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A PATH FOR HORIZING YOUR INNOVATIVE WORK

IMAGE FUSION TECHNIQUE FOR RESTORATION OF IMAGES

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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.

INTRODUCTION

A total variation norm based approach [10] has been adopted to fuse the pixels of the noisy input images. The total variation norm has been used in several image processing applications. 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, 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.

- Single sensor image fusion system
- Multisensor image fusion system

The benefits of multi-sensor image fusion include:

- 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.
- 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.
- Reduced uncertainty – joint information from multiple sensors can reduce the uncertainty associated with the sensing or decision process.

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.

II. RELATED WORK

Mrityunjay Kumar , Pradeep Ramuhalli [1], proposed a total variation (TV) based approach is proposed for pixel level fusion to fuse images acquired using multiple sensors. In this approach, fusion is posed as an inverse problem and a locally affine model is used as the forward model. An intuitive approach for pixel level fusion is to average the input images. Averaging reduces sensor noise but it also reduces the contrast of the complementary features. The least square method is less robust to noise as compared to total variation based approach.

E. Lallier and M. Farooq [12], proposed a novel pixel-level image fusion scheme for thermal and visual images. Each picture element (pixel), in both the thermal and visual images, is assigned a weight proportional to the interest associated with it. The thermal weights are associated with the divergence of the intensity of these pixels from the image mean intensity. The visual weight determination is based on the local variance in space and time of the intensity of the visual pixels. The Wavelets and the Gradient, were the best image fusion methods, but were not as robust as the PLWA method.

Oliver Rockinger, Thomas Fechner [13] proposed a novel approach based on a shift invariant extension of the 2D discrete wavelet transform, which yields an over complete and thus shift invariant multiresolution signal representation. To evaluate temporal stability and consistency of the fused sequence they introduced a quality measure based on the mutual information between the inter-frame-differences (IFD) of the input sequences and the fused image sequence. In the DWT fusion result there are some slight artifacts due to the nonredundant signal representation of the DWT. The experiments shown by them are especially the DWT fusion method is not suited for the fusion of image sequences.

Alexander Wong, William Bishop [14], proposed an efficient and robust approach for MRI–CT image fusion using a phase congruency model. In numerical analysis, there are often situations where the values obtained from the observations contain certain amount of error. Even in the fortunate case where the observations are pure in nature, the numbers of observations are usually not enough to determine the relationship between the dependent and the independent variable. There is a third situation, in which we would like to test different functional relationships for the observations. In all these cases, the least squares methods provides an answer:

- Occasions where the observations contain an error.
- The numbers of observations are not sufficient.
- We want to test different relationships (functional relationships)

The most important application is in data fitting. The best fit in the least-squares sense minimizes the sum of squared residuals, a residual being the difference between an observed value and the fitted value provided by a model.

The least squares criterion has important statistical interpretations. If appropriate probabilistic assumptions about underlying error distributions are made, least squares produces what is known as the maximum-likelihood estimate of the parameters.

This approach is largely invariant to pixel intensity mappings. The randomly selected region of interest for alignment was a region that did not exhibit significant structural characteristics in one of the two modalities. In the absence of significant structural characteristics, the proposed algorithm has difficulty finding a suitable alignment.

Nilamani Bhoi, Dr. Sukadev Meher [15], proposed Total Variation (TV) is applied on noisy image decomposed in wavelet domain for removal of Additive White Gaussian Noise (AWGN). LL subband of a single decomposed noisy image is used to find the horizontal, vertical and diagonal edges. In wavelet domain methods the noisy image is decomposed to around five level of decomposition for efficient denoising. This leads to increase in computational complexity, extra hardware and cost.

Thus, a total variation based approach has been used for denoising the images. The proposed technique for image fusion works on pixel level image fusion.

III SYSTEM IMPLEMENTATION

In the proposed work I have implemented a system at pixel level fusion to fuse images acquired using multiple sensors. The goal of my 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 [1] has been adopted to fuse the pixels of the noisy input images. The underlying idea is to fuse different views of same image.

The proposed fusion process composed of various modules.

Module 1: Image acquisition.

First take images as an input.

Module 2: Addition of Noise to input image.

Add noise in the input images.

Module 3: Segmentation.

Perform segmentation over the noisy images.

Module 4: Denoising on the image

After performing segmentation focus on different salient feature of the segmented images such as denoising.

Module 5: Fused image.

Finally, fuse all the images to form one composite image.

