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# COLORIZATION OF GRAYSCALE IMAGES USING MULTIPLE KERNEL FUZZY C-MEANS CLUSTERING

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***Abstract*— Image processing is any form of signal processing for which the input is an image, the output may be either an image or a set of characteristics or parameters related to the image. The image segmentation is the process of partitioning a digital image in which it is divided into multiple segments. Here we are analyzing a set of sample color images, and coherent regions of homogeneous textures are extracted. A multi-channel filtering technique is used for texture-based image segmentation, combined with a modified Fuzzy C-means (MKFCM) clustering algorithm. For each area of interest, texture descriptors are computed and stored, along with corresponding color information which is used for colorization of a grayscale image with similar textures. The colorization process is performed by chroma replacement. This research finds numerous applications,from classic film restoration and enhancement, to adding valuable information into medical and satellite imaging. This can be used as an enhancement in the detection of objects from x-ray images at the airports. Since the textures extracted from each sample image have no preset size or shape, the texture retrieval methods need to be improved for scale and rotation invariance, which would lead to a better accuracy rate. This method could also be enhanced to store more complete color descriptors to accommodate more complex textures containing multiple colors.***

***Keywords* — Clustering, Fuzzy C-means (FCM), Image segmentation, Multiple kernel.**

## I. INTRODUCTION

Image colorization has been performing through different means since the early 20th century. The methods of image colorization can be classified into two different groups depending on the approach being used. They include Scribble-based and Example-based approaches. Scribble-based colorization techniques require a user to scribble color information onto appropriate regions of the grayscale image and in example-based colorization techniques, it automate this process by providing an example image from which to extract the color information[1].

The quality and accuracy of the results can vary considerably depending on the various example image chosen. These techniques still require user input in the form of swatches, and use simple (pixel- based) texture matching methods which provides the results . Other techniques require the sample images to be of the exact same location as the image to be colorized [6]. This may not always be practical, and may be pointless if a colored image of the same location is already available, this can be called as a disadvantage. The method suggested by Irony used a very robust monochrome texture matching method with spatial filtering[10]. They suggested that the improved results could be obtained by using spatial coherence descriptors, such as the Gabor transform.

A new and innovative method for automating example-based colorization is going to be done. This process combines several state-of-the-art techniques from Digital Image Processing in order to improve the automization of the colorization process, ACTD method is used here.yB analyzing a set of sample color images, coherent regions of homogeneous textures are extracted[8].

A multichannel filtering technique is used for texture-based image segmentation, combined with a modified Fuzzy C-means (FCM) clustering algorithm[2],[3],[4]. Here MKFCM is used. A MKFCM technique is introduced as a framework for the different image-segmentation problems. Here away from the fact that the composite kernels are used only in the kernel FCM (KFCM)[2],[7], a group of kernels is proposed and the derivation is also done for the updating rules for the linear coefficients of the composite kernel. The proposed MKFCM algorithm provides a new flexible vehicle for us to fuse different pixel information in the image segmentation problems. Which means different pixel information represented by the different kernels are combined in a particular kernel space which is supposed to be produce a new kernel.

For each area of interest, texture descriptors[5] are then computed and stored, along with corresponding color information used for colorization of a grayscale image with similar textures. The colorization[9] process is performed by chroma replacement. This finds numerous applications, ranging from classic film restoration and related enhancement, to adding valuable information into medical and satellite imaging. Also, this can be used to enhance the detection of objects from x-ray images at the airports.

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This work includes different section by which the previous work related to this work is briefly explained in the section II and it is followed by the methodology in the section III and the results are produced in the section IV and the work is concluded in section V.

## II. Previous Work

### A. Clustering and Feature Extraction

Naotoshi used Gaussian[8] smoothing in order to remove the smaller areas, combined with a simple K-means clustering algorithm in order to extract regions from filtered images. The segmentation results were satisfactory but lacked accuracy, which can be considered to be the main problem[5]. Texture-based segmentation was recently improved by Dong et al. by using a Fuzzy C-Means (FCM) method to generate the index map and palette[8], and by using the Probabilistic Index Map (PIM) model to improve segmentation accuracy. Once a proper level of clustering has been obtained, smaller regions (with a number of pixels below a predefined threshold) contained inside of a larger region can be removed. Isolated small regions of unique texture are discarded, and the remaining regions are labeled.

Once each region is labeled, a sample area for each texture is extracted[2]. This is done by finding the largest square that can be fitted into each identified contiguous region on unique texture. For each texture, the color descriptor (the dominant color as per the color histogram) and texture descriptors can be extracted and stored.

