Image fusion by Denoising and Segmentation

Prof V.P. Vaidya *

Lecturer in Information Technology
Sipna's college of Engg. And Technology ,Amravati.
India

Prof V.K.Shandilya

Asst.Prof in CMPS
Computer Science and Engg.technology
Sipna's college of Engg. And Technology ,Amravati.
India

***Abstract*:** **With the recent rapid developments in the field of sensing technologies, multisensory systems have become a reality in a growing number of fields such as remote sensing, medical imaging, machine vision and the military applications for which they were first developed. The result of the use of these techniques is a great increase of the amount of data available.**

Image fusion provides an effective way of reducing this increased volume of information while at the same time extracting and increasing all the useful information from the source images. The underlying idea used here is to fuse different views of the same image .For achieving this; first the image is segmented and then fused into a complete image. The fused image provides better information for human or machine perception as compared to any of the input images. A total variation norm based approach has been adopted to fuse the pixels of the noisy input images.

Better results can be obtained on several test images. The goal of image fusion hence achieved and gives better human perception.

Keywords*:* Image fusion, pixel-level fusion, total variation.

INTRODUCTION

With the recent rapid developments in the field of sensing technologies multisensory systems have become a reality in a growing number of fields such as remote sensing, medical imaging, machine vision and the military applications for which they were first developed. The result of the use of these techniques is a great increase of the amount of data available.

Image fusion provides an effective way of reducing this increased volume of information while at the same time extracting and increasing all the useful information from the source images. Fusion integrates redundant as well as complementary information present in input image in such a manner that the fused image describes the true source better than any of the individual images. The exploitation of redundant information improves accuracy and the reliability whereas integration of complementary information improves the interpretability of the image. Image fusion has been used extensively in various areas of image processing such as remote sensing, biomedical imaging, nondestructive evaluation etc. For example, in optical remote sensing Single sensor image fusion system

Multisensor image fusion system, due to physical and technical constraints, some sensors provide excellent spectral information but inadequate spatial information about the scene. On the other hand, there are sensors that are good at capturing spatial information but which fail to capture spectral information reliably. Fusing these two types of data provides an image that has both the spatial and the spectral information. Therefore, only the fused image needs to be stored for subsequent analysis of the scene. Multi-sensor data often presents complementary information about the region surveyed, so image fusion provides an effective method to enable comparison and analysis of such data. The aim of image fusion, apart from reducing the amount of useless data, is to create new images that are more suitable for the purposes of human/machine perception, and for further image-processing tasks such as segmentation, object detection or target recognition in applications such as remote sensing and medical imaging.

The underlying idea used here is to fuse different views of same image. For achieving this; first the image is segmented and then fused into a complete image.

Segmentation is done by minimizing a convex energy functional based on weighted total variation leading to a global optimal solution. Each salient region provides an accurate figure, ground segmentation highlighting different parts of the image. These highly redundant results are combined into one composite segment by analyzing local segmentation certainty.

Images can be acquired with the help of sensors. There are 2 types of sensors.

A. Single sensor image fusion system

The sensor shown could be a visible-band sensor such as a digital camera. This sensor captures the real world as a sequence of images. The sequence is then fused in one single image and used either by a human operator or by a computer to do some task.For example in fig 2.1 object detection, a human operator searches the scene to detect objects such intruders in a security area.

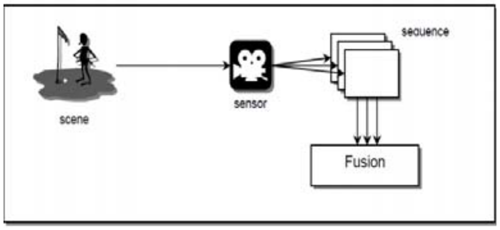

Fig.2.1 Single sensor image fusion system

This kind of systems has some limitations due to the capability of the imaging sensor that is being used. The conditions under which the system can operate, the dynamic range, resolution, etc. are all limited by the capability of the sensor. For example, a visible-band sensor such as the digital camera is appropriate for a brightly illuminated environment such as daylight scenes but is not suitable for poorly illuminated situations found during night, or under adverse conditions such as in fog or rain.

B. Multi-sensor image fusion system

Multi-sensor image fusion systems overcomes the limitations of a single sensor vision system by combining the images from these sensors to form a composite image. Figure 2.2 shows an illustration of a multi-sensor image fusion system. In this case, an infrared camera is supplementing the digital camera and their individual images are fused to obtain a fused image. This approach overcomes the problems referred to before, while the digital camera is appropriate for daylight scenes, the infrared camera is suitable in poorly illuminated ones.

