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Performance Optimization of Image Fusion Using Meta Heuristic Genetic Algorithm

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ABSTRACT : With the ready availability of multiple sensors, the area of information fusion has been receiving increasing attention. For multi-sensor image data, algorithms such as simple average method, Principal Component Analysis (PCA) method, Gradient Pyramid (GP) method, Laplacian Pyramid (LP), Ratio Pyramid (RP) method and Discrete Wavelet Transform (DWT) methods have been successfully applied for image fusion. Another important issue that arises in image fusion: the performance of image fusion is that the performance of the associated algorithms is difficult to evaluate, especially when a clearly defined ground-truth image is not available. Some common measures to assess the performance for image fusion are Mutual information (MI), Tsallis and Renyi divergence based information. However they are difficult to estimate precisely. In this paper, a new approach is proposed for evaluating the performance of image fusion algorithms based on copula functions. To achieve this, copulas are proposed for the estimation of the MI, Tsallis and Renyi divergence based information and these are used to evaluate the quality of image fusion.

Keywords: Copulas; Divergence based information; Tsallis; Renyi; Performance Evaluation; Image Fusion.

I. INTRODUCTION

Image fusion is the process of combining relevant information from two or more images into a single image which should be more informative than any of the input images. Image fusion has been applied widely in the fields of medical imaging, remote sensing image applications, and so on [1]. To evaluate the effectiveness of image fusion techniques, divergence measures are used. Divergence is a measure of distance between the distributions P and Q of two random variables X and Y. One of the commonly used divergences is which has been defined as [1]:

$$D_{KL}(P \| Q) = \int_X p(x) \log \frac{p(x)}{q(x)} dx$$

where $p(x)$ and $q(x)$ are probability density functions of X and Y respectively. Divergence based information can be considered as the special case of the divergence between the joint probability density function and the product of the marginal probability density functions. For example, mutual information is derived from It quantifies the dependence between the joint distribution an With the continuous development of sensor technology, people have more and more ways to obtain images, and the image fusion types are also increasingly rich, such as theImage fusion of same sensor, the multi-spectral image fusion of single-sensor, the image fusion of the sensors with different types, and the fusion of image and non-image. Traditional data fusion can be divided into three levels, which are pixel-level fusion, feature-level fusion and decision-level fusion. The different fusion levels use different fusion algorithms and have different applications, generally, we all research the pixel-level fusion. Classical fusion algorithms include computing the average pixel-pixel gray level value of the source images, Laplacian pyramid, Contrast pyramid, Ratio pyramid, and Discrete Wavelet Transform (*DWT*). However, computing the average pixel-pixel gray level value of the source images method leads to undesirable side effects such as contrast reduction. The basic idea of *DWT* based methods is to perform decompositions on each source image, and then combine all these decompositions to obtain composite representation, from which the fused image can be recovered by finding inverse transform. This method is shown to be effective. However, wavelets transform can only reflect "through" edge characteristics, but can not express "along" edge characteristics. At the same time, the wavelet transform cannot precisely show the edge direction since it adopts isotropy. According to the limitation of the wavelet transform, Donoho et al. was proposed the concept of Curve let transform, which uses edges as basic elements, possesses maturity, and can adapt well to the image characteristics. Moreover, Curvelet Transform has anisotropy and has better direction, can provide more information to image processing [1-2]. Through the principle of Curvelet transform we know that: Curvelet transform has direction characteristic, and its base supporting session satisfies content anisotropy relation, except have multi-scale wavelet transform and local characteristics. Curvelet transform can represent appropriately the edge of image and smoothness area in the same precision of inverse transform. The low-bands coefficient adopts *NGMS* method and different direction high-bands coefficient adopts *LREMS* method was proposed after researching on fusion algorithms of the low-bands coefficient and high-bands coefficient in Curvelet transform.

