EVALUATING MULTIEXPOSURE FUSION USING IMAGE INFORMATION

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Multiexposure Fusion (MEF)

- Consumer cameras have low dynamic range (LDR)
- Natural scenes often contain high dynamic range (HDR)
- Capturing HDR scenes with LDR cameras result in over/under-exposed images

(a) Under-exposed image (b) Over-exposed image

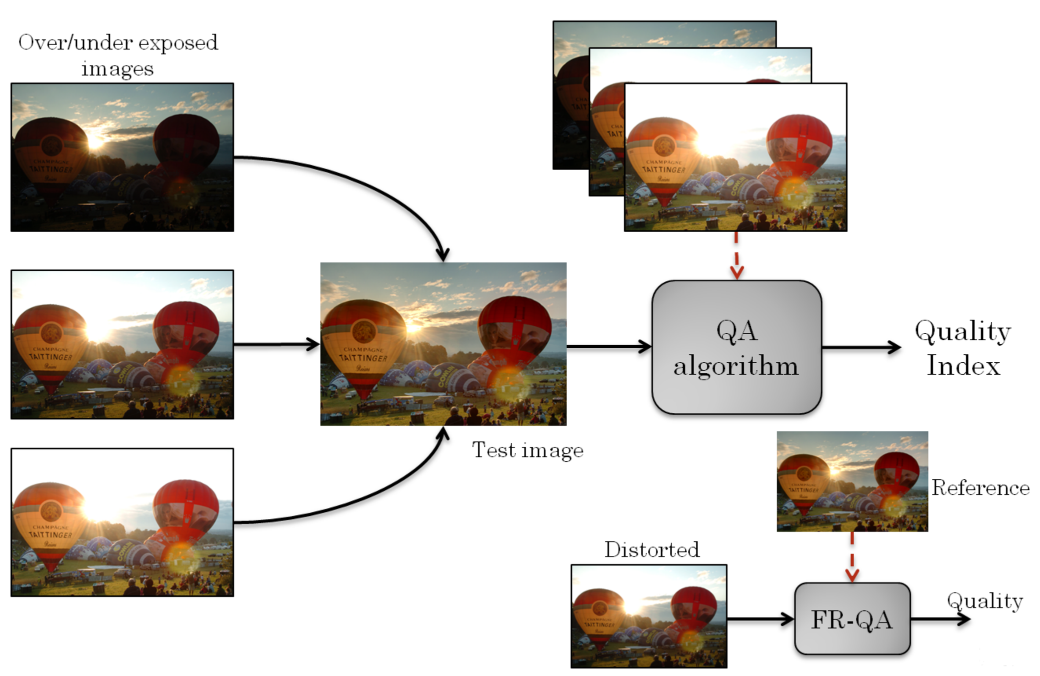
- Combining over/under-exposed images to obtain a single image - Multiexposure fusion

- Several MEF algorithms are available [Metens2007], [Raman2009]

(c) Mertens, 2007 (d) Raman, 2009

We need to differentiate good and bad images automatically - Quality Assessment (QA) of Multiexposure Fusion
Can be useful in tuning the performance of MEF algorithms

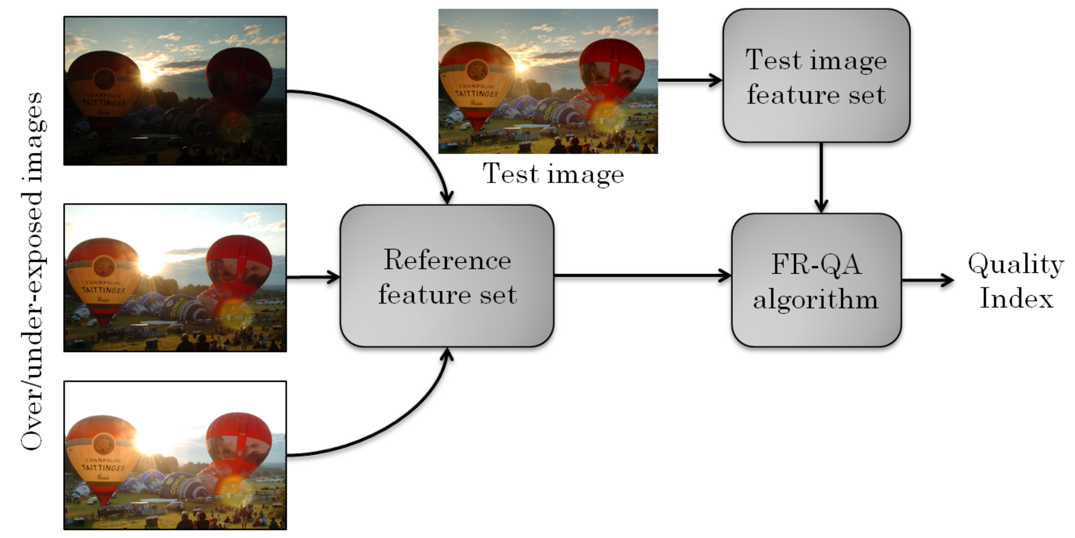
Quality Assessment of MEF



- No true reference available for quality computation
- Not a blind QA problem since ground truth is contained and spread over over/under exposed images
- Challenge: Estimate reference from the under/over exposed images

