Application of Infrared and Visible Image Fusion

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Infrared and visible light image fusion combines infrared and visible light images to provide a more comprehensive image with more features from two photos by extracting the main information from each image and fusing it together.

infrared and visible image fusion | image fusion | multi-scale decomposition | compressed sensing

1. Introduction

Image fusion attempts to use various techniques as enhancement strategies to create rich images with many aspects and information. Combining multiple sensors to produce an image is the process of image fusion. The continuous progress of current science and technology has led to the development of image fusion technology because an image with a single piece of information cannot meet the needs of people[1]. Infrared and visible image fusion[2], multi-focus image fusion, medical image fusion, and remote sensing image fusion are the main branches of image fusion.

Infrared and visible image fusion are commonly used in the above four image fusion techniques. The visible light band, with its high resolution and unusually detailed texture, is most consistent with the visual field of the human eye, producing images very similar to those people see in their daily lives. However, it will be severely disrupted by shielding, weather, and other factors. The ability to recognize and identify targets in infrared images captures thermal targets even in the most challenging weather conditions, such as heavy rain or smoke. On the other hand, low resolution, fuzziness, and poor contrast are further disadvantages of infrared images.

In practical applications, the combination of infrared and visible images can solve various problems. For example, in some cases, operators must simultaneously monitor a large number of visible and infrared images from the same scene, each with its own unique requirements. Humans have found it very challenging to combine information from visible and infrared images just by staring at various visible and infrared images. In some cases with complex backgrounds, infrared images can overcome the constraints of visible images, obtain target information at night or in low-illumination environments, and improve target recognition abilities. By fusing infrared and visible light photos, workflow efficiency and convenience can be greatly improved. At the same time, infrared and visible image fusion is widely used in the fields of night vision, biometric recognition, detection, and tracking [4]. This highlights the importance of infrared and visible image fusion research.

2. Application of night vision

The thermal radiation information of the target object or scene is usually converted to false color images because the human visual system is more sensitive to color images than grayscale photos. Thanks to the use of color transfer technology, the resulting color images have a realistic daytime color appearance, which makes the scene more intuitive and helps the viewer understand the image. **Figure 1** shows an example of blending visible and infrared images at night to achieve color vision.

Figure 1. Example of infrared and visible image fusion for color vision at night. **(a)** visible light images; **(b)** infrared images; **(c)** reference images; **(d)** fusion of images.

Grayscale images are less responsive to human vision than color images. Human eyes are able to distinguish between thousands of colors, but they can only distinguish between about 100 grayscale images. Therefore, it is necessary to color grayscale images, especially because the fusion method of infrared and visible images with color contrast enhancement has been widely adopted in military equipment[3]. In addition, due to the rapid growth of multi-band infrared and night vision systems, there is now greater interest in the color fusion ergonomics of many image sensor signals.

3. Application in the field of biometrics

The subject of facial recognition research is progressing rapidly. The face recognition technology for visual images has been developed to a very advanced stage and has achieved great success[4]. In the case of low light, the face recognition rate using visual technology will be reduced. However, thermal infrared face recognition technology can perform well. **Figure 2** shows images of faces captured in infrared and visible light.

Figure 2. Examples of infrared and visible face images. **(a)** visible light images; **(b)** infrared images.

Although face recognition technology based on visible images has been well studied, there are still significant problems with its practical implementation. For example, the recognition effect can be significantly affected by changes in lighting, facial expressions, background, and so on in the actual scene. To recognize faces, infrared photos can complement information hidden in visible-light photos. In recent years, the application of infrared and visible image fusion based on biometric optimization algorithms has increased. By increasing the amount of computation, this approach can improve identification accuracy and provide more supplementary data for biometrics. The future application of infrared and visible light fusion technology in the field of biometrics will also become more extensive.

However, the growing use of facial recognition technology has also raised some ethical and privacy concerns. For example, while surveillance systems in public places contribute to social security, they also raise questions about whether people's facial information could be stolen and improperly used by outside parties. Various countries where governments are using facial recognition technology to monitor citizens' activities have raised concerns about abuses and human rights violations.

4. Application in the field of detection and tracking

In the field of target detection, visible light and infrared images can work together to detect targets. Bulanon et al.[5] combined the thermal image and visual image of the orange tree crown scene, overcoming the limitations of the two imaging techniques and improving the accuracy of fruit detection. First, fruit can be seen in visible light pictures because of the color difference between the fruit and the tree crown, but because visible light images are sensitive to light fluctuations, fruits can be misclassified. After real-world testing, it is clear that the temperature of the fruit at night is significantly greater than the temperature of the treetop, enabling the resulting infrared image to effectively detect the fruit. Finally, the accuracy of fruit detection has been improved. In order to improve the overall effectiveness of the monitoring system, Elguebaly et al.[6] proposed a target detection method based on the fusion of visible and infrared images.

