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Assessment for multi-exposure image fusion based on fuzzy theory

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Abstract. Image fusion can present details of different images taken in the same scene with different exposures in one image. The quality of a fused image has been often assessed by a single factor. However, inconsistencies may exist among some single evaluation indicators, and thus it is difficult to give a comprehensive evaluation result. We propose a comprehensive image-fusion effect-assessment method which takes into account single-factor indices, such as image information entropy, average gradient, moderate exposure, mutual information, structural similarity index metric, cross-entropy, etc. Based on the fuzzy comprehensive evaluation method, a comprehensive assessment index achieved reflecting a small change in the single indicators and meanwhile overcoming its one-sidedness. Simulation results show that the proposed assessment method is consistent with the subjective assessment and is robust with noise immune.

Keywords: image fusion, quality assessment, fuzzy theory, assessment factor, weight

Ocena fuzije različno osvetljene slike na osnovi mehke logike

S slikovno fuzijo lahko predstavimo dele različnih slik, ki so bile posneta na istem mestu z različnimi osvetlitvami. Kakovost takšne slike je bila do sedaj navadno določena na osnovi enega kriterija, kar je vodilo k nedoslednosti pri evalvaciji. S pomočjo mehke logike v prispevku predlagamo izčrpno metodo za združevanje slik, ki upošteva slikovno informacijsko entropijo, povprečni gradient, osvetlitev, vzajemne informacije, strukturno podobnost metrik in navzkrižno entropijo. Na osnovi predlagane mehke evalvacijske metode smo dosegli ocenitveni indeks, s katerim lahko predstavimo spremembe v enem indikatorju. Rezultati simulacij so potrdili učinkovitost predlagane metode in njeno robustnost glede na šum.

1 Introduction

A traditional digital camera can only record a limited range of contrast, brightness and colors which is far away from what the dynamic range of real-world scenarios exhibits [1, 2]. By changing the exposure to the choice of the scene brightness information, a certain period of the dynamic range can be obtained [3], but a single photo cannot record all the details of a scene [4]. A group of images captured of the same scene with different exposures can provide richer details than a single photo, among which darker pictures can provide details of a bright scene, while brighter pictures are able to display details of shadows, and thus the details of different images can be presented on a single image by a multi-exposure image fusion [5, 6]. A fused image should retain the important details of the original image and should not introduce false information that will affect the image post-processing. Therefore, it requires a reasonable assessment system to judge the effect of fusion, but integration of the image-quality evaluation problem is still a weak link of the image-fusion research [7, 8].

The traditional method of the image-quality assessment can be divided into the subjective and objective evaluation methods. The most intuitive approach to evaluate the fusion effect is a subjective test, because a man is the final evaluator of fusion results. Evaluation results given by all assessment methods should be presented as consistent as possible with the human visual perception. Petrovi [9] assesses the quality of the fusion results using the subjective method. Although a subjective test is simple and straight forward, it also has many shortcomings, such as being time-consuming, expensive, cannot be quantified, and preferring some fusion factors, in addition, the human visual characteristics or mental state affect the assessment results which limits application of a subjective test. In addition, as the application occasions and purposes of image fusion are different, the observers participating in a subjective evaluation must have a considerable level of expertise.

If there is a large amount of data to be processed, the difficulty of a subjective test [10] will increase.

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Compared to the subjective quality evaluation, the objective quality evaluation has some advantages, such as low cost, simple operation, convenient to be performed, easy to parse and embed achieved. The current objective image-quality assessment methods are mainly: objective evaluation based on the statistical properties, such as the mean and standard deviation, degree of deviation, mean variance, covariance; objective evaluation based on the information quantity, such as entropy, cross-entropy, relative entropy/joint entropy, mutual information; evaluation based on a signal-to-noise ratio, such as a signal-to-noise ratio and peak signal–to-noise ratio; gradient-based evaluation [11], such as clarity and spatial frequency; evaluation based on Fuzzy Integral [12]; evaluation based on the wavelet energy rating [13]. However, there are also shortcomings of the above mentioned objective methods: 1) most of them are single-factor evaluation index-based, considering only one aspect of the fused-image features and lacking a global concept; 2) a lot of indicators computed require an ideal image which is usually impossible to be obtained in an actual application of image fusion; 3) analyzing the image data itself, with no experience and knowledge of human image analysis leads to the differences between the evaluation results and the actual fusion .

