Accurate Merging of Sampled Images for Complex Perception
Devlopment
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Abstract— Accurate merging of intended pixels can be achieved in high quality using frequency
domain techniques. Image merging has been used for many reasons like resolution improvement or for
segmentation purposes. We present here a method which could be used in precision engineering and
biological applications where more precise prediction is required of a combined phenomenon. When
pixels are added, its original property is lost but accurate merging of intended pixels can be achieved in
high quality using frequency domain properties of an image. This paper introduces a technique to
merge various images which can be used as a simple but effective technique for overlapped view of a
set of images and producing reduced dataset for review proposes.

Keywords— merging of images, linear integral of frequency density, reduced dataset, compressed
view, predictive analysis.

I. INTRODUCTION

There are several scenarios in image engineering where case exist for multiple object merging
under common denominator scenes and later separating these multi objects present in distinctively in
intensity seperable layers. Many applications require merging of sampled images for complex
perception development. In most cases, for such requirements, images are merged at intensity level.
Even though it gives good perception of combined scene of objects, it is found that they are not
sufficient to analyze certain case. The main problem is incoherent modulation of intensity arising out
of phase properties being lost. In order to compensate these losses, combined phase and amplitude
merge is demanded. We present here a method which gives more precise prediction of a combined
phenomenon used in precision engineering and biological applications.

In the field of image processing, gray level intensity information can be processed easily as the
image is stored as a collection of pixels of various colors or intensities. Images are a collection of pixels
and each pixel is represented by some values depending on the type of the image, dealing them at
intensity level is insufficient for precision management. In gray level digital images, pixels contain
intensity information and we perceive and analyze an image based on the changes in shades of color
intensities or frequencies. It could be scenarios of night vision for security processing or it could be
microscopic vision of biological specimens and culture. Edges are formed due to sudden change in
intensity and we can visualize and identify various objects in an image because of their color, shapes
and texture. It is the rate of change of intensity values which gives the illusion of an object. Each object
in an image generates a unique spectrum of frequencies in frequency domain. An image with many
such objects contains a collection of all those frequencies.

We are introducing the techniques that gives feasibility for creating accurate high fidelity images
through merging. In order to collect all needs of complete information of image, it is necessary and
better to merge the frequencies along with phase to get overlapped view of the objects or images. Such
methods are required for several practices in astronomy, radiology, body implant predictions, fracture
mechanics prediction etc.

In literature, Image merging has been used for many reasons like improving resolution or
implementing segmentation. A novel image restoration algorithm to deblur the image without
estimating the image blur by merging differently blurred multiple images in the spectrum domain using the fuzzy projection onto convex sets (POCS) can be found in. Statistical Region Merging (SRM) and the Minimum Heterogeneity Rule (MHR) have also been used for object merging. The SRM segmentation method not only considers spectral, shape, and scale information, but also has the ability to cope with significant noise corruption and handle occlusions. The MHR used for merging objects takes advantage of its spectral, shape, scale information, and the local and global information. A novel self-adaptive weighted average fusion scheme based on standard deviation of measurements to merge IR and visible images is developed in the special domain using the better recovery tool of total variation optimization. It achieves a high level of fusion quality in global information. Image merging has been used for many reasons like improving resolution or implementing segmentation. Usually merging of different data sets is used in digital image processing to improve the visual and analytical quality of the data. The analyst may need to merge different types of data. In this process, different data such as satellite imagery from the same sensor but with different resolution, satellite imagery from different sensors with varying resolution, digitized aerial photography and satellite imagery or satellite imagery with ancillary information can be merged. There are many techniques for merging like Principal Component, IHS, and Brovey Transform. A technique for multi-image fusion in one-pass through overlapping input images which restores and reconstructs the scene radiance field can be found in. The technique is effective because it maximizes fidelity based on a comprehensive end-to-end system model that accounts for scene statistics, acquisition blurring, sampling, and noise. Also, in computer vision, multisensor image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. Image fusion has become a common term used within medical diagnostics and treatment too. The term is used when certain portions of multiple images of a patient are registered and overlaid or merged to provide additional combined information. Fused images may be created from multiple images from the same imaging modality, or by combining information from multiple modalities, such as magnetic resonance.

