MULTI-EXPOSURE IMAGE FUSION BASED ON INFORMATION-THEORETIC CHANNEL

Qi Zhao⋆ , Mateu Sbert⋆†, Miquel Feixas† and Qing Xu⋆

⋆Department of Computer Science and Technology, Tianjin University, China
†Institute of Informatics and Applications, University of Girona, Spain

We propose a method for multi-exposure image fusion based on information-theoretic channel. In the fusion scheme, conditional entropy, as an information measurement of each pixel in one image to the other image, is calculated through an information channel built between two source images, and then weight maps of the source images are generated. Based on the pyramid scheme, images at every scale are fused by weight maps, and a final fused image is inversely reconstructed.

Introduction

Due to limited color range representation, normal digital cameras usually produce low dynamic range (LDR) images, where details in brighter and darker regions can not be fully captured in one exposure. Multi-exposure image fusion is very popular technique to solve this problem. Generally, the fusion algorithms are performed at pixel level, feature level or decision level [2]. For the fusion algorithms, the key challenge is to choose the information measure or quality measure index for the source image sequence because of its direct influence on detail extraction.

Figure 1: The multi-exposure images from left to right are under-, middle- and over-exposed. Image courtesy of Bartlomiej Okonek.

Theoretical Background

Information Channel

We interpret the two images as random variables and build an information channel between them to calculate pixelwise weights. Given two images, which can be represented by their normalized histograms X and Y, then the channel from X to Y is expressed by a matrix M of conditional probabilities $p(Y|X)$. If there are n bins in X, m bins in Y, the matrix is $n \times m$ dimensional, in which $M(y;x)$ is $p(y|x)$(see the diagram in Fig.2(b)). Similarly, the channel from Y to X is expressed by a $m \times n$ dimensional matrix of $p(X|Y)$.

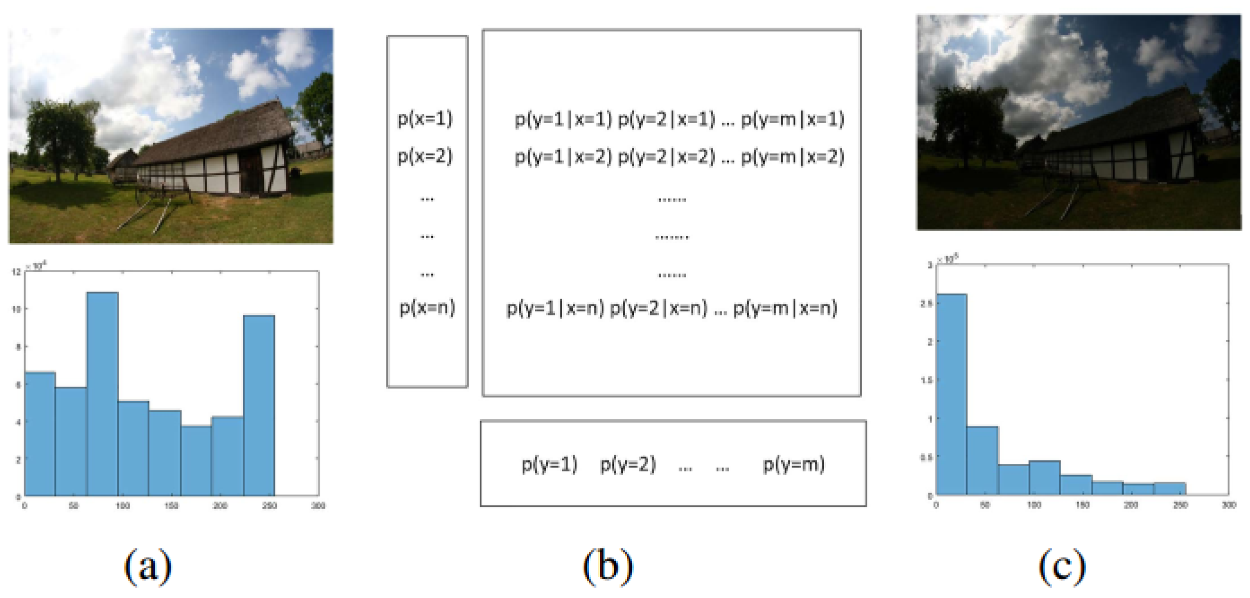

Figure 2: The information channel from image X to image Y.

Conditional Entropy

Based on the information channels, we propose *conditional entropy* to measure specific information and apply it to fusion as information criterion. The conditional entropy of pixel x is formulated by $H(Y|x)$, that expresses the new distribution of Y, or remaining uncertainty, when observing x, and is given by Eq.1.

$$H(Y|x) = -\sum_{y \in Y} p(y|x) \log p(y|x) \tag{1}$$

The normalized weight map can be produced by Eq.2, where W_x and W_y represent weights of x and y, respectively. The pixel with higher conditional entropy means it has higher uncertainty, thus contains less information. Therefore, weights are inversely proportional to conditional entropy.

$$\begin{aligned} W_x &= \frac{H(X|y)}{H(Y|x) + H(X|y)} \\ W_y &= \frac{H(Y|x)}{H(Y|x) + H(X|y)} \end{aligned} \tag{2}$$

Method Overview

Given a sequence of source images (e.g. $\{S_1, S_2, S_3, ...S_k\}$) with increasing exposure time, the fusion algorithm is performed by the following procedure.

