

Multi-Spectral Imaging for Low-Light Environments

By: Nicholas Berger, ECE '19

Abstract

This paper explains the methods via which multiple images can be combined into a single, higher-quality image, known as image fusion. The paper discusses, in depth, multiple computational techniques for image fusion, as well as their applications. Averaging, maximum selection, the Discrete Wavelet Transform (DWT), Intensity-Hue Saturation (IHS), Principal Component Analysis (PCA), and the Laplacian Pyramid are among the techniques this paper elucidates.

Introduction

Image fusion is known as the process of combining multiple images into a single image. The techniques which will be discussed describe methods of extracting the meaningful information from the input images and combining this information into a higher quality output image. This new combined image is now more informative and accurate than any of the individual input images. The purpose of image fusion is to reduce the amount of data necessary to store images, as well as to create images which are more easily interpretable both for humans and machines. (Kaur, Tamanpreet, and Vinod Er. Kumar)

There exists a multitude of different sensors, which provide the means to detect and display information in the form of an image. These sensors convert light waves into signals, or electric currents, that convey information as they pass through or reflect off objects. Image sensors are implemented in a variety of electronic devices, including digital cameras, medical imaging equipment, thermal imaging

devices, radar, and sonar.

Generally, image fusion techniques can be categorized in four distinct levels (Suthakar, Johnson R., et al.):

1. Signal level fusion: signals from different sensors are combined to create a new signal with less unwanted information present in the new signal
2. Pixel/Data level fusion: incorporates data from multiple sources into single data output
3. Feature level fusion: abstracts assorted data features, such as edges, lines, corners, textures, etc., from different sources, and combines them into more informative features instead of the original data
4. Decision level fusion: associates the outputs from multiple fusion algorithms to produce a final image

Image Fusion Algorithms (for Higher Quality Images)

Often it can be difficult to produce an image that includes all relevant objects simultaneously in-focus due to the current state of camera lens technology. To obtain such image quality, image fusion is, consequently, required. In the following section, certain algorithms, which allow for the construction of such an image, will be discussed. (Sahu, Deepak Kumar, and M. P. Parsai)

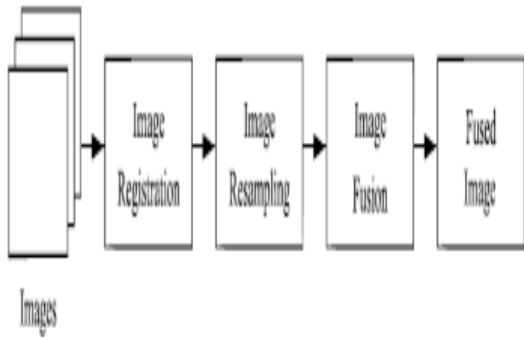


Figure 1. General overview of image fusion (Sahu, Deepak Kumar, and M. P. Parsai)

Averaging

As expected, the sections of images which are in-focus possess a higher resolution than those out-of-focus regions. Now, suppose an attempt is made at fusing two images. Each pixel within each image occupies an intensity value. For each image, the corresponding pixel intensity is summed and, subsequently, divided by 2, to obtain the average. Correspondingly, this algorithm can easily be abstracted for any integer number of images. (Sahu, Deepak Kumar, and M. P. Parsai)

Maximum Selection

As image quality increases with the pixel intensity value, this algorithm selects the in-focus portions from each image by selecting the greatest value for each pixel. For each image, the pixel value is compared to the other. Largest pixel value is then assigned to the corresponding output image pixel. (Sahu, Deepak Kumar, and M. P. Parsai)

Discrete Wavelet Transform (DWT)

A wavelet is a particular type of wave-like oscillation which possesses a certain set of distinct characteristics, namely: it is finite, and its amplitude begins and ends at zero. Via the wavelet transform, the input image is decomposed into three components, each of which possesses different information relevant for the description of the input image. The first component contains the actual information displayed in the image, while the latter two elements describe the spatial relationships among the information carried within the first component. Within the first component, a larger value corresponds to a line or an edge in the physical image. (Sahu, Deepak Kumar, and M. P. Parsai)

The DWT serves as a suitable method for image fusion for several reasons. First, it allows for the reconstruction of images with varying resolutions. Additionally, decomposing the image into its different components, via the DWT, results in an output image that preserve the information in the initial images, allowing the user to obtain the best quality output image. For different input images, the corresponding aforementioned components can be merged. Once the corresponding elements have been combined, the DWT can be reversed, using the Inverse Discrete Wavelet Transform (IDWT), to recover the final fused image.

