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CONTENT BASED IMAGE RETRIEVAL WITH SURF, COLOR HISTOGRAM, SVM AND NN

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Abstract: *Here present an efficient algorithm depend on SURF (Speeded up Robust Features), color histogram, SVM and NN. This method applies the SURF algorithm in the detect and description for images feature; first it applies the SURF feature detector in extracting reference images and matching feature points in the image, respectively. At last in the process of feature points matching; the false matching points are eliminated through this approach. Finally; according to the rest of the match point; it can estimate the space geometric transformation parameters between two images and thus matching process is completed. Here, use SURF algorithm to detect and descript the interest points; and match the interest points by using Surf [1,3]. In this thesis, the same is tried to retrieve with the use of SURF and fed into Support Vector Machine (SVM) and color histogram for further classification. SURF is fast and robust interest points detector which is used in many computer vision applications. To further enhance result use NN technique. To using these techniques to enhances the previous result.*

Keywords: *Matching, Image processing, Surf, Color histogram, NN and SVM*

I. INTRODUCTION

The image matching methods can be roughly divided into two classes; one is the image matching based on image matching and feature matching. Matching method is directly use the figure grey value to determine the space geometry transform between the images, this method can make full use of the information of the figure, so this is also known as the matching method based on integral figure content; it has no feature detection steps; in the feature matching stage; the fixed size window and even whole image matching are adopted in estimation; so the calculation is simple and also easy to be performed. In modern era, very large collections of figure and videos have grown fast. In parallel with this growth the con-tent based retrieval and querying the indexed collections are required to access visual information. Therefore two of the main components of the visual information are texture and colour. The history of the content-based image retrieval can be divided into three phases:

- The retrieval based on artificial notes.
- The retrieval based on vision character of image contents.
- The retrieval based on image semantic features.

The image retrieval that is depend upon artificial notes labels images by using text firstly; in fact it has already vary figure retrieval into traditional keywords retrieval. Problem with the algorithm is that; this brings heavy workload and on the other hand; it still remains subjectivity and uncertainty. Therefore the image retrieval that is based on artificial notes still remains insufficiency, the farther study that adapts vision image features has been come up and become the main study. Then character of this method is image feature extraction impersonally; whether the retrieval is good or not depends on the accuracy of the features extraction. Therefore the research depend on vision features is becoming the focus in the academic community. This feature of vision can be classified by semantic hierarchy into middle level feature and low- level feature. Low-level feature contain colour; texture and inflexion. The middle level contains shape description and object feature. Content based Image Retrieval systems try to retrieve images similar to a user-defined specification or pattern (e.g., shape sketch, image). And their goal is to support image retrieval based on content properties

(e.g., shape, colour, texture), usually encoded into feature vectors [4,5,7]. One of the main advantages of the CBIR approach is the possibility of an automatic retrieval process; instead of the traditional keyword-based approach; which usually requires very laborious and time-consuming previous annotation of database images.
The paper describes as in section II tell about CBIR and in section III gives ideas about SURF technique. Thus in section IV give information about SVM and in section V describe about NN. In section VI discuss the result and at last in section VII discuss the conclusion.

II. CBIR

As processors become increasingly powerful; and memories become increasingly cheaper; the deployment of large image databases for a variety of applications have now become realisable. And databases of art works; satellite and medical imagery have been attracting more and more users in various professional fields. Therefore effectively and efficiently accessing desired images from large and varied image databases is now a necessity. ***CBIR*** or ***Content Based Image Retrieval*** is the retrieval of images based on visual features such as colour; texture and shape. And reasons for its development are that in many large image databases; traditional methods of image indexing have proven to be insufficient; laborious; and extremely time consuming. Therefore these old methods of image indexing; ranging from storing an image in the database and associating it with a keyword or number; to associating it with a categorized description; have become obsolete [8,9,12]. This is not ***CBIR***. In CBIR; each image that is stored in the database has its features extracted and compared to the features of the query image. This involves two steps:
1. Feature Extraction: The first step in the process is extracting image features to a distinguishable extent.
2. Matching: The second step involves matching these features to yield a result that is visually similar[7].