Ref. [14] introduces a structural similarity (Structural Similarity Index Metric, SSIM) theory and proposes a fusion-image quality-evaluation method based on it. Ref. [15] presents a self-contained image-fusion quality-evaluation method on the basis of a human visual system simulation. Optimizing the weighting strategy, Ref. [16] proposes an objective evaluation method based on the fusion-image quality factors, but the above evaluation methods only consider the quality of the fused image itself, without considering the complementary information and the shared information between the source image and the fused image, without distinguishing whether a specific evaluation is falsified or forged deliberately. As a multi-focus image-fusion method, Ref. [17] proposes a comprehensive evaluation method of a contrast compositor, but gives no basis to determine the value of the membership and weight which is a key in determining whether an evaluation result is correct or not.

This paper introduces a fuzzy logic idea and proposes an evaluation method for image fusion based on fuzzy theory. The proposed method takes into account the information entropy, average gradient, moderate exposure, mutual information, structural similarity, cross-entropy and other single-factor indices. Finally it achieves a comprehensive evaluation index by using a fuzzy comprehensive evaluation method which can overcome the one-sidedness of a single index and reflects small changes in the single-factor indicators. The purpose of this approach is to evaluate the subjective image- fusion results (visual assessment) combine with the objective ones, and is more systematic, comprehensive and effective.

2 Assessment for a multi-exposure image fusion based on the fuzzy theory

2.1 Single-factor evaluation

The selection principle of the single factor evaluation indicators for a fused image: (1) the indicators can reflect the quality performance of the image itself, such as information entropy, average gradient, mean-square error, contrast ,etc.; (2)a fused image contains as many useful information of the source-image fusion as possible ; (3) a fused image cannot introduce an artificial false information.

According to the evaluation selection principle, this paper selects the single-factor indicators, such as information entropy, average gradient, moderate exposure, mutual information, structural similarity and cross-entropy. It considers the quality of a fused image itself and takes into account the information of the fused-image result obtained from the source image.

(1) Image information entropy

Assume the image to be fused is F, its size is M × N and its total gray level is L. The information entropy is an important indicator to measure the information richness of an image. It can be calculated as follows:

$$EN = -\sum_{i=0}^{L-1} P_i \log P_i \qquad (1)$$

Where EN is the entropy of the image, P_i is the ratio of pixels N_i with value i and the total pixels of image M × N., i.e. $P_i = \frac{N_i}{M \times N}$, P= $\{P_0, P_1,\ldots,P_{L-1}\}$, reflecting the probability of the image having a different gray value of the pixel distribution.

The larger is the fused-image information entropy, the richer is the information contained and the better is the fusion quality.

(2) Average-gradient image

The average gradient can sensitively reflect the expression ability of the image contrast to minute details and can be used to evaluate the blur degree of an image, while it also reflects small details in the image contrast and textures transform feature [18] which can be expressed as follows:

$$G = \frac{1}{(M-1)(N-1)} \times \sum_{i=1}^{M-1}\sum_{j=1}^{N-1} \sqrt{\frac{((\frac{\partial Z(x_i,y_i)}{\partial x_i})^2 + (\frac{\partial Z(x_i,y_i)}{\partial y_i})^2)}{2}} \qquad (2)$$

In an image, the bigger is the rate of the gray level in a certain direction, the greater is its gradient and the sharper is the image.

(3) Moderate exposure

A moderate exposure is calculated mainly based on the human visual characteristics and on the referred spatial-frequency characteristics of an image. The human eye can clearly see the most of the brightness of the image area in the middle segment under a moderate exposure. It is calculated by the following formula:

$$ME = \exp(-\frac{(F(i,j) - 0.5)^2}{2\sigma^2}) \qquad (3)$$

Where F (i, j) is the fused-image pixel value and σ is the variance.

(4) Structural similarity

The structural similarity between the source images A, B and fused image F can be calculated by the brightness-similarity function, contrast-similarity function and structure-similarity function. It can be used to evaluate the image quality as follows:

$L_{AF}=\frac{2u_A u_F}{u_A{}^2+u_F{}^2}$ where u_A, u_F are the means of images A, F;

$C_{AF}=\frac{2d_A d_F}{d_A{}^2+d_F{}^2}$ where d_A, d_F are the variances of images A, F;

$S_{AF}=\frac{d_{AF}}{d_A d_F}$ where d_{AF} is the covariance of images A, F ;

