Alvaro Pardo
Josef Kittler (Eds.)

LNCS 9423

Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications

20th Iberoamerican Congress, CIARP 2015
Montevideo, Uruguay, November 9–12, 2015
Proceedings

Springer

A Novel Quality Image Fusion Assessment Based on Maximum Codispersion

Silvina Pistonesi[1](✉), Jorge Martinez[1], Silvia María Ojeda[2], and Ronny Vallejos[3]

[1] Departamento de Matemática, Universidad Nacional del sur, Av. Alem 1253, 2do Piso, B8000CPB Bahía Blanca, Argentina
{silvina.pistonesi,martinez}@uns.edu.ar

[2] Facultad de Matemática, Astronomía y Física, Universidad Nacional de Córdoba, Ing. Medina Allende s/n, Ciudad Universitaria, CP 5000 Córdoba, Argentina
ojeda@mate.uncor.edu

[3] Departamento de Matemática, Universidad Técnica Federico Santa María, Av. España 1680, Valparaíso, Chile
ronny.vallejos@usm.cl

Abstract. In this paper, we present a novel objetive measure for image fusion based on the codispersion quality index, following the structure of Piella's metric. The measure quantifies the maximum local similarity between two images for many directions using the maximum codispersion quality index. This feature is not commonly assessed by other measures of similarity between images. To vizualize the performance of the maximum codispersion quality index we suggested two graphical tools. The proposed fusion measure is compared to image structural similarity based metrics of the state-of-art. Different experiments performed on several databases show that our metric is consistent with human visual evaluation and can be applied to evaluate different image fusion schemes.

Keywords: Image fusion-codispersion coefficient-image quality measure

1 Introduction

Image fusion is the process of combining information from two or more images of a scene into a single composite image, which is more informative and suitable for both visual perception and computer processing. Quality assessment of different image fusion schemes is traditionally carried out by subjective evaluations [5]. Even though this method is reliable, it is expensive and too slow for real world applications. Therefore, it is of great interest to provide an objective performance measure able to predict image fusion quality automatically and consistent with human visual perception. Several objective image quality measures for image fusion have been proposed and classified into four groups according to their characteristics: information theory based metrics, image feature based metrics, human perception inspired fusion metrics, and image structural similarity based

A. Pardo and J. Kittler (Eds.): CIARP 2015, LNCS 9423, pp. 383–390, 2015.
DOI: 10.1007/978-3-319-25751-8_46

metrics [2]. In the context of measures based on image structural similarity, Piella's metric [4], Cvejic's metric [1] and Yang's metric [9], were developed.

Recently, a new measure of similarity between images, based on the codispersion coefficient, was suggested by Ojeda et al. [3], namely, the CQ index. This measure takes into account the spatial association in a specific direction h between a degraded image and the original unmodified image. This performance allows a quantification of how well the important information in the source images is represented by the fused image.

In this work, we present a novel quality assessment metric for image fusion based on a modification of CQ index, in the same way as the universal image quality index (Q) is used in Piella's metric. In adition, motivated by the structural similarity index ($SSIM$) map proposed by Wang et al. [8] and the codispersion map developed by Vallejos et al. [6], we presented two graphical tools to analize the performance of our quality index.

The rest of the paper is organized as follows: Section 2 gives a brief introduction of the CQ index, defines the maximum codispersion quality measure and presents two graphical tools. Section 3 presents an overview of the structural similarity based metrics for image fusion. Section 4 includes a description of the proposed metric, whereas Section 5 contains experimental results obtained by using the proposed metric. Finally, Section 6 presents the conclusion of the paper.