The benefits of multi-sensor image fusion include:

1. Extended range of operation – multiple sensors that operate under different operating conditions can be deployed to extend the effective range of operation. For example different sensors can be used for day/night operation.
2. Extended spatial and temporal coverage – joint information from sensors that differ in spatial resolution can increase the spatial coverage. The same is true for the temporal dimension.
3. Reduced uncertainty – joint information from multiple sensors can reduce the uncertainty associated with the sensing or decision process.

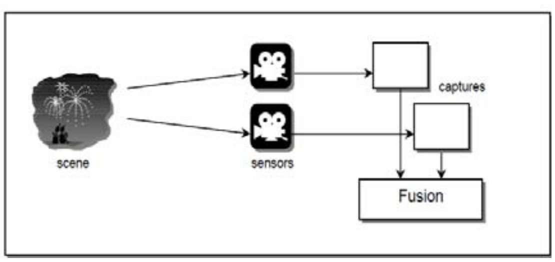

Fig 2.2 Multisensory image fusion system

From the perspective of fusion, features of the observed images that are to be fused can be broadly categorized in the following three classes.

1) Common features: These are features that are present in all the images.

2) Complementary features: Features that are present only in one of the images are called complementary features.

3) Noise: Features that are random in nature and do not contain any relevant information are termed as noise.

The goal of image fusion is to extract information from input images and fused it such that the fused image provides better information for human or machine perception as compared to any of the input images.

I. LITERATURE REVIEW

There are several approaches to the pixel level fusion of spatially registered input images. Most of these methods have been developed for the fusion of stationary input images (such as multispectral satellite imagery). Due to the static nature of the input data, temporal aspects arising in the fusion process of image sequences, e.g. stability and consistency are not addressed.

A generic categorization of image fusion methods is the following:

- *Linear superposition* : This is most straightforward way to build a fused image of several input frames is performing the fusion as a weighted superposition of all input frames. the linear combination of all inputs in a pre-chosen color space (eg. R-G-B or H-S-V), leading to a false color representation of the fused image.
- *Nonlinear methods* : An approach to image fusion is to build the fused image by the application of a simple nonlinear operator such as max or min. If in all input images the bright objects are of interest, a good choice is to compute the fused image by an pixel-by-pixel application of the maximum operator.
- *Artificial neural networks* : By the fusion of different sensor signals in biological systems, many researchers have employed artificial neural networks in the process of pixel-level image fusion. Several researchers modeled this fusion process for the combination of multispectral imagery by a combination of several neural networks.
- *Image pyramids* : Image pyramids consist of multiresolution image analysis and as a model for the binocular fusion in human vision. A generic image pyramid is a sequence of images where each image is constructed by low pass filtering and subsampling from its predecessor.
- *Wavelet transform* : A signal analysis method similar to image pyramids is the discrete wavelet transform. The main difference is that while image pyramids lead to an over complete set of transform coefficients, the wavelet transform results in a nonredundant image representation.
- *Generic multi resolution fusion scheme* : The basic idea of the generic multiresolution fusion scheme is motivated by the fact that the human visual system is primary sensitive to local contrast changes, i.e. edges. The above methods doesn't gives satisfactory result so I proposed a new technique for image fusion.

II. PROPOSED WORK AND OBJECTIVES:

In this project we are proposing a system for pixel level fusion to fuse images acquired using multiple sensors using total variation algorithm. The goal of our theme provides an effective way of reducing this increased volume of information while at the same time extracting and increasing all the useful information from the source images. The aim of image fusion, apart from reducing the amount of data, is to create new images that are more suitable for the purposes of human / machine perception, and for further image-processing. A total variation norm based approach has been adopted to fuse the pixels of the noisy input images. The underlying idea is to fuse different views of same image**.**

The entire process of fusing an image is proposed as follows:

Step1: First take an image as an input.

Step2: Perform segmentation over the captured or input image.

Step3:While performing segmentation focus on different salient feature of the image.

Step4:Finally, fuse all the segments to form one composite image.

Step1: First take an image as an input. This input can be acquired with the help of image acquisition model:

3.1 Image acquisition model

Let $f_0(x, y)$ be the true image, which is inspected by n different sensors and $f1(x,y)$, $f2(x,y)$, ….. ,$f_n(x, y)$ are the corresponding n measurements for $x, y \in \Omega$. The local affine transform that relates the input pixel and the corresponding pixel in the measured images is given by

$$fi(x, y)=\beta i(x, y)fo(x, y) + \eta_i(x; y);\ 1 \le i \le n \qquad (1)$$

Here, $\beta i\ (x, y)$ and $\eta_i(x, y)$ are the gain and sensor noise, respectively, of the i^{th} sensor at location (x , y).

