(std)^4} \sum_{b=1}^{L} (b - mean)^4 P(b)$$

The Kurtosis calculation determines the peak of the distribution of intensity values as they relate to the mean value. This is the fourth texture feature. A kurtosis that has a high value will show a distribution with a sharp peak and a long, thick tail, while a kurtosis that has a low value will show a distribution with a rounded peak and a shorter, thinner tail. The formula for calculating kurtosis is as follows:

$$ENERGY = \sum_{b=1}^{L} [P(b)]^2$$

When calculating the uniformity of the intensity level distribution throughout the histogram's various bins, the energy is measured as a textural characteristic and used as a factor in the calculation. The energy that has a high value demonstrates that the histogram's bins only include a limited number of different intensity value distributions. Calculating energy looks like this:

$$ENTROPY = -\sum_{b=1}^{L} P(b)\log_2[P(b)]$$

The entropy is a statistic that can be used to determine how random the distribution of intensity levels in bins is. If the value of entropy is high, then the distribution of the image's pixels is spread out across a wider range of intensities.

$$SM = 1 - \frac{1}{1+(std)^2}$$

The energy level is the opposite of this measurement. The entropy of the simple image is low, whereas the entropy of the complex image is high. This difference can be calculated as

Using the standard deviation value of each bin in the histogram, the smoothness texture is applied to the image in order to determine the surface attribute of the object being analyzed. It is possible to calculate a

Following the completion of the computation of these texture features, the values are added together to produce a feature vector fv such as the following:

III. EXISTING SYSTEM

Trademarks are words, phrases, symbols, or combinations of the two that are unique and high-quality. These are important reputational assets that can be used to promote quality, innovation, and the manufacturer's standards. This proposed approach will protect trademarks from infringement and conceptual similarities. Retrieval methods that assess trademark visual similarity solve this problem. Checking for identical trademarks is part of the trademark registration procedure. Similarity algorithms assess this visual likeness. Image collections have grown due to the ease with which various acquisition devices may gather photos. Image databases are standardized, yet accessing photos is difficult. This work is challenging. Precision recall is the most common method for assessing the system's performance. The experiment proved the trademark. Shape-based image retrieval works better and yields more than enough results. The little work largely addresses rotational issues.

IV. PROPOSED SYSTEM

The conceptual model of the trademark comparison procedure created in is the foundation for the retrieval method that has been proposed. It gives an overarching perspective on comparing trademarks based on the conceptual similarities between them. The conceptual model is expanded upon by this system, which creates and evaluates a semantic algorithm for retrieving trademarks based on conceptual similarities. The suggested system makes use of natural language processing (NLP) techniques in conjunction with a brand new trademark comparison measure. The word similarity distance method, which was generated from the WordNet ontology, is also a part of the algorithm. WordNet is used in this algorithm because of its lexical associations, which are a reflection of how humans organize their semantic knowledge, and also because it has been demonstrated to be successful in a lot of other works that were done before this one. The Tversky contrast model, which is a well-known model in the theory of similarity, is where the trademark comparison measure originates from. The goal of the approach that we are proposing is to retrieve trademark hypothetical similarities in order to make such comparisons more precise and to provide greater protection against trademark infringement. In addition to this, the systems are able to retrieve the conceptual similarity of trademarks and handle the traditional data retrieval method. The proposed model can then be merged into a reflow system, which can then perform a more complete trademark comparison. This will consider the other two stages of similarity, namely sight and phonetic. The method that determines how closely two trademarks are conceptually related to one another. Text retrieval issues arise when trying to find trademarks that are conceptually identical. The virtually string matching that is applied to text is defined by the system. It is necessary to conduct an analysis of the trademarks in order to have an understanding of the primary conceptual similarities that result from various circumstances. This is the primary emphasis of the, which presents a hypothetical model of the comparison process with the goal of obtaining trademarks that are conceptually comparable to one another. The hash indexing will accept the token key and the synonym key before beginning pre-processing.

