

Mosacing Using Laplacian of Gaussion Method

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Abstract: *Image mosaicing is the act of combining two or more images. It aims to combine images such that no obstructive boundary exists around overlapped regions. Emphasis is given on to create a mosaic image that contains as little distortion as possible from the original images, as well as preserving the general appearance of the original image. Multiresolution representation technique is an effective method for analyzing information contents of signals, as it processes the signals individually at finer levels, to give more accurate results that contains much less distortion. Laplacian pyramid, Gaussian pyramid and Wavelet transform are types of Multiresolution representations. In the proposed work, I have use wavelet transform, Laplacian pyramid using Gaussian pyramid as transforms function in context of simplicity and working satisfactorily in real time domain. Application areas of this subject are widespread in the fields like signal analysis, image coding, image processing, computer vision and still counting. The work in this project will be focused on designing a model which balances the smoothness around overlapped region and the fidelity of blended image to the original image.*

Keywords: *LowPassFilter, GaussionPyramid, Laplacian pyramid*

1. Introduction

The need to combine two or more images into a larger mosaic has arisen in a number of contexts. Panoramic views of Jupiter and Saturn have been assembled from multiple images returned to Earth from the two Voyager spacecraft. In a similar way, Landsat photographs are routinely assembled into panoramic views of Earth. Detailed images of galaxies and nebulae have been assembled from multiple telescope photographs. In each of these cases, the mosaic technique is used to construct an image with a far larger field of view or level of detail than could be obtained with a single photograph. In advertising or computer graphics, the technique can be used to create synthetic images from possibly unrelated components. In psychophysics and the physiology of human vision, evidence has been gathered showing that the retinal image is decomposed into several spatially oriented frequency channels. This explains the use of Multiresolution decomposition in computer vision and image processing research and why Multiresolution Spline approach works well for image mosaic. The basic concept is to decompose the signal spectrum into its sub spectra, and each sub spectrum component can then be treated individually based on its characteristic. For example, most nature signals will have predominantly low frequency components, thus the low-band components contain most of significant information, while for a texture the most significant information often appears in its middle-band component. Thus each channel can be processed separately to obtain more precise results in the technique of Multiresolution. An image

mosaic is typically completed in two stages. In the first stage, the corresponding points in the two, to-be-combined images are identified and registered. This stage is usually referred to as image registration. Not all applications of image mosaicing require registration, such as in movie special effects. In the second stage, the intensities of the images are blended after the corresponding points have been registered.

In this Proposed work, I have design a module that can decompose a given image into number of levels depending on the image size has been discussed. The Multi-resolution process is carried out with the help of Laplacian pyramid using Gaussian pyramid. A blending technique needs to be implemented for combining two or more images into a larger image mosaic. Therefore in this proposed procedure, the images to be blended are first decomposed into a set of band-pass filtered component images. Next, the component images in each spatial frequency band are assembled into a corresponding band pass mosaic. In this step, component images are joined using a weighted average within a transition zone which is proportional in size to the wave lengths represented in the band. Finally, these band-pass mosaic images are summed to obtain the desired image mosaic. Fig1 shows the typical mosaic image. When coarse features occur near borders, these are blended gradually over a relatively large distance without blurring or otherwise degrading finer image details in the neighbourhood of the border.



Figure1: Typical multiresolution mosaic images.

Here the output i.e the resulting blended image is tested with that of original image with the help of the parameter like psnr, mean intensity value, entropy of the image.

