

Morphological Component Analysis for Differentiability of Textures

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ABSTRACT: This project proposes a new texture enhancement method which uses an image decomposition that allows different visual characteristics of textures to be represented by separate components in contrast with previous methods which either enhance texture indirectly or represent all texture information using a single image component. Our method is intended to be used as a preprocessing step prior to the use of texture-based image segmentation algorithms. Our method uses a modification of morphological component analysis (MCA) which allows texture to be separated into multiple morphological components each representing a different visual characteristic of texture. We select four such texture characteristics and propose new dictionaries to extract these components using MCA. We then propose procedures for modifying each texture component and recombining them to produce a texture-enhanced image. We applied our method as a preprocessing step prior to a number of texture-based segmentation methods and compared the accuracy of the results, finding that our method produced results superior to comparator methods for all segmentation algorithms tested. We also demonstrate by example the main mechanism by which our method produces superior results, namely that it causes the clusters of local texture features of each distinct image texture to mutually diverge within the multidimensional feature space to a vastly superior degree versus the comparator enhancement methods.

I. INTRODUCTION

Morphological Component Analysis (MCA) is a new method which takes advantage of the sparse representation of structured data in large over complete dictionaries to separate features in the data based on the diversity of their morphology. It is an efficient technique in such problems as separating an image into texture and piecewise smooth parts or for in painting applications.

The MCA algorithm consists of an iterative alternating projection and thresholding scheme, using a successively decreasing threshold towards zero with each iteration. In this paper, the MCA algorithm is extended to the analysis of spherical data maps as may occur in a number of areas such as geophysics, astrophysics or medical imaging. Practically, this extension is made possible thanks to the variety of recently developed transforms on the sphere including several multiscale transforms such as the undecimated isotropic wavelet transform on the sphere, the ridgelet and curvelet transforms on the sphere. An MCA-inpainting method is then directly extended to the case of spherical maps allowing us to treat problems where parts of the data are missing or corrupted. We demonstrate the usefulness of these new tools of spherical data analysis by focusing on a selection of challenging applications in physics and astrophysics.

The task of decomposing signals into their building atoms is of great interest for many applications. In such problems a typical assumption is made that the given signal is a linear mixture of several source signals of more coherent origin. These problems have drawn a lot of research attention in last years. Independent Component Analysis (ICA) and sparsity methods are typically used for the separation of signal mixtures with varying degrees of success. A classic example is the cocktail party problem where a sound signal containing several concurrent speakers is to be decomposed into the separate speakers. In image processing, a parallel situation is encountered for example in cases of photographs containing transparent layers.

II. LITERATURE REVIEW

2.1 MORPHOLOGICAL COMPONENT ANALYSIS: AN ADAPTIVE THRESHOLDING STRATEGY

Bobin, J. ; Gif sur Yvette ; Starck, J.-L. ; Fadili, J.M.Moudden, Y.

In a recent paper, a method called morphological component analysis (MCA) has been proposed to separate the texture from the natural part in images. MCA relies on an iterative thresholding algorithm, using a threshold which decreases linearly towards zero along the iterations.

This paper shows how the MCA convergence can be drastically improved using the mutual incoherence of the dictionaries associated to the different components. This modified MCA algorithm is then compared to basis pursuit, and experiments show that MCA and BP solutions are similar in terms of sparsity, but MCA is much faster and gives us the possibility of handling large scale data sets.

But the drawback of the system is poor system performance and Computational cost increases as the number of sample increases.

2.2 IMAGE ENHANCEMENT VIA ADAPTIVE UNSHARP MASKING

A. Polesel, G. Ramponi, and V. J. Mathews

This paper proposed to improve the visual appearance of an image by emphasizing its high frequency contents. Two algorithms are used in this paper they are Adaptive Contrast Enhancement Algorithm and Adaptation Algorithm for some specifications.

To emphasize the medium-contrast details in the input image more than large-contrast details such as abrupt edges so as to avoid overshoot effects in the output image. This method specially used to avoid noise amplification and easy to adapt the horizontal and vertical components separately. But the drawback of the system is it creates unwanted edge effects. Different textures in an image are treated as 'single' texture component and it has high computational Complexity

2.3 MICROARRAY IMAGE ENHANCEMENT BY DENOISING USING STATIONARY WAVELET TRANSFORM

X. H. Wang, Robert S. H. Istepanian and Yong Hua Song

This paper propose to denoise the image noises before further image processing using Stationary Wavelet Transform It is well known that wavelet transform is a signal processing technique which can display the signals on in both time and frequency domain.

