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Multi-resolution Representation of Multifocus Image Fusion Using Gaussian and Laplacian Pyramids

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Abstract—Image Processing is the integral part of the surveillance system. Multifocus image fusion is a technique used to fuse multiple images captured with multiple focal lengths. In this paper we have studied the multi-resolution pyramid method used to integrate the multiple multifocus images together. This method is based on the down sampling and up sampling of the images and to apply various operations. Integrated resultant image is having all the focused objects and contain maximum detail.

***Key Words*-Image fusion, multifocus, Gaussian pyramids, Laplacian Pyramid, Band pass Filter**

I. INTRODUCTION

Multifocus image fusion is the process of combining the two or more images, which are taken from multiple shots of the same scene with the same digital camera [1], so as to get a single image with multi-objects distinct. Image fusion is divided into three levels from bottom to up: the data level fusion, the feature level fusion and the decision level fusion [2]. The data level fusion used in image fusion called pixel level fusion. It is the basement of high level image fusion and it is basic building block of image fusion research. The fusion method is designed so as to keep the original data as much as possible, which provides the details that other level fusion methods cannot supply. Pixel level fusion consists of spatial-domain algorithm and transform-domain algorithm, while the former has several fusion rules, such as logistic filtering method, gray-weighting average method, contrast modulation method, etc, and the latter has Laplacian pyramid-based method, wavelet transform fusion, etc. And the wavelet transform fusion method is one of the most important methods in common usage [3~7]. This paper deals with the concept of multifocus image fusion. This means that the focused merged resultant image can be obtained by fusion technique to combine multiple images with diverse focus in the same scene under the same image formation conditions. The merged image includes the more details of information of the original images and improves the details of image. This kind of applications is used in various techniques of the image processing like in the areas of machine vision, digital camera, target recognition, etc. The various image fusion scheme used, which is works on the pixel by pixel basis. This includes many other undesired effects like undesired effects like artifacts and also including reduction in contrast. A Fourier transform representation can be used to separate the various spatial scales of an image. Unfortunately, when we leave the familiar spatial domain for the spatial frequency domain our intuitive feel for the problem is lost. Operating on the Fourier transform of an image, we can no longer "see" local spatial features in a recognizable form. What is really needed is a representation that describes an image at multiple spatial resolutions, and also preserves the local spatial structure that allows us to "see" the picture at each scale. Pyramid representations are ideal for this class of problems [9]. This kind of problem was reduced by working on spatial domain instead of time domain .In order to solve this problem J.M. Ogden & E.H. Adelson proposed a technique known as pyramid technique [10]. So image fusion methods based on Pyramid, which includes Laplacian pyramid, gradient pyramid are easy way to fuse the image and also it retains the level of image without degrading the image quality.

II. GAUSSIAN PYRAMID REPRESENTATION

The Gaussian pyramid is the base structure from which later the Laplacian pyramid is built. It contains a stack of signals (images in the spatial case), where each consecutive level contains a successively lowpass filtered version of the original signal. The lowpass filtered signals can be stored at reduced sampling rate and thus require less storage space. The pyramid is constructed by iteratively applying a lowpass filter and sub sampling of the resulting signal. This process is repeated until a signal length of specific number of levels is not reached. Because ideal lowpass filtering is expensive, a Gaussian filter is used as an approximation (5-tap binomial kernel)[9].

$$G_k(i,j) = \sum_m \sum_n G_{k-1}(2i+m,\ 2+n), k = 1,N$$

The first step in Gaussian pyramid technique is to find out the low-pass filtered image of original image. Let say g0 is the original image and g1 is the computed low pass image from g0 or we may say that this original image g0 have been down sampled or reduced.