Feature map fusion model

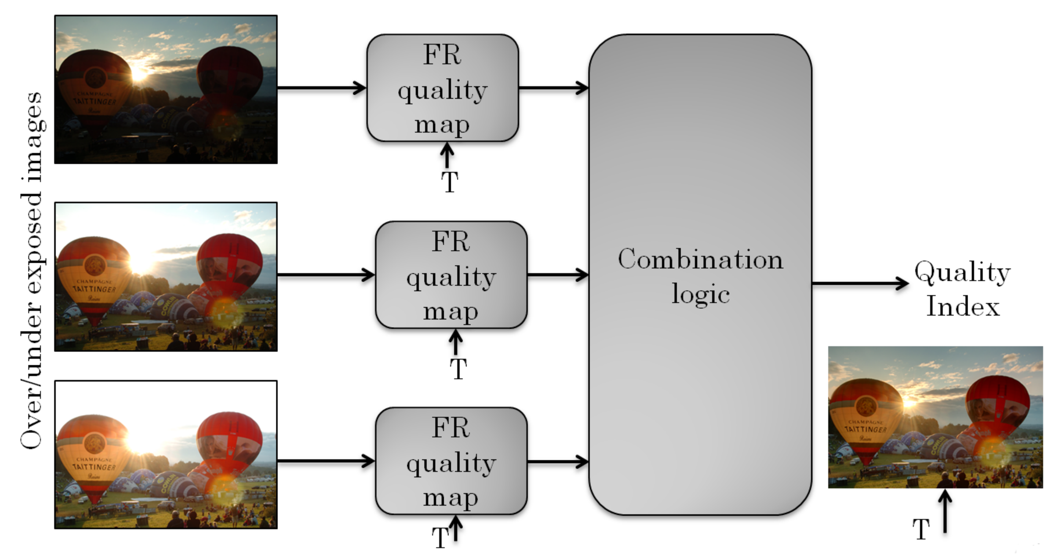
- Relevant features from source images are fused together to obtain a reference feature set
  - Eg: Contrast, Structure, Edge information, spatial frequency, etc.
- Reference feature set is compared against test image feature set to obtain quality index



[Ma2015] Kede Ma, Kai Zeng, and Zhou Wang, "Perceptual Quality Assessment for Multi-Exposure Image Fusion," in IEEE transactions on image processing, vol. 24, no. 11, November 2015

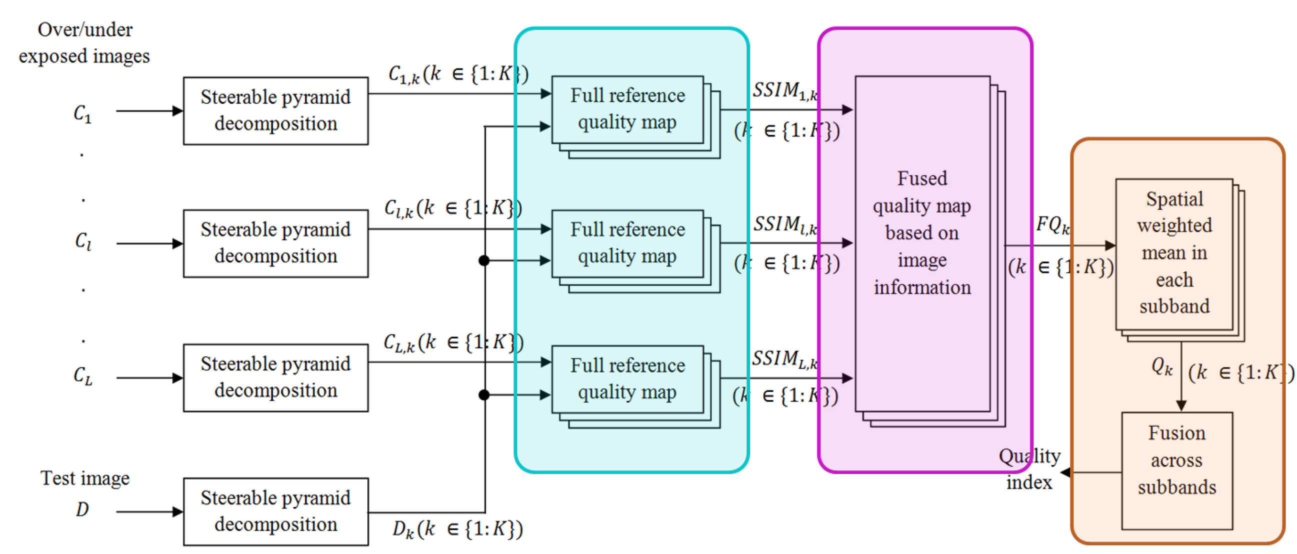
Quality map fusion model

- Assumes true reference for each location in test image is present in one of the source images
- Compute full-reference quality maps of test image with individual source images
- Individual quality maps are fused together to obtain quality index