III. SPEEDED UP R0BUST FEATURE (SURF)

SURF (Speeded up Robust Features) is a robust local feature detector. This is partly inspired by the SIFT descriptor. Therefore standard version of SURF is several times faster than SIFT and claimed by its authors to be more robust against different image transformations than SIFT. And SURF is based on sums of 2D Haar wavelet responses and makes an efficient use of integral images. This uses an integer approximation to the determinant of Hessian blob detector; which can be computed extremely quickly with an integral image (3 integer operations). This uses the sum of the Haar wavelet response around the point of interest. These can be computed with the aid of the integral image. SURF used in this approach to extract relevant features and descriptors from images. This approach is preferred over its predecessor due to its succinct descriptor length i.e. 64 floating point values. In SURF, a descriptor vector of length 64 is constructed using a histogram of gradient orientations in the local neighborhood around each key point. Modified SURF (Speeded up Robust Features) is one of the famous feature-detection algorithms [11,17]. This process is divided in the following steps: first; get feature descriptor of the image using modified SURF; secondly; find matching pairs; using correlation matrix; and remove the mismatch couples by RANSAC(Random Sample Consensus); then; adjust the images by bundle adjustment and estimate the accurate homographic matrix; lastly; blend images by Alpha blending. And comparison of SIFT (Scale Invariant Feature Transform) and Harris detector are also shown as a base of selection of image matching algorithm. And according to the experiments; the present system can make the stitching seam invisible and get a perfect panorama for large image data and it is faster than previous method. SURF approximates or even outperforms previously proposed schemes with respect to repeatability; distinctiveness; and robustness; yet can be computed and compared much faster. And this is achieved by relying on integral images for image convolutions; by building on the strengths of the leading existing detector sand descriptors specially, using a Hessian matrix-based measure for the detector; and a distribution-based descriptor and by simplifying these methods to the essential [18,20]. This leads to a combination of novel detection; description; and matching steps. It approximates or even outperforms previously proposed schemes with respect to repeatability; distinctiveness; and robustness; yet can be computed and compared much faster. At last it is achieved by;

- Relying on integral images for image convolutions
- Building on the strengths of the leading existing detectors and descriptors (using a Hessian matrix-based measure for the detector; and a distribution based descriptor).
- Simplifying these methods to the essential. Therefore this leads to a combination of novel detection; description; and matching steps [20]

IV. SUPPORT VECTOR MACHINE

The Support Vector Machine (SVM) is a state-of-the-art classification method. The SVM classifier is widely used in bioinformatics (and other disciplines) due to its highly accurate; able to calculate and process the high-dimensional data such as gene expression and exibility in modeling diverse sources of data. SVMs related to the general category of kernel methods. And a kernel method is an algorithm that depends on the data only through dot-products. This is the case; the dot product can be replaced by a kernel function which computes a dot product in some possibly high dimensional feature space. It has two advantages: First; the ability to generate non-linear decision boundaries using methods designed for linear classifiers. And second; the use of kernel functions allows the user to apply a classifier to data that have no obvious fixed-dimensional vector space representation. Thus prime example of such data in bioinformatics are sequence; either DNA or protein; and protein structure. Using SVMs effectively requires an understanding of how they work. When training an SVM the practitioner needs to make a number of decisions: how to preprocess the data, what kernel to use; and finally; setting the parameters of the SVM and the kernel [1]. Uninformed choices may result in severely reduced performance. Therefore we aim to provide the user with an intuitive understanding of these choices and provide general usage guidelines [7,13]. All the examples shown were generated using the PyML machine learning environment; which focuses on kernel methods and SVMs.

A. PRELIMINARIES: LINEAR CLASSIFIERS

Support vector machines are an example of a linear two-class classifier. This section explains what that means. Then data for a two class learning problem consists of objects labeled with one of two labels corresponding to the two classes; for convenience we assume the labels are +1 or -1. In what follows boldface x denotes a vector with components xi. Thus notation xi will denote the ith vector in a dataset, f(xi; yi)gni =1, where yi is the label associated with xi. The boundary between regions classified as positive and negative is called the decision boundary of the classifier. The decision boundary defined by a hyper plane is said to be linear because it is linear in the input examples. A classifier with a linear decision boundary is called a linear classifier. Then conversely; when the decision boundary of a classifier depends on the data in a non-linear the classifier is said to be non-linear.

