Multiframe Demosaicing and Super-Resolution of Color Images

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Abstract

- Proposed method
  - Fast and robust hybrid method of super-resolution and demosaicing
    - Based on maximum a posteriori (MAP) estimation technique
      - Minimizing a multiterm cost function
        - » L_1 norm
        - » Bilateral regularization
        - » Tikhonov regularization
        - » Additional regulaization

Introduction

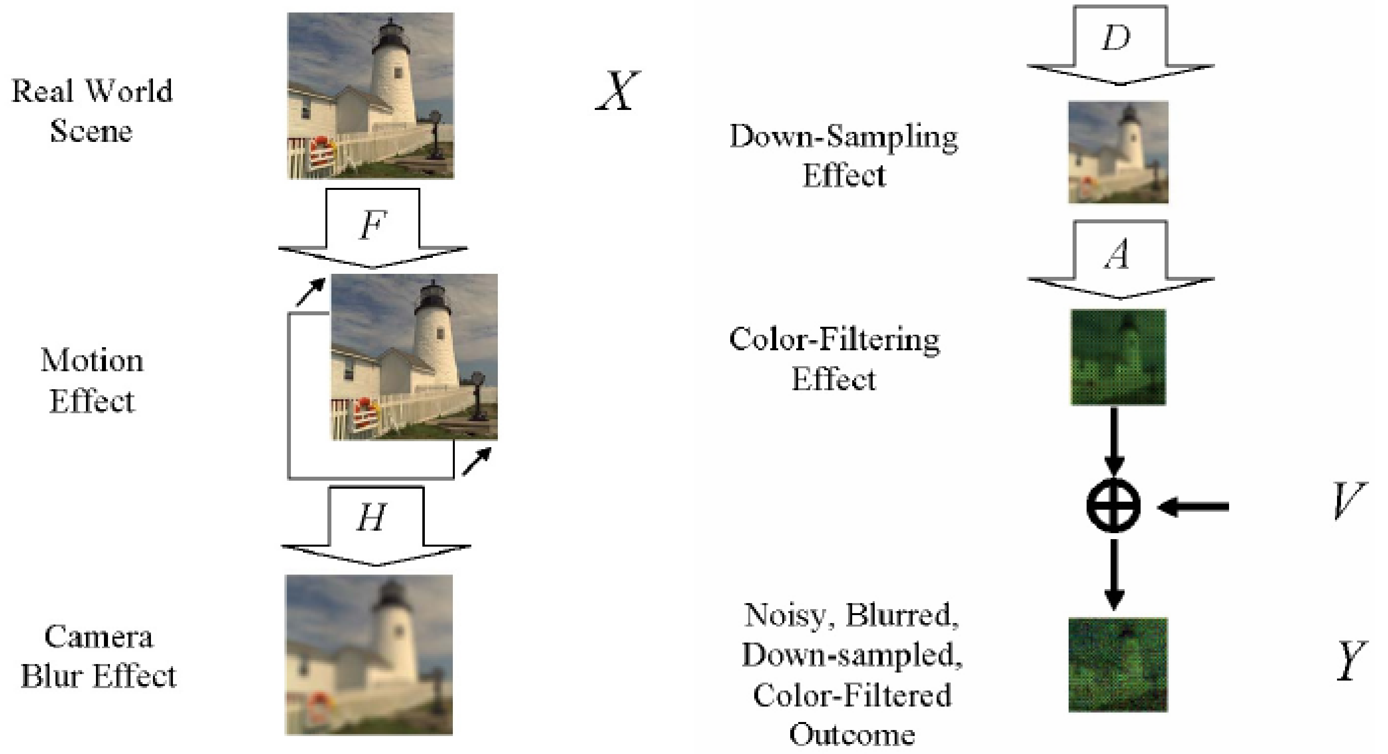


Fig. 1. Block diagram representing the image formation model considered in this paper, where X is the intensity distribution of the scene, V is the additive noise, and Y is the resulting color-filtered low-quality image. The operators F, H, D, and A are representatives of the warping, blurring, down-sampling, and color-filtering processes, respectively.

- Two image reconstruction problems
  - Super-resolution (SR) and demosaicing
    - Limited number of pixels
    - Color-filtering applied on a single CCD array of sensors on most cameras
- In this paper
  - Fast and robust method for joint multiframe demosaicing and color super-resolution

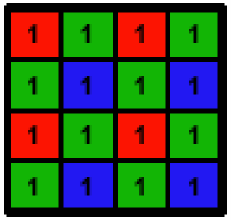
Overview of Super-Resolution and Demosaicing Problems

- Super-Resolution
  - Limited spatial resolution of digital cameras
    - Utilization of optical lens and CCD array
  - Producing high-resolution(HR) images
    - Acquiring and fusing several low-resolution(LR) images of the same scene
  - Aliasing effects in the LR images enable the recovery of the HR-fused image
    - Providing a relative subpixel motion
      - Between the under-sampled input images

- Applying monochromatic SR algorithms to each of the color channels independently
  - Using the color information to improve the accuracy of motion estimation
- Transforming the problem to a different color space
  - Applying only to the luminance channel

◆ Demosaicing

- Each pixel reflects three data measurements
- Reducing production cost
  - Only one color measurement (R, G, or B) per pixel
    - The Bayer pattern
- Values of the missing color bands at every pixel
  - Estimation of the unknown pixel values
    - Linear interpolation of the known ones in each color band independently
      - » Color artifacts
- Independent interpolation of green band
  - More reliable reconstruction than red or blue band



- Gradient-based method
  - Using the second derivative of the red and blue channel
    - Estimation of the edge direction in the green channel
- Spatial and spectral correlations among neighboring pixels
  - Utilization to define the interpolation step
- Iterative MAP method
- Based on one or more of following assumptions
  - More green sensor with regular pattern of distribution than blue or red ones
    - In the case of Bayer CFA
      - » Each red or blue pixel surrounded by four green pixels

- Most algorithms assume a Bayer CFA pattern
  - Each red, green, and blue pixel
    - » Neighbor to pixels of different color bands
- For each pixel, one, and only one, color band value is available
- Unchangeability for pattern of pixels through the image
- Sensitivity for human eye
  - Details in the luminance component of the image than the details in chrominance component
  - Sensitivity of chromatic changes in the low spatial frequency region than the luminance change
- Interpolation should be preformed along and not across the edges
- Different color bands are correlated with each other
- Edges should align between color channels

- Most popular and sophisticated demosaicing method
  - Fail to produce satisfactory results
    - Cheap commercial still or video digital cameras
      - » Small number of CCD pixels decreases
    - Severe aliasing in the color-filtered image
  - For example

(d) : Some color-artifacts on the edges

(e) : Color artifacts are much more evident than (d)

(f) : has less color artifacts than (e)

(f) : lost some high-frequency details

Fig. 2. HR image (a) captured by a 3-CCD camera is (b) down-sampled by a factor of four. In (c), the image in (a) is blurred by a Gaussian kernel before down-sampling by a factor of 4. The images in (a)–(c) are color-filtered and then demosaiced by the method of [16]. The results are shown in (d)–(f), respectively. (a) Original. (b) Down-sampled. (c) Blurred and down-sampled. (d) Demosaiced (a). (e) Demosaiced (b). (f) Demosaiced (c).