$$g_l(i,j) = \sum_{m=-2}^{2}\sum_{n=-2}^{2} w(m,n)\, g_{l-1}(2i+m, 2j+n)$$

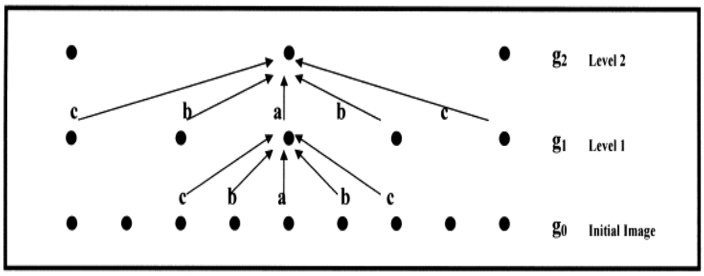
Here for levels 0 < l < N and nodes i, j , 0 < i < C_l, 0 < j < R_l. Here N refers to the number of levels in the pyramid, while
C_l and R_l are the dimensions of the lth level:, It will result in to reduction of both resolution and sample density. This process will keep on performing from one to five samples like g2 will be down sampled of g1 image and g3 will down sampled of g2 image. Filtering is performed by a procedure equivalent to convolution with one of a family of local, symmetric weighting functions. An important member of this family resembles the Gaussian probability distribution [10].

$$g_k = \mathrm{REDUCE}\,(g_{k-1})$$

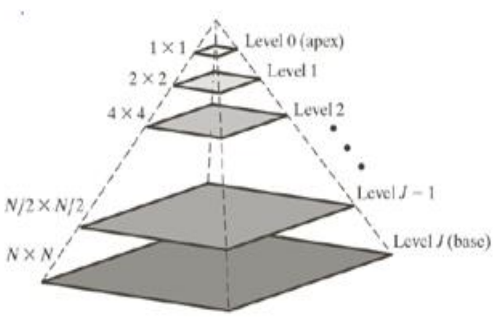
The same algorithm can be used to "expand" an image array by interpolating values between sample points. This device is used here to help visualize the contents of levels in the Gaussian pyramid, and in the next section to define the Laplacian pyramid.
Weight kernel or the weighting pattern is used to generate the pyramid, it is same like the convolution of image with the known pattern. An additional constraint is called equal contribution. This stipulates that all nodes at a given level must contribute the same total weight (=1/4) to nodes at the next higher level. Let $\hat{w}(0) = a$, $\hat{w}(-1) = \hat{w}(1) = b$, *and* $\hat{w}(-2) = \hat{w}(2) = c$ in this case equal contribution requires that $a + 2c = 2b$. These three constraints are satisfied when

$W^{\wedge}(0)=a$
$W^{\wedge}(-1)= W^{\wedge}(1)=1/4$
$W^{\wedge}(-2)= W^{\wedge}(2)=1/4-a/2$

In this case a = 0.4. The shape of the equivalent function converges rapidly to a characteristic form with successively higher levels of the pyramid, so that only its scale changes. However, this shape does depend on the choice of a in the generating kernel. Characteristic shapes for four choices of a are .3, .4, .5, .6. According to it the shape of gaussian pyramid changes and the spike of it become more sharp or flatter [11]. Fig(a).tells about the basic ideology of Gaussian filter where as the level increases from g0 to g4 the number of pixels are decreasing. Like the number of pixel in g0 which correspond to original image as compared to g1 is more by two folds. In Fig(b). it shows how actually the image size decreasing from g0 to gn. The Laplacian Volume pyramid is a 3D extension of the 2D Laplacian image pyramid. With a Laplacian pyramid you can compress data and so it would be possible to use larger data sets or to decrease the hardware requirements. You can achieve with the Laplacian pyramid compression ratios like 10:1, but this is associated with a loss of quality. The construction of one level of the Laplacian pyramid consists of 3 steps. First a 5x5x5 Gaussian low-pass filter called *REDUCE ()* is applied to the original volume data, so you get The Laplacian Volume pyramid is a 3D extension of the 2D Laplacian image pyramid. With a Laplacian pyramid you can