In subsequent frames of the video, object tracking locates the object specified in the current frame. In order to locate the object item in the time series, the object tracking algorithm must determine the relationship between the frames. Single-mode tracking is the most popular but less reliable. If it is at night or in poor lighting conditions, target tracking performance cannot be guaranteed because the quality of the visible image is highly related to the imaging environment. This is similar to the lack of texture in infrared photos, a poor three-dimensional understanding of the scene, and no guarantee of their performance in a particular situation. Therefore, Liu et al.[7] proposed a visual tracking method that combines color images and infrared images, namely RGBT tracking, which can fuse complementary information in infrared and visible images to make target tracking more robust.

5. Application in the field of medical diagnosis

Medical image fusion aims to improve image quality by maintaining specific functions, expanding the use of images in clinical diagnosis, and evaluating medical problems. With the continuous development of clinical application needs, medical image fusion is increasingly proving to have important advantages. Through the study of medical images, computers or clinicians are able to make most medical diagnoses. Different types of medical images employ a variety of imaging techniques and give different emphasis to the depiction of the human body. Computed tomography [8] (CT), magnetic resonance imaging [9] (MRI), single photon emission computed tomography[10] (SPECT), positron emission tomography [11](PET), and ultrasound [12] are examples of common medical techniques. These methods include those that focus on regional metabolic capacity and those that focus on organ structure. If medical images of various modes can be merged, the effectiveness and accuracy of diagnosis will be significantly improved, while removing redundant information and improving image quality. As shown in **Figure 3**, MRI images can better see more deformed soft tissue, while CT scans can better see denser and less twisted tissue. Two different types of photos can then be combined using image fusion technology to provide more precise patient information.

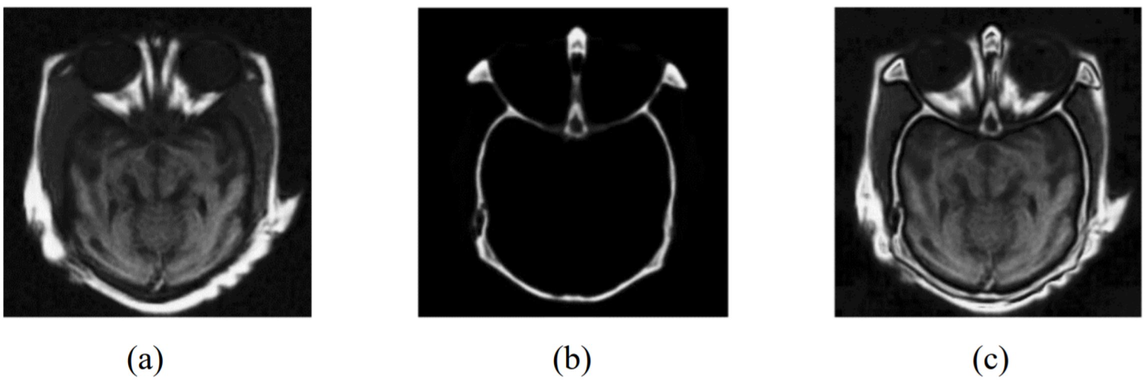

Figure 3. Image fusion in clinical imaging field. (**a**) MRI; (**b**) CT; (**c**) Fused image.

6. Applications in the Field of Autonomous Vehicles

The field of autonomous vehicles is constantly evolving, and vision, radar, and LiDAR sensors are also widely used in autonomous vehicle perception technology. The first step in autonomous driving and a crucial element in deciding how well a vehicle performs is the ability to precisely and properly recognize the surroundings around it. General vision sensors may have trouble identifying things, particularly in low light, intense sunlight, or severe weather, which is a test for self-driving automobiles. In order to increase the visual effects of automated vehicles and the safety and dependability of autonomous driving in challenging conditions, infrared and visible light image fusion has been introduced into the application of the field of driverless vehicles. For usage in the field of autonomous cars, Li [13] et al. suggested a novel two-stage network (SOSMaskFuse) that can efficiently cut down on noise, extract critical thermal data from infrared photos, and display more texture features in visible images. In order to efficiently detect and identify objects even in environments with limited visibility, such as day or night, Choi [14] et al. presented a sensor fusion system that integrates thermal infrared cameras with LiDAR sensors. This system effectively ensures the safety of autonomous vehicles.

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