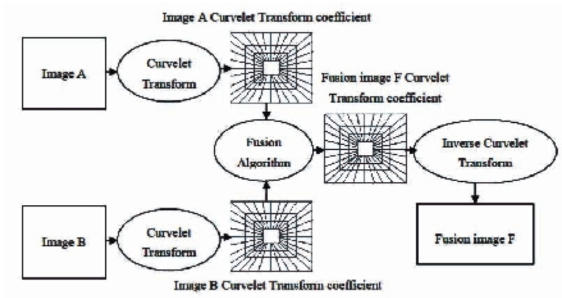

Fig. 1. process of image fusion algorithm base on Curvelet transform.

II. FUSION METHODS

The following summarize several approaches to the pixel level fusion of spatially registered input images. Most of these methods have been developed for the fusion of stationary input images (such as multispectral satellite imagery). Due to the static nature of the input data, temporal aspects arising in the fusion process of image sequences, e.g. stability and consistency, are not addressed. A generic categorization of image fusion methods is the following:

- Linear superposition
- Nonlinear methods
- Optimization approaches
- Artificial neural networks
- Image pyramids
- Wavelet transform
- Generic multiresolution fusion scheme

$$I_{MI}(x, y) = D_{KL}(p_{XY}(x, y) \parallel q_X(x)\, q_Y(y))$$

$$= \iint_{x,y} p_{XY}(x, y) \frac{p_{XY}(x, y)}{q_X(x) q_Y(y)} dxdy$$

where $p_{XY}(x, y)$ is the joint probability density function of the variables x and y, $q_X(x)$ and $q_Y(y)$ are the marginal densities of variable x and y respectively. Mutual information can also be defined in terms of entropy measures as:

$$I_{MI}(x, y) = H(x) + H(y) - H(x, y)$$

where $H(x)$, $H(y)$ and $H(x, y)$ are the Shannon entropies of X and Y and the joint entropy between x and y respectively. If X and Y obey Gaussian distribution, then mutual information becomes [1]: Considering X and Y as two input image, and F as the fused image, then the mutual information based performance measure is defined as [2]:

$$MI_{FXY} = I_{MI}(F, X) + I_{MI}(F, Y)$$

A number of popular divergence measures are given below, these include the Tsallis divergence and the Renyi divergence.Tsallis divergence [2] has been defined as:

$$D_{TS}(P \parallel Q) = \frac{1}{\alpha - 1}\left[\int_X \frac{p^a(x)}{q^{a-1}(x)} dx - 1\right]$$

The Tsallis divergence based performance measure for image fusion is defined as [2]: The key to the calculation of the divergence based information's the estimation of the joint probability density functions. Approaches to this estimation problem can be classified into two categories: Non-parametric and Parametric Methods. The typical Non-parametric methods applied to image processing are often referred to as the joint histogram method [4]. The method usually requires a large amount of data for reliable results, but the operations on small size of pixel neighbors are often required. Moreover, the pixel intensity distributions usually offer more stable information than pixel intensities themselves, while the joint histogram method counts the number of occurrences of pixel intensity pairs. As for the Parametric method, although some multivariate models such as multivariate Gaussian, Gamma distribution have been constructed [5], the distributions of the image pixel. The probably most straightforward way to build a fused image of several input frames is performing the fusion as a weighted superposition of all input frames [9]. The optimal weighting coefficients, with respect to information content and redundancy removal, can be determined by a principal component analysis (*PCA*) of all input intensities. By performing a *PCA* of the covariance matrix of input intensities, the weightings for each input frame are obtained from the eigenvector corresponding to the largest eigenvalue. A similar procedure is the linear combination of all inputs in a pre-chosen color space (eg. *R-G-B* or *H-S-V*), leading to a false color representation of the fused image intensities in the real world usually do not obey the Gaussian or other certain probability distributions. Another simple approach to image fusion is to build the fused image by the application of a simple nonlinear operator such as max or min. If in all input images the bright objects are of interest, a good choice is to compute the fused image by an pixel-by-pixel application of the maximum operator [9]. An extension to this approach follows by the introduction of morphological operators such as opening or closing. One application is the use of conditional morphological operators by the definition of highly reliable 'core' features present in both images and a set of 'potential' features present only in one source, where the actual fusion process is performed by the application of conditional erosion and dilation operators. A further extension to this approach is image algebra, which is a high-level algebraic extension of image morphology, designed to describe all image processing operations. The basic types defined in image algebra are value sets, coordinate sets which allow the integration of different resolutions and tessellations, images and templates. For each basic type binary and unary operations are defined which reach from the basic set operations to more complex ones for the operations on images and templates. Image algebra has been used in a generic way to combine multisensor images Furthermore, the multivariate distributions require that the types of marginal distribution are consistent. That is to say, if the marginals do not have the same type of distributions, for example, one image is Gaussian distributed, and another one is Gamma distributed, then there is no obviously known multivariate distribution model available that can estimate the associated joint probability density functions. Copulas [6] represent a mathematical relationship between theoint distribution and the marginal distributions of random variables. A two-dimensional copula is a bi-variate cumulative distribution function with uniform marginal distributions on the interval [0, 1].

