Multisensor Image Fusion: Concept, Method and Applications

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Abstract: Multisensor image fusion is a process of combining or amalgamating information from multiple sensors. It has been applied to a wide variety of fields such as navigation, military surveillance, remote sensing, medical diagnosis, industrial process control and measurement, intelligent robot, and law enforcement. In this paper, the basic concept, advantage, general structure, methods, applications, and performance evaluation of multisensor image fusion are presented.
Key words: image fusion, data fusion, information fusion, multisensor fusion.

I. Basic Concept

A. Concept

Image fusion refers to the techniques that integrate complementary information from multi-image sensor data such that the new images are more suitable for the purpose of human visual perception and the computer-processing tasks such as segmentation, feature extraction, and object recognition.

By the development of new imaging sensors, such as CCD, forward looking infrared (FLIR) cameras, millimeter wave (MMW) radar, low light television cameras etc, appropriate combination of the available imaging sensors will improve the system performance. Because each kind of imaging sensors is optimized for somewhat different operating range and environmental conditions, it may not receive all the information necessary for detecting an object by human or computer vision. Effective combination of such sensors with different features and/or viewing positions could, therefore, extend the capabilities of the individual ones. This final composite image has more complete and detailed information content. Therefore the composite or fused image is more useful for human perception as well as for automatic computer analysis tasks such as segmentation, feature extraction, and object recognition. Numerous applications that would benefit from the use of multiple sensors include display systems in aviation, remote sensing, surveillance, automated machine vision, and medical imaging.

B. Biological example

In reference [1], the authors gave an example of the rattlesnake (and the general family of pit vipers) which can response to both visual and infrared information. Rattlesnakes possess so called pit organs which are sensitive to thermal radiation through a dense network of nerve fibers. The output of these pit organs is fed to the optical tectum, where it is combined with the nerve signals obtained from the visual sensors, i.e., the eyes. The fusion process is shown in Fig.1.

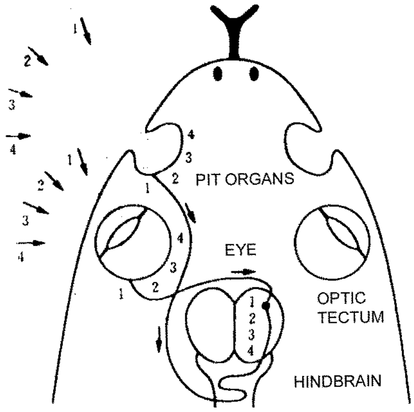
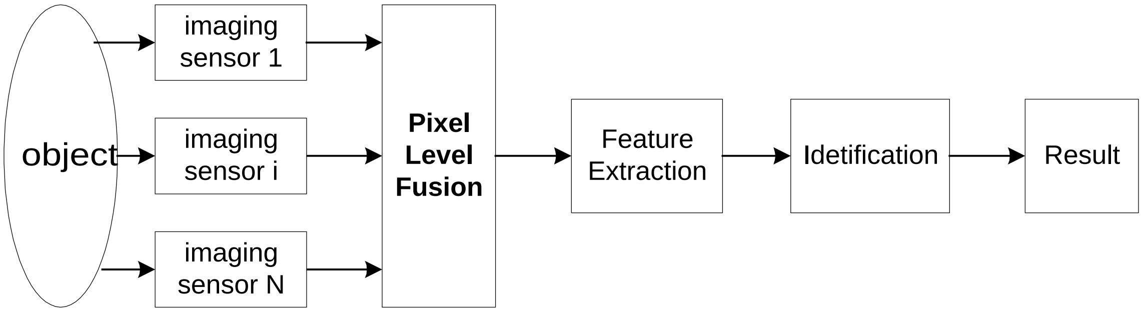


Fig.1 Left eye and pit organ of rattlesnake are receiving information from Region 1 in environment