The SWT method to preprocess the microarray images for removing the random noises. It is used to decompose the texture into horizontal and vertical components and it can represent textures of different directions in different sub-bands But the drawback of the system is Computational cost increases as the number of sample increases and the different textures in an image are treated as 'single' texture component.

2.3 A NON-LOCAL ALGORITHM FOR IMAGE DENOISING

Buades, A. ; Dept. Matemàtiques i Informàtica, UIB, Palma de Mallorca, Spain ; Coll, B. ; Morel, J.-M.

In this paper they propose a new measure, the method noise, to evaluate and compare the performance of digital image denoising methods. We first compute and analyze this method noise for a wide class of denoising algorithms, namely the local smoothing filters. Second, we propose a new algorithm, the nonlocal means (NL-means), based on a nonlocal averaging of all pixels in the image.

Finally, we present some experiments comparing the NL-means algorithm and the local smoothing filters. N-L means algorithm has better results compared to local smoothing filters It can represent textures of different directions in different sub-bands But the drawback of the system is Different textures in an image are treated as 'single' texture component. Degrade the texture characteristics and it has high computational complexity

2.4 IMAGE DECOMPOSITION VIA THE COMBINATION OF SPARSE REPRESENTATIONS AND A VARIATIONAL APPROACH

Jean-Luc Starck, Michael Elad, and David L. Donoho

This paper presents a novel method for separating images into texture and piecewise smooth (cartoon) parts, exploiting both the variational and the sparsity mechanisms. This paper presents the technique to remove the textures and natural parts. It is then compared in the two separate dictionaries.

The separation of image content into semantic parts plays a vital role in applications such as compression, enhancement, restoration, and more. But the drawback of the system is poor system performance and even though it proved to be an efficient method, it cannot be used due to the complexity of the system which includes two different lookup dictionaries.

2.5 PARTIAL DIFFERENTIAL EQUATION-BASED DENSE 3D STRUCTURE AND MOTION ESTIMATION FROM MONOCULAR IMAGE SEQUENCES

De Cubber, G. ; Dept. of Mech. Eng., R. Mil. Acad. of Belgium, Brussels, Belgium ; Sahli, H.

In this study, the authors propose an approach towards dense depth reconstruction, combining robust feature-based structure from motion with the spatial coherence of dense reconstruction algorithms.

To achieve this, a variational framework was set up, minimising the epipolar reprojection error and the image brightness constraint, while preserving discontinuities in the depth field by introducing an anisotropic diffusion term. As initial guess for the iterative solver, a region growing algorithm is proposed which mixes sparse and dense data.

2.6 A FAST IMPLEMENTATION OF TWO-DIMENSIONAL WEIGHTED MEDIAN FILTERS

T.Huang, G.Yang and G.Tang

This paper deals with the implementation of a fast algorithm for two-dimensional weighted median filtering. Because of the vast amount of data that must be handled, the development of fast algorithms is very important.

A fast running algorithm for weighted median filtering, which is based on using a histogram and updating it, is proposed. Experimental results prove the superiority of the proposed algorithm over that of finding the weighted median either by sorting with the Quick Sort or by selecting the r-th order statistic

2.7 SPARSE REPRESENTATIONS IN UNIONS OF BASES

Rémi Gribonval, Member, IEEE, and Morten Nielsen

The purpose of this correspondence is to generalize a result by Donoho and Huo and Elad and Bruckstein on sparse representations of signals in a union of two orthonormal bases. We consider general (redundant) dictionaries and derive sufficient conditions for having unique sparse representations of signals in such dictionaries.

The optimization problem is much easier to handle through the use of linear programming (LP). But the drawback of the system is the dictionaries called Grassmannian dictionaries construction produce the grassmannian packing problem.

2.8 EDGE-GUIDED BOUNDARY DELINEATION IN PROSTATE ULTRASOUND IMAGES

Sayan D. Pathak, Vikram Chalana, David R. Haynor, and Yongmin Kim

Accurate detection of prostate boundaries is required in many diagnostic and treatment procedures for prostate disease. In this paper, a new paradigm for guided edge delineation is described, which involves presenting automatically detected prostate edges as a visual guide to the observer, followed by manual editing.