2. LITERATURE REVIEW /RELATED WORK

For the combination of two or more images various techniques are found in Burt and Adelson method for multiresolution analysis is popular which uses spline functions for blending sub band coefficient based on multiresolution pyramidal representation. This representation requires two steps, in first step two to-be-combined images are decomposed into sub band coefficient by means of pyramidal laplacian operator and in second step spline function are applied to combine sub-band coefficient. It is easily computed and yields satisfactory result. It uses weighting average to blend two overlapped region to evaluate pixel values within transition zone. And to blend all features properly multiresolution analysis is used.[1]

Mosaic techniques have been used to combine two or more images into a new one with an invisible seam, and with as little distortion of each signal as possible. Multiresolution representation is an effective method for analyzing the information content of signals and it also fits a wide spectrum of visual signal processing and visual communication application. Wavelet transform is one kind of multiresolution representations, and has found a wide variety of application in many aspects, including signal analysis, image coding, image processing, computer vision and etc. Due to its characteristic of multiresolution signal decomposition, wavelet transform is used here to do the image mosaic by choosing the width of mosaic transition zone proportional to the frequency represented band. Both 1-D and 2-D signal mosaics is described, and some factors which affect the mosaics is discussed[2]

In a multiresolution spline technique for combining two or more images into a larger image mosaic, the images to be splined are first decomposed into a set of bandpass filtered component images. Next, the component images in each spatial frequency band are assembled into a corresponding band pass mosaic. In this step, component images are joined using a weighted average within a transition zone which is proportional in size to the wave lengths represented in the band. Finally, these bandpass mosaic images are summed to obtain the desired image mosaic. In this way, the spline is matched to the scale of features within the images themselves. When coarse features occur near borders, these are blended gradually over a relatively large distance without blurring or

otherwise degrading finer image details in the neighbourhoods of the border [1].

During my study, I observed that recognition of the quality of a mosaic image is subjective. We generally expect a smooth transition when combining two images of the sky. In some applications, such as combining IC layout images which contain several boxes, we prefer not to over-smooth the sharp edges that exist in the original images. Hence, it is important to build a model for mosaic images that has an objective measure that incorporates certain user parameters so that users can control or improve the behavior of the resultant images.

Energy minimization models have been widely used in combining low-level image properties with higher-level knowledge. They have used the minimization of a blending energy function as our model. Within our blending energy function, two variation terms, image value variation and first derivative variation, are measured and minimized. Image value variation measures the difference between corresponding pixel values of the mosaic image and the to-be-combined image. First derivative variation measures the difference between the first derivative values of the mosaic image and the blended values of each respective first derivative. Our mosaic image can be effectively obtained by minimizing the blending energy function. The quality of the resultant image can be controlled and improved with an additional parameter low-level image properties with higher-level knowledge. They have used the minimization of a blending energy function as our model. Within our blending energy function, two variation terms, image value variation and first derivative variation, are measured and minimized. Image value variation measures the difference between corresponding pixel values of the mosaic image and the to-be-combined image. First derivative variation measures the difference between the first derivative values of the mosaic image and the blended values of each respective first derivative. Our mosaic image can be effectively obtained by minimizing the blending energy function. The quality of the resultant image can be controlled and improved with an additional parameter λ this model can be extended to other customized measurements. For example, perceptual measurement could have been included to measure mosaic images. However, proposing such a perceptual measurement is difficult due to its subjectivity. Therefore, the blending energy function is restricted to the image value variation and the first derivative variation.[3]

2. PROPOSED WORK

For the work to be implemented I require a multiresolution image which I will get by using the laplacian of gaussian pyramid approach.

The proposed approach is as shown in fig2:



Figure1: The Proposed Approach Algorithm.

Read Database:

1. Extract the three input images from the database i.e. A, B, Mask.
2. Convert color images to gray.

3. Call the Blend arbitrary function as these three images as argument along with no of decomposition levels.

Blend arbitrary:

1. Read number of rows & columns of input image matrix.
2. Call Laplacian pyramid function for A and B images with no of levels.
3. Call Gaussian pyramid function for Mask image with number of levels.
4. Also By using Mask as weighted function add two pyramids to get resultant pyramid as for each level.
5. Reconstruct pyramid by using reconstruct function.