- Merging super-resolution and demosaicing into one process
  - Example of multiframe demosaicing

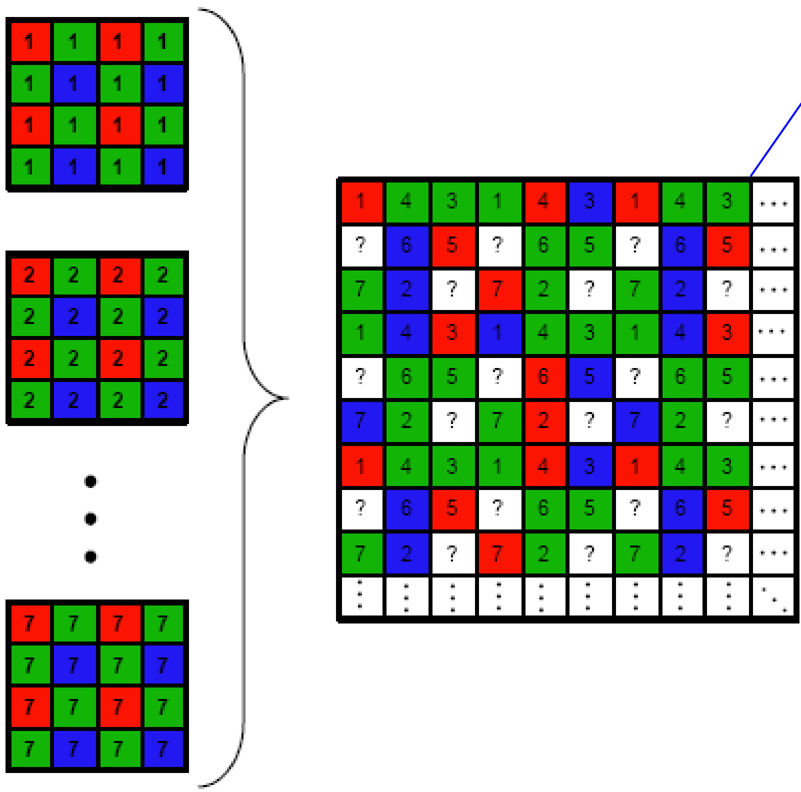


Fig. 3. Fusion of seven Bayer pattern LR images with relative translational motion (the figures in the left side of the accolade) results in a HR image ($\hat{Z}$) that does not follow Bayer pattern (the figure in the right side of the accolade). The symbol "?" represents the HR pixel values that were undetermined (as a result of insufficient LR frames) after the shift-and-add step (the shift-and-add method is extensively discussed in [3], and briefly reviewed in Section III-F).

- Incorrect of assumptions
  - More green pixels than blue or red pixels
  - Any pixel may be surrounded by only red or blue colors
  - One and only one color band value for each pixel
    - LR images of dimension $M \times M$
    - HR output of dimension $rM \times rM$
    - Not enough measurements to fill the HR grid
      - » Symbol “?” in Fig. 3
    - Over-determined cases
      - » More than one color value available
  - Changing the field of view (FOV) of real world LR images

Mathematical Model and Solution Outline

- Mathematical model of the imaging system
  - Forward model of Fig. 1

$$\begin{aligned} \underline{Y}_i(k) &= D_i(k)H(k)F(k)\underline{X}_i + \underline{V}_i(k) \\ &= T_i(k)\underline{X}_i + \underline{V}_i(k) \\ &\quad k = 1,\dots,N \quad i = R,G,B \end{aligned} \tag{1}$$

$$D_i(k) = A_i(k)D(k)$$

where $\underline{X}_i$ and $\underline{Y}_i$ are i^{th} band (R, G, or B) of the HR color frame and the k^{th} LR frame.

$F(k)$ is the geometric motion operator between the HR and LR frames.

$H(k)$ is the camera's point spread function (PSF).

$D_i(k)$ is down-sampling operator, which includes both the color-filtering and CCD down-sampling operations.

$T_i(k)$ is covered to geometric motion, blur, and down-sampling operators.

$\underline{V}_i(k)$ is system noise.

N is the number of available LR frames.

which can be also expressed as

$$\underline{Y} = T\underline{X} + \underline{V},$$

$$\underline{Y} = \begin{bmatrix} \underline{Y}_R(1) \\ \underline{Y}_G(1) \\ \underline{Y}_B(1) \\ \underline{Y}_R(2) \\ \vdots \\ \underline{Y}_B(N) \end{bmatrix}, \underline{V} = \begin{bmatrix} \underline{V}_R(1) \\ \underline{V}_G(1) \\ \underline{V}_B(1) \\ \underline{V}_R(1) \\ \vdots \\ \underline{V}_B(N) \end{bmatrix}, T = \begin{bmatrix} \underline{T}_R(1) \\ \underline{T}_G(1) \\ \underline{T}_B(1) \\ \underline{T}_R(1) \\ \vdots \\ \underline{T}_B(N) \end{bmatrix}, \underline{X} = \begin{bmatrix} \underline{X}_R \\ \underline{X}_G \\ \underline{X}_B \end{bmatrix}. \quad (2)$$

– Size of each matrix

r is resolution enhancement factor

- HR color image $(\underline{X})$: $\left[12r^2M^2 \times 1\right]$
- $\underline{V}_G(k)$ and $\underline{Y}_G(k)$: $\left[2M^2 \times 1\right]$
- $\underline{V}_R(k), \underline{Y}_R(k), \underline{V}_B(k)$, and $\underline{Y}_B(k)$: $\left[M^2 \times 1\right]$
- Geometric motion and blur matrices : $\left[4r^2M^2 \times 4r^2M^2\right]$
- Down-sampling and system matrices (Green band) : $\left[2M^2 \times 4r^2M^2\right]$
- Down-sampling and system matrices (Red and blue band) : $\left[M^2 \times 4r^2M^2\right]$

- Ignored effect of color-filtering model
  - Assumed to be monochromatic

$$\underline{Y}(k) = D(k)H(k)F(k)\underline{X} + \underline{V}(k) \qquad k = 1, \ldots, N \tag{3}$$

  - Consideration of only single frame reconstruction of color image

$$\underline{Y}_i = D_i \underline{X}_i + \underline{V}_i \qquad i = R, G, B. \tag{4}$$

- Classical approach to the multiframe reconstruction
  - Two-step process
    - Solving (4) for each image (demosaicing step)
    - Using the model in (3) to fuse the LR images resulting from the first step
  - Individually process for each R, G, or B band

- MAP approach to multiframe image reconstruction
  - Forward model of (1)
    - Inverse problem (estimation of HR image from LR images)
      - Inverting the forward model without amplifying the effect of noise in LR images
        - » Worse by the system matrix T
    - Using MAP estimator
      - Rich class of regularization functions
      - Way of Lagrangian type penalty terms

$$\underline{\hat{X}} = \underset{\underline{X}}{\operatorname{ArgMin}} \left[\rho\left(\underline{Y}, T\,\underline{X}\right) + \lambda \Gamma\left(\underline{X}\right) \right] \tag{5}$$

where ρ, the data fidelity term, measures the "distance" between the model and measurements.