The edge detection algorithm is comprised of three stages. An algorithm called sticks is used to enhance contrast and at the same time reduce speckle in the transrectal ultrasound prostate image. The resulting image is further smoothed using an anisotropic diffusion filter. In the third stage, some basic prior knowledge of the prostate, such as shape and echo pattern, is used to detect the most probable edges describing the prostate. Finally, patient-specific anatomic information is integrated during manual linking of the detected edges.

The use of edge guidance for boundary delineation can also be extended to other applications in medical imaging where poor contrast in the images and the complexity in the anatomy limit the clinical usability of fully automatic edge-detection techniques.

But the drawback of the system is the algorithm presented here has been shown to reduce inter observer variability in boundary delineation, without introducing any apparent bias and more clinical studies will be necessary to evaluate the impact of improved boundary delineation on treatment outcomes and clinical decision making.

III. PROPOSED SYSTEM

3.1 CONCEPTS

The subject of this paper is the preprocessing of image texture to improve the differentiability of textures with respect to texture features. The motivation for this work is to extract greater performance from any texture-based segmentation method by establishing a general-purpose texture enhancement algorithm. The method we propose method is similar in concept to the manner in which chemical staining provided by the author.

The file contains the function of texture characteristic-based image decomposition using morphological component analysis (TC-MCA), a demo of showing how the TMCA works for enhancing textural differences between different textures in the image and enhancing the texture-based segmentation methods as a pre-processing method. The total size of the videos is used in histopathology to enhance the appearance of differences in tissue composition to aid a pathologist's assessment of a sample.

Our method of enhancing texture differences is analogous to the stain and the effect of this enhancement is to make it easier for different textures to be distinguished by segmentation algorithms. An important property of our method is that it makes no assumptions about the number and type of textures present in an image. Some early texture enhancement methods reduce noise or artifacts in the image to highlight the textures indirectly, for example, the median filter and the Weiner filter. However, these conventional filters degrade the textures in addition to removing noise because of their lowpass-filter-like qualities.

Discontinuity-preserving filters were developed to mitigate this issue to a certain extent, for example, the non-local means filter which can smooth the noise and artifacts in the image while preserving image detail as much as possible. Wavelet-based methods, e.g. VISUShrink, BayesShrink, SUREShrink, were proposed to remove noise by shrinking coefficients in high-frequency sub-bands not exceeding certain thresholds, while preserving the image textures which are represented by coefficients in high-frequency sub-bands that exceed these thresholds. Other methods enhance the textures in the image directly.

Unsharp masking (UM) was proposed to improve the visual appearance of an image by emphasizing its high frequency contents. However, the highpass-filter-like nature of UM causes enhancement of noise and artifacts in the image as well. The same is true of histogram equalization methods. Therefore, some non-linear methods have been proposed to enhance the textures.

Coherence-enhancing anisotropic diffusion is based on the modifications of partial differential equations (PDEs) which can preserve strong discontinuities at edges while removing artifacts from smooth regions. Shock filtering is a transformation of anisotropic diffusion which smooths along the coherent texture flow orientations, and reduces diffusivity at non-coherent structures which enhances textural detail. All of the above methods enhance or suppress all of the "textural" components and "non-textural" components of the image to the same extent, thus, the quantitative difference between texture descriptors for different textures is not much altered. This occurs because all of the different textures in an image are treated as a single "texture" component alongside other non-texture components which results in any transformation to texture being applied to all textures uniformly.

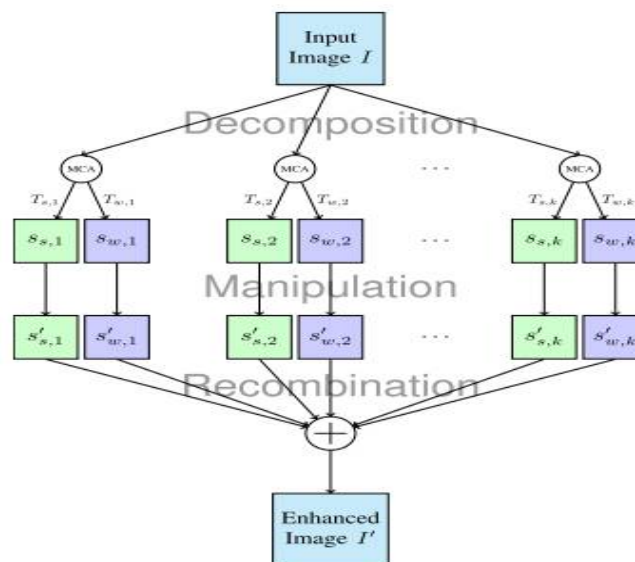


Fig 4.1 Texture Enhancement process

The Morphological Component Analysis (MCA) is a new method which allows us to separate features contained in an image when these features present different morphological aspects.

