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RETREIVAL OF CONTENT BASED HISTOLOGY IMAGES USING MULTIFEATURE FUSION MODEL

[1] P.PAVITHRA, [22]R.KARTHIKA, [3]P.GOKILA
Sri Krishna College of Technology. Coimbatore. -641042.
[1] UG student (CSE), E-Mail ID: pavigpm@gmail.com
[2] UG student's (CSE), E-Mail ID: karthikasriskct@gmail.com
[3] Assistant Professor (CSE), E-Mail ID: p.gokila@skct.edu.in

Abstract — **Content Based Image Retrieval plays a major role in medical activities, education field and in research areas. Feature combination plays a significant role in Content Based Image Retrieval. The aim of this system is to obtain the most representative fusion model for a particular keyword that is associated with multiple query images by automatically combining heterogeneous visual features. The core approach of the system is Multiobjective learning method which aims at understanding the concept of optimal visual-semantic matching function by jointly considering the different preferences of the group of images. In this system, a new strategy called Multiobjective Optimization strategy is employed in order to handle contradictions which arise in the query images associated with the same keyword.**

Index Terms — Multifeature Fusion Model, Multiobjective Optimization, Pareto Archived Evolution Strategy (PAES).

I. INTRODUCTION

A. Image Processing

Image processing is any form of signal processing for which the input is such as a picture or audio-visual frame, the output of image processing may be either an image or a set of characteristics or parameters related to the image. Closely related to image processing are computer graphics and workstation vision. In computer visuals, images are physically made from physical representations of matters, environs, and lighting, as an alternative of being acquired (via imaging devices such as cameras) from normal scenes, as in greatest animated cinemas. Computer visualization, on the other hand, is often measured high-level image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images (e.g., videos or 3D full-body magnetic resonance scans).

The main topics within the arena of image processing include:

- Image restoration-The process of taking an image with some known, or estimated degradation, and restoring it to its original appearance.
- Image enhancement-Involves taking an image and improving it visually. One of the simplest

enhancement techniques are to simply stretch the contrast of an image.

- Image compression-Involves decreasing the classically enormous amount of data by eliminating data that are visually unnecessary and by taking advantage of the redundancy that is inherent in most images.

Image Processing involves

- Image Acquisition
- Image Enhancement
- Image Restoration
- Colour Image processing
- Image preprocessing
- Image Compression
- Image Segmentation
- Object Recognition

B. Image Mining

Image Mining deals with the extraction of implicit information, image data connection, or further patterns not explicitly stored in the images. It is an interdisciplinary endeavor that draws upon expertise in computer vision, image processing, image retrieval, data mining, machine learning, database, and artificial intelligence. There are two key methods. The first method is to mine as of large collections of images alone and the second approach is to mine from the combined collections of images and associated alphanumeric data. It uses rule mining to discover associations between structures. Image indexing and Retrieval, Image segmentation and extraction are two of the principle task in image mining. They are categorized as content-based technique. Efficient image browsing searching and retrieval tools are required by users from various domains, including remote sensing, fashion, medicine, architecture, crime prevention, publishing, etc. There are two frameworks for retrieval: text-based and content-based. The increase in computing power and electronic storage capacity has led to an exponential increase in the amount of digital content available to users in the form of images and video, which form the bases of much entertainment, educational and commercial uses. Consequently, the search for the relevant information in the large space of image and video databases has become more challenging. The processes involved in image mining are

- Image preprocessing
- Transformation and feature Extraction
- Mining and Interpretation

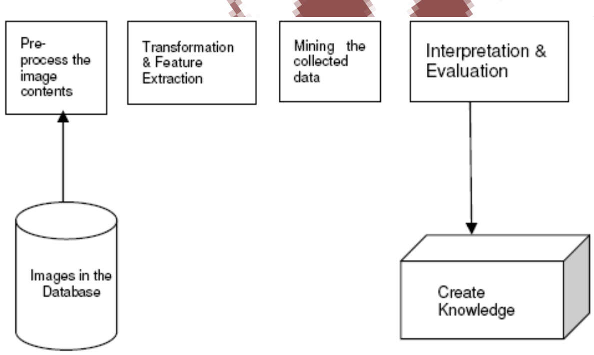


Fig 1.1 Processes in Image Mining

C. Content Based Image Retrieval:

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databanks. Content-based means that the examiner will investigate the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image.

