Feature-Based Image Fusion Quality Metrics

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Abstract. Image fusion quality metrics have evolved from image processing quality metrics. They measure the quality of fused images by estimating how much localized information has been transferred from the source images into the fused image. However, this technique assumes that it is actually possible to fuse two images into one without any loss. In practice, some features must be sacrificed and relaxed in both source images. Relaxed features might be very important, like edges, gradients and texture elements. The importance of a certain feature is application dependant. This paper presents a new method for image fusion quality assessment. It depends on estimating how much valuable information has not been transferred.

1 Introduction

The process of image fusion aims to merge two or more images to produce a new image that is better than the original ones. The term ‘better’ differs from one context to another. In some contexts, it means holding more information. In other contexts, it means getting more accurate result or reading. In general, an image fusion system takes as an input two or more source images and produces one fused image as an output. The fusion process applies a fusion algorithm repeatedly on the source images and/or intermediate output images.

Researchers have developed several definitions of image fusion. In [1] Wald derived a formal definition of image fusion as “a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of ‘greater quality’ will depend upon the application”. In [2] Pohl and Genderen defined image fusion as “the combination of two or more different images to form a new image by using a certain algorithm”. Li et al. [3] defined image fusion as “fusion refers to the combination of a group of sensors with the objective of producing a single signal of greater quality and reliability”. A good survey about data fusion terminologies and definitions is presented by Wald in [1].

Image fusion quality metrics evolved from image processing objective quality measures like MSE, entropy and information measures. In fact, developing an objective quality metric is challenging. Wang has discussed some of the difficulties facing objective quality measures in [5]. These measures have then been realized into image fusion context. The simplest idea is to average quality distance of the fused image from each of the source ones. These measures have been used on overlapping portions of the images to maintain localization. Xydeas and Petrovic [6] estimated fusion performance based on edges in the image. Zhang and Blum [7] used a mixture of Rayleigh probability density functions to model the image histogram and
estimate quality of noisy images. Mutual information measure was examined by Qu [8]. It described the use of joint histogram between a fused image with each of the source images. Local cross-correlation of feature maps of the source and fused images was studied by Zhao in [9]. Buntilov and Bretschneider [10] applied multi-level thresholding to variance maps in order to identify the spatial blocks holding more information and, most likely, should be transferred into the fused image. They concluded that quality measures of image fusion algorithm should be extended to take into consideration segmented regions and weight averaging their contribution in assessment of quality based on their areas and how much information each region holds. They derived a thresholding-based solution in [11]. An excellent survey about quality measures was presented by Blum [12]. Finally, researchers concluded that universal quality index (UQI) founded by Wang and Bovik in [13] and improved in [14], captures localized structural similarities between images. In [15], Piella and Heijmans improved UQI and added a saliency factor for each pair of corresponding blocks (a block from each input image) being examined against the corresponding block in the fused image. They proposed the use of simple information measuring functions like standard deviation, dynamic range and entropy. Many researchers worked on deriving the most suitable and realistic saliency functions to weigh the estimated amount of information being transferred from source images into the fused one. Covariance and quadtree decomposition methods have been investigated in [16] and [17], respectively. In [18], Yang applied the weighting function only where source image do not have structural similarities.

A wide variety of applications, including an automated battle field, can make use of image fusion. A typical scenario is an automated battle field where a swarm of robots are gathering information from a sensor network or directly from the field. Performance may be improved by having some scale defining how good or bad the captured images are before sending them. If a robot is traveling in a dark environment, a visual image will actually provide no data, while a thermal one will be far more informative. However, sometimes the darkness itself is a valuable piece of information. These pieces of information allow the robot to allocate the proper resources, namely the bandwidth, to transmit both images.

This paper adds follows the evolution of image fusion quality metrics and adds another layer that compares source images to the fused one within a feature space that captures the distrust of local information in the source images. The rest of this paper is organized as follows. Section 2 presents related work and highlights the evolution of image fusion quality metrics. Section 3 presents the proposed method and discusses its tuning. Section 4 presents the experiments comparing between proposed modification and other quality metrics. Finally, Section 5 concludes and introduces to possible future advancements.

2 Related Work

Image fusion quality metrics have evolved from image quality metrics. This section follows the evolution journey of image quality metrics into image fusion quality metrics. Throughout this paper, we assume using a two-image (binary) fusion