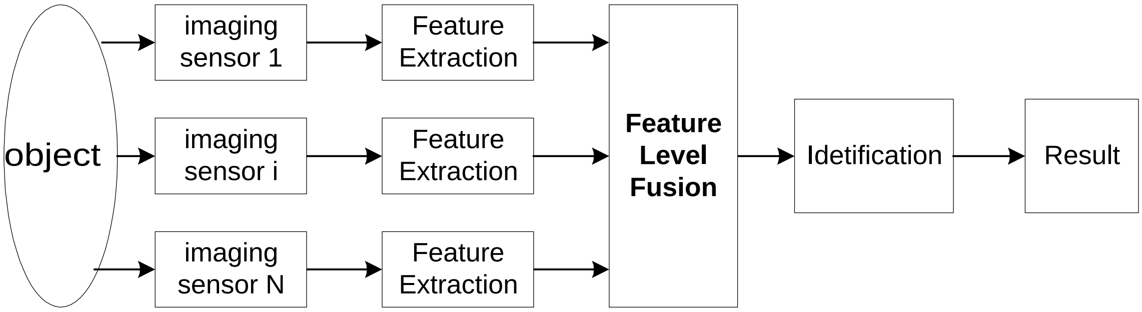
C. Advantages

In principle, fusion of multiple imaging sensor data provides significant advantages over single image source. The first reason is that multi-images obtained by multiple imaging sensors have an inherent redundancy. The second reason is that complementary information from multiple imaging sensors allows features in the environment to be perceived that are impossible to perceive using just individual sensor separately. In essence, multisensor image fusion system possess the following potential to provide:
i) information from multiple viewpoints;
ii) extended spatial and temporal coverage;
iii) improved accuracy.
iv) robust and fault-tolerant operation.

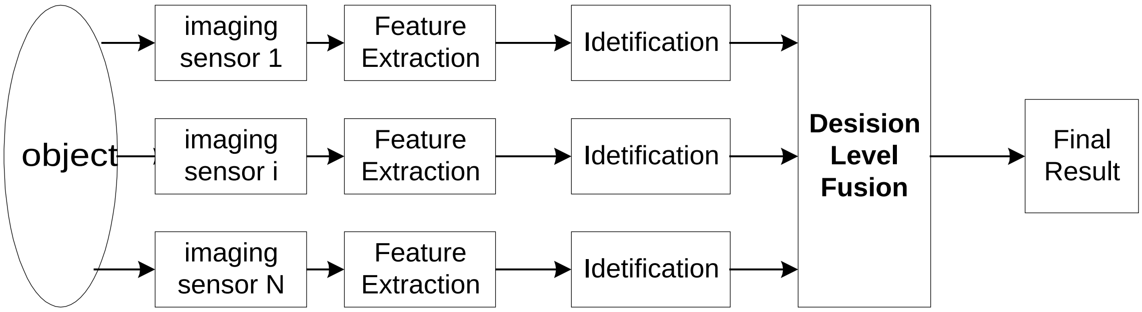
II. General fusion structure



(a)Pixel level fusion



(b)Feature level fusion



(c)Decision level fusion

Fig.2 Three hierarchy levels of multisensor data fusion

Image fusion can be categorized to three different processing levels according to the stage at which the fusion takes place. They are as follows.

a) Pixel level fusion (Low level fusion)

In pixel level image fusion, the raw images obtained from different sensors are fused to provide a new image. An illustration of the concept of pixel based fusion is visualized in Fig. 2(a). Pixel level image fusion can be helpful for a human observer to more easily detect and/or recognize potential targets.

b) Feature level fusion (Medium level fusion)

Feature level image fusion is also called medium level fusion. The idea is to extract some features on the original images of each separate sensor and then combine these features in an overall feature vector. Typical features include edges, corners, lines, etc.

c) Decision level fusion (High level fusion)

Decision level fusion represents a method that individual decisions are made on each imaging sensor. Then these decisions are fused to generate the final decision.

This paper mainly reviews methods, applications and performance evaluation of the pixel level image fusion.

III. Image fusion methods

This section describes the methods to multiple image fusion. Some methods of pixel-level remote sensing images are not included in this paper. Readers who have interests in it please consult the reference [2].