$$C(u, v) = F_{XY}(F_X^{-1}(u), F_Y^{-1}(v))$$

where $C(u,v)$ is called copula distribution function, and $u = FX(x)$, $v = FY(y)$ are the marginal cumulative probability distributions for variables X and Y respectively. The familiar copula functions have been listed below . Moreover, the copula density is derived by [7]:

$$c(u, v) = \frac{\partial^2 C(u,v)}{\partial u \partial v} = \frac{\partial^2 C(F_X(x), F_Y(y))}{\partial u \partial v}$$

$$= \frac{\partial^2 F_{XY}(x,y)}{f_X(x) f_Y \partial x \partial y} = \frac{f_{XY}(x,y)}{f_X(x) f_Y(y)}$$

where $c(u,v)$ is the copula density function, $f_{XY}(x,y)$ is the joint probability density function of X and Y and $f_X(x)$, $f_Y(y)$ are the marginal probability density functions respectively. The mutual information can be written entirely in terms of copula density function as: Similar to mutual information, the Tsallis divergence based information may be expressed in terms of the copula density [8]:

$$I_{MI}(X, Y) = \iint f_{XY}(x,y) \log \frac{f_{XY}(x,y)}{f_X(x) f_Y(y)} dxdy$$

$$= \iint_{[0,1]} c(u,v) \log(c(u,v)) dudv$$

In the following experiment, a 5000 × 2 dataset, with a bivariate Gaussian distribution are randomly generated with different Pearson correlation from 0 to 1 [10]. The Mutual Information is computed by using both Gaussian assumption based method which is shown in equation and copula method. Tsallis and Renyi divergence based information with parameters equal to 0.8 and 1.5 respectively have been computed using a Gaussian copula, and the copula parameters estimated by using the Canonical Maximum Likelihood (CML) [9] technique. The results are given in Figure 1. It may be observed that, for the Gaussian distributed data, the result of copula based mutual information is very close to the Gaussian assumption based mutual information. Moreover, the parameters of Tsallis and Renyi based divergence can be adjusted so that they may offer better ability to control the measurement sensitivity, and hence better image fusion accuracy than conventional divergence. where (*a*) is an infrared image and (*b*) is visible light image [10]. Several algorithms including the Simple Average Method (*AVER*), Principal Component Analysis (*PCA*) Method, Gradient Pyramid (*GP*) Method, the Laplacian Pyramid (LP) Method, Ratio Pyramid (*RP*) and the Discrete Wavelet Transform (*DWT*) have been applied for the fusion of the two images, and the results are given in. Toevaluate these methods, firstly, the mutual information based performance measure was computed for all these algorithms. The results indicate the *PCA* method performs the best, since this method gives the highest *MIFXY* value, while other methods obtained approximately similar *MIFXY* values. However there is a dichotomy in these observations, as the *PCA* method is the worst performing by observing. Note that there is a human in the visible image, but is not in the fused image at all [7]. Since *PCA* fused image is very close to the visible image, so that a very high mutual information is found between *PCA* fused image and the visible image. The *PCA* fused image is 'very distant' from infrared image, and so the mutual information between *PCA* fused image and the infrared is very low, however mutual information is always great or equals to 0. The *PCA* fused image still has very high mutual information with input images and is mistakenly considered as the best algorithm. This measure cannot indicate