Γ is the regularization cost function.

λ is a scalar for properly weighting the first term (data fidelity cost) against the second term (regularization cost).

Manually choosing λ
Using visual inspection

◆ Monochromatic spatial regularization

- Tikhonov regularization
  - The form of $\Gamma(\underline{X}) = \|\Lambda \underline{X}\|_2^2$
    - Λ is a matrix capturing some aspects of the image
      - » General smoothness
  - Penalty of energy in the higher frequencies

Using to reconstruct
the luminance component of
the demosaiced images

- Bilateral-TV (B-TV) regularization
  - Achieving reconstructed images with sharper edges

$$\Gamma(\underline{X}) = \sum_{l=-P}^{P} \sum_{m=-P}^{P} \alpha^{|m|+|l|} \left\| \underline{X} - S_x^l S_y^m \underline{X} \right\|_1 \quad (6)$$

where S_x^l is operator to shifting the image by l pixels in horizontal direction.
S_y^m is operator to shifting the image by m pixels in vertical direction.
α is scalar weight $0 < \alpha < 1$, applying to give a spatially decaying effect to the summation of the regularization term.
P is the size of the corresponding bilateral filter kernel.

◆ Color regularization

– Minimizing vector product norm of any two adjacent color pixels

- Similar edge location and orientation of different bands
- The vector (outer) product of $\underline{M}:[m_r, m_g, m_b]^T$ and $\underline{N}:[n_r, n_g, n_b]^T$

$$\left\|\underline{M} \times \underline{N}\right\|_2^2 = \left[|M||N| sin(\Theta)\right]^2$$
$$= \left\|\vec{i}\left(m_g n_b - m_b n_g\right)\right\|_2^2 + \left\|\vec{j}\left(m_b n_r - m_r n_b\right)\right\|_2^2$$
$$+ \left\|\vec{k}\left(m_r n_g - m_g n_r\right)\right\|_2^2$$

where Θ is the angle between theses two vectors.

◆ Data fidelity

– Least-squares (LS) cost function

- Cost function to measure the closeness of the measured data
- Minimizing the L_2 norm of the residual vector

$$\rho\left(\underline{Y}, T\,\underline{X}\right) = \left\|\underline{Y} - T\,\underline{X}\right\|_2^2 \tag{7}$$

- Detection of a statistical study of the noise properties
- Using L_1 norm

$$\rho\left(\underline{Y}, T\,\underline{X}\right) = \left\|\underline{Y} - T\,\underline{X}\right\|_1 \tag{8}$$

- Speedup for the special case of translation motion and common space-invariant blur
  - Considering translational motion model and common space-invariant PSF
    - Exchange of the operators H and $F(k)$ $\left(F(k)H = HF(k)\right)$
    - Rewrite (1)

$\forall k\ H(k) = H$, when all images are acquired with the same camera.

$$\underline{Y}_i(k) = D_i(k)F(k)H\underline{X}_i + \underline{V}_i(k)$$

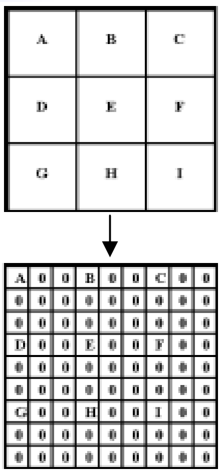
$$k = 1,\ldots,N \quad i = R,G,B. \tag{9}$$

    - Substituting $\underline{Z} = H\underline{X}$
      - Separating inverse problem into the much simpler subtasks
        - » Fusing the available image and estimating a blurred HR image from the LR measurements ($\hat{\underline{Z}}$)
        - » Estimating the deblurred image $\hat{\underline{X}}$ from $\hat{\underline{Z}}$

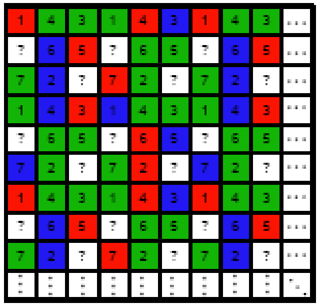
where $\hat{\underline{Z}}$ is the weighted mean of all measurements at a given pixel, after proper zero filling and motion compensation.

      - Shift-and-add operation

- Computation of shift-and-add operation



1. Computation of relative motion between all LR frames
2. Construction of set of HR images by up-sampling each LR frame by zero filling
3. Registering HR frames with respect to the relative motion of the corresponding LR frames
4. Pixel-wise mean or median operation on the nonzero values of these HR frames



Multiframe Demosaicing

- MAP estimation method
  - Fusing and demosaicing a set of LR frames
  - MAP-based cost functions
    - Enforcement of similarities between the raw data and the HR estimate (data fidelity penalty term)
    - Encouragement of sharp edges in the luminance component of the HR image (spatial luminance penalty term)
    - Encouragement of smoothness in the chrominance component of the HR image (spatial chrominance penalty term)
    - Encouragement of homogeneity of the edge location and orientation in different color bands (intercolor dependencies penalty term)

Data fidelity penalty term

- Measurement of the similarity between the resulting HR image and the original LR images
  - L_1 norm minimization of error term
    - Presence of uncertainties such as motion error

$$J_0(\underline{X}) = \sum_{i=R,G,B} \sum_{k=1}^{N} \left\| D_i(k) H(K) F(k) \underline{X}_i - \underline{Y}_i(k) \right\|_1 . \qquad (10)$$

    - Treatment of the simpler case of common space invariant PSF and translational motion
    - Using two step method (Eq. (9))
      - » Easiness to interpret and has a faster implementation

$$J_0(\underline{X}) = \sum_{i=R,G,B} \left\| \Phi_i (H \underline{\hat{X}}_i - \underline{\hat{Z}}_i) \right\|_1 \qquad (11)$$

where Φ is a diagonal matrix with diagonal values equal to the square root of the number of measurements

◆ Spatial luminance penalty term

- Importance of the edges in the luminance component of the reconstructed HR image
  - Sensitivity of human eye
- Applying B-TV regularization to the luminance component
  - Calculation of luminance image

$$\underline{X}_L = 0.299\underline{X}_R + 0.597\underline{X}_G + 0.114\underline{X}_B$$

- Luminance regularization term

$$J_1(\underline{X}) = \sum_{l=-P}^{P} \sum_{m--P}^{P} \alpha^{|m|+|l|} \left\| \underline{X}_L - S_x^l S_y^m \underline{X}_L \right\|_1. \quad (12)$$

◆ Spatial chrominance penalty term

- Requiring spatial regularization for the chrominance
  - Less sensitivity of HVS
- Using a simpler regularization
  - Based on L_2 norm

$$J_2(\underline{X}) = \left\| \Lambda \underline{X}_{C1} \right\|_2^2 + \left\| \Lambda \underline{X}_{C2} \right\|_2^2 \quad (13)$$

where $\underline{X}_{C1}$ is I layer in the YIQ color representation.
$\underline{X}_{C2}$ is Q layer in the YIQ color representation.