A. Average and weighted averaging

The straightforward approach to image fusion is to take the average of the source images. Averaging increases the signal to noise ratio, but reduces the contrast where there are polarity reversed or complementary features.

In weighted averaging method, the optimal weighting coefficients, with respect to information content and redundancy removal, can be determined by a principal component analysis (PCA) of all input intensities [3]. By performing a PCA of the covariance matrix of input intensities, the weightings for each input image are obtained from the eigenvector corresponding to the largest eigenvalue.

B. Color mapping

A method similar to the one above is the linear combination of all input images in a pre-chosen color space, leading to a false color representation of the fused image. Toet [4] proposes the combination of a false color representation with a nonlinear preprocessing for the fusion of FLIR and LLTV imagery. The resulting color rendering enhances the visibility of certain details and preserves the specificity of the sensor information. The researcher in the Lincoln Laboratory at Massachusetts Institute of Technology [5-9] used biological models of opponent-color processing to fuse low-light visible and thermal IR imagery, and rendered it in real time in natural colors. In reference [10], the authors investigated the conditions for which the fusion of visible and thermal images may result in a single composite image with extended information content, and tested the capability of the methods proposed by Waxman et al. to enhance the situational awareness of observers operating under specific conditions.

C. Nonlinear methods

Therrien et al employed spatially adaptive and nonlinear processing to fuse the images obtained by image intensifier (II) tubes and forward looking infrared (IR) sensors [11]. The raw images are each separated into spatially high pass and low pass components. The low pass components are fused to insure that an appropriate background level of intensity is maintained and that differences in local luminance existing in either II or IR will not be eliminated by the fusion process. The fusion of high pass components is to retain detail where it is present in either the II or the IR images.

D. Optimization approach (Bayesian optimization)

Sharma and Pavel proposed a simple adaptive procedure for estimating sensor characteristics and the relationships between sensors, and for fusing the sensor images [12]. The procedure is based on locally linear estimates of the transformation between sensors under the assumptions of independence and normality. In reference [13], the authors present a probabilistic method for image fusion based on an image formation model in which the sensor images are noisy, locally linear functions of an underlying, true scene. A Bayesian framework then provides for maximum likelihood or maximum a posteriori estimates of the true scene from the sensor images. Maximum likelihood estimates of the parameters of the image formation model involve (local) second order image statistics, and thus are related to local principal component analysis. In reference [14] Lafert et al proposed a hierarchical statistical image fusion method.

E. Markov Random Fields and Simulated Annealing

In the Markov Random Field (MRF) approach to image fusion [15-16], the fusion task is expressed as an optimization problem. The MRF is used to define an appropriate cost function, which describes the fusion goal and a global optimization strategy such as simulated annealing is employed in search of the global optimum of this cost function.

Usually the input images are described as sets of coupled random fields.

In reference [17] the authors proposed an alternative construction for the Markov random field, which concentrated only on the construction of the image boundary map, leaving the pixel values fixed. Coupled with the use of an appropriately designed Iterative Conditional Modes (ICM) algorithm, it is hoped may be operated in real time for image fusion.

F. Artificial neural network

Inspired by the fusion of different sensor signals in biological systems, artificial neural networks (ANNs) have recently been employed in the fusion process. Three kinds of neural networks for image fusion are as follows.

a) Neural network based on bimodal neurons

In reference [1,18], Newman and Hartline distinguished six different types of bimodal neurons merging visual image and thermal image, which they categorized as: AND, OR, Visible-Infrared, Visible-Suppressed-Infrared, Infrared-Enhanced-Visible and Infrared-Suppressed-Visible neurons. Some researchers have further researched on it [19-20].

b) Multi-layered perceptron

Fechner and Godlewski proposed an image fusion method using a multi-layer perceptron (MLP) neural network [21]. They trained a MLP for generating a mask designating the area of interest in the FLIR image, which should be pass into the composite image. The learning capability of neural networks is exploited in order to produce optimal image fusion masks given by a human expert.

c). Pulse-coupled neural network

In essence, the PCNN is composed of an array of integrated-and fire neurons with one neuron for each input pixel [22-23]. In such a system, the neurons corresponding to bright pixels reach firing threshold faster than the neurons corresponding to duller pixels. Thus, firing rate is proportional to brightness. In PCNN, when a neuron fires it sends some of the resulting signals to its neighbors. This linking can cause a near-threshold neuron to fire earlier than it would have otherwise. This leads to synchronization of the pulses across large regions of the image.