This includes three steps to get an enhanced image. They are Decomposition, Manipulation and Recombination.

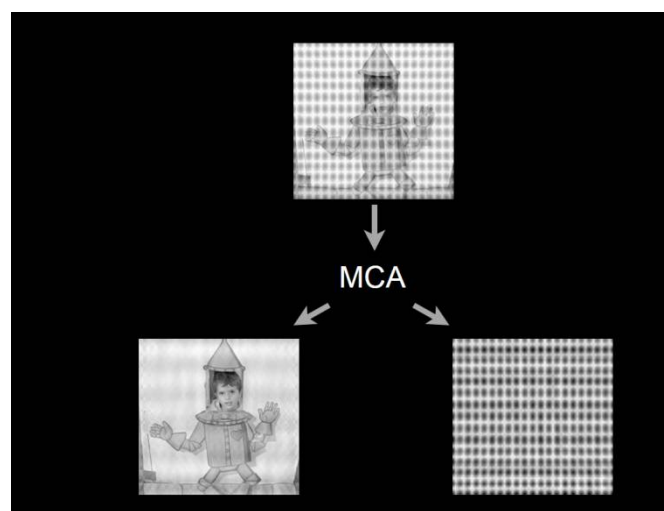


Fig 4.2 Morphological Component Analysis

Fig. 4.2 shows the result of a texture-cartoon separation experiment. The first morphological component is depicted in the middle of Fig. 4.3 and the second one on the left. The picture on the up depicts the original image. The over complete dictionary in this case is taken as the union of the curvelet transform and the global DCT.

3.2 METHODOLOGY

3.2.1 Texture Decomposition

A texture characteristic is broadly defined any property of a texture that can be quantified. Fig. 4.1 shows a schematic of the proposed method to enhance textural differences by manipulating certain texture characteristics in certain ways. Intuitively, each step functions as follows:

1) The image is decomposed to several pairs of components where each pair consists of a component that strongly exhibits a particular texture characteristic and a component that weakly exhibits it, or exhibits opposite characteristics, e.g. a “coarse” component and a “fine” component;

2) The components are manipulated to enhance the texture characteristics they are meant to capture, e.g. a high-coarseness component is manipulated so that so it becomes coarser, a low-coarseness (fine) component is manipulated so that it becomes finer;

3) The manipulated components are recombined to obtain an image in which textures are more different from each other than in the original image with respect to the chosen texture characteristics.

The decomposition process has various methods. They are,

- A. MCA: Standard “Cartoon+Texture” Decomposition
- B. MCA: Decomposition by Multiple Texture Characteristics
- C. Manipulation of the Image Components
- D. Re-Combination of the Manipulated Components

3.2.2 Texture Manipulation

In previous section the input image is decomposed into $s_{s,i}$ and $s_{w,i}$ according to 4 specific texture characteristics, where $i = 1,2,3,4$ represent coarseness, contrast, directionality and line-likeness respectively. By modifying each of the individual texture components described in and recombining them, the textures can be manipulated to be more different with respect to the specific characteristics represented by the modified components. In this section, the various manipulations that are applied to transform the components are discussed.

- A. Manipulations for the Coarseness-Decomposed Components
- B. Manipulations for the Contrast-Decomposed Components
- C. Manipulations for the Directionality-Decomposed Components
- D. Manipulations for the Line-Likeness-Decomposed Components

3.3 TEXTURE CHARACTERISTICS & THEIR DICTIONARIES

The two key points in decomposing the image according to texture characteristics are:

- 1) The selection of texture characteristics and
- 2) The selection of filters used as dictionaries

3.3.1 Texture Characteristics

Human visual perceptual characteristics were selected for our MCA framework because they describe the texture closely to how human beings perceive the texture leading to intuitive morphological components. The following characteristics from Tamura descriptor were selected as the basis of decomposition:

- 1) coarseness: a measure of the number of edges in a local square neighbourhood of radius;
- 2) contrast: a measure of the variance of the intensities of the pixels in a local window;
- 3) directionality: a measure of the mean edge direction in a local window;
- 4) line-likeness: a measure of the variance of the edge direction in a local window;

For each of the above characteristics, we propose a pair of dictionaries to represent the strong and weak characteristic components, e.g., for the characteristic of coarseness, the image is decomposed to coarse (strong) and fine (non-coarse, weak), components.