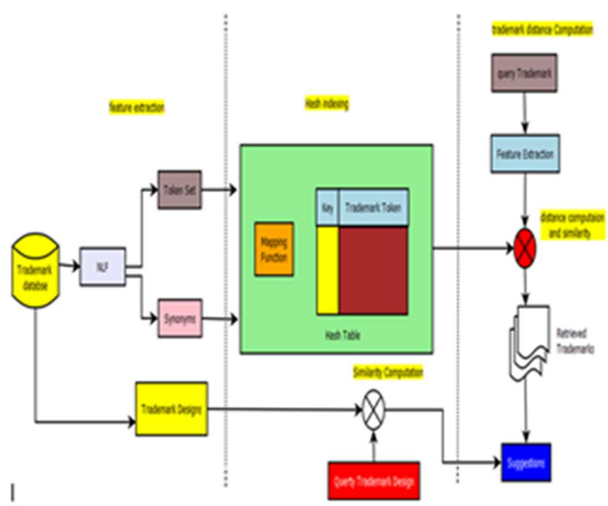


Figure: Architectural diagram proposed system

It will then utilize the indexing in that key to generate a new trademark for the user that is comparable to the user requirement trademark. The token and its synonyms are the feature extractions that are defined here. The proposed retrieval method is used to develop a trademark reflow technique, and the algorithm is then evaluated based on how conceptually comparable the techniques are. The list of retrieval trademarks has been saved in a database in preparation for potential future usage of trademarks in further trademark retrieval concepts. A hashing technique is used to list the factors in order to cut down on the amount of additional time needed throughout the find procedure. The trademark is used as the key index for the hash indexing process. A user is able to submit a text that he wants to trademark through a process called trademark retrieval. If the trademark is already present in the system, then it is forwarded to the trademark matching process, after which it returns any documents that are comparable to the user. In the event that a trademark does not already exist in the system, the trademark will be saved in the database. The lexical resource is used, and then hash indexing is applied to that trademark in order to generate a new trademark that can be used to acquire the user. The return document is then sent to the user.

Goals

To discover Conceptual similarity to improve their accuracy and security and to enable the system to retrieve trade-marks' conceptual similarities identify logo similarities using SIFT features in order to prevent logo trademark issues; Use similarity distance to reduce the extra cost of protection.

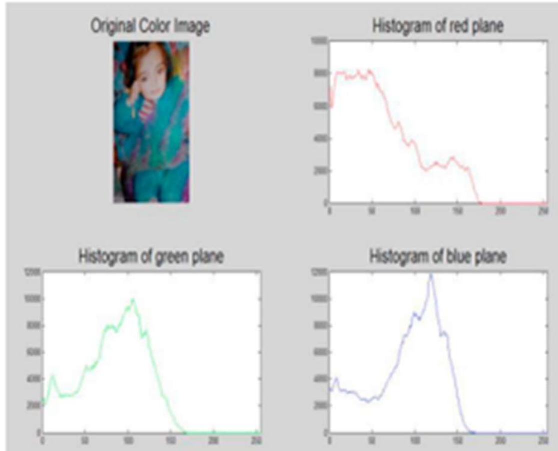
V. MATERIALS AND METHODS

Feature extraction:

The CBIR system proposed in this work determines the features in the image utilizing its optical contents such as color signature, shape and color texture. Fig. 1 represents the block diagram of the proposed method and the details of each process will be illustrated in the following sections.

Extraction using Color Histogram:

It is one of the basic features considered so far for the extraction purpose for the easy extraction of images. For color and shape feature extraction many approaches are described earlier. Techniques used in (Aher, 2014) give an overview of CBIR techniques. For the color feature two categories of histograms are available: one is intensity image histogram and second is color histogram. Color images use color histograms. There is widespread use of histogram method because of usefulness in picture retrieval which are its robustness, computational simplicity with effectiveness. While categorizing a image it is commonly checked as a 2D mapping shown as $J : x \rightarrow v$ where $X \times Y$ pixels x is equal to = [i, j] corresponds to v and here i lies between 1, 2,..., X and j is 1, 2,..., Y responds as y-axis and X to x-axis respectively. Sometimes v is intensity values lies in range of 0–255. Histogram represents values through which images are classified for further retrieval. A color image represents three values at each pixel for red, green and blue color. Color histogram (ballard) related technique is done for sorting features. This is achieved by calculating RGB values of each image in database at first. Then these values are converted to HSV and 3d histogram was computed for all images and stored in a Matlab's .mat file, this was termed as trained dataset. When query image was given its features are extracted with the same procedure and similarity was computed between them. Our work uses RGB images as input .At first we found out RGB values for image and then those were converted to HSV. In a Histogram based extraction technique, an image is characterized by its color distribution or histogram.



A histogram basically represents colors of image and occurrence of these colors at different levels irrespective of the type of image is under consideration in the form of a graph. Now for testing purpose image taken as query and images in the collection are examined to compute color histogram using MATLAB. At first input image is read in MATLAB workspace by using MATLAB function imread('imagename'). Then histogram is generated for that image using imhist ('imagename') function. Following fig 1 explains how a histogram looks like:
Original color image shows the input Image and for this image RGB histogram is generated. The RGB values are converted to HSV and histogram are generated are stored in different bins .Then values obtained are stored in number of bins. The values so obtained are stored in .mat file. Each time we have to find out results we will load this .mat file called model name. Now comes the execution part for query image. For query image too we will generate histogram and their values are quantized into number of bins. As now we have extracted values for both query image as well as database images so we are going to measure similarity. Now Euclidean distance is calculated. After that images will be sorted and matching results are displayed for specific query image. We have used three datasets for calculating results using color feature based extraction as explained earlier. For all these datasets we have executed our code and output was analysed for each. The methodology of work carried out for feature extraction is explained with the help of following fig 2 and fig 3 flow diagram and algorithm is written further.

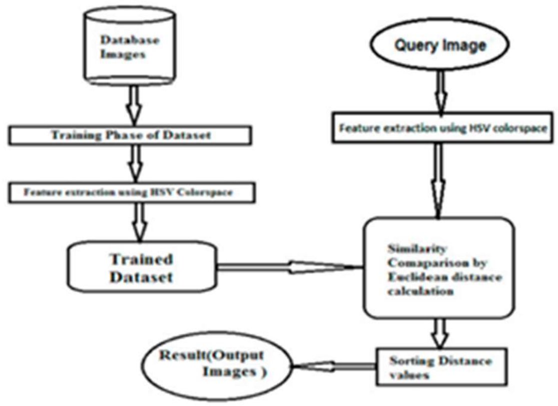


Figure: Methodology for Color Feature Extraction

Following steps explains the algorithm followed for retrieval of images from dataset.