G. Image pyramids

Image pyramids have been initially described for a multi-resolution image analysis and as a model for the binocular fusion in human vision. An image pyramid can be described as collection of low- or band-pass copies of an original image in which both the band limit and sample density are reduced in regular steps. The basic strategy of image fusion based on pyramids is to use a feature selection rule to construct a fused pyramid representation from the pyramid representations of the original data. The composite image is obtained by taking an inverse pyramid transform. Several pyramid-based fusion schemes have been proposed in recent years. They are briefly introduced as follows.

a) Laplacian pyramid

A set of band-pass copies of an image is referred to as the Laplacian pyramid due to the similarity to a Laplacian operator. Each level of the Laplacian pyramid is recursively constructed from its lower level by the following four basic steps: blurring (low-pass filtering); subsampling (reduce size); interpolation(expand); and differencing (to subtract two images pixel by pixel) in the order we have given[24]. In the Laplacian pyramid, the lowest level of the pyramid is constructed from the original image.

The Laplacian pyramid was first introduced as a model for binocular fusion in human stereo vision [25-26]. The implementation used a Laplacian pyramid and a maximum selection rule at each point of the pyramid transform.

b) Ratio-of-low pass pyramid

The ratio of lowpass or contrast pyramid, which was introduced by Toet [27-28], is very similar to a Laplacian pyramid. The RoLP was originally intended for use explicitly by human observers. Every level of RoLp is the ratio of two successive levels of the Gaussian pyramid.

In [27-30] a ratio of low pass pyramid and the maximum selection rule were used for visible-to-IR image fusion. In [31], similar pyramid structure and a noise-based selection rule were used to merge millimeter wave sensor image with synthetic graphics.

c) Gradient pyramid

The gradient pyramid can be generated by applying gradient operators to each level of the Gaussian pyramid [32]. This produces, the horizontal, vertical, and diagonal pyramid sets for each source in the Gaussian pyramid. Burt proposed an image fusing scheme which based on a gradient pyramid and an activity measure within a small window rather than just a single point[33].

In reference [34], Sims and Phllips demonstrated the qualitative and quantitative results of the above three image data fusion algorithms and their target signature variation. They descried the three methods for comparison along with a easier to understand process developed for their implementation.

d) Morphological pyramid

A morphological pyramid can be constructed by the successive filtering of the original image with a sequence of nonlinear morphological operators (such as the open-close filter) and a specialized subsampling scheme [35]. The application of morphological pyramid to image fusion can be referenced [36-37].

H. Wavelet transform

A method similar to the image pyramid fusion scheme is based on the discrete wavelet transform.

a) Discrete wavelet transform

The discrete wavelet transform is computed by the recursive application of lowpass and highpass filters in each direction of the input image (i.e. rows and columns) followed by subsampling [38-39]. The wavelet transform offers certain advantages over the Laplacian pyramid-based techniques. The size of the wavelet transform is the same size as the original image whereas the Laplacian pyramid is 4/3 times the size of the original image. The wavelet representation provides directional information whereas the Laplacian pyramid does not supply spatial orientation in the decomposition. Since the wavelet basis functions can be chosen orthogonal, the information at each layer of the decomposition is unique. On the other hand, the Laplacian pyramid carries redundancy between the different resolutions. There are many references on image fusion based on discrete wavelet transform [40-49].

b) Wavelet frame

It is well known that the discrete wavelet transform results in a shift variant signal representation, i.e. a shift of the input signal yields a nontrivial modification of the transformation coefficients [40]. When applied to pixel-level image fusion, this results in a shift depended fusion scheme. To overcome this problem, Rockinger proposed an image fusion method based on a shift invariant extension of the discrete wavelet transform which yields an overcomplete signal representation, called wavelet frames. Due to the shift invariant signal representation obtained by the wavelet frame representation, the fusion results are temporarily stable and consistent [50-52].