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipments are not capable of providing such data convincingly. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. However, the standard image fusion techniques can distort the spectral information of the multispectral data while merging. Data fusion method for land cover (LC) classification that combines remote sensing data at a fine and a coarse spatial resolution can be found in. This classifier uses all image information (bands) available at both fine and coarse spatial resolutions by stacking the individual image bands into a multi dimensional vector.

We are introducing here spatial domain and frequency domain techniques that merging in frequency domain gives better performance as it preserves key properties of original images in a better way. In spatial domain techniques, we directly deal with the image pixels. The pixel values are manipulated to achieve desired result. In frequency domain methods the image is first transferred to frequency domain means Fourier transform of the image and then all merging operations are performed on Fourier transform of the image and by taking then inverse Fourier transform is performed to obtain resultant image.

II. SPECTRAL TREATMENT
The repetitive nature or the frequency characteristics of images can be analyzed using spectral decomposition methods like Fourier analysis. The precision of fusion much depends on the phase properties of pixels in streams rather than the individual intensity property which can yield only a coarse merge. In an RXC (Row x Column) digital image, positions u and v indicate the number of repetitions of the sinusoid in those directions. Therefore the wavelengths along the column and row axes are

\[ \lambda_u = \frac{C}{u} \quad \text{and} \quad \lambda_v = \frac{R}{v} \text{ pixels} \]

and the wavelength in the wavefront direction is

\[ \lambda_{wf} = \sqrt{\left(\frac{C}{u}\right)^2 + \left(\frac{R}{v}\right)^2}. \]

The frequency is the fraction of the sinusoid traversed over one pixel,

\[ \omega_u = \frac{u}{C}, \quad \omega_v = \frac{v}{R} \quad \text{and} \quad \omega_{wf} = \frac{1}{\sqrt{(\frac{C}{u})^2 + (\frac{R}{v})^2}} \text{ cycles.} \]

The wave front direction is given by,

\[ \Theta_{wf} = \tan^{-1}\left(\frac{\omega_u}{\omega_v}\right) = \tan^{-1}(\frac{vC}{uR}) \]

It is well known that edges in an image are generated by high frequencies and human vision system is more sensitive to edges as compared to constant or slow varying intensities and high frequency coefficients tend to be very small and they can be quantized very effectively without distorting the results to achieve data reduction. This paper also exploits this fact for data reduction of the images after merging by utilising a threshold T in algorithm B.

### III. IMPLEMENTATION

This section describes the algorithms used for precision merging. We have created a prototype implementation for object merging using the following algorithms –

**Merging in spatial domain:**

**A. Algorithm**

Initialization:

- Set the value for number of images/layers 'n'
- Align the images or layers so that number of samples is same.
- Normalize the image values \(i(x, y)\) to 0-1

While all pixels \((x, y)\) in the image are not seen do ADD corresponding intensities of all n images
Result(x, y) = i_1(x, y) + ...... + i_n(x, y)

**Merging in frequency domain:**

Linear integral of frequency density from different images like in different windows of FFT, is a promising approach to create better accuracy. In the total spectral spread, the images differ by spectral density per window. This spectral strength corresponding to each image at corresponding windows is independent of intensity. We make use of this fact in the following algorithm and its unique success is shown in the following figures.

Suppose there are 'n' images to be merged each of size RXC (Row x Column). In frequency spectrum of an RXC digital image, positions u and v indicate the number of repetitions of the sinusoid in those directions. We scale each sinusoid with a prominence coefficient before integration for perception control. As per definition of Fourier Transform, frequency spectrum of image 'i' can be represented by the following formulae:

$$\text{FFT}(i(x, y)) = I(u, v) = \sum_{x} \sum_{y} i(x, y) \exp[-j2\pi(u x/R + v y/C)]$$

Hence,

$$I(u, v) = \sum_{x} \sum_{y} i(x, y)[\cos(\Theta) - j \sin(\Theta)]$$

Where,

$$\Theta = 2\pi(ux/R + vy/C)$$

Same can be rewritten as:

$$I(u, v) = \sum_{x} \sum_{y} i(x, y)[R\Theta - I\Theta]$$

Where, R and J stand for real part and imaginary part of Fourier Spectrum. Suppose, there are n images to be merged and each image pixel p can be represented as p_{xyn} in 3D domain of n images then its corresponding frequency P_{uvn} can be calculated by the following equation:

$$P_{uvn} = a_n \sum_{x} \sum_{y} i_n(x, y)[R\Theta - I\Theta]$$

And,

$$P_{\text{integral}} = \sum_{n} P_{uvn}$$

Where a_1, a_2, ......, a_n are prominence coefficients.