The goal of fusion is to estimate $fo(x, y)$ from

$fi(x, y),\ 1 \le i \le n$.

In many applications such as radar imaging and visual and IR imaging, the complementary as well as redundant information are available at the local level in the measured images. The main advantage of the local affine transform model is that it can relate this local information content in a mathematically convenient manner. For example, as an extreme case, two sensors i and j ($i \neq j$; $1 \le i, j \le n$) have complementary information at location (x,y) if $\beta i\ (x, y) \neq \beta j\ (x, y)$ and $\beta i\ (x, y)$,$\beta j\ (x, y)$ € $\{0,1\}$. Similarly, these two sensors have redundant information if $\beta i\ (x, y) = \beta j\ (x, y)$

Step2: Perform segmentation over the captured or input image by using total variation algorithm.

3,2 Total variation norm for image fusion

In order to estimate $fo(x, y)$ from eq. (1), we assume that $fo(x, y); fi\ (x, y) \ge 0$

($1 \leq i \leq n$). This assumption is valid for many imaging devices such as digital cameras, IR cameras, etc. and does not limit the proposed algorithm in any way since data not satisfying this requirement (*i.e.*, with negative pixel values) can always be transformed using a simple linear transformation to make the pixel values positive. Furthermore, we also assume that sensor noise $\eta_1(x, y)$, $\eta_i(x, y)$,…, $\eta_n(x, y)$ are zero mean random variables and are independent of each other. The standard deviation of $\eta_i(x, y)$ σ_i is denoted as σ_i, and σ_i is assumed to be known *a priori* and independent of spatial location (x, y).

$$\begin{pmatrix} f_1 \\ \vdots \\ f_n \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_n \end{pmatrix} f_o + \begin{pmatrix} \eta_1 \\ \vdots \\ \eta_n \end{pmatrix}$$
$$\Rightarrow \mathrm{f} = \beta f_o + \eta$$

Step3: While performing segmentation focus on different salient feature of the image such as denoising and deconvolution.

3.3 The Matlab package implements total variation (TV) based image denoising, deconvolution etc.

Denoising

The problem of image noise removal or denoising is, given a noisy image f: $\Omega \rightarrow$ R to estimate the clean underlying image u. For (additive white) Gaussian noise, the degradation model describing the relationship between f and u is

f= u+η ,

where η is i.i.d. Gaussian distributed.

The tvdenoise command implements TV-based denoising:

u = tvdenoise(f, lambda)

Deblurring (deconvolution) The image deblurring problem is to recover u from a given blurry and noisy image f. For Gaussian noise, the degradation model is

f=Ku+η

where K is the blur operator. For simplicity, the tvreg package is limited to the easier case of deconvolution, where Ku=φ*u with some point-spread function φ, and φ is assumed to be known exactly.

The tvdeconv command implements TV-based deconvolution:

u = tvdeconv(f, lambda, psf)

It solves for u approximately equal to f*psf. Parameter lambda balances between deblurring accuracy and denoising, where smaller lambda implies stronger denoising (but at the cost of deblurring accuracy).

Input image f

Deblurred image u

Step4: Finally, fuse all the segments to form one composite image.The total variation norm has been used in several image processing applications. In this project we propose to use total variation norm for image fusion. Better results can be obtained on several test images, and the performance assessment of the final fusion results also are evaluated by using several classical evaluation methods like Root Mean Square Error or Peak Signal to Noise Ratio.

The proposed fusion algorithm was applied to two different datasets: (i) medical imaging and (ii) aircraft navigation. For each dataset, only two input images were considered for the fusion process and these two inputs were co-registered.

The sensor noise was simulated by adding zero mean white Gaussian noise to the input images. For ease of quantitative analysis of the fusion performance, the variance of the noise for each input image was selected appropriately to get the same level of signal-to-noise (SNR) ratio for all the input images, where the SNR was computed using the following expression:

$$\mathrm{SNR} = 10\log_{10}\frac{\text{Signal Variance}}{\text{Noise Variance}}\,dB$$

III. CONCLUSION

The goal of image fusion is to compare the information content in the fused image and the corresponding input images. Therefore, the similarity index will be computed by comparing the fused images with the noiseless versions of the corresponding input images.

A total variation algorithm has been used for fusing an image. An output that will be generated by a fused image will generate much better results as compared to the original image.

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