CBIR is desirable because most web based image search engines rely purely on metadata and this produces a lot of garbage in the outcomes. Also having humans physically enter keywords for images in a large database can be ineffective, classy and may not capture every keyword that defines the image. Thus a system that can screen images based on their content would provide better indexing and return more accurate results. In CBIR, images are automatically indexed by summarizing their visual contents through automatically extracted quantities, or features, such as color, texture or shape. Thus, low-level numerical features, mined by a computer, are replaced for higher-level, text-based, physical annotations or keywords.

In inception of CBIR, many techniques have been developed along this direction and many rescue systems, both study and viable, have been built. Low-level features such as colors, textures and shapes of objects are widely used for CBIR. However, in specific uses, such as medical imaging, low-level features play a substantial role in defining the content of the data. A typical content based image retrieval system is depicted in Fig 1.2.

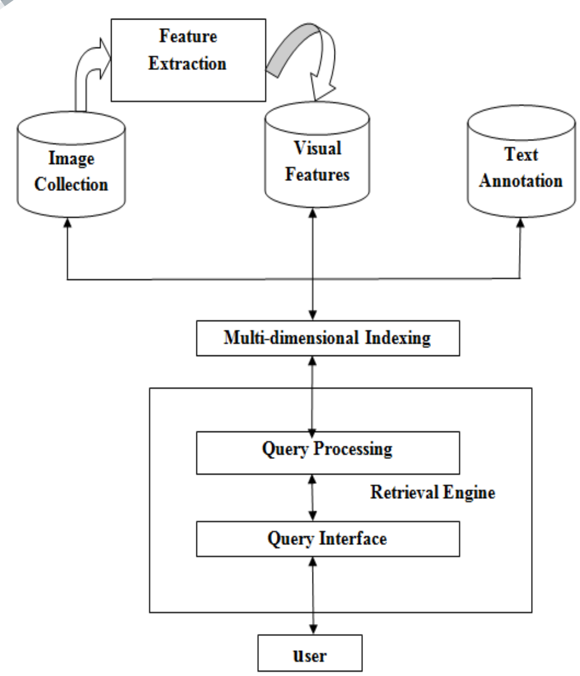


Fig 1.2 Image Retrieval System Architecture

II. EXISTING SYSTEM

A. Content Based Image Retrieval for Histology Image Collection Using Visual Pattern Mining

1) Methodology

For Image Collection purpose BOF is adapted for Text Categorization and Text Retrieval. The significant idea is the creation of a codebook i.e. the visual vocabulary is codified as code words. The four steps to classify images using a BOF representation: (1) feature extraction and representation, (2) codebook construction, (3) the BOF representation of images, and, finally, (4) training of learning algorithms. Three Strategies have been considered for the visual word construction

- First Strategy uses raw block
- Second uses SIFT
- Third strategy involves DCT

The visual dictionary or codebook is built using a clustering or vector quantization algorithm applied to learn a set of representative visual words from the whole collection. The k-means algorithm is used in this work to find a set of centroids that correspond to the code words. The density matching property of vector quantization is employed here to identify the density of high-dimensioned data i.e. commonly occurring data. In data mining, k-means clustering is a technique of cluster analysis which aims to partition n observations into k clusters. Feature selection is the technique of selecting a subset of relevant features for building robust learning models. The main goal of the Visual pattern Mining is to find visual patterns that can be associated with the high-level annotations. Classification is a data mining function that assigns items in a collection to target categories or classes used to accurately predict the target class for each case in the data. Automatic image annotation is the process by which a computer system automatically assigns metadata in the form of captioning or keywords to a digital image.

2) Limitations

- Clustering algorithm has not a great influence in the classification of natural images compared with a random selection of code words.
- Though the annotation task the method showed a competitive performance: an increase of 47% in the histology data set, it is very difficult task.
- Histology pictures are chiefly difficult to analyze because of their high variability and complex visual structure.