B. KERNELS: FROM LINEAR TO NON-LINEAR CLASSIFIERS

In many applications a non-linear classifier provides better accuracy. Yet; linear classifiers have advantages; one of them being that they often have simple training algorithms that scale well with the number of examples [9, 10]. This begs the question: Can the machinery of linear classifiers be extended to generate non-linear decision boundaries? Therefore furthermore; can we handle domains such as protein sequences or structures where a representation in a fixed dimensional vector space is not available? The naive way of making a non-linear classifier out of a linear classifier is to map our data from the input space X to a feature space F using a non-linear function.

The quadratic complexity is feasible for low dimensional data; but when handling gene expression data that can have thousands of dimensions; quadratic complexity in the number of dimensions is not acceptable. And Kernel methods solve this issue by avoiding the step of explicitly mapping the data to a high dimensional feature-space.

Gaussian kernel is defined by:

$$K(\mathbf{x_i},\mathbf{x_j}) = \exp\left(-\frac{\left\|\mathbf{x_i}-\mathbf{x_j}\right\|^2}{2\sigma^2}\right) \qquad (2)$$

Where k > 0 is a parameter that control the width of Gaussian. It plays a similar role as the degree of the polynomial kernel in controlling the exibility of the resulting classifier. We saw that a linear decision boundary can be kernelized i.e. its dependence on the data is only through dot products. In order for this to be useful, the training algorithms need to be kernelizable as well [6]. It turns out that a large number of machine learning algorithms can be expressed using kernels | including ridge regression, the perceptron algorithm, and SVMs [16].

V. COLOR HISTOGRAM

In figure processing and photography; a color histogram is a presentation of the distribution of colors in an image. To digital figures; a color histogram represents the number of pixels that have colors in each of a fixed list of color ranges that span the image’s color space; the set of all possible colors. Then color histogram can be made for any kind of color space; although the term is most often used for three-dimensional spaces like RGB or HSV. To monochromatic figures; the term intensity histogram may be used instead. To the multi-spectral figures; where each pixel is represented by an arbitrary number of measurement; the color histogram is N-dimensional; with N being the number of measurements taken. Therefore each measurement has its own wavelength range of the light spectrum; some of which may be outside the visible spectrum. And if the set of possible color values is sufficiently small; each of those colors may be placed on a range by itself; then the histogram is merely the count of pixels that have each possible color. Thus most often; the space is divided into an appropriate number of ranges; often arranged as a regular grid; each containing many similar color values. Then color histogram may be presented and displayed as a smooth function defined over the color space that approximates the pixel counts. And like different kinds of histograms; the color histogram is a statistic that can be viewed as an approximation of an underlying continuous distribution of colors values. Therefore color histograms are flexible constructs that can be built from images in various color spaces, whether RGB, chromaticity or any other color space of any dimension. Histogram of a figure is produced first by discretization of the colors in the image into a number of bins; and counting the number of image pixels in each bin. Take example; a Red–Blue chromaticity histogram can be formed by first normalizing color pixel values by dividing RGB values by R+G+B, then quantizing the normalized R and B coordinates into N bins each.

VI. NEURAL NETWORKS

Artificial neural networks may either be used to gain an understanding of biological neural networks; or for solving artificial intelligence problems without necessarily creating a model of a real biological system. Then real; biological nervous system is highly complex: artificial neural network algorithms attempt to abstract this complexity and focus on what may hypothetically matter most from an information processing point of view. Good performance (e.g. as measured by good predictive ability; low generalization error); or performance mimicking animal or human error patterns; can then be used as one source of evidence towards supporting the hypothesis that the abstraction really captured something important from the point of view of information processing in the brain. The other incentive for these abstractions is to reduce the amount of computation required to simulate artificial neural networks; so as to allow one to experiment with larger networks and train them on larger data sets. Therefore application areas of ANNs include system identification and control game-playing and decision making (backgammon, chess, racing) pattern recognition; sequence recognition (gesture, speech, handwritten text recognition) medical diagnosis; financial application; data mining (or knowledge discovery in databases; "KDD") visualization and e-mail spam filtering.