Laplacian pyramid :

1. Read number of rows & columns of input image matrix.
2. Call Laplacian pyramid function for input image with no of levels.
3. Get particular level Laplacian matrix by taking subtraction of that level Gaussian Matrix & expanded version of previous Gaussian Matrix.

Gaussian pyramid:

1. Read number of rows & columns of input image matrix.
2. Calls the function reduce which convolve the input matrix with LPF matrix structure & sub sample it by 2 then return the Gaussian pyramid which is formed.
3. Get compliment of mask.

3.1 Multiresolution Approach.

A common characteristics of image is that neighbouring pixel are highly correlated. To represent the image directly in terms of the pixel values is therefore inefficient most of the encoded information is redundant. The first task in designing an efficient, compression code is to find a representation which in effect decorrelates the image pixels this has been achieved through predictive and transform technique.

Here I have describe a new technique for removing image correlation which combine features of predictive and transform methods.

Following are the two important pyramid structures.

In this section I have present a highly efficient "pyramid" algorithm for performing the required filtering operations and also I have show that the pyramid structure is ideally suited for performing the splining steps as well.

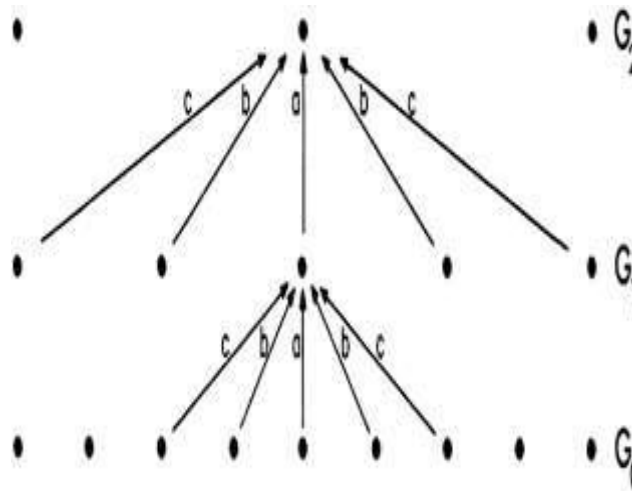


Figure2 :A one-dimensional graphical representation of the iterative REDUCE operation used in pyramid construction.

Each row of dots represents nodes within a level of the pyramid. The value of each node in the zero level is just the gray level of a corresponding image pixel. The value of each node in a high level is the weighted average of node values in the next lower level. Note that node spacing doubles from level to level, while the same weighting pattern or generating kernel" is used to generate all levels. The level-to-level averaging process is performed by the function REDUCE.[4] A sequence of low-pass filtered images G_0, G_1, \dots, G_N can be obtained by repeatedly convolving a small weighting function with an image. With this technique, image sample density is also decreased with each iteration so that the bandwidth is reduced in uniform one-octave steps. Sample reduction also means that the cost of computation is held to a minimum. Figure 1 is a graphical representation of the iterative filtering procedure in one dimension. Each row of dots represents the samples, or pixels, of one of the filtered images. The lowest row, G_0 , is the original image. The value of each node in the next row, G_1 , is computed as a weighted average of a sub array of G_0 nodes, as shown. Nodes of array G_2 are then computed from G_1 using the same pattern of weights. The process is iterated to obtain G_2 from G_1 , G_3 from G_2 and so on. The sample distance is doubled with each iteration so that successive arrays are half as large in each dimension as their predecessors. After imagining these arrays stacked one above the other, the result is the tapering data structure known as a pyramid. If the original image measures $2N + 1$ by $2N + 1$, then the pyramid will have $N + 1$ levels. Both sample density and resolution are decreased from level to level of the pyramid. For this reason, shall call the local averaging process which generates each pyramid level from its predecessor a REDUCE operation [4]. In case of image mosaicing generally two types of pyramidal operations are used, i.e. Laplacian pyramid and Gaussian pyramid. In this project I am applying Laplacian function on two input images and Gaussian function on masked image for finer resolution. In case of pyramidal blending I can mosaic different part of various images i.e. I can combine right part of one image to the left part of another image. Due to this pyramidal blending, the obstructive boundaries get converted into smooth transition region.