- First step is loading of database images in the MATLAB workspace by specifying directory where dataset is kept.
- For all the images in database convert RGB values to HSV values by above specified formula.
- Then there is generation of histogram for hue, saturation & value and values are quantized into bins.
- After this, a file is created named as .mat to store values obtained of database images.
- Now, next step is loading of the Query image.
- Implement again the functionalities of steps 2 and 3 to find HSV values in Query image.
- As values are obtained, determine the distance parameter of Values calculation obtained with respect to Query image with trained dataset.
- Sort the distance values to determine relevance of images to query image.
- Displaying and representation (all the output images) on GUI. For both query image as well as database images we have to extract features that what we have done, histogram is generated for three values separately for hue, saturation and value. Histogram generation was explained earlier in this section.

Low-level Image Features:

Color: A color signature for a region/whole image is produced using color correlogram or color histograms. There are also other color models like RGB (i.e., red, green, blue) and HSV (i.e., hue, saturation, value) used for color signatures. The problem with using this feature is that it is difficult to achieve something like human vision, since there are individual differences in human vision.

Texture: Texture produces a mathematical characterization of a repeating pattern in the image (e.g., smooth, sandy, grainy, stripy). It reduces an area/region to a set of numbers that can be used as a signature for the region. Although this has proven to work well in practice, it is difficult for people to understand.

Shape: Although shape belongs to the realm of object recognition, it is difficult and so less commonly used. All objects have closed boundaries and shape interacts strongly with segmentation. These low-level features (e.g., color, texture, and shape) can be used to describe image contents individually, but the description retrieved from them is insufficient. In this context, scale-invariant feature transform (SIFT), image histograms, and CNN convolutional neural network (CNN)-based computer vision techniques are more useful for extracting informative content. In addition, feature aggregation techniques, including vectors of locally aggregated descriptors, Fisher vectors, and bags of visual words provide fixed-length vectors, which can help in approximating the performance of similarity metrics .

Color features extraction:

Color feature is an essential component for image retrieval. For huge image databases, image retrieval using the color feature is very successful and effective. Although color feature is not a persist parameter, because it is subjected to many non-surface char acteristics for example, the taking conditions such as illumination, characteristics of the device, the device view point. The steps of the color feature extraction are shown below:

1. Color planes values RGB are separated into individual matrices namely; Red, Green and Blue matrices.
2. For each color matrix color histogram is calculated.
3. Variance and median of color histogram are calculated.
4. The summation of all row variances and medians is calculated.
5. The calculated features of all matrixes (R, G and B) are combined as feature vector.
6. The feature vectors are stored in the features database.

Shape features extraction:

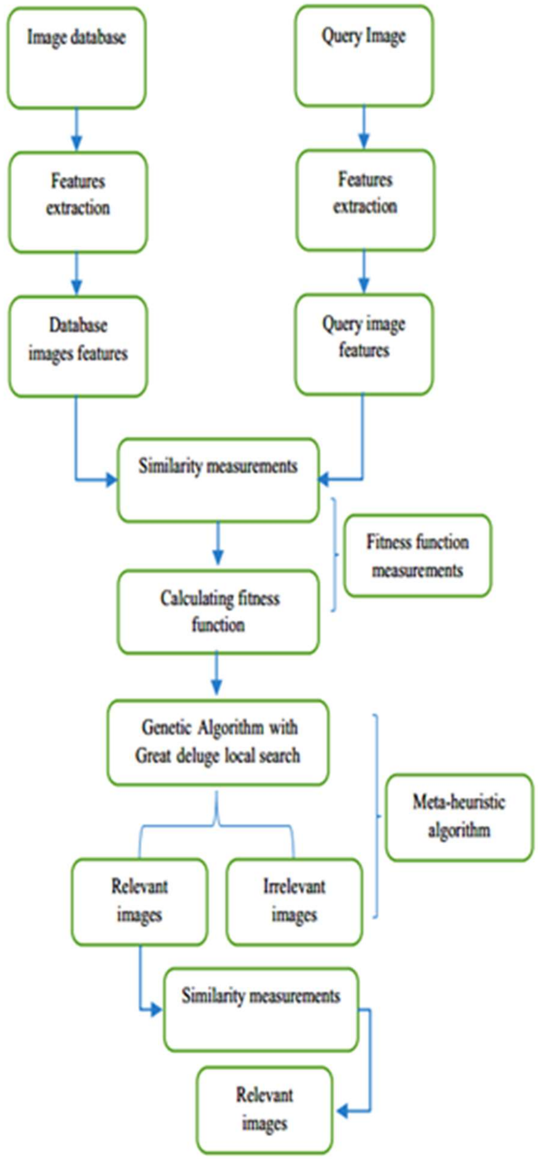
The shape feature extraction mainly aims to capture the properties of the shape of the image items. This eases the process of shape storing, transmitting, comparing against, and recognizing. The shape features should be free of rotation, translation, and scaling. To store, transmit, or recognize shape, an efficient way to find the shape features is investigated.