The structural similarity between A and F is calculated as follow:

$$SS_{AF}=[L_{AF}{}^a]\times[C_{AF}{}^b]\times[S_{AF}{}^c] \qquad (4)$$

SS_{BF} can be calculated similarly and the structural similarity among A, B and F is as follow:

$$SS_{ABF}=SS_{AF}+SS_{BF} \qquad (5)$$

(5) Mutual information (MI)

MI reflects a measure of correlation between two variables, or a variable that contains a measure of the information quantity of another variable. The greater is the value, the richer is the fused-image information obtained from the original image and the better is the fusion effect. The source images are A and B whose gray value ranges are [0, L_1] and [0, L_2] ,respectively; F is a fused image whose gray value range is [0, L]. Mutual information of F and A, B is denoted as I_{FA} and I_{FB}, respectively.

$$I_{FA}=\sum_{i=0}^{L_1}\sum_{j=0}^{L}P_{FA}\log_2\frac{P_{FA}}{P_F P_A} \qquad I_{FB}=\sum_{i=0}^{L_2}\sum_{j=0}^{L}P_{FB}\log_2\frac{P_{FB}}{P_F P_B} \qquad (6)$$

Where P_A, P_B and P_F are the probability densities of A, B and F, P_{FA} and P_{FB} are the joint probability densities of the two group images. Considering I_{FA} and I_{FB}, formula (5) gives mutual information of fused image F obtained from source images A and B.

$$M_F^{AB}=I_{FA}+I_{FB} \qquad (7)$$

(6) Cross-entropy

Cross-entropy directly reflects the gray distribution information difference between two images. The smaller is the cross-entropy, the more information of the processed image is retained from the source image and the better is the image processing effect. The formula is as follows:

$$UE_{FA}=\sum_{i=0}^{L-1}P_{Ai}\log_2\frac{p_{Ai}}{q_{Fi}} \qquad UE_{FB}=\sum_{i=0}^{L-1}P_{Bi}\log_2\frac{p_{Bi}}{q_{Fi}}$$
$$UE_{FAB}=UE_{FA}+UE_{FB} \qquad (8)$$

where p_{Ai}, p_{Bi}, q_{Fi} are the gray distribution probabilities of source images A and B and fused image F. C_{FA} and C_{FB} are the cross-entropy of image A and F, B and F, C_{FAB} represent the cross-entropy among images A, B, F.

2.2 *Assessment of a multi-exposure image- fusion algorithm*

As the image evaluation is inherently uncertain, the fuzzy theory can be used to process the images. This paper proposes a fuzzy evaluation algorithm which takes into account the information entropy, average gradient, moderate exposure, mutual information, structural similarity, cross-entropy and other single-factor indices, using the fuzzy comprehensive evaluation method, a comprehensive evaluation can be done and objective evaluation results can be given.

Definition 1. A mapping called $\underset{\sim}{f}: X\to\mathscr{F}(Y), x\mapsto \underset{\sim}{f}(x)=\underset{\sim}{B}$ is a fuzzy mapping from X to Y.

According to the definition, a fuzzy mapping is promotion of a point-set mapping. Under mapping $\underset{\sim}{f}$, point x will become fuzzy set $\underset{\sim}{B}$.

Here, we only consider the correspondence between fuzzy mapping and fuzzy relationship in a limited domain.

Proposition1. set X={x_1,x_2,…,x_n},Y={y_1,y_2,…,y_m}.

(1) Given a fuzzy mapping

$$\underset{\sim}{f}: X\to\mathscr{F}(Y), X_i\mapsto \underset{\sim}{f}(x_i)=\underset{\sim}{B}=\frac{r_{i1}}{y_1}+\frac{r_{i2}}{y_2}+\ldots+\frac{r_{im}}{y_m} \qquad (9)$$
$$=(r_{i1},r_{i2},\ldots,r_{im})\in\mathscr{F}(Y) \quad i=(1,2,\ldots,n)$$