### B. Content Based Image Retrieval

Content-Based Image Retrieval (CBIR) is the ability to retrieve images by analyzing their content. This gained a lot of attention in recent years[1]. Gabor transforms are also the central part of the Homogenous Texture Descriptor (HTD), which offers a simple yet powerful method for storing texture information for retrieval. HTD is part of the “Multimedia Content Descriptor Interface” of the MPEG-7 standard, which has been successfully used in the fields of Image Classification and Content-based image retrieval[5].

The LIRe and the img (Rummager) image retrieval systems have implemented some additional MPEG-7 descriptors such as the Edge Histogram, along with a recently developed set of Compact Composite Descriptors (CCD) that can be used to retrieve images in various situations[5].

In this research, a new process for automated colorization is proposed by combining these techniques in a new and innovative way.

## III. Methodology

1. Images are collected and stored.
2. Preprocessing is done.
3. Features are extracted and stored.
4. Clustering is done with Kernalization.
5. MKFCM is done using kernalization.
6. Colour descriptors and texture descriptors are created and it is stored in the database.
7. Its texture descriptor is created.
8. And colorization is done.

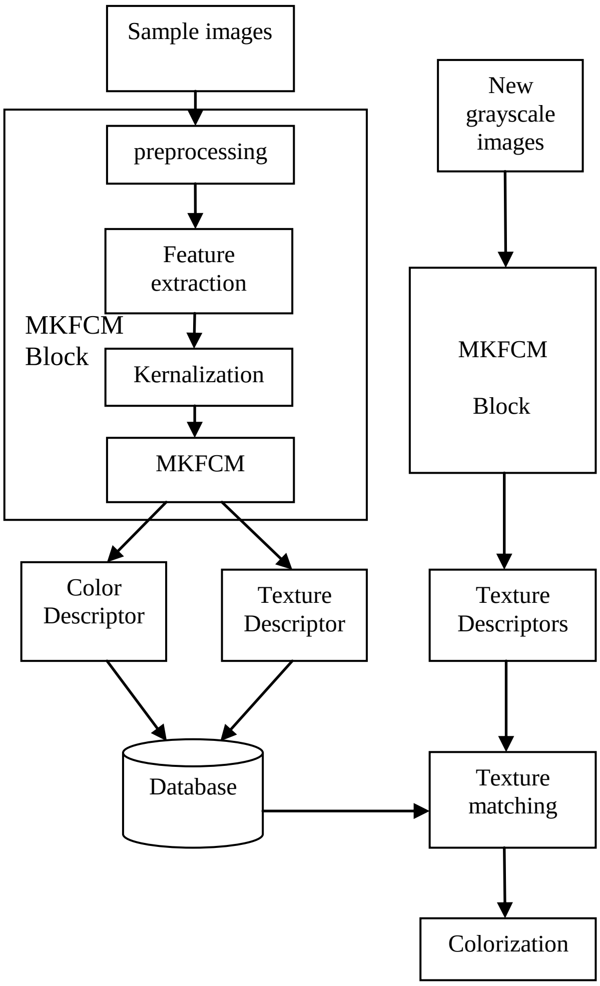


Figure 1: Architecture of the system

The initial process is to analyze several sample color images and it is processed so that the different textures present in each image can be identified and extracted. In order to effectively segment the image based on texture, the multi-channel filtering approach suggested by Malik and Perona[1] is used.. A clustering algorithm is then used in order to effectively and accurately segment the regions of homogeneous texture previously identified and extract a representative sample for each texture, here Multiple kernel fuzzy C-means algorithm is used. The texture descriptors and color information are computed for each texture, and stored in a database.

Then take new grayscale image that needs to be colorized based on the texture and color information present in the database. The segmentation and feature extraction process takes place as previously described. For each texture identified, the texture descriptors are computed, and used to locate the best matching texture present in the sample database. Once the best matching texture is identified, the corresponding color information is extracted, and applied to the segmented region of the grayscale image. Figure 1 shows an overview of process used in this work.