To store, transmit, or recognize shape, an efficient way to find the shape features is investigated. The selected features are independent from any mathematical transformation. A colored image has three values per each pixel, to extract the features we convert the color image into one two-dimensional array, and that made according to Craig, formula as follows

$$I_g = [I_r \quad I_g \quad I_b] * \begin{bmatrix} 0.2989 \\ 0.587 \\ 0.114 \end{bmatrix}$$

Where Ig is the combined 2D matrix, Ir, Ig, Ib are the color components which construct the colored image. Ig is represented as the grey level combined image. As a preprocessing step: noise reduced by using median filter. Median filter is beneficial to reduce salt and pepper noise

and speckle noise. Also, median filter has edge preserving property it is used where blurring of edges is undesirable. Median filter with width w and length l algorithm is as follows:
.:



1. Around each pixel collect all pixels with length l/2 and width w/2 around it.
2. Sort all collected pixels.
3. Update the pixel value by the pixel value in the middle order in the previous list

After applying the median filter, the image becomes almost without noise data. Then the neutrosophic clustering algorithm is applied to separate pixels with very near values and to ignore indeterminate pixels from the gray image. The algorithm is as follows:

1. Select k centroids pixel values.
2. For each pixel assign random membership value to each centroid.
3. Assign T, N values with the image I and F value with the inverse of T.

4. Calculate the new centroid value as the weighted mean of the pixel values, where the weight is the member ship value to that centroid but the weight magnitude if it the pixel is not indeterminate and tininess if it is indeterminate.
5. Update the membership values as one over the ratio of the overall differences between the centroid and the pixels' values, and the differences between the pixel values and all other centroid values.
6. Update the image I by applying the mean filter over pixels with significant values.
7. If the updated membership values are almost equal to it before update then stop otherwise go to step 3 again.

Finally apply the canny algorithm to find the edges around the similar pixels (grouped pixels). In this work Canny edge detection method was used for shape features extraction, edge based shape representation was used, which gives a numerical information about image, these information is constant, even the size, direction, and position of the objects in the image are changed. After applying canny edge detection method different shapes can be obtained which exists in the Ig image and then the shaped content indices are extracted and stored in the database in form of feature vector.

Color texture features:

Color texture features classification is an essential step for image segmentation using CBIR. Thus, this work proposes an approach that is based on texture analysis to classify color texture instead of segmentation alone.

Grey-level co-occurrence matrix (GLCM) :

The GLCM is a robust image statistical analysis technique [27– 30]. GLCM can be defined as a matrix of two dimensions of joint probabilities between pixels pairs, with a distance d between them in a given direction h [30]. Haralick [31] extracted and defined 14 feature from the GLCM for the texture features classification. But these 14 features are highly correlated, so in our research we avoided this problem by using five features for the comparison. The Steps of the color texture features extraction is shown below:
1. Filtering the input image using the 5 x 5 Gaussian Filters.
2. Filtered image is divided into 4 x 4 blocks.
3. For each block Standard Deviation, Homogeneity, mean value, Contrast and Energy are calculated using GLCM, these features were calculated based on four directions as diagonally (45 and 135), vertically (0x) and horizontally (90x).
4. The extracted features are stored in the feature database.

Semantic image annotation and retrieval:

The proposed strategy for histology image retrieval is oriented to produce a set of semantic image annotations through visual con tent analysis. Our framework aims to build a general and complete visual representation of images that can provide enough evidence of the presence or absence of certain histopathology concepts. Fig. shows the three fundamental steps in our framework: first, the extraction of multiple visual features is performed on the input images.

Second, the new content representation is build integrating all visual features using kernel functions. Third, this content representation is used to detect histopathology concepts. After generating automatic annotations, the result can be used to search images with similar annotations or just to index the input images in the retrieval system.