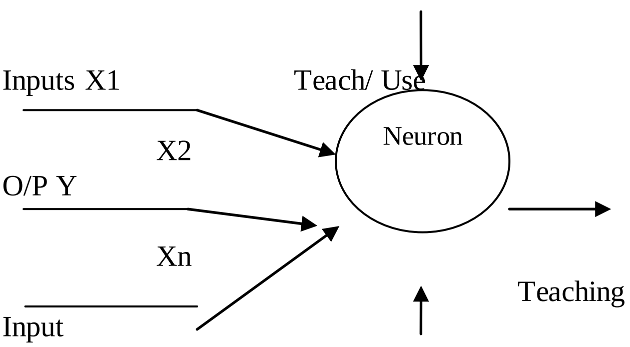

Figure 1: Simple ANN

A. Architecture of artificial neural network

The basic architecture consists of three types of neuron layers- input; hidden; and output. And in feed-forward networks; the signal flow is from input to output units; strictly in a feed-forward direction. Then data processing can extend over multiple layers of units; but no feedback connections are present. The recurrent networks contain feedback connections. The contrary to feed-forward networks; the dynamical properties of the network are important. Therefore in few cases; the activation values of the units undergo a relaxation process such that the network will evolve to a stable state in which these activations do not change anymore.

B. Feed Forward Neural Networks

Feed-forward ANNs allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Thus feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. And they are extensively use in pattern recognition. It is a type of organisation is also referred to as bottom-up or top-down. Then single-layer perceptron; multilayer perceptron and radial basis function are types of feed forward neural networks.

VII. RESULT DISCUSSION

The following figures show the result of the CBIR by using SURF, COLOR HISTOGRAM, SVM and NN. This technique gives better result as compare to previous techniques.

After obtaining all the necessary terms, SURF,SVM and colour histogram , for a number of images in our database; implemented the results in the final equation. Surprisingly a number of inconsistencies kept appearing in terms of the colour distances between certain images. After using the colour histogram technique along with SURF And SVM, we get improvement in Accuracy as given below.