Therefore,

$$P_{\text{integral}} = a_1 \sum_{x} \sum_{y} i_1(x, y)[R\Theta - I\Theta] + ...... + a_n \sum_{x} \sum_{y} i_n(x, y)[R\Theta - I\Theta]$$

Actual values of these prominence coefficients will be adjusted by visual perception according to the application and requirement. Further study of perception coefficients is beyond scope of this project.

**B. Algorithm**

**Initialization:**

- Set the value for number of images/layers 'n'
- Align the images or layers so that number of samples is same.
- Normalize the image values i(x,y) to 0-1
- Identify the highest frequency (Max. Frequency) from frequency spectrum of the input image.
- Set threshold T=Max. Frequency * x Where 0<x<1

While all pixels(x,y) in the images are not seen do ADD corresponding density of frequencies of all n images

$$\text{Result}(u, v) = a_1 \text{FFT}(i_1(x, y)) + ...... + a_n \text{FFT}(i_n(x, y))$$

Remove all frequencies below threshold 'T' to achieve data reduction.

Take inverse FFT to visualize the merged image.
IV. RESULT AND ANALYSIS

The experiments were aimed at developing a system to merge images in such a way that all images can be seen together in high fidelity without much loss of information because of the overriding intensity factors.

The comparative study was performed over ten images for merging in spatial domain as well as in frequency domain by using Algorithm A and Algorithm B as discussed in section 3. It is found by visual inspection that merging in spatial domain as well as frequency domain both gives similar results if the objects in input images are spatially separate or non-overlapping from each other whereas merging in frequency domain outperforms if objects in the images are getting overlapped in merged image. Merging in frequency domain is capable of keeping fine details of all input images. For these merging studies images were selected with fixed dimensional accuracy at pixel levels and objects were mapped over them. Hence a quantitative analysis of imaging error is avoided. This technique can be useful in surveillance where the observer is supposed to see multiple pictures coming from many cameras at a time as it gives ease to the observer to view multiple images at a time in a single screen as well as with reduce data load. If we merge more than 2 images, we can get further compressed view.

Tiger's paw is more clearly seen in second image.

Merging itself is a form of data reduction and it is possible to further reduce the data required to represent the merged images by retaining frequencies with higher coefficient values. This feature has been implemented by providing a threshold T in algorithm B of section 3. High frequency coefficients tend to be very small and they can be quantized very effectively without distorting the results to achieve compression. The effect of data reduction achieved by us on merged images can be seen in Fig below. A reduction
ration of 10 (10:1) means that the first data set has 10 information carrying units for every 1 unit in the reduced data set. An attempt has been made to show that it is not required to preserve all frequencies to visualize the merged image; the best reduction ratio for a specific application depends on the application and can be chosen iteratively as more reduction comes with more loss of information. The specific outputs of Fig. 4 demonstrate that in this case, reduction ratio of 8 can be achieved without any visible loss whereas reduction ratio of 22 shows significant loss as body of the tiger got merged with the background.

![Reduction Ratio Images]

Reduction ratio of 8 can be achieved easily without any visible loss. Image with Reduction ratio of 22 shows significant loss as body of the tiger got merged with the background.

V. CONCLUSION

This work has developed a simple but effective technique for object merging using linear integration of spectral density in corresponding windows. The images merged in this way has displayed improved precision, which is capable of being used in different application like fracture prediction in solids, multi cellular integration in biology and visualization of body implants. This project demonstrates that the linear integral of frequency density of merging images retains the details of all original images accurately and it can be viewed in a single frame and simultaneously provide a data reduced form. This fact can be widely utilised at many places like, body implant predictions, creating secure currency, fracture mechanics prediction etc.

REFERENCES