2 The Image Quality Metric

Let $x = \{x_{i,j} | 1 \leq i \leq N, 1 \leq j \leq M\}$ and $y = \{y_{i,j} | 1 \leq i \leq N, 1 \leq j \leq M\}$, with $N, M \in \mathbb{N}$, the original and test image signals, respectively. The quality index CQ was introduced by Ojeda et al. [3] and it is defined as follows:

$$CQ(h) = \widehat{\rho}\,(h)\, l(x,y) c(x,y), \tag{1}$$

where $\widehat{\rho} = \dfrac{\sum\limits_{s,s+h \in D} a_s b_s}{\sqrt{\widehat{V}_x\,(h)\, \widehat{V}_y\,(h)}}$, is the sample codispersion coefficient in the direction h, with $s = (i,j)$, $h = (h_1, h_2)$, $D \subset Z^d$, D finite set, $a_s = x\,(i + h_1, j + h_2,) - x\,(i,j)$, $b_s = y\,(i + h_1, j + h_2,) - y\,(i,j)$, $\widehat{V}_x\,(h) = \sum\limits_{s,s+h \in D} {a_s}^2$, and $\widehat{V}_y\,(h) = \sum\limits_{s,s+h \in D} {b_s}^2$. It is obvious that $|\widehat{\rho}\,(h)| \leq 1$. The codispersion coefficient captures different levels of spatial similarity between two images by considering different directions in two-dimensional space. In (1), $l(x,y) = \dfrac{2\bar{x}\bar{y}}{\bar{x}^2 + \bar{y}^2}$ and $c(x,y) = \dfrac{2S_x S_y}{{S_x}^2 {S_y}^2}$, are the luminance and contrast components, respectively, where $\bar{x}$ and $\bar{y}$ are the sample average values of images x and y, S_x, S_y and S_{xy} are the deviations of x and y and covariance between x and y, respectively.

2.1 Maximum Codispersion Quality Index: $CQ_{\max}$

In this section, a novel measure to quantify similarity between two images is introduced. This measure is labeled the $CQ_{\max}$ index, and it is an intermediate and necessary step in the definition of our proposal to evaluate image fusion methods. In each evaluated window w, the $CQ_{\max}$ index, is defined as the maximum value of $CQ(h)$. This implies that $CQ_{\max}$ can seek the direction h that maximizes the CQ in the window w. Note that this direction may not be unique.

$$CQ_{\max}(h|w) = \max_{\{h\,:\,p(h)\,\geq\,p_0\}} \widehat{\rho}\,(h|w)\,l(x,y|w)c(x,y|w), \tag{2}$$

where $p\,(h)$ is the proportion of the pixels in the image corresponding to the direction h in the window w and p_0 is the threshold.

We propose to use a sliding window approach: starting from the top-left corner of the two images x, y, a sliding window of a fixed size block by block over the entire image until bottom-right corner is reached (for more details see [7]). Finally, $CQ_{\max}$ is determined by averaging all CQ local maximum quality indexes for all the windows $w \in W$

$$CQ_{\max} = \sum_{w \in W} \frac{CQ_{\max}(h|w)}{|W|}, \tag{3}$$

with W the family of all windows and $|W|$ is the cardinality of W.

2.2 Graphical Tools: Visual Inspection of $CQ_{\max}$

In order to describe the result of $CQ_{\max}$ application, we proposed two graphical tools: $CQ_{\max}$ *index map* and *h direction map*. The $CQ_{\max}$ *index map* allows to visualize locally the information about the quality degradation of the image. According to this map, the brightness indicates the magnitude of the local $CQ_{\max}$ index, and more brightness means better quality. The *h direction map*, depictes the direction h in which $CQ_{\max}$ reaches the maximum value considering the CIELab color space to represent the three components: h norm, h_1 and h_2. In this map two different situations may arise. First, $CQ_{\max}$ index values achieved in equal norm directions but different orientation correspond to equal lightness but different colors in CIELab space. In the second situation, directions with same orientation but different norm correspond to similar colors with different lightness. Note that if $CQ_{\max}$ is reached in two o more directions, we choose the lowest norm direction. See Fig. 1.

3 Image Fusion Metrics

In this section, a brief overview of state-of-the-art image structural similarity fusion metrics is presented.