### A. Texture Segmentation

A two dimentional Gabor filter is used here for segmentation. It consist of a sinusoidal plane wave of a given frequency and a given orientation, which is modulated by a


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two-dimensional Gaussian envelope. The gabor filters are obtained by using the following method :

$g(x,y,\lambda,\sigma,\gamma) = \exp[-\gamma(x'^2 + \gamma^2 y'^2)/\sigma^2]\cos[2\Pi\ (x'/\lambda)]$

$$x' = x\cos\cos\Theta + y\sin\sin\Theta \quad (1)$$

$$y' = -x\sin\sin\Theta + y\cos\cos\Theta \quad (2)$$

where, $\sigma$ is the width of the Gaussian envelope;
$\gamma$ is the special aspect ratio;
$\lambda$ is the wavelength of the filter;
$\Theta$ is the orientation of the filter.

Pseudo code is as follows :

Step 1 For orientation $\Theta$ = 0to$\Theta$ =3 Π/4 step Π/4.
Step 2 For $\lambda$=0.3to 0.5 step 0.1.
Step 3 Calculate Gabor(4,4,1/ $\lambda$,0.56*$\Theta$,0.5)

Gaussian smoothing was used inorder to remove the smaller areas. In this work, smoothing is performed by calculating the mean values of the gray-level intensities between neighboring pixels. The Gabor response values for each pixel is added, and normalized. This technique is very effective for identifying and segmenting areas of homogeneous textures in an image. This information can then be used for clustering.

### B. *Feature Extraction*

The contiguous region of unique texture enhanced by the Gabor filters and identified by the segmentation algorithm are then isolated and extracted. Blob filtering is used in order to remove the smaller clustered areas. The center of gravity of each blob is used to extract a sample image representative of that particular texture.

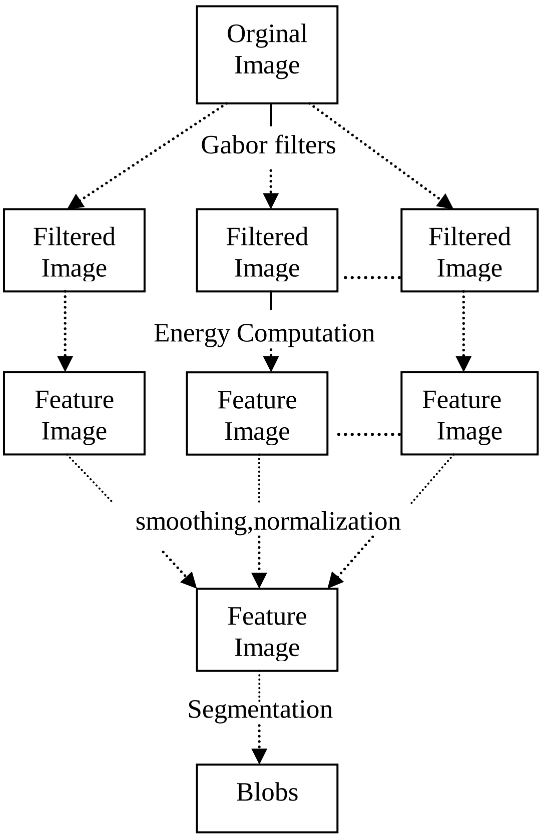


Figure 2: Feature extraction using Gabor Filters

The texture image is stored both in color for a reference to the color component (Chroma) of the texture and in gray-scale for texture matching. This forms the library of textures and corresponding color information that can be used for the ECTD process. Fig 2 explains the feature extraction process done in this work.

### C. *Clusteing*

MKFCM concept is introduced inorder to solve the image-segmentation problems. The MKFCM algorithm provides flexible vehicle for us to fuse different pixel information presented in image-segmentation problems. That means, different pixel information represented by the different kernels are combined in the kernel space which will produce a new kernel.

Before the introduction of the MKFCM, we first list some necessary Mercer kernels' properties in the following .

*Theorem :*

Let $k1$ and $k2$ be kernels over $\Xi \times \Xi$, $\Xi \subseteq Rp$, and $k3$ be a kernel over $Rp \times Rp$. Let function $\psi: \Xi \rightarrow Rp$

1) $k(\mathbf{x}, \mathbf{y}) = k1(\mathbf{x}, \mathbf{y}) + k2(\mathbf{x}, \mathbf{y})$ is a kernel.
2) $k(\mathbf{x}, \mathbf{y}) = \alpha k1(\mathbf{x}, \mathbf{y})$ is a kernel, when $\alpha > 0$.
3) $k(\mathbf{x}, \mathbf{y}) = k1(\mathbf{x}, \mathbf{y})k2(\mathbf{x}, \mathbf{y})$ is a kernel.
4) $k(\mathbf{x}, \mathbf{y}) = k3(\psi(\mathbf{x}), \psi(\mathbf{y}))$ is a kernel.