Fig(a): Gaussian pyramid ideology



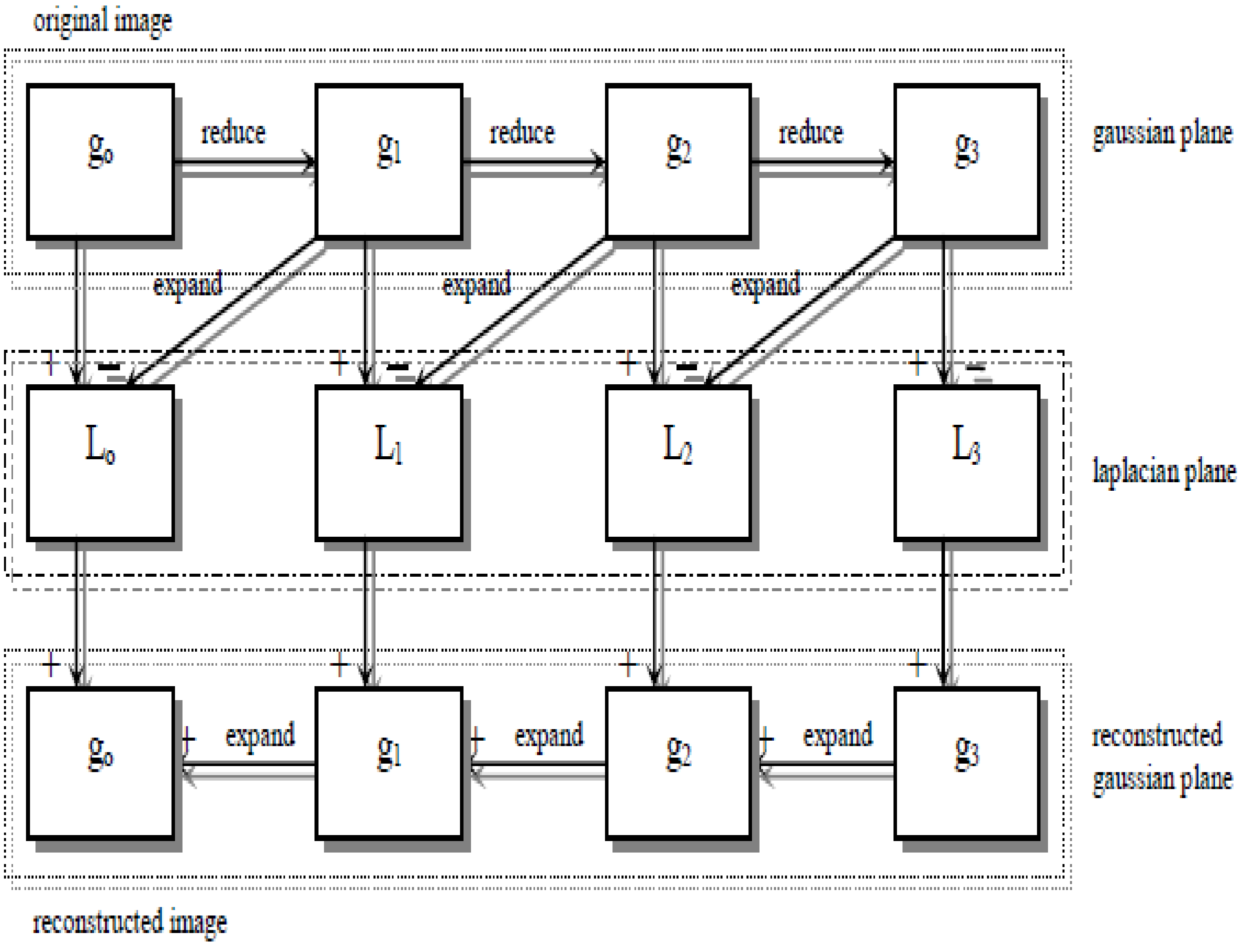
Fig(b): Gaussian pyramid structure

III. GAUSSIAN PYRAMID REPRESENTATION

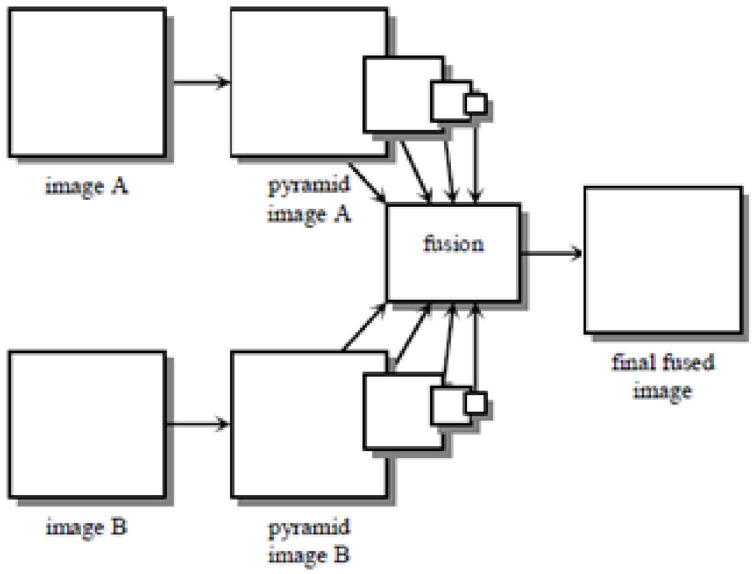
The Laplacian Volume pyramid is a 3D extension of the 2D Laplacian image pyramid. With a Laplacian pyramid you can compress data and so it would be possible to use larger data sets or to decrease the hardware requirements. You can achieve with the Laplacian pyramid compression ratios like 10:1, but this is associated with a loss of quality. The construction of one level of the Laplacian pyramid consists of 3 steps. First a 5x5x5 Gaussian low-pass filter called REDUCE () is applied to the original volume data, so you get a lower resolution version of the input data. This new level of the Gaussian pyramid has only the half resolution at each dimension. If you apply the inverse function of REDUCE () which is called EXPAND () you get an approximation of the level before, here the original data set, which have the same resolution. If you calculate the differences between the input data and the expanded data you get the respective level of the Laplacian pyramid. If you repeat these several times, but not to the possible top level, you get the Laplacian pyramid. Since the differences are nearly 0 and are also uniformly quantized you need fewer memory to store it, but it is also an error involved. The error depends on the number and the distribution of the quantization levels [12]. You store only the highest level of the Gaussian pyramid which is not stored in the Laplacian pyramid and the Laplacian pyramid. The Laplacian pyramid can thus be used to represent images as a series of band-pass filtered images, each sampled at successively sparser densities. It is frequently used in image processing and pattern recognition tasks because of its ease of computation. We were able to extract the text from the background