c) Steerable dyadic pyramid

A steerable dyadic wavelet transform [53] combines the properties of a discrete dyadic wavelet transform with the analysis along arbitrary orientations. The transform is implemented as a filter bank consisting of polar separable filters. An image fusion algorithm based on multiscale analysis along arbitrary orientations is presented.

d) Multiwavelet

Multiwavelets have several advantages in comparison to scalar wavelets, such features as short support, orthogonality, symmetry, and vanishing moments which are known to be important in signal processing [54]. A scalar wavelet except the Haar system can not posses all these properties at the same time [55]. On the other hand, a multiwavelet system can simultaneously provide perfect reconstruction while preserving length (orthogonality), good performance at the boundaries (via linear-phase symmetry), and a high order of approximation (vanishing moments)[56-57].

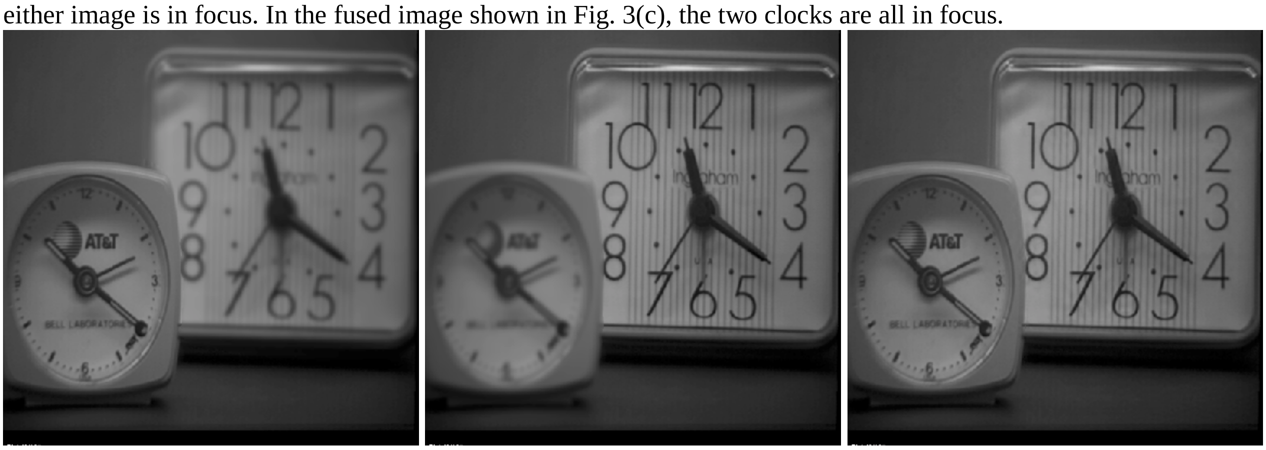
Li and Wang examined the application of discrete multiwavelet transform (DMWT) to multisensor image fusion. The discrete multiwavelet decomposition coefficients of the input images are approximately combined, and the new image is obtained by taking the corresponding discrete multiwavelet reconstruction of the fused coefficients [58].

IV. Applications

Multiple image fusion is widely used in a variety of fields. The following paragraphs describe some military and nonmilitary applications of image fusion.

A. Digital camera applications (multi-out-focus image)

To inexpensive cameras, due to the limited depth-of-focus of optical lenses (especially such with long focal lengths) it is often not possible to get an image which is in focus everywhere [59]. One possibility to overcome this problem is to take several images with different focus points and combine them together into a single composite image which finally contains the focused regions of all input images [40-41,58]. The following images illustrate this approach. Fig. 3(a) and Fig. 3(b) show a pair of images containing two clocks with different distances toward the camera, and only on clock in either image is in focus. In the fused image shown in Fig. 3(c), the two clocks are all in focus.