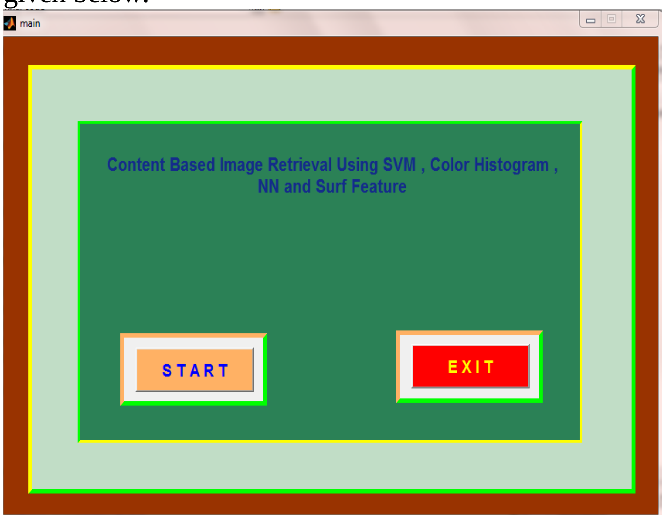

Figure 2: GUI layout

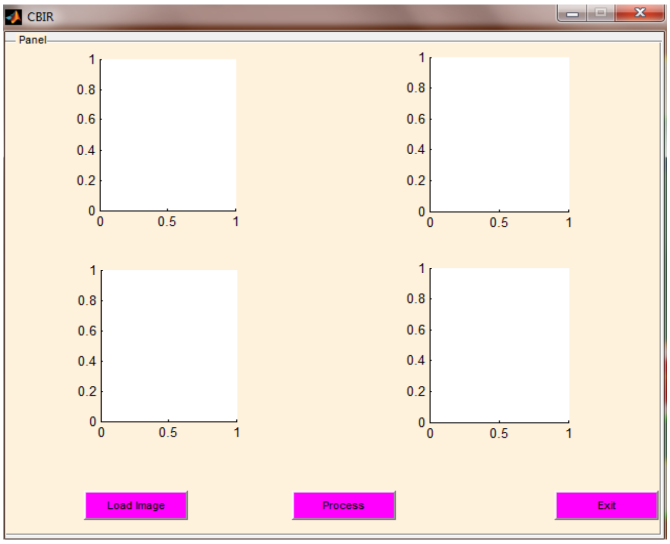

Figure 3: GUI layout after clicking start button

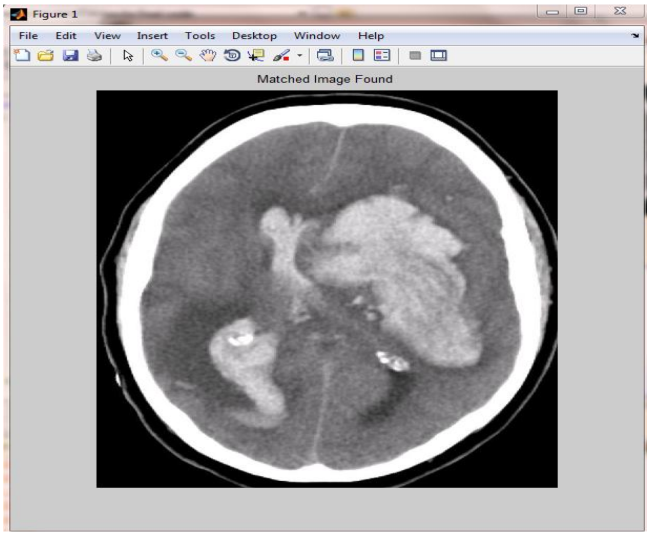

Figure 6: Matched image

Figure 4: Loading original image

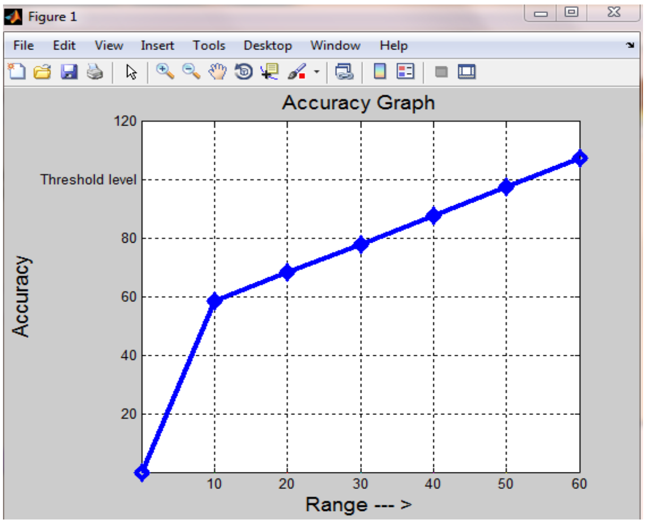

Figure 7: accuracy graph

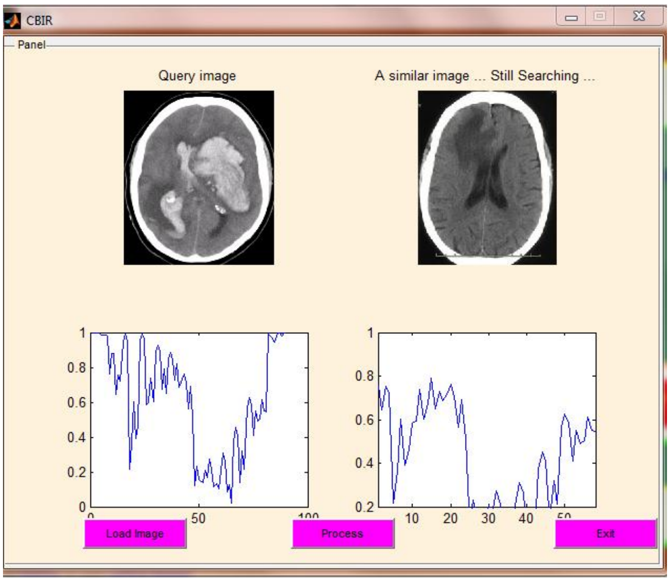

Figure 5: After processing the image

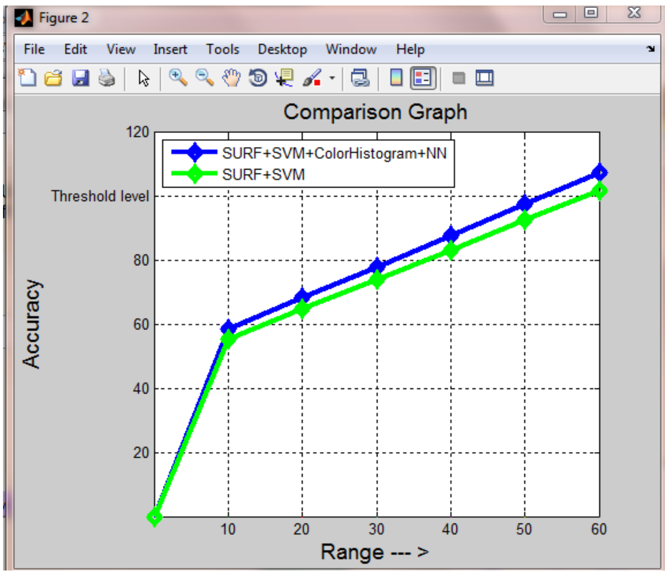

Figure 8: Comparison graph between previous and propose technique

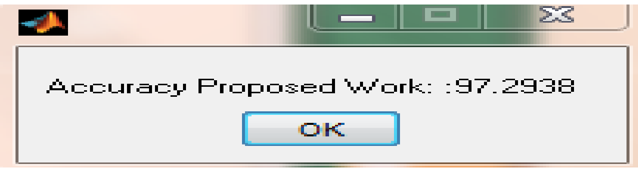

Figure 9: Accuracy value

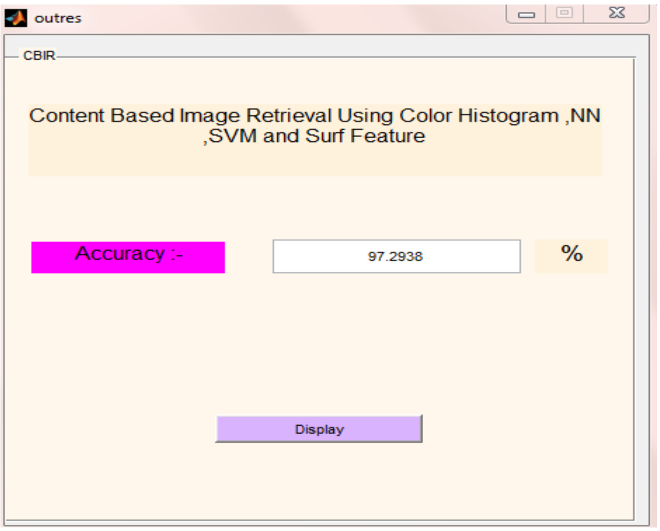

Figure 10: GUI layout with accuracy

The above figure shows the result CBIR by using SURF, color histogram, SVM and NN. The propose technique has good accuracy as compare to previous technique its accuracy up to 97.2938% from figure 10.

VIII. CONCLUSION

Proposed a technique for figure Matching depended up on SURF Algorithm using SVM Classifier, NN feed forward and color histogram. Content-Based Image Retrieval (CBIR) is a challenging work which retrieves the similar figures from the large database. At last most of the CBIR system uses the low-level features such as color; texture and shape to extract the features from the images. Many CBIR techniques have been proposed earlier but they were not good enough and can be temporarily tampered with so the work was not fulfilled. CBIR alone with Surf and SVM Method could not provide better results. Therefore use CBIR with Surf, SVM, NN and color histogram providing enhance results. Better accuracy results of Content Based Image Retrieval with Surf, SVM color histogram and NN.

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