3.3.2 Dictionaries of Each Characteristic

The dictionaries $T_{s,i}$ and $T_{w,i}$ are proposed in this section. With the same principle of the dictionary selection in the standard MCA, the dictionaries proposed in this paper should satisfy:

- 1) They can highlight the components corresponding to a certain texture characteristic, and

2) They are insensitive to the other texture characteristics.

Depending on the texture characteristics the dictionaries are chosen.

1. Dictionaries for Coarseness: Coarseness quantifies the number of edges in the local texture.
2. Dictionaries for Contrast: Contrast measures the variance of the grey scale intensities in a local area.
3. Dictionaries for Directionality: Directionality of texture measures the orientation of the local texture.
4. Dictionaries for Line-Likeness: The decomposition based on line-likeness requires two dictionaries corresponding to textures with very similar, and very different direction in every local region, respectively.
5. Analysis of the Insensitivity: In this section, we apply the transformations to the components with the opposite texture characteristics, that is, we apply the dictionaries for the weak component of a texture characteristic to the strong component, and vice versa.

3.4 BLOCK DIAGRAM OF PROPOSED SYSTEM:

The following figure shows the various steps of feature extraction or shape extraction.

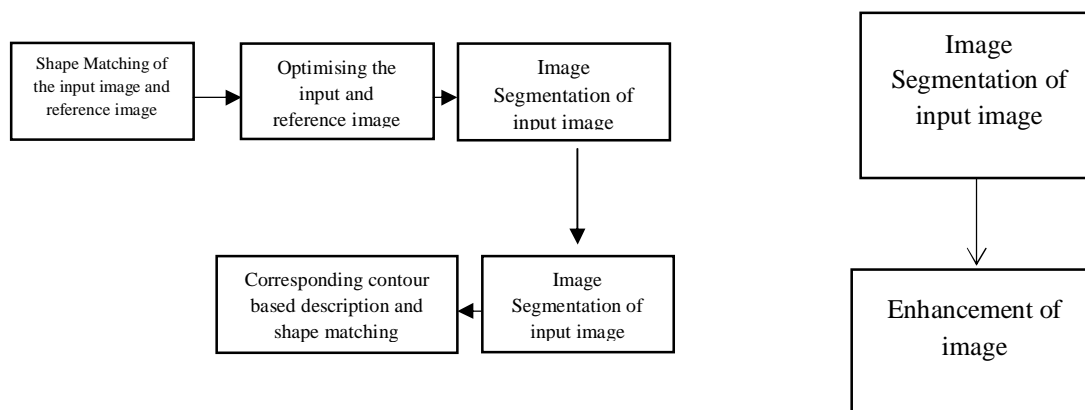


Fig 4.3 Block diagram for proposed method

Face is taken as the input. The corners and edges of the face which are considered as the feature are also taken for reference. First of all shape matching of the input image and reference image is done. Then the optimization of input image and reference image should be taken. Then after the multiple segmentation of image, enhancement of image should be done and finally the shapes can be matched.

3.4.1 Shape Matching Algorithm:

Matching of the face which is taken as an input, and reference image .

3.4.2 Optimisation Algorithm:

Optimization of the input image and the reference image by taking a serious analysis of the input image and reference image. For imagery, optimisation involves choosing a suitable graphic compression format. Compression reduces the image file size and consequently the time it takes to download and display in a browser.

Common compression types include GIF, JPEG and PNG. Many compression formats reduce file size by removing information from the image. For example, the JPEG format reduces overall tonal range to reduce file size reducing the tonal range means that highlights and shadows become less pronounced.

Reducing the number, and file size of the images can be a significant issue for websites with large subscriber bases such as news sites. Site owners are charged for the amount of information downloaded from their sites. The more popular the site and larger the images the greater the traffic costs.

3.4.3 Image Segmentation Algorithm:

The features of the faces including the corners and faces are taken in advance for segmentation, in order to compare the images. Segmentation partitions an image into distinct regions containing each pixels with similar attributes. To be meaningful and useful for image analysis and interpretation, the regions should strongly relate to depicted objects or

features of interest. Meaningful segmentation is the first step from low-level image processing transforming a grey scale or colour image into one or more other images to high-level image description in terms of features, objects, and scenes. The success of image analysis depends on reliability of segmentation, but an accurate partitioning of an image is generally a very challenging problem.