(a) (b) (c)

Fig.3 Image fusion example for digital camera applications: (a) source image focus on small clock; (b) source image focus on large clock; (c) fused image

B. Medical diagnosis

With the development of new imaging methods in medical diagnostics, such as, computed tomography (CT), ultrasound, positron emission tomography (PET), and nuclear magnetic resonance (MR) provide exquisite anatomic detail and can often assist the physician to localize abnormal masses. These imaging methods have their characteristics respectively. For example, CT images provide excellent views of bones and other dense structures whereas MR images provide excellent views of soft tissues. In certain clinical areas, it is useful to be able to visualize both soft and dense tissues simultaneously. So fusion of images of various kinds would be useful for patient diagnosis, as well as treatment planning [35-36,60-62]. The following images illustrate the fusion of a CT and a MRI image.

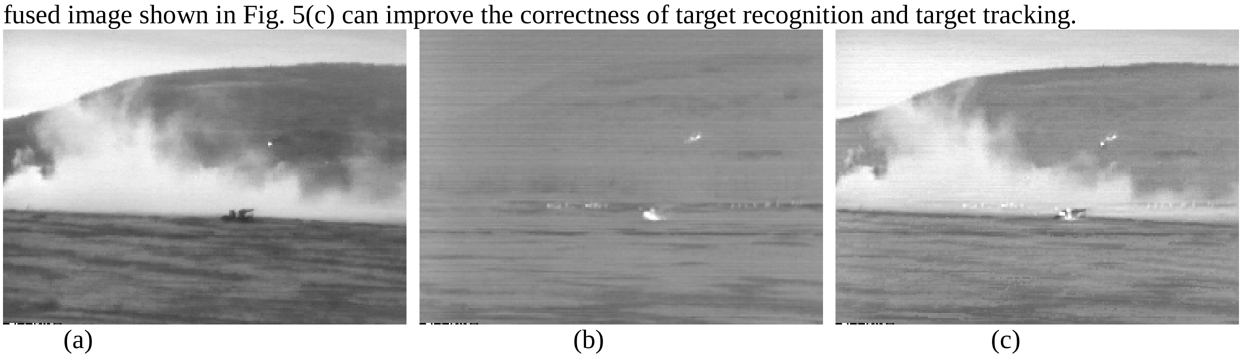
(a) (b) (c)

Fig.4 Image fusion example for medical diagnosis applications: (a) source CT image; (b) source MRI image; (c) fused image.

C. Military surveillance (target detection)

Multisensor image fusion found widely applications in military surveillance[4,10-11,27-30,63-68]. In reference [63] the authors proposed a non-real-time color sensor fusion system flown on a NASA F/A-18. Flight videotape was recorded from an image intensified CCD and a long-wave infrared sensor. Then the two sensor videotape sequences were combined into a single fused color or grayscale representation. Fleet aviators showed that color fusion improved target detection. The researchers in the Lawrence Livermore National Laboratory, USA, developed some systems fused information contained in registered images from multiple sensors to reduce the effects of clutter and improve the ability to detect surface and buried land mines [65-67].

In the example given below, two images of the same scene are shown. Fig. 5(a) is a visual image clearly showing a truck, some smoke and a mountain in the background. Fig. 5(b) is a thermal infrared image on which both targets (the truck and a helicopter) are clearly (but partly) visible. The infrared image also allows one to see through the smoke. The fused image shown in Fig. 5(c) can improve the correctness of target recognition and target tracking.