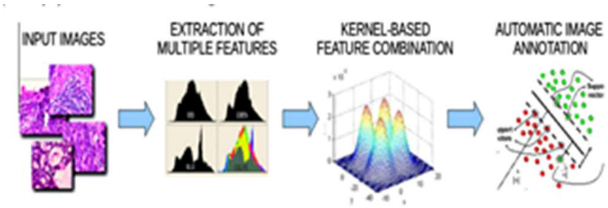


Image features

Feature extraction is an important task for image analysis and understanding and there are different approaches to address this problem. Global features for characterizing whole scenes have been proposed using color histograms and MPEG7 features. Likewise, global descriptors such as textures and down-scale representations have been evaluated in medical imaging. One important advantage of using a global image description strategy is that it is unnecessary to specify a model for objects or regions that images may contain. On the contrary, global features provide a holistic image representation that characterizes the composition of the whole image. We modeled histopathology images as a set of global histogram features, taking into account that pathology patterns may have high visual variabilities that are characterized by different feature sets. For instance, as it is shown in Fig. 1, the NPC pattern, high-lighted in dotted lines (green), contains a mixture of the textures inside the nodule, the edges provided by the cleft, and the density of the palisading cells. To describe the different visual characteristics of histopathology patterns, seven feature spaces have been selected: gray scale histogram, invariant feature histogram, local binary patterns, RGB color histogram, bag of SIFT features, Sobel histogram and Tamura texture histogram. These seven low-level features are complementary with respect to the kind of measure they do over image pixels, since they apply different computations to build the histograms. However, some of them measure similar visual properties on images, such as Tamura texture and local binary patterns, both modeling texture patterns, but using different approaches (statistical and deterministic, respectively). Also, the invariant feature histogram and SIFT features are intended to identify characteristics that are invariant to rotations and translations. The invariant feature histogram follows an integral approach that sums globally over rotation and create a histogram over translation. On the other hand, the bag of SIFT features is based on a learned dictionary of rotation invariant visual patterns that are counted in each image to construct a histogram of frequencies.

The global features were chosen to create a general and broad repertory, in contrast to approaches that carefully select visual features for the specific problem at hand. The relevant features for each high-level concept are automatically chosen by a feature fusion process to be described below. All histogram features are global content descriptors that do not allow identifying spatial location of objects or patterns. This represents an advantage when dealing with histopathology images, in which pathology patterns are spread around the image such as lymphocyte infiltration, in which lymphocytes can be seen covering different tissue regions. Elastics is another example of a stroma's property that can be seen along the complete tissue slide. In that sense, the set of histograms provides different measures to detect variations in the global image composition that can be exploited to reveal its semantic meaning

Kernel functions

Kernel methods are an alternative family of algorithms and strategies to perform machine learning. One of the main distinctive characteristics of kernel methods is that they do not emphasize the representation of objects as feature vectors. Instead, objects are characterized implicitly by kernel functions that mea sure the similarity between two objects.

A kernel function induces an implicit high-dimensional feature space where, in principle, it is easier to find patterns. Informally, a kernel function measures the similarity of two objects. Formally, a kernel function, k : X X ! R, maps pairs (x, z) from a set of objects X, the problem space, to the real space; a kernel function implicitly generates a map, U:X ? F, where F corresponds to a Hilbert space, called the feature space.

The dot product in F is calculated by k, specifically k(x, z) = hU(x), U (z)iF. One can deal with histograms as simple data vectors, regardless their probability distribution properties. In that sense, we can calculate the dot product between histograms treating them as high dimensional feature vectors. This operation will be herein denoted as the identity kernel, since it induces a feature space that is equivalent to the input space. On the other hand, we can harness the structure of histogram data by evaluating the similarity measure between two histograms in a more meaningful way. The histogram intersection is a similarity function devised to calculate the common area between histograms as follows:

$$k_{\cap}(A,B) = \sum_{i=C}^{m} min(a_i, b_i) \qquad (1)$$

Where bn) are histograms. This similarity measure has been shown to satisfy the Mercer's properties. This is important when using learning methods, such as SVM, since it guarantees the optimal solution of the associated convex optimization problem. Another advantage of this kernel is that it can be efficiently computed; in fact, recently proposed a very efficient technique to train SVM that use the histogram inter section kernel. Using the histogram intersection kernel with SVM, we are mod eling a non-linear classification rule in a high-dimensional feature space. This particular property of kernel method solutions, all laws us to capture the high variability of visual patterns along the same semantic concept. This special property will be discussed in the next Subsection

Combination of kernels

As discussed before, pathology concepts are characterized by different types of features including colors, textures and edges. Given two images, a similarity measure may be calculated by applying a kernel function to a pair of images represented by a particular type of feature histogram. For instance, when using the Gray Histogram, we can distinguish if an image has the same brightness level as another one, while using local binary patterns, we can evaluate if they have similar low-level tissue composition. This provides a repertory of kernels that compare images according to different visual properties. Now, we want to equip the classification system with the ability to adjust the importance of each feature when dealing with a particular semantic concept. Formally, there is a set of kernels fki : X X ! Rgi , where i indicates the type of visual features used to calculate the similarity. Notice that despite the fact that the different kernels use different features to calculate the similarity, all of them have the same domain, i.e., they are image kernels. The problem is how to use these different image kernels to calculate an overall similarity measure for images. The new similarity measure would correspond to a kernel function that induces a new image representation space. ka is defined as a linear combination of the n individual histogram kernels

The weights allow parameterizing the kernel giving higher or lower importance to each individual feature. Notice that the linear combination of kernel functions, associated to different visual features, is implicitly defining a new feature space whose structure may be adapted to better recognize a particular semantic concept. In particular, it has been shown that a linear combination of two kernels is a valid kernel provided that the associated weights are all positive. In addition, the linear combination of two kernels leads to a new feature space that is isomorphic to the Cartesian product of the individual feature spaces. The problem now is to find a vector of weights a maximizes the performance of the kernel ka in an image classification task. In the case of histopathology images, different concepts require different classifiers that emphasize the appropriate visual features. Herein we use the kernel alignment strategy to build an adapted kernel function for each concept. Each adapted kernel function is expected to emphasize those visual features that allow to better recognize the presence (or absence) of the corresponding concept in a given image. Kernel-target alignment measures how appropriate a kernel function is for solving a specific classification problem. In particular, the alignment of two kernels with respect to a sample S, is defined as:

$$A_S(k_1, k_2) = \frac{\langle K_1, K_2 \rangle_F}{\sqrt{\langle K_1, K_1 \rangle} \sqrt{\langle K_2, K_2 \rangle_F}} \quad (3)$$