Segmentation techniques are either contextual or non-contextual. The latter take no account of spatial relationships between features in an image and group pixels together on the basis of some global attribute, e.g. grey level or colour. Contextual techniques additionally exploit these relationships, e.g. group together pixels with similar grey levels and close spatial locations.

3.4.4 Thresholding

Thresholding is the simplest non-contextual segmentation technique. With a single threshold, it transforms a grey scale or colour image into a binary image considered as a binary region map. The binary map contains two possibly disjoint regions, one of them containing pixels with input data values smaller than a threshold and another relating to the input values that are at or above the threshold. The former and latter regions are usually labelled with zero (0) and non-zero (1) labels, respectively. The segmentation depends on image property being thresholded and on how the threshold is chosen.

Generally, the non-contextual thresholding may involve two or more thresholds as well as produce more than two types of regions such that ranges of input image signals related to each region type are separated with thresholds. The question of thresholding is how to automatically determine the threshold value.

3.4.5 Texture Enhancement Algorithm:

Enhancement or enlarging of the picture for the analyzing the faults, similarities in it. Texture is an important feature of natural images; hence, a variety of image texture applications has been intensively studied by many researchers. Image texture is defined as a function of the spatial variation in pixel intensities. Smith and Chang have defined texture as visual patterns, which have properties of homogeneity and not resulting from only a single colour or intensity.

In the image, texture features capture information about repeating patterns. Texture analysis can be classified into three models: structural, statistical, and signal theoretic methods. Therefore, the analysis of texture parameters is a useful approach for increasing the information accessible from images. In texture enhancement technique, which is based on mask operation, each pixel is modified according to value of the neighbourhood around the pixel of interest. One important aspect of an image, which enables us to perform this, is the notion of frequencies.

Fundamentally, the frequencies of an image are the amount, by which the gray values change with distance. High-frequency components are characterized by huge changes in gray values over small distances; examples of high frequency components are edges and noise. On the other hand, low-frequency components are parts of the image, which are characterized by little change in the gray values.

Fractional differential mask can further preserve the low-frequency contour feature in those smooth areas, and nonlinearly keep the high-frequency marginal feature in those areas, where the gray-level changes heavily, and also enhances texture details in those areas, where the gray-level does not change evidently.

3.4.6 Contour Based Shape Representation And Description:

Representation of shapes by considering the outline of the figure. Extraction and representation of contours are challenging problems and are crucial for many image processing applications. In this study, given a membership function that returns the score of a point belonging to a contour, we propose a method for contour representation based on the principal curve (PC) of this function. The proposed method provides a piecewise linear representation of the contour with fewer points while preserving shape.

IV. RESULT AND DISCUSSION

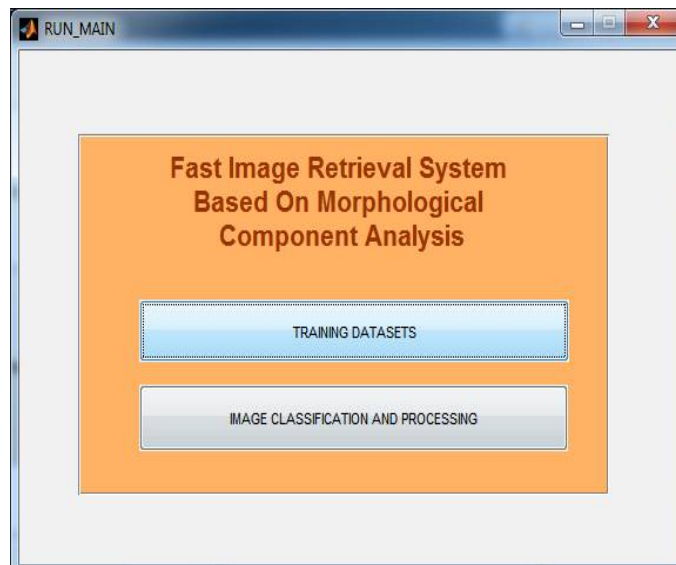


Fig :GUI of initial settings

The above figure shows the graphical user interface of the training sets and the database.