The general framework of MKFCM aims to minimize the same objective function as the single fixed KFCM,[2] i.e.,

$$Q = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij} \| \Box_{com}(x_j) - o_i \|^2 \quad (3)$$

or

$$Q = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij} \| \Box_{com}(x_j) - \Box_{com}(o_i) \|^2 \quad (4)$$

For MKFCM, it still updates $u_{ij}$. The difference is that the kernel function $k$ in these equations is replaced by the combined kernel $k_{com}$, where $k_{com} = k_1 + \alpha k_2$ and $k_{com} = k_1 k_2$ .

When the number of parameters in the combined kernel is small, the parameters can be adjusted by trial and error. For instance, the parameter $\alpha$ in the $k$com = $k1 + \alpha k2$ can be selected by testing a group $\alpha$ in a predefined range or set. While the number of parameters in the combined kernel is large, the more feasible method is automatically adjusting these parameters in the learning algorithms. For example, in machine learning community, a widely used composite kernel is the linear combination of several kernels, i.e., $k$com = $w1k1 + w2k2 + \ldots + wlkl$. Some learning algorithms that adjust the weights $wi$ automatically in typical kernel learning methods like multiple-kernel regressions and classifications have been studied. It contains set os n data points $X = x_{i=1 \text{ to } n}$

1. Set the number c of clusters and k of kernels.
2. Initialize the membership value, u .
3. Calculate the coefficients $\alpha$ and $\beta$

$$\alpha_{ick} = k_k(x_i,x_i) - 2\sum_{j=1to\ n} u_{jc}k_k(x_i,x_j) + \sum_{j=1to\ n} \sum_{j'=1to\ n} u_{jc}u_{j'c}k_k(x_j,x_j)$$

$$\beta_k = \sum_{i=1to\ n} \sum_{c'=1to\ c} u_{ic}\ \alpha_{ick}$$

4. Calculate the weights.

$$w_k = \frac{1/\beta_k}{1/\beta_1 + 1/\beta_2 + \ldots 1/\beta_m}$$

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5. Calculate the distances.

$$D_{ic}^{2}=\sum_{k=1 to M} \alpha_{ick}\, w_{k}^{2}$$

6. Calculate the membership.

$$U_{ic} = \frac{1}{\sum_{c'=1 to C} \left( \frac{D_{ic}^{2}}{D_{ic'}^{2}} \right)^{1/m-1}}$$

The orginal image and the result obtained after doing MKFCM is shown in Fig 3 .

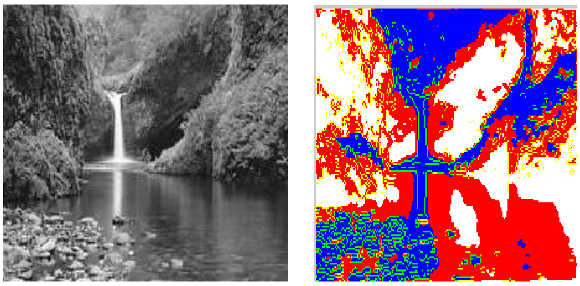

Figure 3 : Result before and after MKFCM

The application of multiple or composite kernels in the FKCM has its own advantages. In addition to the flexibility in selecting kernel functions, it also offers a new approach to combine different information from multiple heterogeneous or homogeneous sources in the kernel space[2]. Specifically, in image-segmentation problems, the input data involve properties of image pixels sometimes derived from very different sources[3].Therefore, we can define different kernel functions purposely for the intensity information and the texture information separately, and we then combine these kernel functions and apply the composite kernel in MKFCM to obtain better image-segmentation results[2]. Examples that are more visible could be found from multitemporal remote sensing imagesand the pixel information in these images inherits from different temporal sensors. As a result, we can define different kernels for different temperature channels and apply the combined kernel in a multiple-kernel learning algorithm[2].

*D. Texture Matching*

The grayscale image processing is done prior to texture matching to get the accurate results. And in the next step the segmentation and feature extraction processes are then repeated for the new grayscale image to be colorized. These processes are used exactly in the same manner, and since no color information was used in order to perform the segmentation of the sample images.

Compact Composite Descriptors (CCD) is a descriptor combining several descriptors. The Descriptors are part of the new Visual Multimedia Content Description Scheme (VICODEs), it is proposing a set of specialized descriptors tuned for different types of images. Testing of the descriptors was performed using the img (Rummager) [1] application, as well as with the DLLs provided by the authors. The descriptors used for this work include: The MPEG-7 Edge Histogram Descriptor (EHD) represents the spatial distribution of five different types of edges: four directional edges and another one non-directional edge. So edges play the most important role for image perception, they can be used for image-to-image matching to retrieve images with similar semantic meaning.