If the source images contain identical resolutions, the process for wavelet-based image fusion is as detailed above. The DWT is applied to both images (assuming there are two input images), resulting in a decomposition of each original image. Fusion is to occur only between images of the same level such that their individual components can be fused. After obtaining the fused components, the IDWT is implemented to achieve the final fused image. Figure 2 exemplifies this process of fusing two images of initially identical resolutions.

However, it is often the case that the source images are of differing resolutions. Prior to the application of any fusion techniques, the images must, therefore, be modified such that they are of the same size and operate under the same coordinate system. In this case, the DWT is applied only to the image with greater resolution, resulting in the decomposition of this image only. Here, the components of the higher-resolution image are to be fused with the original pixels of the lesser-resolution image. This process results in a fused representation, as was obtained with the two images of identical quality, and, again, via the IDWT, the final fused image is received. (Suthakar, Johnson R., et al.)



Figure 2A. Image 1 left in-focus
(Suthakar, Johnson R., et al.)



Figure 2B. Image 2 right in-focus
(Suthakar, Johnson R., et al.)



Figure 2C. Image 3 fused via DWT
(Suthakar, Johnson R., et al.)

Intensity Hue Saturation (IHS)

The IHS method of image fusion is an effective means of merging images of differing resolutions. Any colored image is fundamentally comprised of red (R), green (G), and blue (B) colors. These bands of the images are converted into IHS elements, replacing the intensity values of the original images.

By performing the inverse IHS transform, a high-resolution, fused image is created. IHS is successful in enhancing the spatial details, as well as the textural characteristics of the fused image. The IHS transformation is largely used for geological mappings as it can allow for the combination of diverse forms of data into a single data set. The IHS method, however, often results in substantial color distortion and cannot be used to enhance input image features. (Suthakar, Johnson R., et al.)

Principal Component Analysis (PCA)

The PCA transformation is a statistical technique used to simplify a data set. The objective of this technique is to reduce the dimensionality of multivariate data, while maintaining as much of its pertinent information as possible. PCA converts a correlated data set to one that is uncorrelated and is often more interpretable than the original data. By transforming correlated variables into uncorrelated ones, PCA is able to determine an optimal and compact description of the original data set. These uncorrelated variables are titled principal components. The directionality first principal component is identical to the maximum variance of the data set, or the direction in which the data is most spread-out. The second principal component points in the direction perpendicular to the first. Similarly, the third principal component points in the direction perpendicular to the first two, and so on. Figure 3 illustrates a sample data set in order to help visualize the fundamentals of PCA. The larger vector depicts the principal component of the data set, while the shorter vector, perpendicular to the first, represents the data's second principal component.

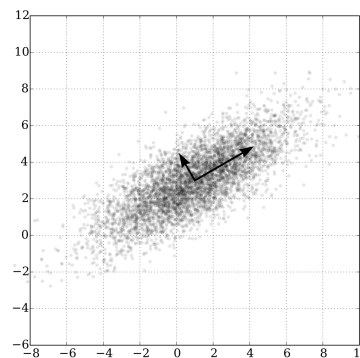


Figure 3. Principal Component Analysis on sample data set ("Principal Component Analysis")

Regarding the image fusion process, the PCA transform helps to reduce any redundancy present within the data of the input images. The PCA technique generates several uncorrelated images, with the first principal component containing a higher resolution than the multispectral images. The inverse PCA transform is subsequently applied to obtain the final fused image. (Suthakar, Johnson R., et al.)