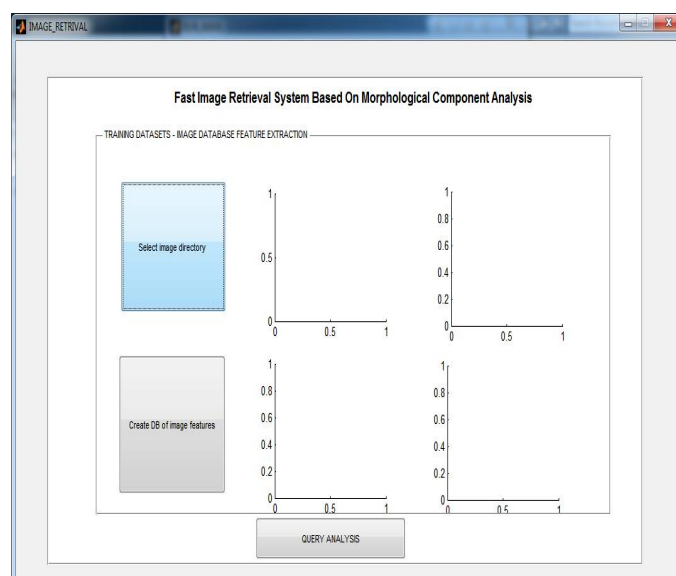


Fig:Image retrieval based on MCA

Image retrieval based on MCA, 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 databases.

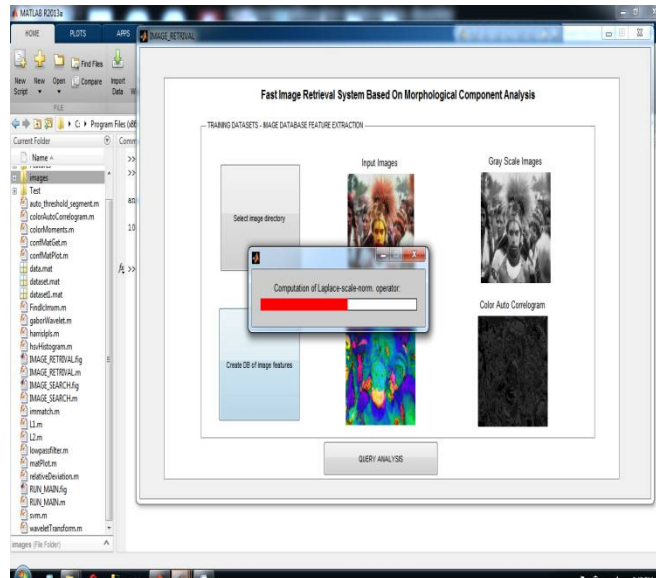


Fig:Computation of image retrieval

The above diagram shows the computation of retrieved image.

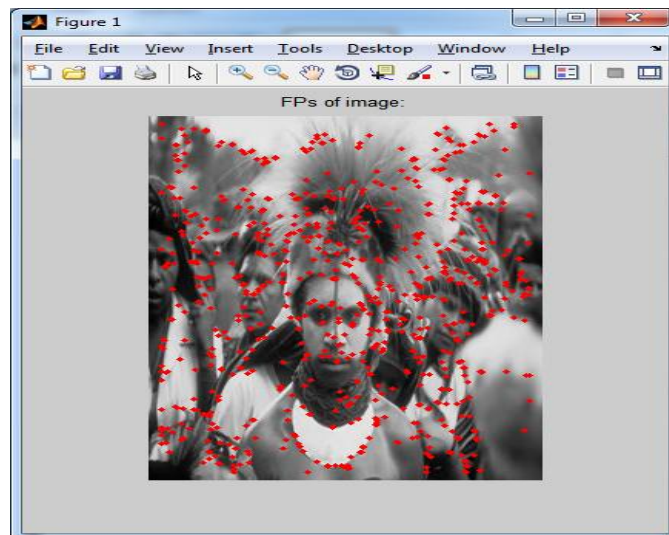


Fig:FP's of image

Frame rate, also known as frame frequency, is the frequency (rate) at which an imaging device displays consecutive **images** called frames. The term applies equally to film and video cameras, computer graphics, and motion capture systems. Frame rate is expressed in frames per second (**FPS**).