C. Content-Based Histopathology Image Retrieval Using a Kernel-Based Semantic Annotation Framework

1) Methodology

The problem of automatic image annotation using kernel methods, causing in a cohesive framework that includes:

- Multiple features for picture representation,
- A feature integration and selection mechanism
- An automatic semantic image annotation strategy.

Pathology concepts are characterized by different types of features including colors, textures and edges. Given two images, a resemblance measure may be considered by applying a kernel function to a pair of images represented by a particular type of feature histogram. In our kernel-based framework visual features can have arbitrary structure as long as they are provided with a valid kernel function. We estimated the Identity Kernel and the Histogram Intersection Kernel to process histogram features. Representing non-linear patterns using RBF Kernel is especially useful in image classification tasks, wherever learning algorithms want to distinct complex regions in the feature space. The approach generates multiple annotations according to the visual contents, allowing extending the functionality to new required search terms (Query by example paradigm).

The method uses machine learning to translate non-linear patterns in visual feature spaces into a more explicit semantic format that is used to rank images efficiently.

2) Limitations

- In this paper we report the tricky of semantic image retrieval for histopathology images, using an automatic annotation strategy.
- The combination approach which includes the automatic weighting of features following a kernel alignment strategy did not show a significant improvement in the final performance.

D. Problem Definition

Content based Image Retrieval plays a major role in Histology image Retrieval. Several projects have been carried out for the image retrieval by considering single features or kernel functions. The existing system often relies on tags associated with the images and the single low level features. Because of the single low level features, accuracy is often limited due to the unreliable outputs from the feature metrics. If two different features are being compared with the similar metric, their scale, domain and distribution may be entirely dissimilar due to the intrinsic descriptor nature. In order to avoid this, a late fusion strategy is employed. But it would not work out because they assume equal importance of features in fusion. There are several issues regarding Histology image retrieval. To resolve these issues, mutifeature fusion model is employed to retrieve histology images.

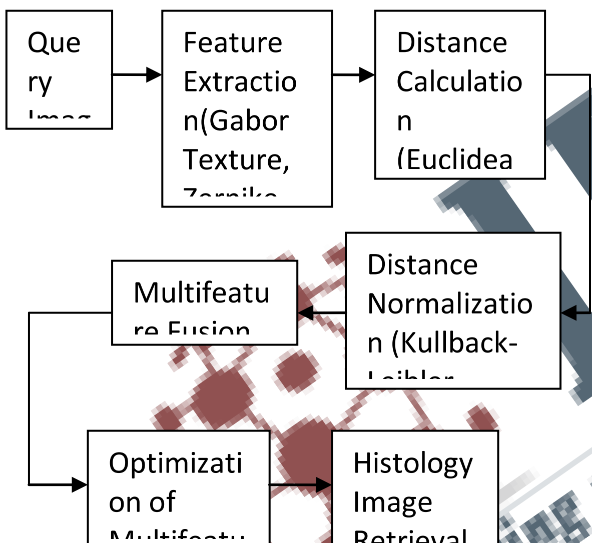


Fig 1.3 Block diagram of Histology Image Retrieval

E. Proposed Methodology

Histology image retrieval method aims at retrieving images with relevant semantic meanings based on pictorial content. In individually query process, the user initially has in mind a semantic term that can be associated with a exact keyword, and then uses multiple query images that represent the semantic term for retrieving more images that are relevant to the query on the semantic level. In the future method, we use multiple images, a representative query group, in the CBIR method for demonstrating individual semantic term. The main focus of the proposed approach is to derive a fusion model for heterogeneous visual features. The proposed approach is able to automatically learn the relative importance of each feature space corresponding to the keyword from its associating representative query group. The learning of a suitable feature fusion model is posed as an optimization problem. The optimization is approved out using a multiobjective learning (MOL) method, which involves a multiobjective optimization (MOO) strategy. The main advantage in the MOL method is that it is able to find a multifeature model that can simultaneously encapsulate differ-end aspects of the most representative visual patterns for individual concept, without however conveying fixed relevance factors to each feature.