Where, k1, k2 are kernel functions; K1, K2 are matrices corresponding to the evaluation of the kernel functions on a sample S; and h iF is the Frobenius inner product defined as hA; BiF ¼ P i P j AijBij. Given the binary labels for a training set, in which 1 indicates the presence of one selected concept and indicates the absence of that concept in the image, we can build a target function to optimize the kernel alignment measure. Defining y: X{1,1} as the binary label for an image in X, the problem space, the target kernel k⁄ is then defined as k⁄ (x, z) = y(x)y(z). The target kernel k⁄ is the optimal kernel for solving the given classification task, since it explicitly reveals whether the objects x and z are in the same class or not. The goodness of a given kernel k is measured in terms of how much it aligns with the target kernel in a training sample. Formally this is expressed as:

$$A_S^*(k) = A_S(k, k^*) \quad (4)$$

The problem of finding appropriate weights for ka then becomes the problem of finding the weights a that maximize the target alignment this problem is solved by transforming it to an equivalent quadratic programming problem and is the strategy followed in this work. This kernel combination strategy is in fact a type of feature fusion task, but performed at the kernel level, making it an integral part of the learning process. The main advantage is that features are optimally combined during the learning process depending on the particular type of classification problem to be solved. After combining the basic kernel functions, we also composed the resulting kernel with a Radial Basis Function (RBF) to emphasize non-linear patterns in the representation space. Given the optimally combined kernel we use it to compute the RBF kernel as follows:

$$k_C(x,z) = exp(-(k_\alpha^*(x,x) + k_\alpha^*(z,z) - 2k_\alpha^*(x,z))/2\sigma^2) \quad (5)$$

Image Retrieval: Back-End Research

A vast majority of the existing research conducted on image retrieval has focused on the back-end portion of the process. CBIR, RF, AIA, web image search and indexing are some of the key back-end retrieval techniques that have been explored at length. Most of the above-mentioned back-end techniques will be discussed in this section.

Content-based Image Retrieval

CBIR systems emerged to overcome the limitations of the existing text-based image retrieval systems. Digital images that are mined using CBIR systems are most often represented by using a set of visual features. Figure 5 shows that typical CBIR systems generally have two phases: the offline phase and the online phase. The offline phase extracts and stores visual feature vectors retrieved from the images in the database. The online phase enables users to initiate retrieval operations by collecting the query image from the user. In the final step, CBIR systems provide a set of images that are visually similar or relevant to the given query image. This approach has a major drawback due to the initial assumption that semantic resemblance is always represented by visual similarity. The semantic gap (i.e., the gap between higher-level contextual meaning and low-level image features) is the main reason for this problem. Although Yahoo and Google achieved promising results for large-scale applications, addressing and solving the semantic gap issue remains a crucial challenge for CBIR. The increasing popularity of smart devices and social media platforms has acted as an indicator of a required paradigm shift in CBIR research. Research works emphasizing the key components of CBIR systems have been carried out, focusing on image representation, feature extraction, and similarity computation.

Low-level Feature-based CBIR

Several low-level features have been explored for encoding image content for CBIR systems:

Color feature: For CBIR systems, color is the most popular and commonly used low-level descriptor. For color representation, various color spaces have been defined. The color spaces best perceived by humans are - RGB, LUV, HSV, YcrCb etc. For CBIR systems, multiple color descriptors and features have been explored, including color histogram, color coherence vector, color-covariance matrix, etc. Most color feature-based systems are unable to express high-level image semantics. Averaging the color of all pixels in a region as a color feature has been proposed as a solution to this problem; however, this creates another problem by affecting the image quality for subsequent processing.

Texture feature: Texture is one of the most crucial features of an image and is widely used in pattern recognition systems. Compared to color features, texture features can be more meaningful in semantic contexts because of their ability to represent a group of pixels. The difference in texture can be useful in denoting the differences between the areas of images with similar colors. Texture can be of different categorizations. Mainly, it is categorized into two **types:** statistical and structural. However, the shapes of objects that are present in the image determine the semantic representation of the texture features, and these features are sensitive to noise

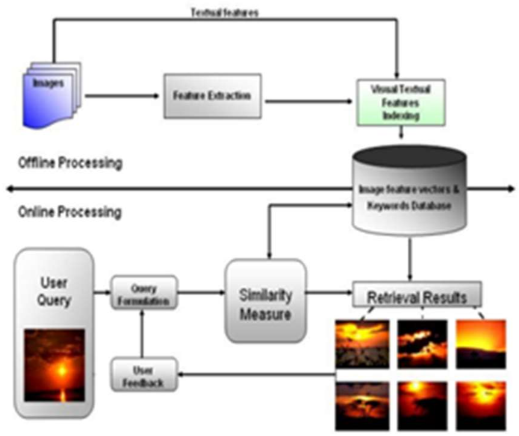


Figure: A typical Content Based Image Retrieval System

Shape feature: Binary images for image retrieval can be achieved through shape-based query image processing. The user provides the query as a shape image, and then features are extracted from the shape and compared with the database features for constructing a CBIR system. A method was proposed in that depend on shape-based queries using contour-based edge points in a binary image environment, working with rotation-invariant features. Developed a mechanism for a shape based CBIR system proposed a technique for a shape-based image retrieval system, which retrieves the shape images from an MPEG7 binary image database to complete the retrieval. Based on signature histograms that are constructed from the border of the objects, also provides a shape based CBIR system