3.1 Image Structural Similarity-Based Metrics

Wang's Metric $SSIM$: Wang et al. proposed the $SSIM$ index for the corresponding regions in images x and y, defined as [8]

$$\begin{aligned} SSIM(x,y) &= [l(x,y)]^{\alpha}\,[c(x,y)]^{\beta}\,[s(x,y)]^{\gamma} \\ &= \left(\frac{2\bar{x}\bar{y}+C_1}{\bar{x}^2+\bar{y}^2+C_1}\right)^{\alpha}\left(\frac{2S_xS_y+C_2}{{S_x}^2+{S_y}^2+C_2}\right)^{\beta}\left(\frac{S_{xy}+C_3}{S_xS_y+C_3}\right)^{\gamma}, \end{aligned} \quad (4)$$

where $\overline{x}$ and $\overline{y}$ are the sample average values of images x and y, S_x, S_y and S_{xy} are the sample deviations and the sample covariance, respectively. The parameters α, β and γ, adjust the realtive importance of the three components. The constants C_1, C_2 and C_3 are included to avoid instability when denominators are very close to zero. In order to simplify the expression (4), Wang et al. set $\alpha = \beta = \gamma = 1$ and $C_3 = C_2/2$. This results in a specific form of the $SSIM$ index:

$$SSIM(x,y) = \frac{(2\bar{x}\bar{y}+C_1)\,(2S_{xy}+C_2)}{(\bar{x}^2+\bar{y}^2+C_1)\left({S_x}^2+{S_y}^2+C_3\right)}\;. \quad (5)$$

A previus version of this approach is known as Q index and is written as [7]

$$Q(x,y) = \frac{2\bar{x}\bar{y}}{\bar{x}^2+\bar{y}^2}\,\frac{2S_xS_y}{{S_x}^2+{S_y}^2}\,\frac{S_{xy}}{S_xS_y} = \frac{(4\bar{x}\bar{y}S_{xy})}{(\bar{x}^2+\bar{y}^2)\left({S_x}^2+{S_y}^2\right)}\;. \quad (6)$$

The following image structural similarity fusion metrics are based on (5) and (6) measures.

Piella's Metric Q_W: Piella and Heijmans proposed three fusion quality metrics based on Wang's Q index [4]. These are:

$$Q_S(x,y,f) = \frac{1}{|W|}\sum_{w\in W}\left[\lambda\,(w)\,Q\,(x,f|w) + (1-\lambda\,(w))\,Q\,(y,f|w)\right], \quad (7)$$

$$Q_W(x,y,f) = \sum_{w\in W} c\,(w)\left[\lambda\,(w)\,Q\,(x,f|w) + (1-\lambda\,(w))\,Q\,(y,f|w)\right], \quad (8)$$

$$Q_E(x,y,f) = Q_W\,(x,y,f)\cdot Q_W\,(x',y',f')^{\alpha}\,, \quad (9)$$

where the weight $\lambda\,(w)$ is defined as

$$\lambda(w) = \frac{s\,(x|w)}{s\,(x|w)+s\,(y|w)}\;. \quad (10)$$

where $s\,(x|w)$ and $s\,(y|w)$ are the local saliencies of the two input images x and y within the window w, respectively. In the Piella's implementation, $s\,(\cdot|w)$ is the variance of image within window w and the coefficient $c\,(w)$ in (8) is $c(w) = \dfrac{\max\left\{s\,(x|w)\,, s\,(y|w)\right\}}{\sum_{w'\in W}\max\left\{s\,(x|w')\,, s\,(y|w')\right\}}$. In (9), $Q_W\,(x',y',f')$ is the Q_W calculated with the edge images x', y' and f', and α is a parameter that weighs the edge contribution information.