The VICODEs (CCD) Fuzzy Spatial Based Scalable Composite Descriptor (BTDH) was developed to be used for the Medical Radiology Images. This descriptor uses the brightness and texture characteristics and the spatial distribution of the brightness and texture characteristics in one compact 1D vector. To extract this brightness information, a fuzzy unit has to classifies the brightness values of the image's pixels into different clusters. The cluster centers are calculated using Gustafson Kessel Fuzzy Classifier.

The VICODEs (CCD) Auto Descriptor Selector (ADS) is a feature of the application that automatically selects the proper descriptor for each image. This method provides a very easier and accurate texture matching method.

*E. Colorization.*

Once the proper segmentation is obtained and appropriate colors are identified, placing the color in the correct areas of the test image can be achieved in the YCbCr color space[1]. The advantage of this color space is that it separates the luminance (Y) component from the color components (Cb and Cr are the blue-difference and red difference Chroma components)[1]. It is possible to replace the Chroma components while preserving the luminance information of the image. In this, the Chroma component of the test image is replaced with the colors corresponding to the matching textures from the library of images.

## IV. Results

The result obtained is given by fig 5. The colorization process is done perfectly with the reduced noise, the kernalization is shown in fig 4. Here the figure is divided as different kernels and the outputs are shown. ie. Various channels are produced. The kernelization is used to produce multiple kernels and thereby produces the MKFCM results. This kernels are combined together to produce the multiple kernel images.

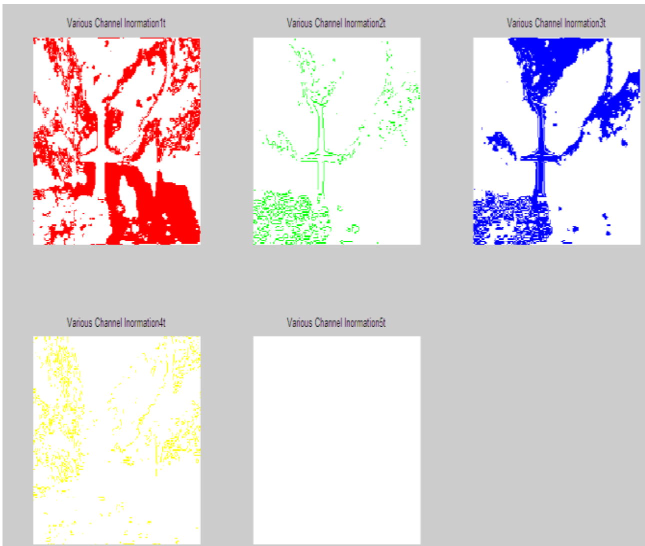

Figure 4 : Kernalization

This is used to produce the MKFCM output and there by it is used to produce the color image. The MKFCM output is shown



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in the fig 3. The difference can be viewed perfectly by this figure. The Fuzzy C-means clustering shows very good segmentation results, but is still sensitive to noise and fails to segment areas of homogeneous textures and to overcome this MKFCM is introduced.

Figure 5 : Colorized image

## V. CONCLUSION

In this work, a new method for automating colorization process is implemented. The process is combined with several techniques from Digital Image Processing in order to improve the automation of the colorization process. This includes Gabor-based image segmentation which is combined with an improved fuzzy C-means clustering, extraction and storage of the Texture and Color Descriptors, and a texture-based color retrieval technique. The MKFCM is used for the clustering. Considering the image-segmentation problems under the MKFCM framework, the proposed algorithms provide a significant flexibility in selecting and combining different kernel functions. Thus as a conclusion the system for colorization of gray scale images can be prepared by including various features. This research finds numerous applications, ranging from classic film restoration and enhancement, to adding valuable information into medical and satellite imaging and can be used to enhance the detection of objects from x-ray images at the airports.

The future development can be done in certain features. Since the textures extracted from each sample image have no preset size or shape, the texture retrieval methods still need to be improved for scale and rotation invariance, which would lead to a better accuracy rate. This method could also be enhanced to store more complete color descriptors in order to accommodate more complex textures containing multiple colors.. The testing conducted as part of this research proved that the ability to combine these techniques in order to automatically colorize grayscale images is a viable option.

## VI. ACKNOWLEDGEMENT

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