To construct a fuzzy matrix, take (r_{i1},r_{i2},…,r_{im}), (i = 1,2, ..., n) as a row, the fuzzy relationship is uniquely determined as:

$$\underset{\sim}{R}_f=\begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1m}\\ r_{21} & r_{22} & \ldots & r_{2m}\\ \ldots & \ldots & \ldots & \ldots\\ r_{n1} & r_{n2} & \ldots & r_{nm}\end{bmatrix} \qquad (10)$$

where $\underset{\sim}{R}_f(x_i,y_j)=r_{ij}=f(x_i)(y_j)$

(2) Given the fuzzy relationship

$$R=\begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1m}\\ r_{21} & r_{22} & \ldots & r_{2m}\\ \ldots & \ldots & \ldots & \ldots\\ r_{n1} & r_{n2} & \ldots & r_{nm}\end{bmatrix}$$

so $\underset{\sim}{f}_R: X\to\mathscr{F}(Y), x_i\mapsto \underset{\sim}{f}_R(x_i)=(r_{i1},r_{i2},\ldots,r_{im})\in\mathscr{F}(Y)$, where $\underset{\sim}{f}_R(x_i)(y_j)=r_{ij}=\underset{\sim}{R}(x_i,y_j), i=1,2,\ldots,n, j=1,2,\ldots,m.$ $\underset{\sim}{f}_R$ is a fuzzy mapping from X to Y.

Both (1) and (2) determine fuzzy mapping $\underset{\sim}{f}_R$.

Definition 2. Mapping $\underset{\sim}{T}$: $\mathscr{F}(X)\to\mathscr{F}(Y), \underset{\sim}{A}\mapsto\underset{\sim}{T}(\underset{\sim}{A})=\underset{\sim}{B}$ is a fuzzy transformation from X to Y.

By definition, a fuzzy transformation is a generalization of a collection transformation, i.e. under the $\underset{\sim}{T}$ mapping, fuzzy set $\underset{\sim}{A}$ can be converted into fuzzy set $\underset{\sim}{B}$.

Definition 3. $\underset{\sim}{T}$ is a fuzzy linear transformation from X to Y , $R_T\in\mathscr{F}(X\times Y)$ satisfies $\underset{\sim}{T}(A)=\underset{\sim}{A}\circ\underset{\sim}{R}_T(\forall\underset{\sim}{A}\in F(X))$, i.e. $\underset{\sim}{T}$ is induced by fuzzy relation $\underset{\sim}{R}_T$.

Proposition 2. Let X = {x_1, x_2 ... x_n}, Y = {y_1, y_2... y_m}, then:

(3) The fuzzy relationship is as follows:

$$R=\begin{bmatrix} r_{11} & r_{12} & \dots & r_{1m} \\ r_{21} & r_{22} & \dots & r_{2m} \\ \dots & \dots & \dots & \dots \\ r_{n1} & r_{n2} & \dots & r_{nm} \end{bmatrix}, \forall \underset{\sim}{A} = \text{A}=(a_1, a_2, ..., a_n) \in \mathscr{T}(X),$$

According to Definition 3, the fuzzy linear transformation (obtained by a max-min synthesis operation) is:

$$\underset{\sim}{T}_R : \mathscr{T}(X) \to \mathscr{T}(Y), \underset{\sim}{A} \mapsto \underset{\sim}{T}_R(\underset{\sim}{A}) = A \circ R_f = B = (b_1, b_2, ..., b_m) \in \mathscr{T}(Y) \quad (11)$$

where $b_j = \overset{n}{\underset{i=1}{\vee}} (a_i \wedge r_{ij}) \quad (j = 1, 2, ..., m)$.

According to Definition 3, fuzzy linear transformation $\underset{\sim}{T}_R$ is:

$$\underset{\sim}{T}_R(\underset{\sim}{A}) = A \circ R \quad (12)$$

Based on the above fuzzy theory, a multi-exposure image evaluation algorithm is proposed to evaluate the fusion effect in the following steps:

Step 1. The determined factor set X, X = {x_1, x_2... x_n} is the n type of a single evaluation factor in image fusion;

Step 2. Fusion algorithm S, S = {s_1, s_2... s_m} is the fusion result of the m-kind of the fusion algorithms;

Step 3. Single factor judgment

$\underset{\sim}{f} : X \to \wp(S), x_i \mapsto \underset{\sim}{f}(x_i) = (r_{i1}, r_{i2}, ..., r_{im}) \in \mathscr{T}(S)$ known by Proposition 1; fuzzy relation $\underset{\sim}{R}_f \in \mathscr{T}(X \times S)$ can be induced by map $\underset{\sim}{f}$ i.e. $\underset{\sim}{R}_f(x_i, s_j) = \underset{\sim}{f}(x_i)(s_j) = r_{ij}$, therefore $\underset{\sim}{R}_f$ can be expressed by fuzzy matrix $R \in \mu_{n \times m}$ as follows:

$$R=\begin{bmatrix} r_{11} & r_{12} & \dots & r_{1m} \\ r_{21} & r_{22} & \dots & r_{2m} \\ \dots & \dots & \dots & \dots \\ r_{n1} & r_{n2} & \dots & r_{nm} \end{bmatrix}$$

R is called a single-factor evaluation matrix. According to, Proposition 2, fuzzy relation $\underset{\sim}{R}$ can be induced in fuzzy linear transformation $\underset{\sim}{T}_f$ from X to S.