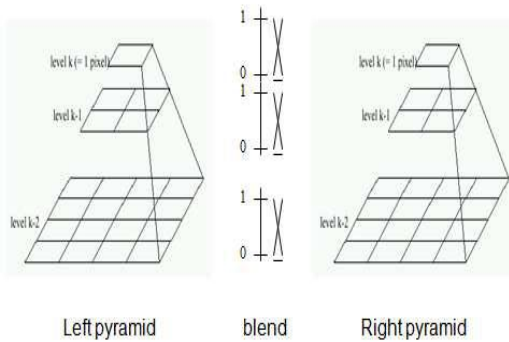


Figure3:pyramidal Blending Model

In this blending left part of one image is get blend with the right part of another image. In case of blending, the pixel values of images are mixed in each other in such a way that, the image view should be clear so that the boundary should be invisible. In pyramidal blending mixing of images are done with new appearance but without loss of original image appearance. The Figure 2 shows the blending model of an apple at a different Laplacian levels.

3.2 The Laplacian pyramid using gaussian

The Gaussian pyramid is a set of low-pass filtered images. In order to obtain the band-pass images required for the multiresolution spline I can subtract each level of the pyramid from the next lowest level. Because these arrays differ in sample density, it is necessary to interpolate new samples between those of a given array before it is subtracted from the next lowest array. Interpolation can be achieved by reversing the REDUCE process. That is by EXPAND operation. Let G image obtained by expanding G_l K times. Then,

$$G_{l,0} = G_l, \dots\dots\dots(1)$$

And for $K > 0$

$$G_{l,k} = \text{EXPAND}[G_{l,k-1}] \dots\dots\dots(2)$$

By EXPAND I mean,

$$G_{l,k}(i,j) = 4 \sum_{m,n=-2}^2 G_{l,k-1} \left(\frac{2i+m}{2}, \frac{2j+n}{2} \right) \dots\dots\dots(3)$$

Here, only terms for which $(2i + m)/2$ and $(2j + n)/2$ are integers contribute to the sum. Note that $G_{l,1}$ is the same size as G_{l-1} , and that $G_{l,1}$ is the same size as the original image[4]. I now define a sequence of band-pass images L_0, L_1, \dots, L_N . For, $0 < l < N$,

$$L_l = G_l - \text{EXPAND}[G_{l+1}] = G_l - G_{l+1,1} \dots\dots\dots(4)$$

Because there is no higher level array to subtract from G_N , I define $L_N = G_N$. Just as the value of each node in the Gaussian pyramid could have been obtained directly by convolving the weighting function W_l with the image, each node of L_l can be obtained directly by convolving $W_l - W_{l+1}$ with the image. This difference of Gaussian-like functions resembles the Laplacian

operators commonly used in the image processing, so I refer to the sequence L_0, L_1, \dots, L_N as the Laplacian pyramid.[2]

3.3 Decomposition /Blending Level

To obtained the pyramidal multiresolution representation it is necessary to decompose the image but the level of decomposition depends upon the size of the image therefore prior to process the image all three images that is the image A Image B and Mask image must be of same size also the width of transition zone is depend on the information represented in each band i.e the Level.

3.4 Mask

The mask signal is a binary representation which describes how two signals will be combined. For example, two signals A and B will be combined to form a mosaic signal, and the mask signal S is a binary signal in which all points inside the mosaic region are set to 1 and those outside the mosaic region are set to 0.[1][5][6].