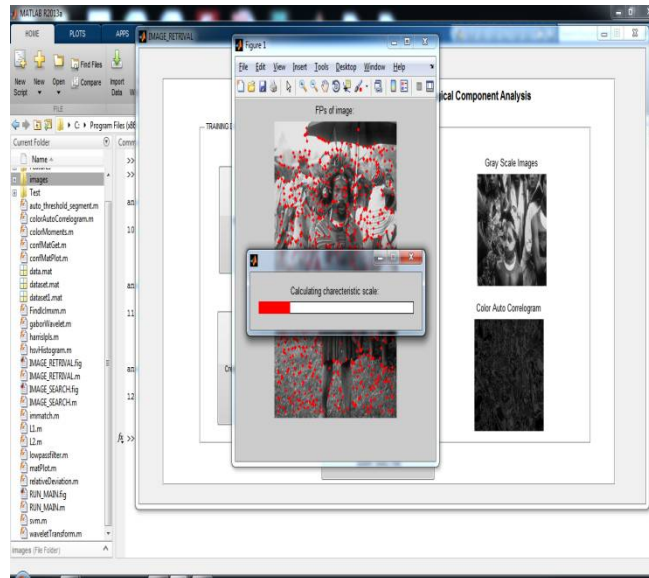


Fig: Calculating Characteristic scale

Characteristic scale is used to determine the threshold of the image.

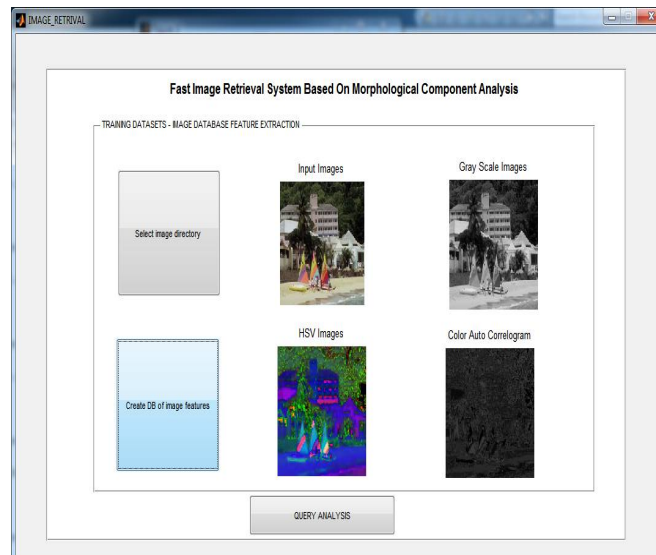


Fig: Training Datasets

With the size of image databases increasing dramatically, the usefulness of such information is dependent on how well it can be accessed and searched and how well knowledge can be extracted from it. Our ability to generate data currently far outstrips our ability to explore, analyze and let alone understand it.

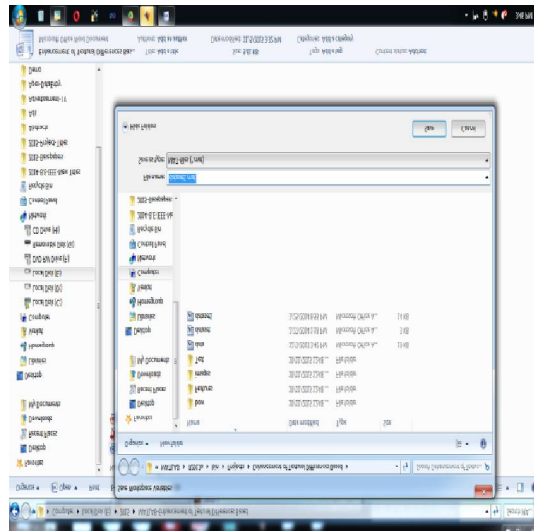


Fig: Saving the Output

V. CONCLUSION

We novelly proposed to decompose the texture image using the MCA method according to different texture characteristics: coarseness, contrast, directionality and line-likeness. For every morphological component, we proposed transformations to enhance the characteristic captured by that component. The experimental results showed that the proposed texture enhancement method successfully enhanced the difference between textures with respect to the chosen texture characteristics while better preserving their visual appearance compared to other methods which led to improved texture based segmentation results.

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International Journal of Innovative Research in Science, Engineering and Technology

An ISO 3297: 2007 Certified Organization

Volume 5, Special Issue 3, March 2016

6th International Conference in Magna on Emerging Engineering Trends 2016 [ICMEET 2016]
On 10th & 11th March, 2016

Organized by

Dept. of ECE, EEE & CSE, Magna College of Engineering, Chennai-600055, India.

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