Step 4. To determine factor fuzzy subset A, which is one of the key aspects of the comprehensive evaluation, the matrix analysis is used, i.e. the result of the comprehensive evaluation of the m-fusion should be a fuzzy subset on S:

B=(b_1,b_2,…b_m)∈T(S), where b_j (j=1,2,…m). The result reflects the position occupied in the comprehensive evaluation by the effect of the j-kind fusion algorithm s_j (i.e. the membership of fuzzy set B to s_j : B(s_j) = b_j) .As comprehensive evaluation B depends on the weights of each factor, it should be on fuzzy set X A=(a_1,a_2,…a_n)∈T(X) and $\sum_{i=1}^{n} a_i = 1$, where a_i is the weight factor for the i-th factor, obtained by using the max-min synthesis operation. Comprehensive evaluation $\underset{\sim}{B}$ can be achieved by:

$$\underset{\sim}{B} = A \circ R.$$

A mathematical model of a fuzzy judgment is as follows:

$$\xrightarrow{A \in \mathscr{T}(X)} \boxed{\underset{\sim}{R}_f \in \mathscr{T}(X \times S)} \xrightarrow{B = A \circ R \in \mathscr{T}(S)}$$

where X is the index set of the image-fusion evaluation, S is the effect set of the image fusion, A is the weight set of the image evaluation factors and B is the dominance hierarchy value of all the fusion- algorithm effects in the comprehensive evaluation.

2.3 Weight determination

Weight determination is critical in the fuzzy comprehensive evaluation. It reflects the position occupied by various factors or role in the overall decision-making process, and can affect the result of a comprehensive decision directly. The weight is usually given empirically, to capture the actual situation to a certain extent, and the evaluation results are more realistic, but the weight given empirically is often subjective and sometimes cannot objectively reflect the actual situation, meaning that the evaluation results may be distorted. The current main methods of weight determination are the Dephi method, expert-estimation method, AHP judgment-matrix analysis method, etc. This paper uses the judgment-matrix analysis method.

(1) Identify judgment value $f_{xj}(x_i)$ of the compared pair-wise factors

Arbitrarily select a pair of indices (x_i, x_j) from evaluation set X = { information entropy x_1, average gradient x_2, moderate amount of exposure x_3, structural similarity x_4, interactive information x_5, cross- entropy x_6, $f_{xj}(x_i)$ is the "important-degree" judgment value of index x_i relative to x_j, be calculated as shown in Table 1.

Table 1: The judgment value for the factor importance.

(u_i, u_j) the importance of grades	$f_{xj}(x_i)$	$f_{xi}(x_j)$	**Remark**
u_i and u_j "equally important"	1	1	
u_i and u_j "somewhat important."	3	1	
u_i and u_j "obviously important."	5	1	
u_i and u_j "highly important"	7	1	
u_i and u_j "absolutely important "	9	1	
the importance of the u_i and u_j is between each grade	One of 2,4,6,8	1	The median value of two levels of determination

The result of a pair-wise factor comparison is:

$$f_{xu}(x_v)=\begin{bmatrix} & x_1 & x_2 & x_3 & x_4 & x_5 & x_6 \\ x_1 & 1 & 3 & 3 & 1 & 4 & 3 \\ x_2 & 1 & 1 & 1 & 1 & 3 & 2 \\ x_3 & 1 & 5 & 1 & 2 & 3 & 5 \\ x_4 & 1 & 3 & 3 & 1 & 2 & 3 \\ x_5 & 1 & 1 & 1 & 1 & 1 & 1 \\ x_6 & 1 & 1 & 1 & 1 & 5 & 1 \end{bmatrix}, u, v = 1,2,3,4,5,6$$