III. DESIGN METHODOLOGY

A. Feature Extraction

The extraction and analysis of useful visual features in histology images are an essential step. In this research is on discussing how to obtain suitable fusion models of features. The proposed multi feature combination approach is independent of selected features or their distance metrics. Evaluation of different features is out of the scope of this research. Due to the nature of this particular dataset of histology images, texture features are suitable for analyzing their visual patterns. In this examination, we designated some commonly used texture features together with architectural features due to their prominent characteristics for histology image analysis. Without losing generality, the eight features selected here to describe histology image contents Gabor textures, Tamura textures, Zernike moments, Scale-invariant feature transform (SIFT)-based dictionary, Discrete cosine transform (DCT) dictionary[9], Gray-level co-occurrence matrix (GLCM), MPEG-7 edge histogram (EH), MPEG-7 Homogeneous textures (HT). Unless specified otherwise, these features are extracted from 3×3 blocks of an image and then concatenated into one feature vector for that image.

1) *Gabor textures (GT):*

Gabor filters possess an outstanding ability of filtering in the spatial and frequency domain. Gaussian harmonic function is used, and seven different frequencies, freq = [1, 2, . ., 7], are considered to compute seven descriptor values per block providing 63 descriptors.

2) *Zernike moments (ZMs):*

ZMs have many necessary properties, such as rotation invariance, robustness to noise, expression efficiency, fast computation, and multilevel illustration for telling the shapes of patterns. The absolute values of the coefficients of the Zernike polynomial approximation are computed per block, providing 72 descriptors in each region.

3) *Scale-invariant feature transform (SIFT)-based dictionary:*

SIFT feature is known for its ability in handling intensity, rotation, scale and affine variations. Each block in the process is represented by the rotation-invariant feature descriptor, using a histogram of 128 bins.

4) *Discrete cosine transform (DCT) dictionary:*

DCT histograms are invariant to translation and rotation. Each block is represented by the coefficients of the DCT, applied to each channel of the RGB colour space. The 21 most significant coefficients per channel are preserved.

B. Distance Calculation and Normalization

In this module feature distances are calculated using a specifically defined distance metric of each feature space and then, all the obtained distances are normalized. The Statistical Normalization is computed as

d=$\frac{d'-\mu}{\sigma}$

The distribution of distances might be more precisely approximated using other probability distribution functions (PDFs). Finally, to select the best distribution approximation for the underlying data, the Kullback Leibler (KL) divergence is evaluated between the histogram of actual distances and the estimated PDF. The KL Divergence is calculated by using the formula

$$D_{\mathrm{KL}}(P\|Q) = \int_{-\infty}^{\infty} p(x) \ln \frac{p(x)}{q(x)}\, \mathrm{d}x,$$

In this research, six types of PDFs are considered, including Normal, Gamma, Laplace, Log-norm, Rayleigh, and Exponential. The goal of normalization is to guarantee the appropriateness of comparing different measurements that differ in scale and domain, though preserving the underlying features of the data. In this research, distance metrics computed from different image features are normalized based on the fitted probability density functions for their corresponding feature spaces.

C. Optimal Representation of a Semantic Keyword

In this system a group of query images, referred to as the representative query group, to approximate a suitable representation for one keyword. For a given keyword, let us use RCG to denote a representative group, where G is the complete image set. To improve the discriminative power of the low-level features, two kinds of representative query samples are considered. R+ contains the most relevant samples for the corresponding keyword, referred to as positive group; R− represents negative group in which the samples are irrelevant to the keyword of concern but may look similar to the positive query samples; R = R+ Ụ R−. If new histology keywords are added or the database is populated with new images in new theories, new illustrative query groups for the incoming concepts need to be generated.

The Optimization of fusion model is achieved by MOO Strategy. Taking in to the consideration of single objective function, MOO strategy is to find general optimum across several conflicting objectives. Hence it is widely used in the real-life optimizations.

D. Multifeature Image Ranking and Retrieval

The aim of MOL method is to define a suitable multi feature model for the visual representation of a specific histological keyword and it retrieves images based not only on the words that are part of the query, but also cogitates the outstanding attributes within the vocabulary that could potentially provide information about the query. This algorithm usually generates a set of potential Pareto optimal solutions Φ = {A1,A2,A3, ...}. Thus, a second step is required to decide which one of these solutions is the most appropriate or feasible. The meaning of optimum in our particular task can be described as to find the "optimal" multifeature distance in which all the points representing the positive samples in the target multi feature space are closely gathered around the generalized centroid while the points for the negative samples are randomly scattered around the generalized centroid.