Main contribution

- Show that quality map fusion model can perform on par with feature map fusion model
- Structural similarity metric (SSIM) quality map fusion using image information



- SSIM based pairwise quality map
- Quality map mixing using image information
- Local contrast based weighting

E. P. Simoncelli and W. T. Freeman, "The steerable pyramid: A flexible architecture for multi-scale derivative computation," Proc. IEEE Int. Conf. Image Proc., pp. 444-447, Oct 1995

Quality map mixing using Image Information

Quality map

SSIM index between Input Image-l and Test Image-t is given as

$$SSIM_{l,k}(i,j) = \frac{2\sigma_{t-l,k}(i,j) + C_2}{\sigma^2_{t,k}(i,j) + \sigma^2_{l,k}(i,j) + C_2}$$

- Structure and contrast computed in multiscale multiorientation subbands

Image Information

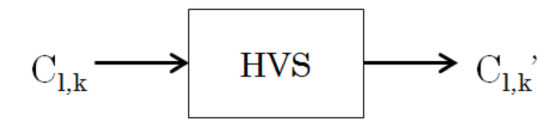


Figure: Perceptual model for bandpass coefficients in input image

$$I(\vec{C}_{l,k}(i,j); \vec{C'}_{l,k}(i,j) | \hat{s}_{l,k}(i,j)) = \frac{1}{2}\log_2\left(\frac{|\hat{s}^2_{l,k}(i,j)\mathbf{K}_{U_{l,k}} + \sigma^2_w \mathbf{I}|}{|\sigma^2_w \mathbf{I}|}\right)$$

- Captures information perceived from an over/under-exposed image

Quality map mixing

Pick SSIM at each location corresponding to input image with maximum information

$$FQ_k(i,j) = SSIM_{l^*,k}(i,j), \text{ where } l^*(i,j,k) = \arg\max_{l \in \{1,2,\ldots,L\}} I(\vec{C}_{l,k}(i,j); \vec{C'}_{l,k}(i,j) | \hat{s}_{l,k}(i,j))$$

Contrast based spatial pooling and overall score

$$Q_k = \sum_{i=1}^{I_k}\sum_{j=1}^{J_k} e_k(i,j) FQ_k(i,j) \qquad Q = \prod_{k=1}^{K} (Q_k)^{\beta_k}$$

Results

- MEF Quality Assessment Database [Ma2015] - 17 source image sequences
- Test images from 8 fusion algorithms for each sequence

Table: Spearman Rank Order Correlation Coefficient between subjective and objective scores

Source sequence	Proposed model	[Ma '15]	[Xydeas '00]	[Piella '03]
Balloons	**0.9048**	0.8333	0.6667	0.4524
Belgium house	**0.9940**	0.9701	0.7785	0.467
Lamp 1	**0.9762**	**0.9762**	0.7857	0.4048
Candle	0.9048	0.9286	**0.9762**	0.5476
Cave	**0.8333**	**0.8333**	0.7143	0.5714
Chinese garden	**0.9762**	0.9286	0.6905	0.5238
Farmhouse	0.9048	**0.9286**	0.7381	0.2857
House	0.8333	**0.8571**	0.5952	0.4048
Kluki	**0.9762**	0.7857	0.2619	0.1190
Lamp 2	**0.8571**	0.7143	0.7619	0.5476
Landscape	**0.8571**	0.5238	0.0238	0.1429
Lighthouse	0.8571	**0.8810**	0.5000	0.0714
Madison capitol	0.8571	**0.8810**	0.5238	0.4762
Memorial	**0.9048**	0.8571	0.7619	0.6667
Office	**0.9519**	0.7832	0.2771	0.4579
Tower	0.9048	**0.9524**	0.5714	0.5714
Venice	**0.9701**	0.9341	0.9102	0.3114
Average	**0.9096**	0.8570	0.6198	0.4131

- Our method does much better than [Xydeas '00] and [Piella '03], which are also quality map fusion methods
- Our QA model achieves state of the art performance, and much better performance for Landscape and Office sequences

Conclusion

- Show that quality map fusion does as well as feature map fusion [Ma2015]
- Future work - Develop QA algorithms for dynamic scenes

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