- Intercolor dependencies penalty term
  - Penalty of the mismatch between locations or orientations of edges across the color bands
  - Vector outer product norm of all pairs of neighboring pixels

$$J_3(\underline{X}) = \sum_{l=-1}^{1}\sum_{m=-1}^{1}\Big[\left\|\underline{X}_G \otimes S_x^l S_y^m \underline{X}_B - \underline{X}_B \otimes S_x^l S_y^m \underline{X}_G\right\|_2^2 + \left\|\underline{X}_B \otimes S_x^l S_y^m \underline{X}_R - \underline{X}_R \otimes S_x^l S_y^m \underline{X}_B\right\|_2^2 + \left\|\underline{X}_R \otimes S_x^l S_y^m \underline{X}_G - \underline{X}_G \otimes S_x^l S_y^m \underline{X}_R\right\|_2^2\Big] \qquad (14)$$

where $\otimes$ is the element by element multiplication operator.

◆ Overall cost function

- Summation of the cost functions

$$\underline{\hat{X}} = \underset{\underline{X}}{\mathrm{ArgMin}}\left[J_0(\underline{X}) + \lambda' J_1(\underline{X}) + \lambda'' J_2(\underline{X}) + \lambda''' J_3(\underline{X})\right]. \quad (15)$$

- Applying to minimize cost function
  - Calculation of derivative of (15) with respect to one of the color bands
    - Assuming the other two color bands are fixed
  - Computing the derivative with respect to the other color channels
  - For example

$$\nabla \underline{\hat{X}}_G^n = H^T \Phi_G^T sign\left(\Phi_G H \underline{\hat{X}}_G^n - \Phi_G \underline{\hat{X}}_G^n \right) + \lambda' \sum_{l=-P}^{P} \sum_{m=-P}^{P} \alpha^{|m|+|l|} \times 0.5870 \times \left[I - S_y^{-m} S_x^{-l} \right]$$
$$+ sign\left(0.2989\left(\underline{X}_R^n - S_x^l S_y^m \underline{X}_R^n\right) + 0.5870\left(\underline{X}_G^n - S_x^l S_y^m \underline{X}_G^n\right) + 0.1140\left(\underline{X}_B^n - S_x^l S_y^m \underline{X}_B^n\right)\right)$$
$$+ \lambda'' \sum_{l=-1}^{1} \sum_{m=-1}^{1} \left[2\left(\mathbf{X}_\mathbf{B}^{\mathrm{l,m}} - S_x^{-l} S_y^{-m} \mathbf{X}_\mathbf{B}\right)\left(\mathbf{X}_\mathbf{B}^{\mathrm{l,m}} \underline{X}_G - \mathbf{X}_\mathbf{B} S_x^l S_y^m \underline{X}_G\right)\right.$$
$$\left. + 2\left(\mathbf{X}_\mathbf{R}^{\mathrm{l,m}} - S_x^{-l} S_y^{-m} \mathbf{X}_\mathbf{R}\right)\left(\mathbf{X}_\mathbf{R}^{\mathrm{l,m}} \underline{X}_G - \mathbf{X}_\mathbf{R} S_x^l S_y^m \underline{X}_G\right)\right]$$
$$+ \lambda''' \Lambda^T \Lambda\left(-0.1536 \times \underline{X}_R + 0.2851 \times \underline{X}_G - 0.1316 \times \underline{X}_B\right) \quad (16)$$

where S_x^{-l} and S_y^{-m} define the transposes of matrices S_x^l and S_y^m , respectively. Shifting effect in the opposite directions.

$\mathbf{X}_\mathbf{R}$ and $\mathbf{X}_\mathbf{B}$ stands for the diagonal matrix representations of the red and blue bands.

$\mathbf{X}_\mathbf{R}^{\mathrm{l,m}}$ and $\mathbf{X}_\mathbf{B}^{\mathrm{l,m}}$ are diagonal representations of these matrices shifted by l and m pixels in the horizontal and vertical directions, respectively.

- Matrices H, Λ, Φ, D, S_x^l, and S_y^m, and their transposes
  - Blur, high-pass filtering, masking, down-sampling, and shift

- Implementation in a fast and memory efficient way

– Gradient of the other channels

- Computation in same way

– Calculation of the HR image estimate iteratively

$$\hat{\underline{X}}_i^{n+1} = \hat{\underline{X}}_i^{n} - \beta \nabla \hat{\underline{X}}_i^{n} \qquad i = R, G, B \tag{17}$$

where the scalar β is the step size.

Related Methods

- Novel method for combining the information from multiple sensors
  - Assumption of affine relation
    - Between the intensities of different sensors in a local neighborhood
    - Estimating the red channel
      - Project green and blue channels to the red channel
      - Applying SR algorithm on the LR images in red channel
    - Invalid for some pixels
      - Simply ignored

- Another MAP estimation method
  - Solving the same joint demosaicing/super-resolution problem
  - Using L_2 norm data fusion term
    - Weakness to such errors

Experiments

- Creating LR images
  - Sifted this HR image (3CCD) by one pixel in the vertical direction
    - To simulate the effect of camera PSF
  - Symmetric Gaussian low-pass filter of size 5 x 5 with standard deviation equal to one
  - Subsampled by the factor of 4 in each direction
  - Applying the same process with different motion vectors
    - Vertical and horizontal directions
    - Using to produce 10 LR images from the original scene
  - Adding Gaussian noise to the resulting LR frames
    - To achieve a signal-to-noise ratio (SNR) equal to 30 dB
    - Subsampling each LR color image by the Bayer filter

◆ First experiment

– Model of (1)

a: Original image | b: LR image demosaiced by the method in [14] | c: LR image demosaiced by the method in [44] | d: Shift-And-Add image.

Fig. 4. HR image (a) is passed through our model of camera to produce a set of LR images. (b) One of these LR images is demosaiced by the method in [14]. (c) The same image is demosaiced by the method in [16]. Shift-and-add on the ten input LR images is shown in (d).