Spatial location: Spatial location is an important feature for CBIR systems. Objects or regions that exhibit similar texture and color properties can be identified and represented using those features. To represent spatial location, the minimum bounding box and the spatial centroid of regions were used in. The problem with these approaches is that the semantic information is not represented effectively. The authors in introduced an image retrieval system that placed emphasis on the spatial relationship between image contents. For image retrieval, modeling of the relationship between image objects is performed. In this approach, objects are initially detected and then the image labels are determined. After that, utilizing the binary patterns, the spatial relationships are coded. Based on the similarity between the binary patterns, a matching score is computed for performing image retrieval.

Addressing the Semantic Gap Problem

Researchers have followed several approaches to develop high-level semantic-based CBIR. Two major groups for these endeavors are supervised and unsupervised learning-based techniques and fusion-based image retrieval techniques. Generally, a single similarity measure is not enough to achieve robust image ranking with significant perceptual meaning. To address this problem, learning-based solutions can be leveraged. To speed up the image retrieval operations, image classification can play a crucial role during the pre-processing phase. On the other hand, for speeding up the retrieval process and enhancing visualization performance for unlabeled images, unsupervised learning can be quite useful.

Supervised and unsupervised learning: Image clustering can be used first to handle unstructured image collections; the subsequent classification techniques along with the distance metrics form the image retrieval process. Previously, most CBIR research focused on similarity metrics and feature extraction techniques. To overcome the scalability problem faced by most CBIR systems while dealing with large digital image databases, clustering and fast classification components have been identified as practical solutions, partitioning images into homogeneous categories unsupervised. Clustering can be categorized into two major types - hard clustering (elements belong to specific groups) and fuzzy clustering (elements share memberships to multiple groups). Recent clustering approaches allow data instances from different clusters to be issued from different density functions. These techniques can be categorized as statistical modeling, relational, and objective-function-based paradigms. Other clustering approaches, such as spectral clustering algorithms, have also been proposed for grouping similar images into homogeneous clusters and then using the achieved partition information to enhance the retrieval process. Objective function optimization techniques have also been explored with popular algorithms like the K-means algorithm. According to various research works , unsupervised learning, that is, clustering techniques becomes more useful when metadata is collected along with visual descriptors. For supervised learning, Bayesian classification has been explored in several research works. Some other researchers have utilized support vector machine (SVM)-based image classification techniques. Moreover, decision tree methods such as ID3, C4.5, and CART have also been explored to predict high-level categories and associate image color features with keywords.

Multimodal fusion and retrieval: Various image retrieval techniques relying on image and text modalities have been proposed. Some fusion techniques that can be useful for image retrieval and image annotation have also been explored. The traditional fusion approach, which requires ground truth for validating the obtained rules, focuses on learning optimal rules for fusing multiple classifier outputs. Another fusion approach formulates multi-modal fusion as a two-fold problem, which proved to be more effective than the naïve approach. This approach first performs statistical modeling of the modalities and then uses unsupervised learning to optimize the solution. The offline-based approach makes the fusion learning approaches more practical. Context-dependent fusion (CDF) is another technique that has been explored. In the CDF approach, initially the training samples are grouped into homogenous context clusters by a local fusion approach.

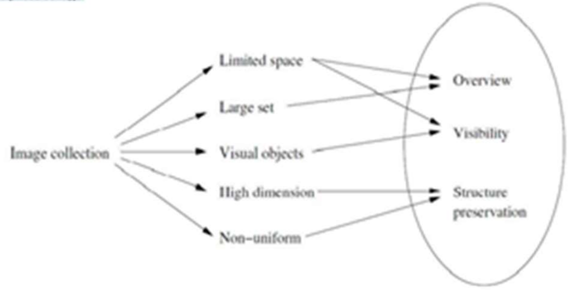
Image mining for CBIR: Image-mining-based CBIR systems execute image retrieval operations based on the similarity between images, which is defined in terms of extracted features. The optimum cluster-based image retrieval approach introduced in leverages the similarity information and improves the interaction of the users with image retrieval systems. The description of images based on color 10 characteristics and compact feature vectors representing typical color distributions is used to create the image index. The system emphasizes reducing the search time and space and creating image clusters using RGB components of color images.

Image Retrieval: Front-End Research

With the rapid growth of image databases, smart and efficient techniques to manage and query large image collections are currently very much in demand. In the previous section, we discussed techniques that mostly emphasize the back-end research of image retrieval. However, due to the emergence of touch-based smart devices, 13 such as smartphones, tablets, and touch screens, lately there have been some front-end research works on image retrieval.