Cvejic's Metric Q_C: Cvejic et al. defined a performance measure as [1]

$$Q_C(x,y,f) = \sum_{w \in W} \mathrm{sim}\,(x,y,f|w) \cdot Q\,(x,f) + (1 - \mathrm{sim}\,(x,y,f|w)) \cdot Q\,(y,f)\,, \quad (11)$$

with $\mathrm{sim}\,(x,y,f|w) = \begin{cases} 0, & \text{if} \quad \frac{\sigma_{xf}}{\sigma_{xf}+\sigma_{yf}} < 0, \\ \frac{\sigma_{xf}}{\sigma_{xf}+\sigma_{yf}}, & \text{if} \ \ 0 \leq \frac{\sigma_{xf}}{\sigma_{xf}+\sigma_{yf}} \leq 1, \\ 1, & \text{if} \quad \frac{\sigma_{xf}}{\sigma_{xf}+\sigma_{yf}} > 1\,. \end{cases}$. The weighting factor depends on the similarity in spatial domain between the input and fused image.

Yang's Metric Q_Y: Yang et al. proposed another way to used $SSIM$ for fusion assessment [9]:

$$Q_Y\,(x,y,f) = \begin{cases} \lambda\,(w)\,SSIM\,(x,f|w) + (1-\lambda\,(w))\,SSIM\,(y,f|w)\,, \\ \qquad \text{if } SSIM\,(x,y|w) \geq 0.75, \\ \max\left\{SSIM\,(x,f|w)\,, SSIM\,(y,f|w)\right\}, \\ \qquad \text{if } SSIM\,(x,y|w) < 0.75\,. \end{cases} \quad (12)$$

the local weight $\lambda\,(w)$ is as the definition in (10).

4 Proposed Image Fusion Performance Metric CQ_M

We use the $CQ_{\max}$ index defined in (3) and following the structure of Piella metric's, (8), to define the quality index CQ_M for image fusion as

$$CQ_M(x,y,f) = \sum_{w \in W} c\,(w)\,[\lambda\,(w)\,CQ_{\max}(h|w)\ (x,f) + (1-\lambda\,(w))\,CQ_{\max}(h|w)\ (y,f)]\ . \quad (13)$$

The closer the $CQ_M(x,y,f)$ value to 1, the higher the quality of the fused image.

5 Experimental Results and Analysis

To test the performance of the proposed approach, we have carried out three experiments. In the first experiment, the $CQ_{\max}$ index was tested in different types of distortions (see Fig. 1) and compared to the results with Q index and the mean subjective rank (MSR) evaluation obtained from [7] (all images have equal mean square error (MSE)). Their $CQ_{\max}$ maps and h directions maps are presented. In the second and third experiments, the following image fusion algorithms were evaluated, Laplacian Pyramid (LP), Ratio Pyramid (RP), Discrete Wavelet Transform (DWT), and Shift Invariant DWT (SIDWT), the performances of which were subjetively tested and accepted in the literature. For simulation of these methods, the "Image Fusion Toolbox", provided by Rockinger, is used (available from: http://www.metapix.de/toolbox.htm/). For the four image fusion algorithms, for both, the second and the third experiments, the approximation coefficients of the two input images averaged and the larger absolute values of the high sub-bands is selected. In the second experiment we performed a 3-level decomposition and in the third, a 4-level decomposition was used. For our metric, we set $p_0 = 0.75$, the minimum proportion of pixels that is necessary to capture spatial information in different directions, and w window size used was 8×8 pixels. For Piella's and Cvejic's metrics we used the same window size and for Yang's metric, $C_1 = C_2 = 2 \times 10^{-16}$ and the w window size used was 7×7 pixels[1] .

First Experiment: The $CQ_{\max}$ exhibits very consistent concordance with the Q results and with the MSR evaluation. The $CQ_{\max}$ index maps (Fig. 1, second row), show a consistency with perceived quality measurement.