In this system PAES is used since it performed well on a range of multiobjective optimization tasks when compared with Niched Pareto generic algorithm and non-dominated sorting genetic algorithm. After obtaining optimal multifeature distance fusion model of an image, histology images can be ranked and retrieved based on the multifeature distances with respect to the query keyword.

IV. IMPLEMENTATION AND RESULT

Implementation of Feature Extraction

1) Gabor Feature

INPUT IMAGE OUTPUT IMAGE

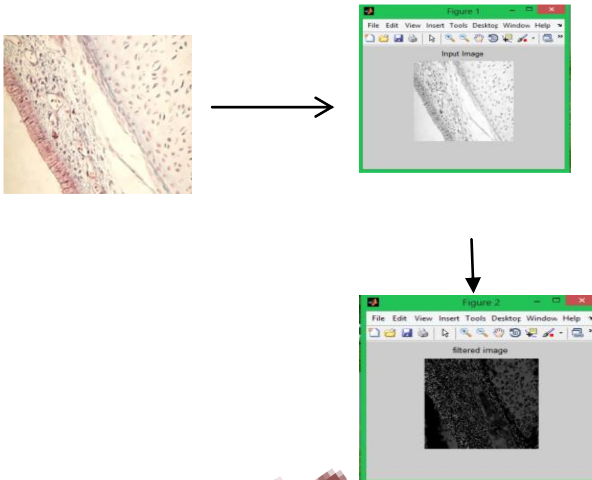
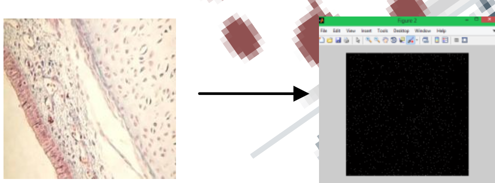