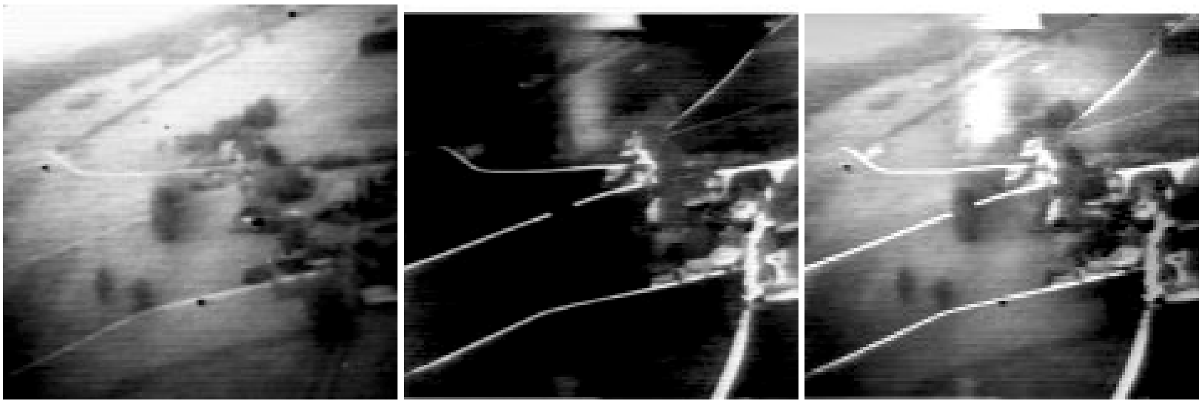


(a) (b) (c)

Fig.5 Image fusion example for military applications: (a) source image from CCD sensor; (b) source image from thermal IR sensor; (c) fused image.

D. Navigation aid

To improve the visibility of objects in scene under poor atmospheric conditions (such as night, fog or heavy rain), several image fusion methods have been used and achieved very good performance [5-9,47,69]. For example, the researchers of Lincoln Laboratory in the Massachusetts Institute of Technology have developed some night devices, which are very useful for a multitude of military and civilian applications. Some typical sensor suite includes conventional CCD, low-light-level television (LLLTV), color CCD, thermal imaging forward-looking-infrared (FLIR) sensor, etc. Fig. 6(a) and Fig. 6(b) show a pair of FLIR and LLLTV images. Due to the high thermal contrast the (hot) roads appear very clear in the FLIR image. The thin road on the left side is not visible in the LLLTV image. The light spots appear only in the LLLTV image. The FLIR image exhibits glare effects and periodic scanner interference visible as a ripple effect. The fused result shown in Fig. 6(c) preserves all the useful information from the two source images.



(a) (b) (c)

Fig.6 Image fusion example for navigation applications: (a) source image from CCD camera; (b) source image from thermal IR sensor; (c) fused image.

E. Law enforcement

Concealed weapon detection is an increasing important topic in the general area of law enforcement, and image fusion has been identified as a key technology to enable progress on this topic [43-46]. The existing imaging sensing mechanisms include thermal infrared, millimeter wave, visual, and X-ray sensors. Fig.7(a) and Fig.7(b) show a pair of visual and millimeter-wave images. The visual image provides the outline and the appearance of the people while the millimeter-wave image shows the existence of a gun. From the fused image shown in Fig.7 (c) it can be easily seen that the person on the right has a concealed gun underneath his cloth.

(a) (b) (c)

Fig.7 Image fusion example: (a) source image from CCD camera; (b) source image from MMW sensor; (c) fused image.

It should be note that these illustrative application examples are limited. Others applications include industrial process control [70],quality and defect inspection [71], intelligent robots[72], etc. With the development of multi-image fusion technique, the applications both in military and nonmilitary will be more abroad.

V. Performance evaluation

In general terms the requirements of an image merging process are as follows: it must preserve all valid and useful pattern information from the source images, and at the same time it must not introduce any new pattern elements, or artifacts, that could interfere with subsequent analysis [26]. However, it is almost never possible to combine images without introducing some form of distortion.

In current literature, the fusion results can be evaluated visually or objectively. Some common used quantitatively performance measures are listed as follows. Some of them need an ideal composite image while some others do not. But it should be note that the best criterion should be linked with the specific application.

A. RMSE

The root mean square error (RMSE) is used as the evaluation criteria of fused method.
The RMSE between the reference image R and the fused image F is

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{m=1}^{M}\sum_{n=1}^{N}\left[R(m,n) - F(m,n)\right]^2}{M \times N}} \tag{1}$$

where R(m,n) and F(m,n) are the pixel value at the (m,n) coordinates of the reference image and the fused image, respectively. The image size is M×N.