Since the low-frequency content of a signal are often sufficient in many instances (such as the content of an image), and the detail information resembles the high frequency components (such as edge of an image), thus, the width of the transition zone T is chosen according to the wave length represented in each band. That is, for lower frequency components, the width of transition zone T is chosen to be larger than that of higher frequency components. This implies that low-frequency components "bleed" across the boundary of mosaic region further than high-frequency components do.

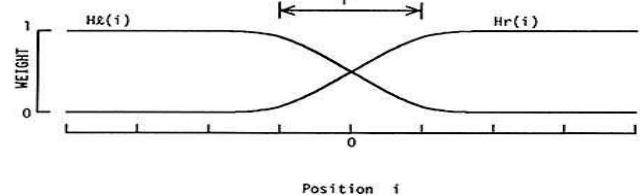


Figure4:Weighted Average Technique.

3.5 Blending

The images to be joined overlap so that it is possible to compute the gray level value of points within a transition zone as a weighted average of the corresponding points in each image [5]. Suppose that one image, $Fl(i)$, is on the left and the other, $Fr(i)$, is on the right, and that the images are to be blended at a point \hat{i} (expressed in one dimension to simplify notation). Let $Hl(i)$ be a weighting function which decreases monotonically from left to right and let $Hr(i) = 1 - Hl(i)$. Then, the blended image F is given by $F(i) = Hl(i - \hat{i}) Fl(i) + Hr(i - \hat{i}) Fr(i)$ [5]. It is clear that with an appropriate choice of H , the weighted average technique will result in a transition which is smooth. However, this alone does not ensure that the location of the boundary will be invisible. Let T be the width of a transition zone over which Hl changes from 1 to 0. If T is small compared to image features, then the boundary may still appear as a step in image gray level, albeit a somewhat blurred step. If, on the other hand, T is large compared to image features, features from both images may appear superimposed within the transition zone, as in a photographic double exposure. The size of the transition Zone, relative to the size of

image features, plays a critical role in image blending. To eliminate a visible edge the transition width should be at least comparable in size to the largest prominent features in the image [5]. Therefore at a particular decomposition i.e. blending level by getting the difference of image pixel value within a transition zone using getpixel method the edge can be smoothed with weighted average technique and set the corresponding pixel using set pixel method.

3.6 Color Recovery Level

As after blending there is loss of color of combine image. The color can be recovered using the image on which the cropped portion is paste as a reference image. For that I have used the Haar transform.

4. Result Analysis and Discussion

The earlier work on this topic is based on designing a model which balances the characteristics of blended image to that of original image based on two parameters i.e. image value variation and first derivative variation. By adjusting this parameter λ , the subjective quality of the mosaic image is improved.

As shown below:

AVERAGE SCORE OF OUR SUBJECTIVE TEST FOR IMAGE

	$\lambda = 0.1$	$\lambda = 0.2$	$\lambda = 0.5$	$\lambda = 1.0$
Tower	2.9	2.8	4.3	4.9
Butterfly	3.5	3.3	3.3	3.3
Landscape	3.8	3.9	4.0	3.9
Arena	3.5	4.0	4.4	3.4

Here in my project I have tried to perform mosaic in such a way that combined image features should be as close as possible to the input image and try to measure them with the help of three parameters.

1. Peak signal to noise ratio (PSNR)

2. Mean Value intensity

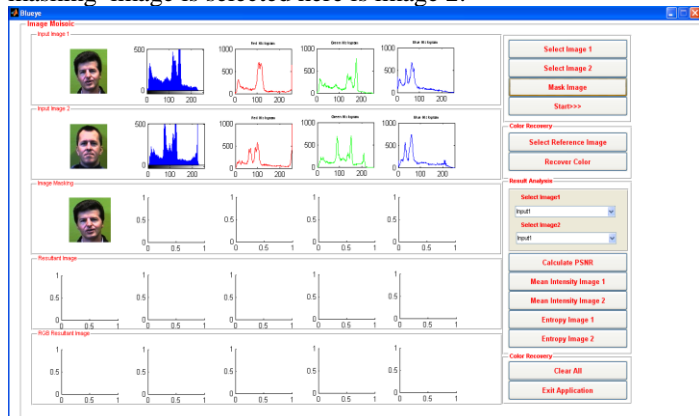
3. Entropy

PSNR is Signal to noise ratio. More the value, good is the result.