◆ Reconstruct a HR image with reduced color artifacts

a: Reconst. with luminance regul. b: Reconst. with inter-color regul. c: Reconst. with chrominance regul. d: Reconst. from LR demosaiced [44]+SR[3]

Fig. 5. Multiframe demosaicing of this set of LR frames with the help of only luminance, intercolor dependencies, or chrominance regularization terms is shown in (a)–(c), respectively. The result of applying the super-resolution method of [3] on the LR frames each demosaiced by the method [16] is shown in (d).

- Applying the super-resolution method of [3] on the raw (Bayer filtered) data (before demosaicing)

a: Reconst. with luminance regul. b: Reconst. with inter-color regul. c: Reconst. with chrominance regul. c: Reconst. from LR demosaiced [16] + SR[3]

Fig. 6. Result of super-resolving each color band (raw data before demosaicing) separately considering only bilateral regularization [3] is shown in (a). Multiframe demosaicing of this set of LR frames with the help of only intercolor dependencies-luminance, intercolor dependencies-chrominance, and luminance-chrominance regularization terms is shown in (b)–(d), respectively.

- Result of the implementation of (15) with all terms
  - Using parameters: $\beta = 0.002, \alpha = 0.9, \lambda' = 0.01, \lambda'' = 150, \lambda''' = 1.$
  - Batter quality than the LR input frames or reconstruction methods

a: Reconst. with all terms.

Fig. 7. Result of applying the proposed method (using all regularization terms) to this data set is shown in (a).

– Comparing the performance of each of methods

Table 1. Quantitative comparison of the performance of different demosaicing methods on the lighthouse sequence. The proposed method has the lowest S-CIELAB error and the highest PSNR value.

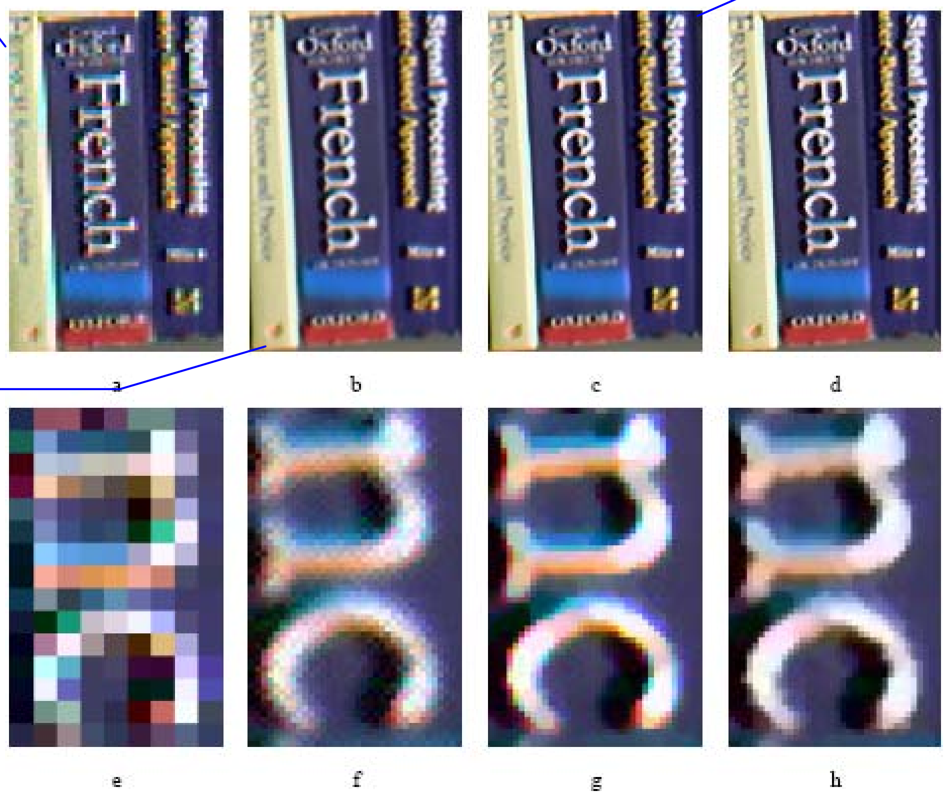
	Shift-And-Add	LR Demosaiced [16] +SR [3]	Only Lumin.	Only Orient.	Only Chromin.
S-CIELAB	1.532×10^{11}	1.349×10^{11}	7.892×10^{10}	6.498×10^{10}	4.648×10^{10}
PSNR (dB)	17.17	19.12	17.74	20.10	20.35
	SR [3] on Raw Data	Lumin.+Orient.	Orient.+Chrom.	Lumin.+Chrom.	Full
S-CIELAB	5.456×10^{10}	4.543×10^{10}	4.382×10^{10}	3.548×10^{10}	3.365×10^{10}
PSNR (dB)	19.28	20.79	20.68	21.12	21.13

◆ Second experiment

– Using 30 compressed images captured from a commercial webcam(PYRO-1394)

(a) One of the input LR images

(b) shift-and-add result increasing resolution by a factor of 4 in each direction



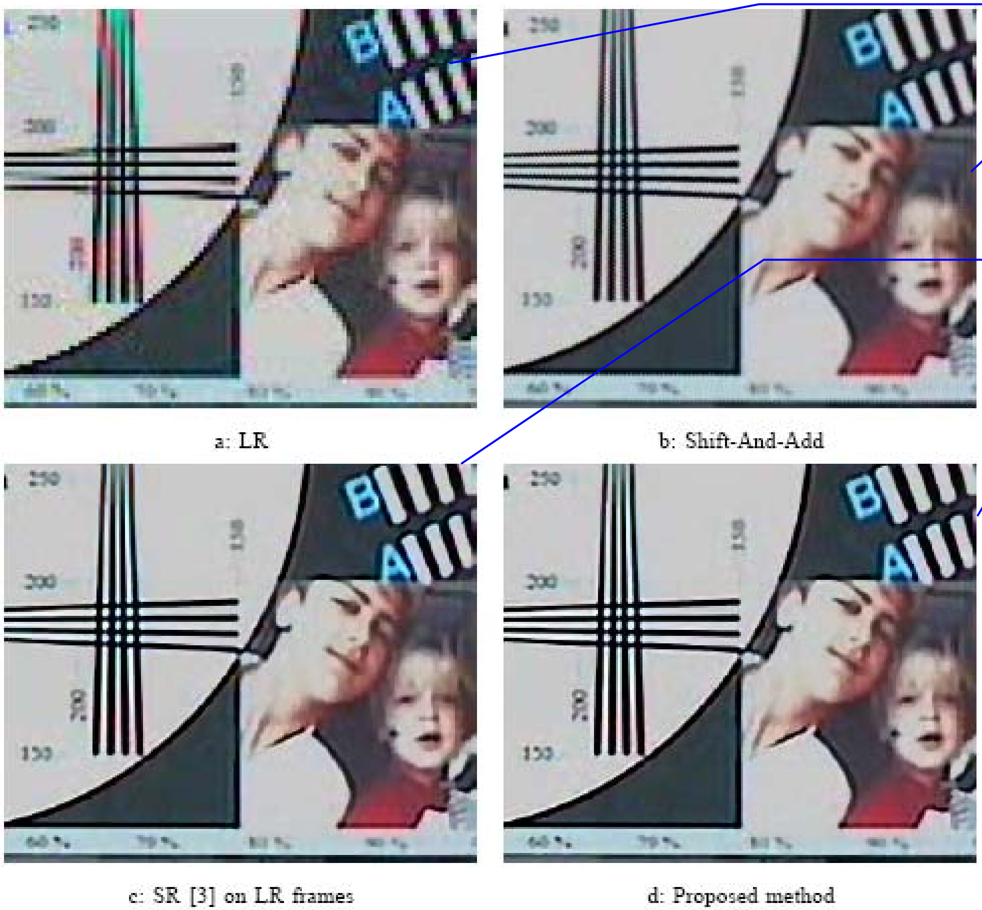
(c) Result of the individual implementation of the super-resolution [3] on each color band