B. NLSE

The normalized least-squares error (NLSE) between two images is defined as

$$NLSE = \sqrt{\frac{\sum_{m=1}^{M}\sum_{n=1}^{N}[R(m,n) - F(m,n)]^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}[R(m,n)]^2}} \tag{2}$$

where the variables are defined as above.

C. MI

The mutual information (MI) between the reference image R and the fused image F

$$MI = \sum_{i=1}^{L}\sum_{j=1}^{L} h_{R,F}(i,j)\log_2 \frac{h_{R,F}(i,j)}{h_R(i)h_F(j)} \tag{3}$$

where $h_{R,F}(i,j)$ indicates the normalized joint gray level histogram of images R And F, $h_R(i)$ are $h_R(i)$ the normalized marginal histograms of the two images, and L is the number of gray levels.

D. Standard deviation

The standard deviation (SD), which is the square root of the variance, reflect the spread in the data, So a high contrast image will have a high variance, and a low contrast image will have a low variance.

Let us denote the intensity distribution of an image by $P = \{p(0), p(1), \cdots, p(g), \cdots, p(L-1)\}$, where $p(g)$ is the first-order histogram probability.

The grey average value of the image is

$$\bar{g} = \sum_{g=0}^{L-1} g \cdot p(g) \tag{4}$$

Then the standard deviation of the image is defined as follows:

$$\sigma_g = \sqrt{\sum_{g=0}^{L-1}(g - \bar{g})^2 p(g)} \tag{5}$$

E. Entropy

The entropy of an image is a measure of information content. It is the average number of nits needed to quantize the intensities in the image. Its definition as

$$H = -\sum_{g=0}^{L-1} p(g)\log_2 p(g) \tag{6}$$

where p(g) is the probability of grey g, and the range of g is [0,...,L-1].

F. Difference entropy

The difference entropy between two images reflects the difference between the average amount of information they contained. Its definition is,

$$\Delta H = |H_R - H_F| \tag{7}$$

where H_F and H_R are the entropy of the fused image and the reference image.

G. Cross entropy

Let $P = \{p(0), p(1), \cdots, p(g), \cdots, p(L-1)\}$ and $Q = \{q(0), q(1), \cdots, q(g), \cdots, q(L-1)\}$ denote the grey distributions of two images. Cross entropy can evaluate the information difference between them,

$$\mathrm{CEN}(P:Q) = \sum_{g=0}^{L} p(g)\log_2 \frac{p(g)}{q(g)} \tag{8}$$

If there is reference image in the fusion process, the equation () can directly used to calculate the cross entropy of the fused image and the reference image. If there is no reference image during the fusion process, we can calculate the cross entropy of the source images and the fused image i.e., CEN(A:F) and CEN(B:F). The overall cross entropy is defined as

$$\mathrm{CEN}_{\alpha} = (\mathrm{CEN}(A:F) + \mathrm{CEN}(B:F)) / 2 \tag{9}$$

$$\mathrm{CEN}_{\beta} = \sqrt{(\mathrm{CEN}^2(A:F) + \mathrm{CEN}^2(B:F)) / 2} \tag{10}$$

H. Spatial Frequency

Consider an image of size M×N, where M equals to the number of rows and N the number of columns. The row and column frequencies of the image are given by

$$RF = \sqrt{\frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=1}^{N-1} [F(m,n) - F(m,n-1)]^2} \tag{11}$$

and

$$CF = \sqrt{\frac{1}{MN} \sum_{n=0}^{N-1} \sum_{m=1}^{M-1} [F(m,n) - F(m-1,n)]^2} \tag{12}$$

The total spatial frequency of the image block is then

$$SF = \sqrt{(RF)^2 + (CF)^2} \tag{13}$$

VI. Conclusions

This paper introduced the basic concept, general structure, methods, applications, and performance evaluation of multiple image fusion. Multisensor image fusion combines different sources of image information into a composite image which is more suitable to human perception and computer analysis. Applications of image fusion range from military surveillance, navigation, medical diagnosis, law enforcement, to remote sensing. With the development of hardware, software, and algorithms, it can be expected that the applications of image fusion will be more deep and abroad.

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