Fig 4.1 Gabor Feature Extractions

2) Scale Invariant Feature Transform

INPUT IMAGE OUTPUT IMAGE



3) Discrete Cosine Transform

INPUT IMAGE OUTPUT IMAGE

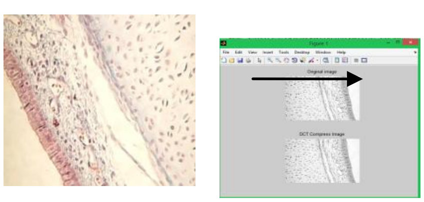


Fig 4.2 SIFT and DCT Feature Extraction

4) Zernike Moments

INPUT IMAGE OUTPUT IMAGE

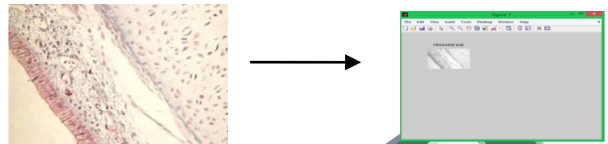


Fig 4.3 Zernike Moments Feature Extraction

5) Implementation of Distance Calculation

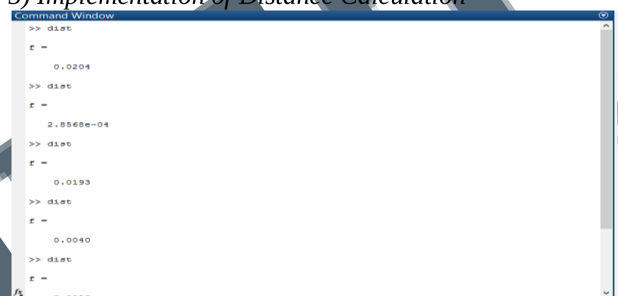


Fig 4.4 Distance Calculation from the extracted features

6) Implementation of Distance Normalization

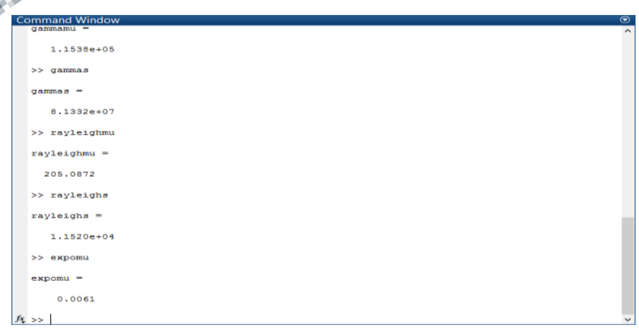


Fig 4.5 Calculation of Parameters in PDF

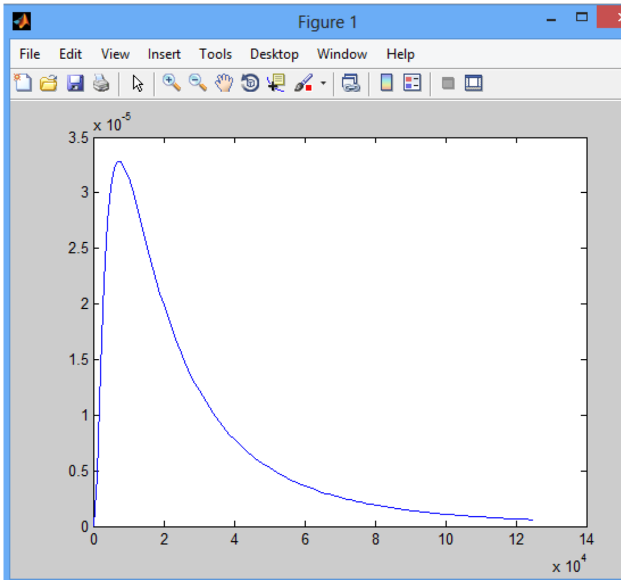


Fig 4.6Log-Normal Distribution

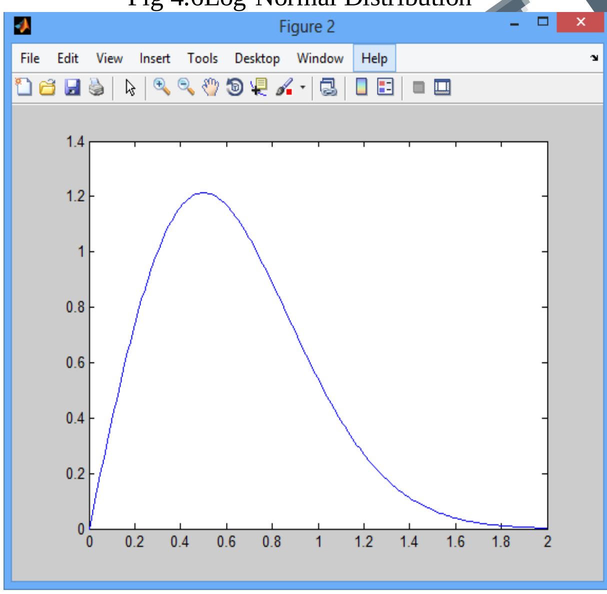


Fig 4.7 Rayleigh Distribution

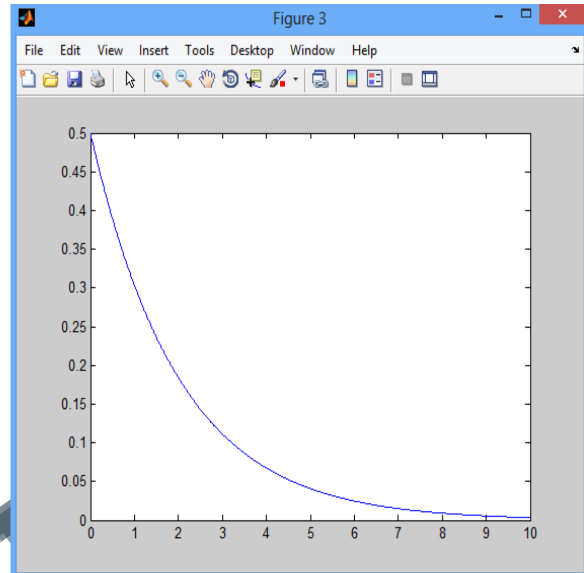


Fig 4.8 Exponential Distribution

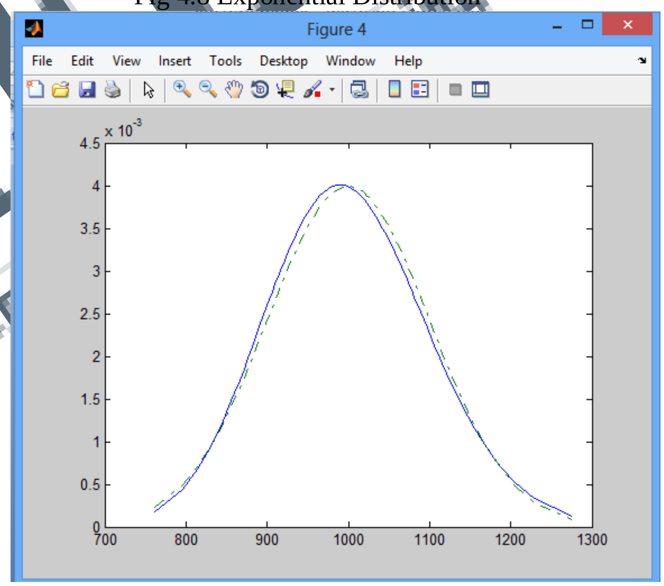


Fig 4.9 Gamma Distribution

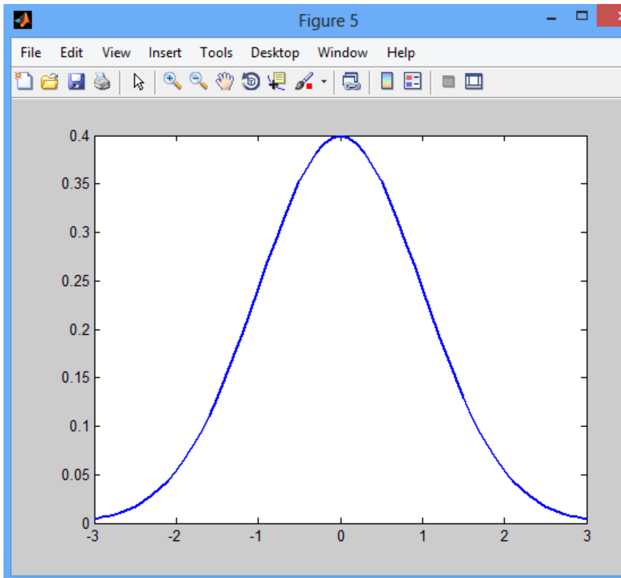


Fig 4.10 Normal Distribution

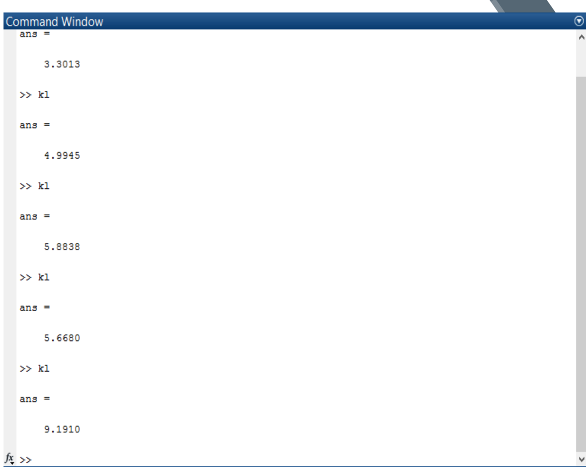


Fig 4.11KL Divergence Calculation

V. CONCLUSION

This report proposes a strategy for multifeature-based retrieval in histology image databases. In the implementation it does the work of extracting multiple features efficiently from an image. Since the system used Gabor, SIFT, DCT, Zernike moments to extract the different features, it would be very helpful in fusing those images and can be retrieved easily. From those extracted features, distances are calculated in an efficient manner. These distance calculations are used for normalizing those distances.

VI. FUTURE WORK

In the future work, representative query images are taken and it is divided in to positive group and negative group for the purpose of calculating a distance matrix between representative samples to centroid covering multiple feature spaces. After calculating a distance matrix, a set of objective functions are taken and those functions are constructed by combining weighted linear combinations and feature specific distances. These combinations will be expected to give the outcome as optimized feature distance matrix.

VII. REFERENCE

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