Laplacian Pyramid

Akin to the previously discussed methods for image fusion, the idea of the pyramid transform is to take the pyramid transforms of the source images and use these transformed images to create a pyramid transform of the fused image. The fused image is then obtained by taking the inverse pyramid transform. The pyramid transform is advantageous in that it can provide information pertaining to distinct contrast changes.

The Laplacian Pyramid applies a pattern-selective approach to image fusion, resulting in an image fusion that is not performed pixel-by-pixel. A pyramid decomposition is performed on each input image. The ensuing decompositions are subsequently integrated to form a combined representation, which, via the inverse pyramid transform, can be used to reconstruct the fused image. The Laplacian Pyramid scheme can employ various methods of combination, including the averaging and selection methods detailed above. (Sahu, Deepak Kumar, and M. P. Parsai)

Applications of Image Fusion

Image fusion has become an increasingly common piece of technology used to enhance the representation and interpretation of images in a multitude of fields, including, but not at all limited to, vision systems, medical diagnostic tools, robotics, and the military. Image fusion can be employed to aid in object identification, classification, and change detection. For instance, fused images are quite useful in order to maximize the amount of information extracted from a data imaging source, i.e. a satellite. In addition, the introduction of more source image data serves to improve the classification accuracy of remote sensing applications. Furthermore, change detection is a term used to describe the recognition of an object's state change over time. Image fusion

pertaining to change detection is particularly useful in the preservation of natural resources and urban development as it can provide quantitative analyses of the spatial distribution relating to the subject of interest. The United States Department of Defense is particularly interested in the applications of image fusion to aid efforts in the following fields: ocean surveillance, air-to-air/surface-to-air defense, battlefield intelligence, target surveillance and acquisition, and strategic warning and defense. (Sahu, Deepak Kumar, and M. P. Parsai)

Conclusion

Image fusion is the process by which a higher resolution image is produced via the extraction of all relevant data from a combination of lesser-resolution source images. This paper demonstrates some of the most effectively implemented methods, such as the Discrete Wavelet Transform (DWT), Intensity-Hue-Saturation (IHS), Principal Component Analysis (PCA), and Laplacian Pyramid, as well as their applications, to attain these higher-resolution images via image fusion. As technology continues on its path of rapid advancement and the amount of the world's available data multiplies, so too will the need to process images at increasingly higher resolutions never before achieved.

References

1. Davidson, Michael W. "Spatial Resolution in Digital Images." *Molecular Expressions Microscopy Primer: Specialized Microscopy Techniques - Fluorescence Digital Image Gallery - Normal African Green Monkey Kidney Epithelial Cells (Vero)*, 11 Feb. 2016.
2. Flusser, Jan, et al. "Image Fusion: Principles, Methods, and Applications.", Academy of Sciences of the Czech Republic, 2007.
3. Kaur, Tamanpreet, and Vinod Er. Kumar. "A Video Fusion Using Wavelet Transformation Techniques." *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, vol. 4, no. 6, Nov. 2016.
4. "Principal Component Analysis." *Wikipedia*, Wikimedia Foundation, 26 Mar. 2019.

5. Sahu, Deepak Kumar, and M. P. Parsai. "Different Image Fusion Techniques –A Critical Review." *International Journal of Modern Engineering Research (IJMER)*, vol. 2, no. 5, 2012, pp. 4298–4301.

6. "Spectral Resolution." *Natural Resources Canada*, Natural Resources Canada, 23 Nov. 2015.

7. Sroubek F., Flusser J., and Zitov ˇ a B., "Image Fusion: A Powerful Tool for Object Identification", in: 'Imaging for Detection and Identification, (Byrnes J. ed.), pp. 107-128, Springer, 2006

8. Suthakar, Johnson R., et al. "Study of Image Fusion- Techniques, Method and Applications." *International Journal of Computer Science and Mobile Computing*, vol. 3, no. 11, Nov. 2014, pp. 469–4766.

9. Teo, Tee-Ann, and Chi-Chung Lau. "Pyramid-Based Image Empirical Mode Decomposition for the Fusion of Multispectral and Panchromatic Images." *EURASIP Journal on Advances in Signal Processing*, vol. 2012, no. 1, 2012.