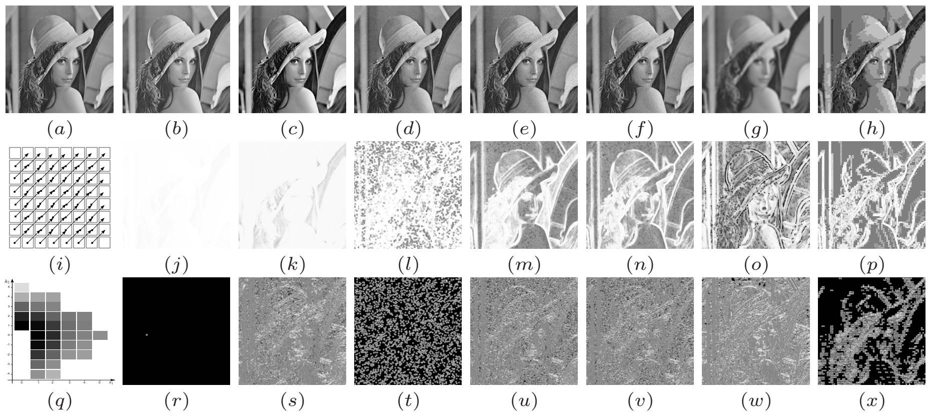

Fig. 1. (a) Original Lena image; image contaminated with: (b) Mean Shift, MSR = 1.59, $Q = 0.9894$, $CQ_{\max} = 0.9894$; (c) Contrast Stretching, MSR = 1.64, $Q = 0.9372$, $CQ_{\max} = 0.9378$; (d) Impulsive Salt Pepper Noise, MSR = 3.32, $Q = 0.6494$, $CQ_{\max} = 0.7765$; (e) Multiplicative Speckle Noise, MSR = 4.18, $Q = 0.4408$, $CQ_{\max} = 0.5249$; (f) Additive Gaussian Noise, MSR = 4.27, $Q = 0.3891$, $CQ_{\max} = 0.4859$; (g) Blurring, MSR = 6.32, $Q = 0.3461$, $CQ_{\max} = 0.4083$ and (h) JPEG Compression, MSR = 6.68, $Q = 0.2876$, $CQ_{\max} = 0.4037$; all images have equal MSE; (i) $h = (1, 1)$ direction in a 8×8 window size, $p\,(h) = 62/64$; $(j) - (p)$ $CQ_{\max}$ index map (brightness indicates better quality); (q) Reference of h direction map; $(r) - (x)$ h direction maps.

The Mean Shift distortion, does not change the structure information of Lena image, therefore it corresponds to a very bright $CQ_{\max}$ index map. By contrast, the JPEG Compression contaminated image $CQ_{\max}$ index map

[1] The same setting that appears in [1],[4],[9].

(Fig. 1 (o)) exhibits many areas with dark pixels, showing a poor quality. In Fig. 1 (q) a black color covering the entire map except from a patch implies that in $h = (1, 0)$ or $h = (0, 1)$ the index reaches the maximum similarity. In Fig. 1 (u) and (v), the h direction maps present a similar appearance; they are predominant shades of fuchsia, indicating that the maximum similarities were reached, e.g. in $h = (3, -1)$ or $h = (4, -1)$.

Second Experiment: 32 sets of infrared (IR) and visual images (V) from "TNO UN Camp" database are used as source images (see Fig. 2). The evaluation results of the metrics for this image set are shown in Fig. 2 (g). In all schemes, the metrics assign the highest values to LP and SIDWT methods and the lowest to RP. The Kendall τ rank correlation coefficient reveals that CQ_M has reasonable agreement with Q_W ($\tau = 0.706$), Q_C ($\tau = 0.771$) and Q_Y ($\tau = 0.770$), respectively. These outcomes are consistent with those obtained by Lui et al. [2].

Third Experiment: "Medical" database including magnetic resonance imaging (MRI) and computed tomography (CT) images, and "Clock" database