Similarity-based Visualization

A visual overview of the entire image database is provided in most image browsing systems, which are coupled with the required operations for navigating the images of interest. Several research works have proposed image browsing techniques as an effective alternative to back-end based image retrieval systems such as CBIR. Generally, CBIR techniques are useful for users who have clear and specific goals regarding their search items, while similarity based image browsing is more useful for those focusing on surfing or browsing image collections. A major challenge in similarity-based image browsing is arranging the images based on their visual similarities. Researchers have proposed several approaches for browsing images. In the authors used spiral-based and concentric-based representation techniques for displaying similar images, keeping images with more similarity closer to the center. Visualizing an image database by linking similar images using pathfinder networks was proposed. Based on the viewpoints used for capturing photos, community photos were arranged. The authors proposed a different kind of approach by using a dynamically generated photo collage to visualize an image collection. Following the user interactions, an automatic selection of images is performed for composing the photo collage.



Some popularly used visualization schemes for large image collections are as follows –

- Relevance-ordered (Google Images)

- Time-ordered (Timeline and Time Quilt)
- Clustered (Gallery layout with multi-dimensional scaling)
- Hierarchical (Google Image Swirl)
- Composite (Mix of two or more of the above-mentioned ones)

Three modes for visualization in terms of user presentation are –

Static (No motion involved)

Moving (Constant motion

Interactive (Motion triggered during user interaction) considering recognition success and user preference, some researchers stated that static style visualization proves to be more suitable compared to moving presentation

Experimental Setup

Most of the experiments are conducted on a PC with an Intel i7-4770K 3.50GHz CPU with 32GB DDR3 memory, and a GeForce GTX 760 graphics card. However, we used the Tesla K40 GPU card for developing auto encoder models.

The overall view of how the experiments are performed.

Logo Recognition

Feature Detection and Description

Application of CDS to logo detection and recognition requires establishing a matching criterion and verifying its probability of success. Let $R \subset R2 \times R128 \times [-\pi,+\pi] \times R+$ denote the set of interest points extracted from all the possible reference logo images and X a random variable standing for interest points in R. Similarly, we define $T \subset R2 \times R128\times [-\pi,+\pi] \times R +$ as the set of interest points extracted from all the possible test images (either including logos or not) and Y a random variable standing for interest points in T . X and Y are assumed drawn from existing (but unknown) probability distributions. Let's consider SX = {X1, . . . , Xn}, SY = {Y1, . . . , Ym} as n and m realizations with the same distribution as X and Y respectively. To avoid false matches we have assumed that matching between YJ and X is assessed if The intuition behind the strong criterion above comes from the fact that when KYJ |X >> KYj |X , the entropy of the conditional probability distribution K.|X will be close to 0, so the uncertainty about the possible matches of X will be reduced. The reference logo SX is declared as present into the test image if, after that the match in SY has been found for each interest point of SX , the number of matches is sufficiently large (at least τ |SX | for a fixed $\tau \in [0, 1]$, being $1 - \tau$ the occlusion factor tolerated). We summarize the full procedure for logo detection and recognition.

Goals

To discover Conceptual similarity to improve their accuracy and security and to enable the system to retrieve trade-marks' conceptual similarities identify logo similarities using SIFT features in order to prevent logo trademark issues; Use similarity distance to reduce the extra cost of protection.

VI. CONCLUSION

The rising number of cases of fraud and data similarities, which information retrieval systems are not equipped to deal with because of their similarities to trademarks, served as the impetus for this effort. The focus on similarities throughout the process of trademarking, which becomes apparent when more than two or more trademarks have an equivalent or significant semantic implant; the benefits and drawbacks of using each data similarity reflow technique are outlined below. The operation of the system, as well as conceptual similarities across trademarks such as equal or pertinent semantic implant the desire for a hypothetical model of trademark retrieval is dependent on the hypothetical similarity of the two marks. The primary language processing technique, data channels, and lexical resources for determining the degree of hypothetical similarity between several trademarks

The system is being stimulated for the improvement of fraud cases that are best on data processing similarities, where the data retrieval system does not manage this particular set of difficulties. The system makes improvements to the existing trademarks find system by legislating and applying rectifications to the discover process for hypothetically identical trademarks. In order to determine the degree of conceptual similarity that exists between two trademarks, the system makes use of natural language processing algorithms, knowledge sources, and a lexical resource. Verify furthermore that the comparison of the trademarks in terms of their conceptual similarities. A future piece of work to increase the accuracy of the suggested semantic algorithm ought to include a study comparing the application of different lexical resources.

This effort was inspired by fraud, data similarities (which IR systems can't handle), and trademark similarity. Trademark similarity and semantic reflow are state-of-the-art. Two trademarks with comparable semantic implantation are emphasized. Reflow data similarity's pros and cons are examined. Trademark similarities praise semantic insertion. TM retrieval model; using lexical, knowledge, and NLP, the model compares two trademarks. Analyze trademarks. Focusing on theoretically relevant trademarks helps trademark search engines. Comparing lexical resources will improve algorithm accuracy.

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