- Build information channels between adjacent source images, separately, e.g., S_1-S_2, S_2-S_3, ..., S_{k-1}-S_k.
- Based on the channels, calculate the corresponding information maps for each image pair based on the information criteria.
- Normalize information maps in the reference of the first pair maps to get same scale weight maps of all source images.
- Carry out Laplacian pyramid decomposition for each source image, and perform fusion with the filtered weight maps at each level on the channels L, a, b.
- Reversely reconstruct the final fused image by all the fused layers.

Results

In Fig.3, we compare the fusion results produced by I1, I2, which are employed in fusion by Bramon et al. [1] with our conditional entropy (CE) measure.

Figure 3: Fused results by I1, I2 and conditional entropy(CE).

In Fig.3, it can be seen that the fused result by CE has the best contrast. Moreover, we can see the information maps generated by CE has more details and differences in different areas.

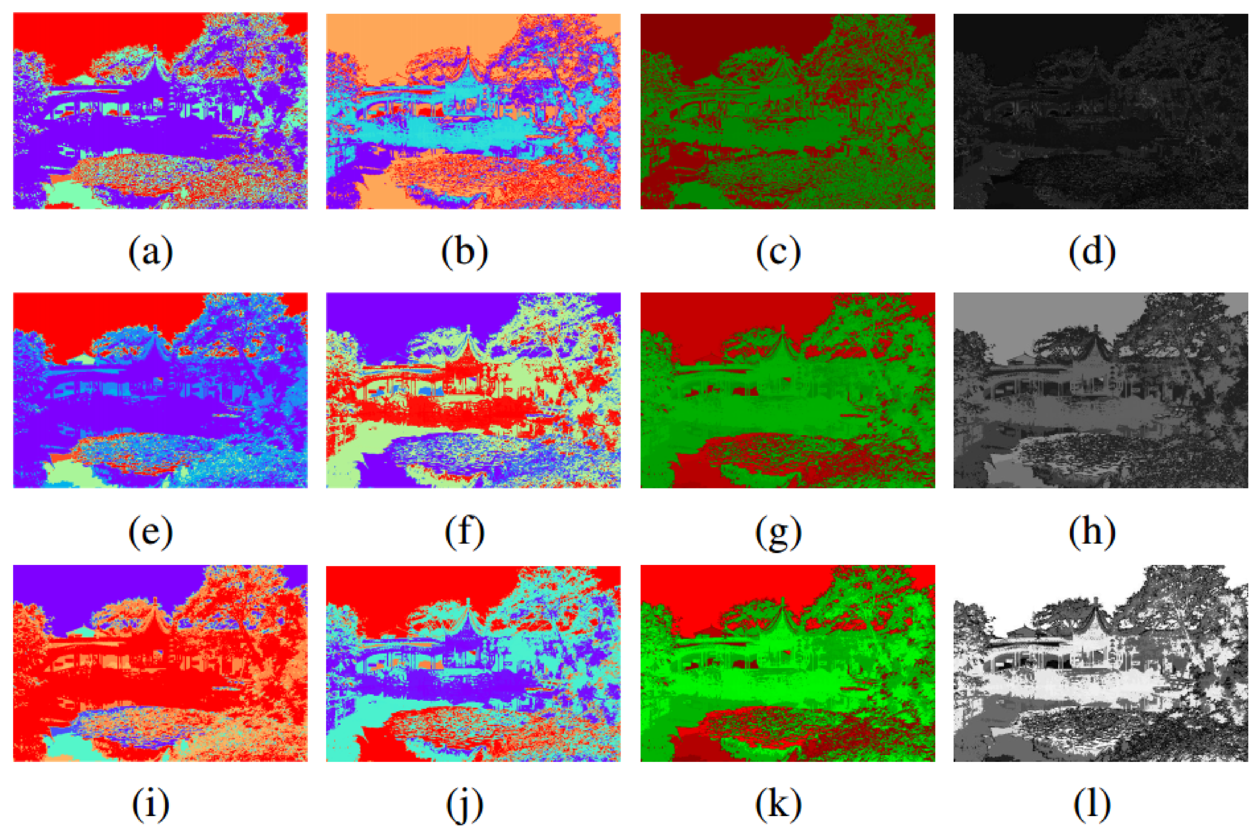

Figure 4: The columns from left to right are respectively information maps of X, information maps of the Y, dominance map and weight difference map measured by I_1, The rows from top to bottom are corresponding maps by I_1, I_2 and conditional entropy.

Figure 5: Comparison of results by different methods, which were obtained from MEF database created by Zeng et al. [3].

From these results, we observe that our algorithm can preserve more details and contrast in the over- and under exposed regions.

Conclusions

We have proposed a multi-exposure fusion approach based on the channel of conditional entropy. Instead of considering each source image independently, we consider the information that each image in a pair contains about the other one. The fused results by the proposed method preserve more details than other methods. The information of each pixel is obtained by global luminance distribution, being thus easy to implement. Nevertheless, there are also some places that need to improve.

- Consider the color information, not only gray information, to improve the colorfulness.
- Solve the noise introduced in the uniform region.
- Generalize to real-time application by graphics card implementation.

Acknowledgements

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