Module design and implementation

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

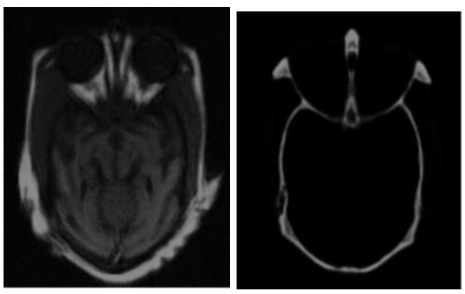
Module 1 : Image acquisition model

First images as an input. This input can be acquired with the help of 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 $fi(x, y) = \beta i\ (x, y)\ fo\ (x, y) + \eta_i(x; y);\ 1 \le i \le n$ **(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 $fi(x, y),\ 1 \le i \le n$.



(a) MRI image (b) CT scan image

Module 2 : Addition of Noise

When aerial photographs are produced for remote sensing purposes, noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process. Each element in the imaging chain such as lenses, film, digitizer etc. contributes to the degradation.

Image denoising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. So, inorder to improve the quality of a degraded image first noise is added (i.e Gaussian noise) to the images and then it is removed by using total variation algorithm.

The images are corrupted by additive white Gaussian noise with standard deviation σ leading to a signal-to-noise ratio. For TV reconstructions, we choose the parameter δ such that it reflects the noise level in the image

$$\delta = \tau\sqrt{mn\sigma},$$

Module 3: Segmentation

Perform segmentation over the captured or input image.

For performing chanvese segmentation following steps are performed:

- First Threshold value is evaluated by partial differential equation.
- The values which are defined below are then passed in the partial differential equation.
- If the final value obtained is greater than zero i.e.(phi>0) then segmentation is performed inside.
- If the final value obtained is less than zero i.e.(phi<0) then segmentation is performed outside.

Module 4 : Total variation method for image denoising

After performing segmentation focus on different salient feature of the

segmented images such as denoising. This can be achieved by using total variation algorithm.

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

$(1 \leq i \leq n)$. 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).

Module 5: Fused image

Finally, fuse both the images to form one composite image in such a way that the fused image gives much more better perception as compared to original images

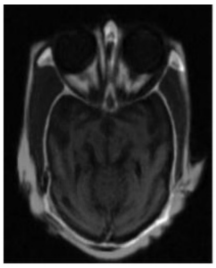


Fig.Fused image

The comparison results of the proposed fusion algorithm and least square method are presented in this section. The proposed fusion algorithm was applied to the dataset of medical imaging. For the 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 :

$$\text{SNR}=10\log_{10}\frac{Signal\ Variance}{Noise\ Variance}\text{Db}$$

Comparision between Least square method and proposed method..

[1] Test image set1

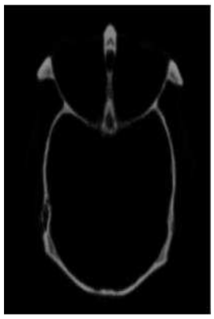


Fig a.CT scan image

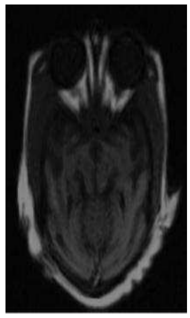


Fig.b MRI image

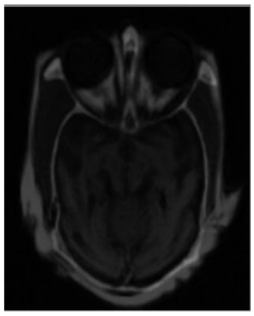


Fig.3.1 Fused image by Least Square

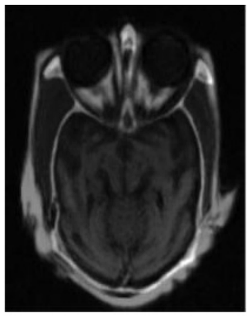


Fig.3.2 Fused image by Total variation

From the Fig.a and Fig.b shows the original images of CT scan and MRI image and Fig.3.1 shows the fused image by Least square method with SNR= 1.8283 dB whereas above Fig.3.2 shows the fused image by proposed algorithm i.e. Total variation algorithm with SNR= 13.1475 dB

IV. CONCLUSION

The proposed fusion method is applied to several different types of datasets of medical imaging. The results on these data indicate the feasibility of the proposed approach. Thus, an output that is generated by a fused image gives much better results as compared to the original image.

Image fusion has been growing number of fields of applications. The proposed work i.e. total variation framework for pixel level image fusion has wide range of application area, such as remote sensing, medical imaging, remote sensing, satellite imaging, image classification, robot vision, concealed weapon detection, multi-focus image fusion, battle field monitoring, digital camera application, military applications etc.

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