(d) Implementation of (15), which has increased the spatial resolution, removed the compression artifacts, and also reduced the color artifacts.
Using parameter:

$$\beta = 0.004, \alpha = 0.9,$$
$$\lambda' = 0.25, \lambda'' = 500,$$
$$\lambda''' = 5.$$

Fig. 8. Multiframe color super-resolution implemented on a real data sequence. (e)–(h) are the zoomed images of the (a)–(d), respectively.

- Third experiment
  - Using 40 compressed images of a test pattern from a surveillance camera



(a) One of the input LR images

(b) the shift-and-add result increasing resolution by a factor of 4 in each direction

(c) Result of the individual implementation of the super-resolution [3] on each color band

(d) Implementation of (15) which has increased the spatial resolution, removed the compression artifacts, and also reduced the color artifacts

$$\beta = 0.004, \alpha = 0.9, \lambda' = 0.25,$$
$$\lambda'' = 500, \lambda''' = 5.$$

Fig. 9. Multiframe color super-resolution implemented on a real data sequence. These images are zoomed in Fig. 10.

– Zoomming Fig. 9

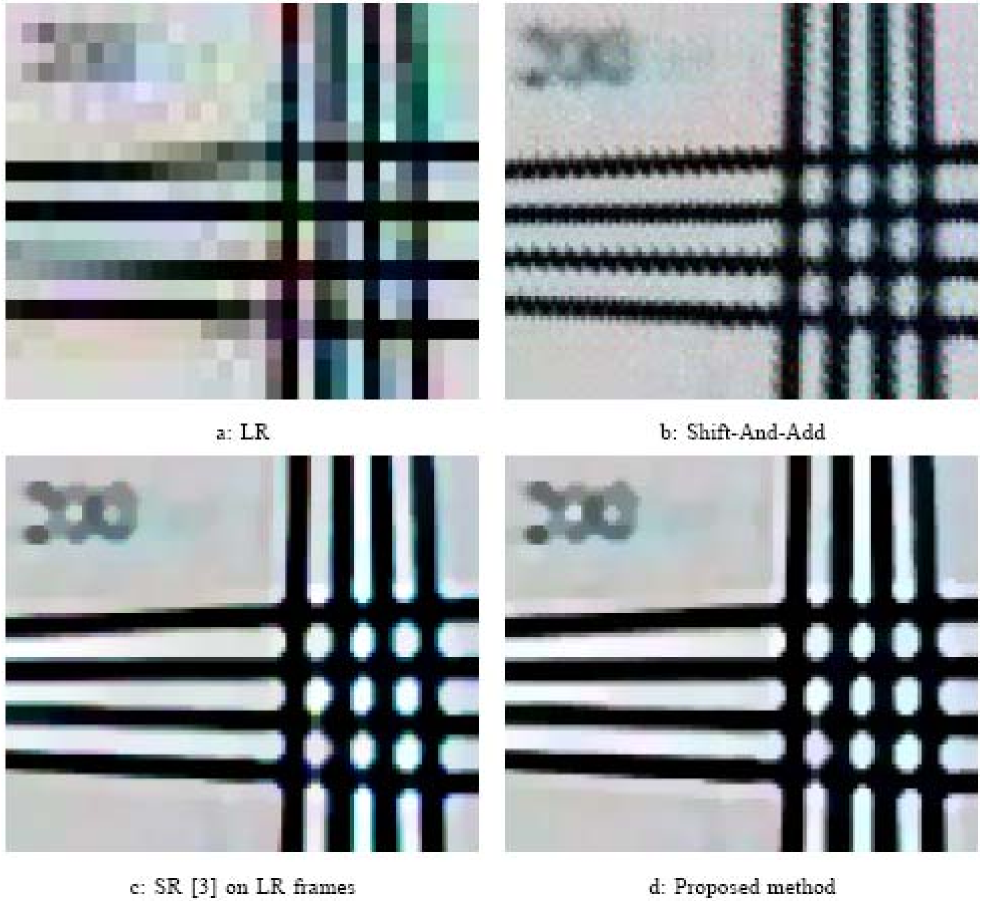
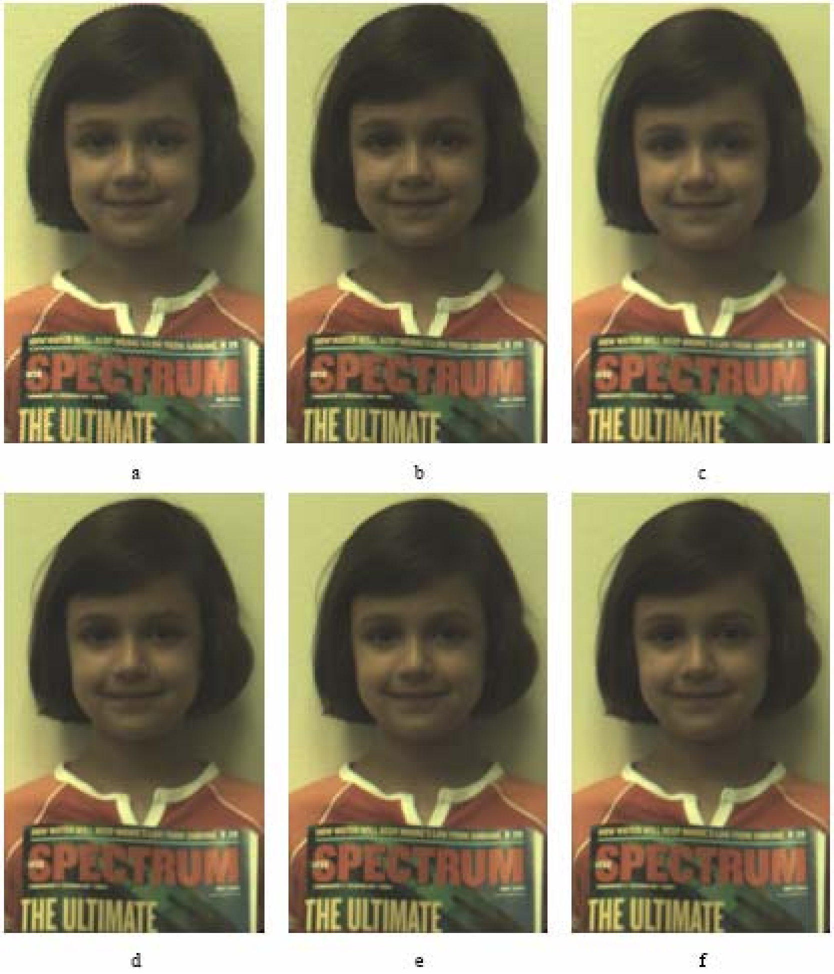