Mean value intensity is the color level of that image.

Entropy is the Density of the Pixel with respect to region.

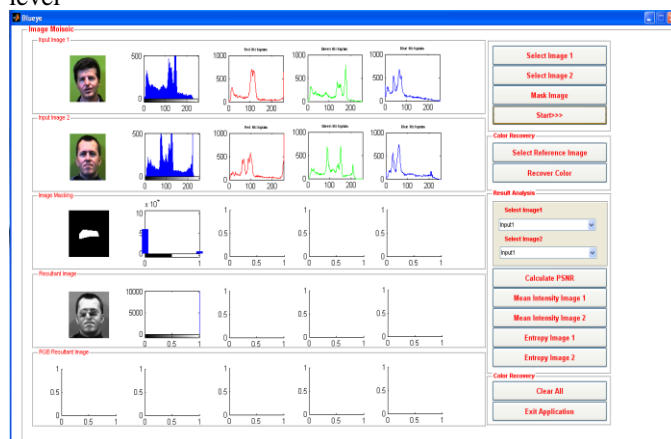
1. First image 1 & image 2 is taken as two input images then the masking image is selected here is image 2.



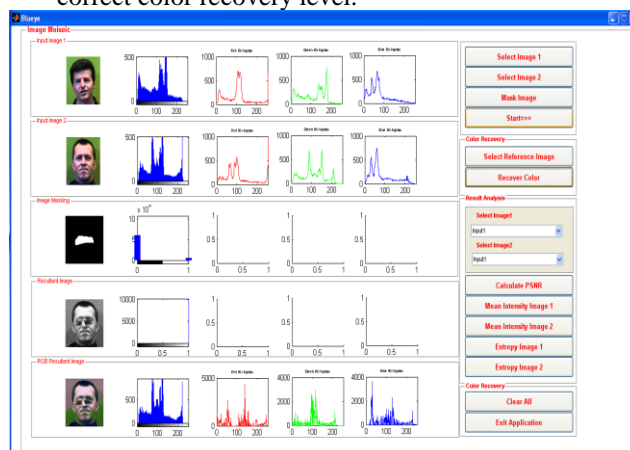
2. selecting mask from image 1



3. Starting Blending operation by entering correct blending level



3. To recover color selecting image 2 as reference image with correct color recovery level.



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Blending Level	Color Recovery Level	PSNR	MI1	MI2	ENT1	ENT2
1	0.10	9.20	0.47	0.41	17.655	17.630
2	0.20	9.24	0.47	0.46	17.655	17.764
3	0.30	9.21	0.47	0.38	17.655	17.659
4	0.40	9.06	0.47	0.47	17.655	17.526
5	0.50	9.23	0.47	0.40	17.655	17.642
6	0.60	9.23	0.47	0.42	17.655	17.617
7	0.70	9.23	0.47	0.40	17.655	17.661
8	0.80	9.24	0.47	0.46	17.655	17.739

Therefore from the above table it can be conclude that as the blending level and color recovery level increases the resultant combine image feature values are nearer to the input images feature value.

5.Conclusion

As it is stated that Humans recognize moisaic image subjectively while computer vision algorithm measures a mosaic image objectively. Therefore by taking into consideration this fact.the proposed model provide solution to the problem of mosaic image that can be measured based on three parameter that is PSNR,Mean Value Intensity,entropy of the image.Therfore although the method for obtaing multiresolution images are different I can encorporate different parameter to measure the quality of mosaic image.if Instead of position based object based mosacing is done then this model can be best suited to application like filmmaking ,photogammetry etc.

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