(2) Construct the judgment matrix

Substituting the above judgment value into the below formula just get:

$$b_{ij} = \frac{f_{xj}(x_i)}{f_{xi}(x_j)}, i, j = 1,2,3,4,5,6$$

The judgment matrix is:

$$B=\begin{bmatrix}1 & 2 & 2 & 1 & 4 & 3\\ \frac{1}{2} & 1 & \frac{1}{5} & \frac{1}{3} & 3 & 2\\ \frac{1}{2} & 5 & 1 & \frac{1}{3} & 3 & 5\\ 1 & 3 & 3 & 1 & 2 & 3\\ \frac{1}{4} & \frac{1}{3} & \frac{1}{3} & \frac{1}{2} & 1 & \frac{1}{5}\\ \frac{1}{3} & \frac{1}{2} & \frac{1}{5} & \frac{1}{3} & 5 & 1\end{bmatrix}$$

(3) Determination of important-degree coefficient a_i

Calculate maximum characteristic root λ_{max} of judgment matrix B, i.e. λ is the maximum value satisfying the below formula

$$\begin{bmatrix}\lambda-1 & 2 & 2 & 1 & 4 & 3\\ \frac{1}{2} & \lambda-1 & \frac{1}{5} & \frac{1}{3} & 3 & 2\\ \frac{1}{2} & 5 & \lambda-1 & \frac{1}{3} & 3 & 5\\ 1 & 3 & 3 & \lambda-1 & 2 & 3\\ \frac{1}{4} & \frac{1}{3} & \frac{1}{3} & \frac{1}{2} & \lambda-1 & \frac{1}{5}\\ \frac{1}{3} & \frac{1}{2} & \frac{1}{5} & \frac{1}{3} & 5 & \lambda-1\end{bmatrix}=0$$

λ_{max} = 6.9178, eigenvectors ξ is:

$$\xi=(0.53098,\ 0.22517,\ 0.50082,\ 0.60097, 0.12092, 0.20188]$$

A can be achieved by normalization:

$$A=\left[0.24349, 0.10325, 0.22966, 0.27558, 0.05545, 0.092573\right]$$

3 Results and discussion

Image fusion made by using the Pyramid [19] and wavelet transforms [20] is the major multi-scale decomposition method. Based on the multi-resolution analysis, the image is decomposed into sub-images at different scales and orientations. These sub-images represent different features in the image to meet the fusion needs better. Experiments presented in this paper are mainly for the multi-resolution fusion algorithms. The experiment results are given for the methods such as the Laplacian pyramid, contrast-ratio pyramid, pyramids and MKV gradient of Exposure Fusion (EF, http://research.edm.uhasselt.be/~tmertens/)method [21] and one-layer wavelet-decomposition fusion algorithm. As shown in Fig. 1 (test image) and Fig. 2 (captured image), the decomposition layers of the first four pyramid fusion methods are three. In the low-frequency part they take the average value of the image gray scale and in the high-frequency part they take its maximum value.

Table 2 shows the evaluation index calculated by using single factor, such as the information entropy, average gradient, moderate exposure, mutual information, structural similarity and cross-entropy of the fusion image.

(a) Image sequence of a multi-exposure

(b) Laplacian Pyramid (c) Contrast Pyramid (d)Ratio of a low-pass Pyramid

(e) Gradient Pyramid (f)M.K.V. Exposure Fusion
(g) One layer decomposition of Wavelet Transform

Figure 1. Multi-resolution image fusion algorithm (Standard test images)

As seen from Table 3, there are inconsistencies between the single evaluation indices. It is difficult to obtain a comprehensive evaluation result by using a single factor.

Table 3 shows evaluations of the fusion effect obtained by using single factors according to Table 2:

Table 3: The evaluation results of a fig. 1 obtained by using a single factor

single factor	(b) (c) (d) (e) (f) (g)
Entropy	f>d>g>c>e>b
Average gradient	c>f>b>e>g>d
Moderate amount of exposure	f>d>e>b>c>g
Structural similarity	d>f>b>c>d>e
Mutual information	f>g>c>e>b>d
Cross-entropy	g>e>b>d>c>f

To achieve a comprehensive evaluation using the fuzzy comprehensive evaluation method, the considered single- factor indices are the information entropy, average gradient, moderate exposure, mutual information, structural similarity, cross-entropy, etc.