in an image by using 3 levels of the Laplacian pyramid. We used the K-Means algorithm to segment the 3 images obtained at each level of the pyramid. The text, which has a stronger response to the filters, forms one cluster, while the background areas with little intensity variation form a separate cluster [13]. However, for segmenting multilingual documents, analysis of the frequency content of the image alone is inadequate. In addition to the frequency information, the orientation information also needs to be extracted,for

IV. CONCLUSION AND FUTURE SCOPE

Along this research, some image fusion approaches have been studied. All of them were found reliable fusion methods in multifocus applications, and in conjunction they gave acceptable results in multifocus fusion schemes, excepting the spatial frequency approach. As previously mentioned, due to the subjective characteristic of the fusion quality evaluation, it is difficult to conclude which method the best one is for certain. The number of decomposition levels in the multi resolution approaches, was found to influence image fusion performance. However, using more decomposition levels do not necessarily implies better results. Methods to choose the appropriate number of levels should be studied. All the fusion techniques use the absolute value of the image transform coefficients as an activity measure. There are other possibilities to calculate activity. Finally, it will be interesting to include the prior knowledge of the source images, if available, in the activity measure and thus decision rules. Thus this kind of technique is best suited for muti resolution, multifocus and multi exposure images. It can also be further trained using various optimization techniques.



Fig(c): Gaussian and Laplacian pyramid block diagram



Fig(d): Schematic diagram of the Laplacian Pyramid fusion method

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