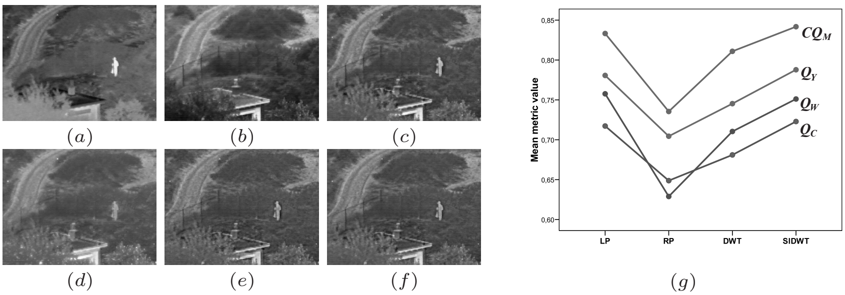

Fig. 2. A image of the "TNO UN Camp" database: (a) IR image and (b) V image; and (c) – (f) fused image obtained by: LP, RP, DWT and SIDWT methods; (g) fusion metrics performance according to image fusion methods.

Table 1. Objective evaluations of different image fusion metrics for the fused images in "Medical" and "Clock" databases.

Image	Methods	Metric			
		Q_W	Q_C	Q_Y	CQ_M
"Medical" database	LP	**0.8089**	0.6247	**0.6874**	**0.8391**
	RP	0.6319	0.6053	0.6182	0.6903
	DWT	0.7314	0.6190	0.6368	0.7718
	SIDWT	0.7780	**0.6587**	0.6692	0.8169
"Clock" database	LP	**0.9272**	0.8284	0.8816	**0.9451**
	RP	0.7878	0.7564	0.7879	0.8257
	DWT	0.9139	0.7919	0.8471	0.9362
	SIDWT	0.9217	**0.8368**	**0.8853**	0.9413

containing multi-focus images are used. In both, as it is seen in Table 1, CQ_M assigns the highest values to LP and SIDWT methods, followed by DWT and the worst values correspond to RP method. The proposed measure has a coherent behavior with the perceptual evaluations.

6 Conclusion

In this paper, we have proposed an objective image fusion performance index based on maximum codispersion. The amount of information in image features, carried from the source images to the fused image, is considered as the measure of fusion algorithm performance. This amount is calculated by means of the maximum codispersion index, considering different directions which can be visually inspected through the two graphical tools proposed. Experimental results confirm that the novel measure gives good results when evaluating different fusion schemes, correlates well with the subjective criteria, and shows good agreement with the state-of-the-art metrics presented, rendering a considerable improvement over them.

References

1. Cvejic, N., Loza, A., Bull, D., Canagarajah, N.: A similarity metric for assessment of image fusion algorithms. International Journal of Signal Processing **2**(3), 178–182 (2005)
2. Liu, Z., Blasch, E., Xue, Z., Zhao, J., Laganière, R., Wu, W.: Objective Assessment of Multiresolution Image Fusion Algorithms for Context Enhancement in Night Vision: A Comparative Study. IEEE Trans. Pattern Anal. Mach. Intell. **34**(1), 94–109 (2012)
3. Ojeda, S.M., Vallejos, R.O., Lamberti, P.W.: Measure of similarity between images based on the codispersion coefficient. Journal of Electronic Imaging **21**(2), 023019-1–023019-5 (2012)
4. Piella, G., Heijmans, H.: A new quality metric for image fusion. In: Proc. Int. Conf. on Image Process (ICIP), vol. 3, pp. 173–176 (2003)
5. Toet, A., Franken, E.M.: Perceptual evaluation of different image fusion schemes. Displays **24**(1), 25–37 (2003)
6. Vallejos, R., Osorio, F., Mancilla, D.: The codispersion map: a graphical tool to visualize the association between two spatial variables. Statistica Neerlandica **69**(3), 298–314 (2015)
7. Wang, Z., Bovik, A.C.: A universal image quality index. IEEE Signal Processing Letters **9**(3), 81–84 (2002)
8. Wang, Z., Bovik, A.C., Sheikh, H.R., Simoncelli, E.P.: Image Quality Assessment: From Error Visibility to Structural Similarity. IEEE Transactions on Image Processing **13**(4), 600–612 (2004)
9. Yang, C., Zhang, J., Wang, X., Liu, X.: A Novel Similarity Based Quality Metric for Image Fusion. Inf. Fusion **9**(2), 156–160 (2008)