(1) The data in Table 2 written in matrix Fare:

Table 2: The evaluation index of Fig. 1 obtained by using a single factor

single factor	Fig.1(b)	Fig.1(c)	Fig.1 (d)	Fig. 1 (e)	Fig.1(f)	Fig.1(g)
Entropy	7.2864	7.2974	7.3792	7.2893	7.5594	7.3776
Average gradient	11.414	13.618	10.036	11.191	12.398	10.406
Moderate amount of exposure	0.018031	0.017539	0.018608	0.018138	0.089032	0.017162
Structural similarity	0.037108	0.036242	0.035789	0.037374	0.030431	0.037333
Mutual information	24.475	24.485	24.31	24.478	25.357	24.498
Cross entropy	0.029398	0.028148	0.028911	0.029769	0.026699	0.029836

$$F=\begin{bmatrix} 7.2864 & 7.2974 & 7.3792 & 7.2893 & 7.5594 & 7.3776 \\ 0.018031 & 0.017539 & 0.018608 & 0.018138 & 0.089032 & 0.017162 \\ 0.013416 & 0.018453 & 0.017646 & 0.013558 & 0.030975 & 0.014464 \\ 0.037108 & 0.036242 & 0.035789 & 0.037374 & 0.030431 & 0.037333 \\ 24.475 & 24.485 & 24.31 & 24.478 & 25.357 & 24.498 \\ 0.029398 & 0.028148 & 0.028911 & 0.029769 & 0.026699 & 0.029836 \end{bmatrix}$$

(2) For each row data of normalized matrix F, the standardized formula can be expressed as:

$$F(i,1:n)=\frac{F(i,1:n)-\min(F(i,1:n))}{\max(F(i,1:n))-\min(F(i,1:n)))}$$

By using formula (15) matrix F is normalized as follows:

$$F=\begin{bmatrix} 0 & 0.040296 & 0.34014 & 0.010639 & 1 & 0.33432 \\ 0.38479 & 1 & 0 & 0.32238 & 0.65958 & 0.10339 \\ 0.0121 & 0.0052575 & 0.020127 & 0.013582 & 1 & 0 \\ 0.96172 & 0.83702 & 0.77174 & 1 & 0 & 0.99416 \\ 0.15822 & 0.16739 & 0 & 0.16044 & 1 & 0.18025 \\ 0.86042 & 0.46202 & 0.70522 & 0.97871 & 0 & 1 \end{bmatrix}$$

(3) The Membership function is:

$$R=\sin(F*pi/2)$$

The Single-factor membership matrix is:

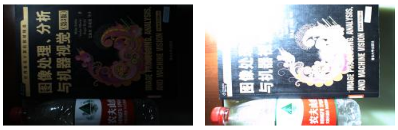
$$R=\begin{bmatrix} 0 & 0.063255 & 0.50922 & 0.016711 & 1 & 0.50135 \\ 0.56829 & 1 & 0 & 0.48503 & 0.8604 & 0.16169 \\ 0.019006 & 0.0082584 & 0.03161 & 0.021334 & 1 & 0 \\ 0.99819 & 0.96741 & 0.93641 & 1 & 0 & 0.99996 \\ 0.24599 & 0.25991 & 0 & 0.24935 & 1 & 0.27937 \\ 0.97606 & 0.66369 & 0.8947 & 0.99944 & 0 & 1 \end{bmatrix}$$

The Evaluation method to determine the weight of the preceding image fusion known as A is:

$$A=[0.24349 \quad 0.10325 \quad 0.22966 \quad 0.27558 \quad 0.05545 \quad 0.092573]$$

(4) The fuzzy comprehensive evaluation results are:

$$B=A\circ R$$
$$=[\,0.44212 \;\; 0.463 \;\; 0.47213 \;\; 0.44098 \;\; 0.61744 \;\; 0.5224]$$



(a) Image sequence of a multi-exposure

(b) Laplacian Pyramid (c) Contrast Pyramid (d) Ratio of a low-pass Pyramid

(e) Gradient Pyramid (f) M.K.V. Exposure Fusion (g) One-layer decomposition of the Wavelet Transform

Figure 2. Multi-resolution image-fusion algorithm (photographed images)

according to the judgment algorithm, the maximum value of matrix B enabling to a better fusion effect is, on the contrary, the opposite. Therefore, Fig.1 (f) shows the best fusion effect.

Using the above method and parameter settings Fig.2, the empathy fuzzy-evaluation results can be obtained as follows:

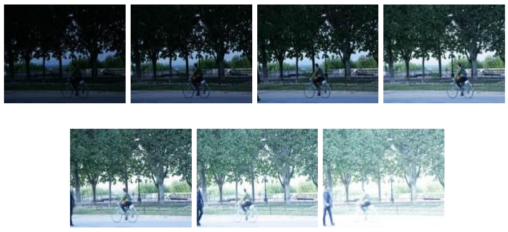
$B=[0.47408 \quad 0.62028 \quad 0.48986 \quad 0.4517 \quad 0.51074 \quad 0.40633]$,

Using the judgement algorithm (Fig. 2 (c)) the fusion effect is the best.