Fig. 9. Multiframe color super-resolution implemented on a real data sequence. A selected section of Fig. 9(a)–(d) are zoomed in (a)–(d), respectively. In (d), almost all color artifacts that are present on the edge areas of (a)–(c) are effectively removed. (a) LR. (b) Shift-and-add. (c) SR [3] on LR frames. (d) Proposed method.

◆ Fourth experiment (Girl image)

– Using 31 uncompressed (raw CFA) images from video camera



(a) One of the input LR images demosaiced by [14]

(b) one of the input LR images demosaiced by the more sophisticated [16]

(c) Result of applying the proposed color-super-resolution method on 31 LR images each demosaiced by [14] method

(d) Result of applying the proposed color-super-resolution method on 31 LR images each demosaiced by [16] method

The result of applying our method on the original un-demosaiced raw LR images (without using the inter color dependence term) is shown in (e)

(f) Result of applying our method on the original un-demosaiced raw LR images.

$$\beta = 0.002, \alpha = 0.9, \lambda' = 0.1, \lambda'' = 250, \lambda''' = 25.$$

Fig. 11. Multiframe color super-resolution implemented on a real data sequence.

– Zoomming Fig. 11

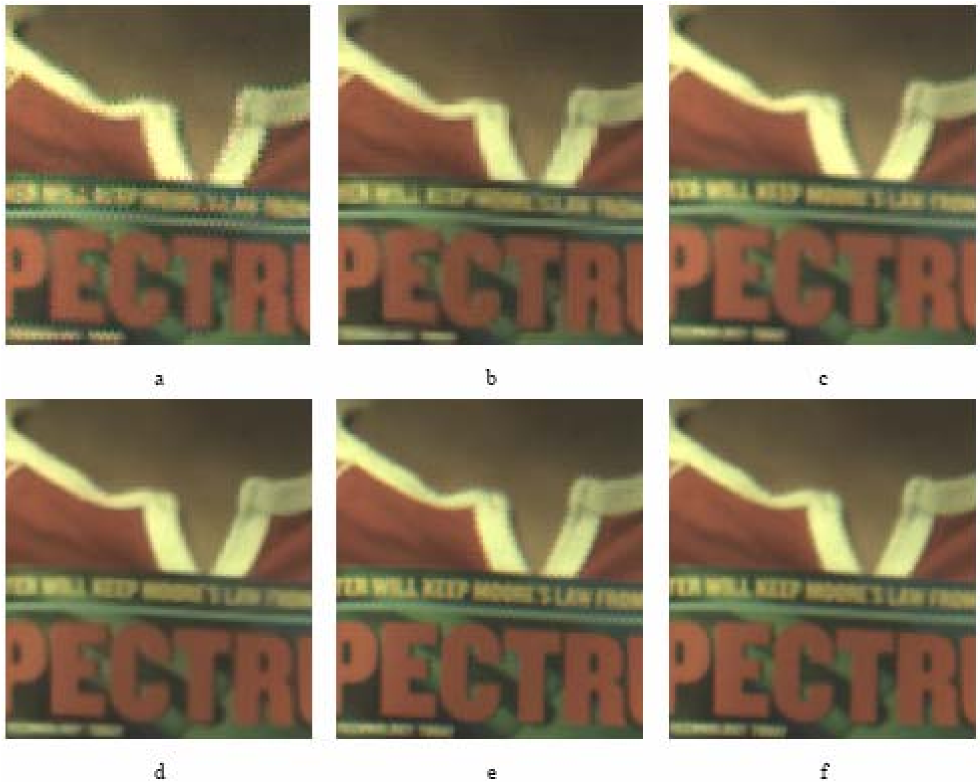


Fig. 12. Multiframe color super-resolution implemented on a real data sequence (zoomed).

◆ Fifth experiment (bookcase image)

– Using 31 uncompressed (raw CFA) images from video camera

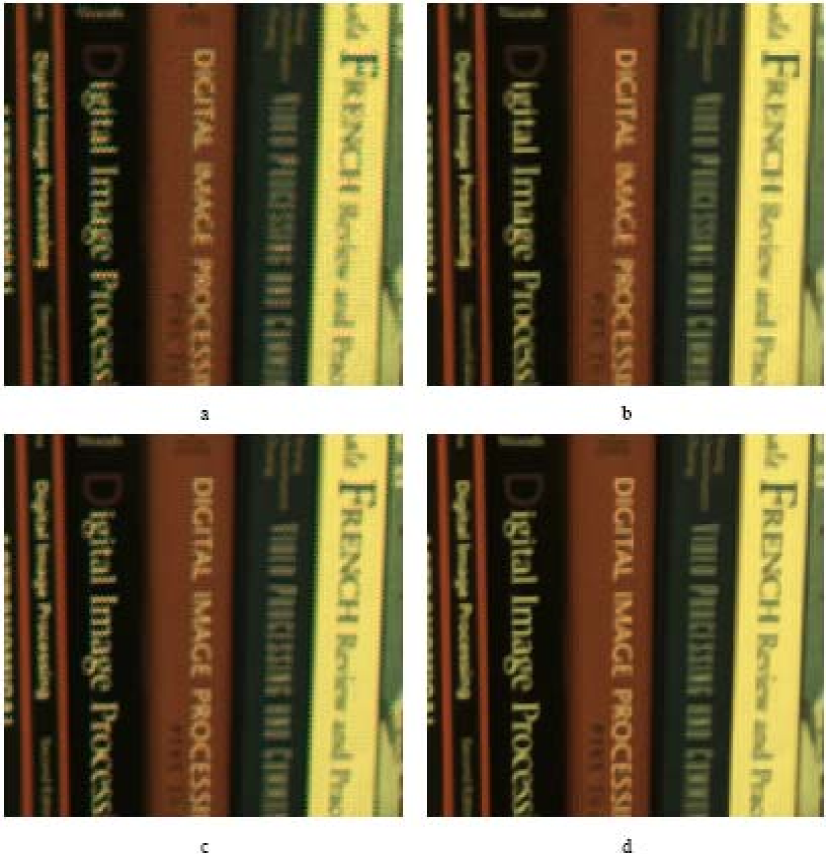


Fig. 13. Multiframe color super-resolution implemented on a real data sequence.