Using the above method and parameter settings, the empathy fuzzy evaluation results can be obtained as follows:

$B=[0.71601 \; 0.62177 \; 0.43844 \;\; 0.70033 \; 0.43956 \; 0.59715]$

Using the judgment algorithm (Figure 3 (b)) enables the best fusion effect.



(a) Image sequence of a multi-exposure

(b) Laplacian Pyramid (c) Contrast Pyramid (d) Ratio of low-pass Pyramid

(e) Gradient Pyramid (f) M.K.V. Exposure Fusion (g) One-layer decomposition of the Wavelet Transform

Figure 3. Multi-resolution image-fusion algorithm (motion object)

As seen from Fig. 1 (standard test chart), fusion algorithm f (MKV EF) provides a clearer effect than the other algorithms in the indoor scene and all the screen brightness visual effects are the best. In Fig. 2 (captured image) and Fig. 2(a), the first image scene is dark, the second picture shows extensive exposure scenarios, the exposure image sequence is less and the fusion effect of algorithm c (gradient pyramid) has a high contrast, clear details and the best visual effects. The evaluation results of the multi-group exposure images with no moving target (still images) show that the subjective (visual) exacted on methods are consistent with the objective (the proposed method) evaluation methods and give the order of the other fusion algorithms according to their fusion effect.

Table 4:The Evaluation index of Fig. 2 calculated by using a single factor

single factor	Fig. 2(b)	Fig.2(c)	Fig. 2(d)	Fig. 2(e)	Fig. 2(f)	Fig. 2(g)
Entropy	7.2961	7.3956	7.2392	7.2811	7.622	7.2395
Average gradient	5.5332	9.1728	5.3881	5.2992	6.2181	5.8165
Moderate amount of exposure	0.038042	0.04284	0.050318	0.037474	0.089934	0.042604
Structural similarity	0.012527	0.013018	0.012329	0.012516	0.010416	0.012103
Mutual information	25.736	21.61	28.101	27.177	20.512	23.394
Cross-entropy	0.048672	0.044865	0.049084	0.049281	0.042643	0.047413

Table 5: Evaluation index of Fig. 3 calculated by using a single factor

single factor	Fig. 2(b)	Fig. 2(c)	Fig. 2(d)	Fig. 2(e)	Fig. 2(f)	Fig. 2(g)
Entropy	7.4239	7.4595	7.3071	7.4093	7.375	7.3539
Average gradient	28.215	42.233	22.963	27.821	27.594	30.565
Moderate amount of exposure	0.04832	0.043488	0.050708	0.048688	0.099384	0.058513
Structural similarity	0.059425	0.05495	0.059231	0.059401	0.048592	0.056867
Mutual information	73.35	75.303	71.473	73.351	69.715	72.65
Cross-entropy	0.011318	0.010827	0.011287	0.01136	0.010882	0.010949

As shown in Fig. 3, for the multiple- exposure image sequence with moving objects[22], ghosting can be seen in each fusion algorithm. Algorithm d (ratio of the low-pass pyramid) is better, but the best result evaluated by the proposed algorithm is given in Fig.3 (b), this is because none of the fusion algorithms considers the moving objects ,thus resulting in an evaluation error.

As can be seen from the results evaluated by the proposed algorithm, the MKV EF algorithm achieves a better fusion effect with a greater number of multi-exposure image sequences ,thus reflecting the actual scene, though it is not ideal for a small number of the image sequences and a large exposed area . The pyramid-fusion algorithms given above are not suitable for the multi-exposure image-fusion sequences with a moving target.

4 Conclusion

The ultimate goal of image fusion is to be used in subsequent applications. Fused-image evaluation f plays an important role in the image-fusion theory. Selection of a fusion algorithm can be performed by using quantitative indicators and an effective evaluation. The proposed fuzzy comprehensive evaluation method takes into account several single-factor indices, such as information entropy, average gradient, moderate exposure, mutual information, structural similarity, cross-entropy,etc., and can achieve a comprehensive evaluation result, overcoming the one-sidedness of a single indicator while reflecting minor changes in the single- factor indicators. Experiments of several test and capture images show that the proposed method evaluates the fusion results for a static-scene image objective correspondingly to the visual evaluation.

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