(a) One of the input LR images demosaiced by [14]

(b) one of the input LR images demosaiced by the more sophisticated [16]

(c) Result of applying the proposed color-super-resolution method on 31 LR images each demosaiced by [14] method

(d) Result of applying the proposed color-super-resolution method on 31 LR images each demosaiced by [16] method

$$\beta = 0.002, \alpha = 0.9, \lambda' = 0.1, \lambda'' = 250, \lambda''' = 25.$$

– Zoomming Fig. 13

a b

Fig. 14. Multiframe color super-resolution implemented on a real data sequence. The result of applying our method on the original un-demosaiced raw LR images (without using the inter color dependence term) is shown in (a). (b) Result of applying our method on the original un-demosaiced raw LR images.

◆ Sixth experiment (Window sequences)

– Using 30 uncompressed (raw CFA) images from video camera

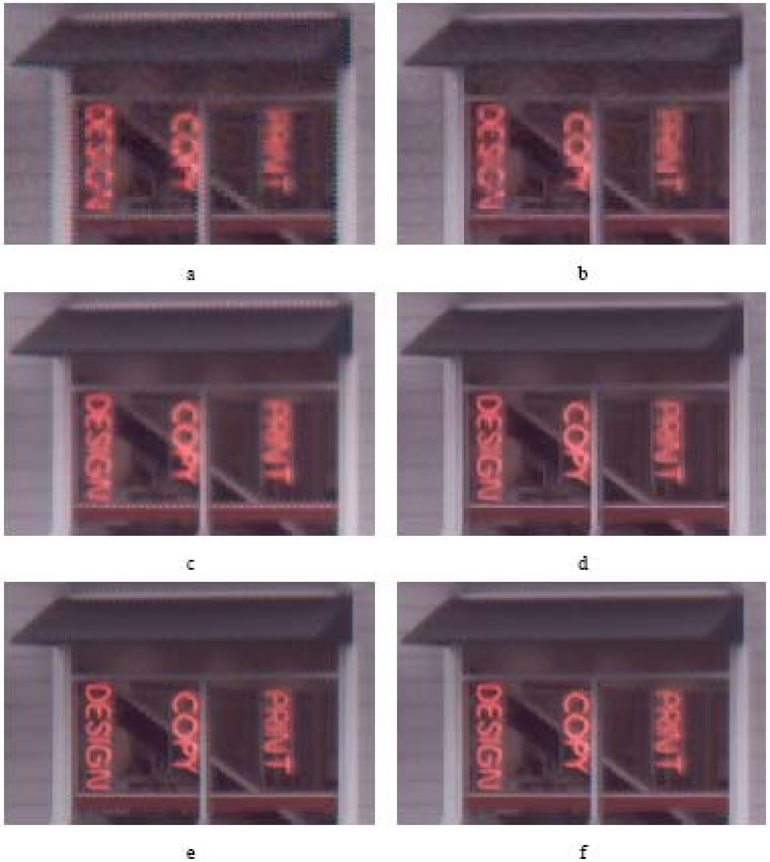


Fig. 15. Multiframe color super-resolution implemented on a real data sequence.

(a) One of the input LR images demosaiced by [14]

(b) one of the input LR images demosaiced by the more sophisticated [16]

(c) Result of applying the proposed color-super-resolution method on 31 LR images each demosaiced by [14] method

(d) Result of applying the proposed color-super-resolution method on 30 LR images each demosaiced by [16] method

The result of applying our method on the original un-demosaiced raw LR images (without using the inter color dependence term) is shown in (e)

(f) Result of applying our method on the original un-demosaiced raw LR images.

$$\beta = 0.002, \alpha = 0.9, \lambda' = 0.1, \lambda'' = 250, \lambda''' = 25.$$

Discussion and Future Work

- Demosaicing and super-resolution
  - Increasing the spatial resolution and reducing the color artifacts
    - Using L_1 norm and bilateral regularization
    - Matrix-vector operation
      - Locally execution on pixel values on the HR grid
      - Parallel processing
- Subpixel motion estimation
  - Essential part of any image fusion process
  - Analyzing subpixel motion estimation from colored filtered images

Appendix I

- Derivation of the intercolor dependencies penalty term
  - From (14)

$$\underline{L} = \left\| \underline{X}_G \otimes S_x^l S_y^m \underline{X}_B - \underline{X}_B \otimes S_x^l S_y^m \underline{X}_G \right\|_2^2 \quad \otimes \text{ is commutative}$$

$$\underline{L} = \left\| S_x^l S_y^m \underline{X}_B \otimes \underline{X}_G - \underline{X}_B \otimes S_x^l S_y^m \underline{X}_G \right\|_2^2.$$

  - Differentiable dot product
    - By rearranging $\underline{X}_B$
      - Diagonal matrix $\underline{\mathbf{X}}_{\mathbf{B}}$
    - By rearranging $S_x^l S_y^m \underline{X}_B$
      - Diagonal matrix $\underline{\mathbf{X}}_{\mathbf{B}}^{\mathrm{l,m}}$

$$\underline{L} = \left\| \mathbf{X}_{\mathbf{B}}^{\mathrm{l,m}} \underline{X}_G - \underline{\mathbf{X}}_{\mathbf{B}} \otimes S_x^l S_y^m \underline{X}_G \right\|_2^2. \tag{18}$$

– Using the identity

$$\frac{\partial \left\| \mathbf{Q}\underline{C} \right\|_2^2}{\partial \underline{C}} = \frac{\partial \left(\underline{C}^T \mathbf{Q}^{\mathbf{T}} \mathbf{Q} \underline{C} \right)}{\partial \underline{C}} = 2\mathbf{Q}^{\mathbf{T}} \mathbf{Q} \underline{C}$$

– Differentiation with respect to green band

$$\frac{\partial \underline{L}}{\partial \underline{X}_G} = 2\left(\mathbf{X}_{\mathbf{B}}^{\mathrm{l,m}} - S_x^{-l} S_y^{-m} \mathbf{X}_{\mathbf{B}} \right) \left(\mathbf{X}_{\mathbf{B}}^{\mathrm{l,m}} \underline{X}_G - \mathbf{X}_{\mathbf{B}} S_x^l S_y^m \underline{X}_G \right).$$