whether the images are fused symmetrically. To avoid this type of error, the Fusion Symmetry (*FS*) is introduced to solvethis problem. The *FS* has been defined as [11]:

$$FS = abs\left(\frac{I_{FX}(F,X)}{I_{FX}(F,X) + I_{FY}(F,Y)} - 0.5 \right)$$

where *IFX()* is a modified measure of mutual information, for the Tsallis divergence based information, or Renyi divergence based information, and other type of divergences. The smaller the FS, the better the performance of image fusion. All the results of image fusion performance the Gaussian copula was applied and *CML* method used to estimate the copula parameter. The FS measure is much better than the simple sums of information between fused image and infrared image, visible image respectively. This measure is called Fusion Factor (*FF*). The next step is to compare the methods between mutual information, Tsallis and Renyi divergence based information. Since fusion symmetric measure is obviously better than fusion factor, hence only fusion symmetry measure is considered. According to the rule: the smaller FS, the better the performance of image fusion. Based on this measure, all of these image fusion algorithms can be ranked by using FS measure as:

Mutual information:

LP > *AVER* > *DWT* > *GP* > *RP* > *PCA*

Tsallis divergence based information with parameter $\alpha = 3$.

LP > *AVER* > *DWT* > *GP* > *RP* > *PCA*

Renyi divergence based information with parameter $r = 3$.

LP > *AVER* > *DWT* > *GP* > *RP* > *PCA*

It may be observed that the performance of these three information based measures is exactly the same, and is also consistent with the rankings observed. It should be noted that the significant advantage of Tsallis and Renyi method is that they can adjust the associated parameters to obtain be discrimination [6]. For example, in the method of mutual information, *DWT* = 0.1146 is very close to *GP* = 0.1179. If Tsallis method is used, and if the parameter is adjusted to $\alpha = 3$, the results obtained are: *DWT* = 0.1338 and *GP* = 0.1409. Here the difference between *DWT* and *GP* measures become clearer. This characteristic is useful for the situations when the very similar results are obtained, and the performance of image fusion is to be evaluated. In this approach to image fusion, the fusion task is expressed as an bayesian optimization problem. Using the multisensor image data and an a-prori model of the fusion result, the goal is to find the fused image which maximizes the a-posteriori probability. Due to the fact that this problem cannot be solved in general, some simplifications are introduced: All input images are modeled as markov random fields to define an energy function which describes the fusion goal. Due to the equivalence of of gibbs random fields and markov random fields, this energy function can be expressed as a sum of so called clique potentials, where only pixels in a predefined neighborhood affect the actual pixel. The fusion task then consists of a maximization of the energy function. Since this energy function will be non-convex in general, typically stochastic optimization procedures such as simulated annealing or modifications like iterated conditional modes will be used. Image pyramids have been initially described for multiresolution image analysis and as a model for the binocular fusion in human vision. A generic image pyramid is a sequence of images where each image is constructed by low pass filtering and sub sampling from its predecessor. Due to sampling, the image size is halved in both spatial directions at each level of the decomposition process, thus leading to an multiresolution signal representation. The difference between the input image and the filtered image is necessary to allow an exact reconstruction from the pyramidal representation. The image pyramid approach thus leads to a signal representation with two pyramids: The smoothing pyramid containing the averaged pixel values, and the difference pyramid containing the pixel differences, i.e. the edges. So the difference pyramid can be viewed as a multiresolution edge representation of the input image [11]. The actual fusion process can be described by a generic multiresolution fusion scheme which is applicable both to image pyramids and the wavelet approach. There are several modifications of this generic pyramid construction method described above. Some authors propose the computation of nonlinear pyramids, such as the ratio and contrast pyramid, where the multistage edge representation is computed by an pixel-by-pixel division of neighboring resolutions. A further modification is to substitute the linear filters by morphological nonlinear filters, resulting in the morphological pyramid. Another type of image pyramid - the gradient pyramid - results, if the input image is decomposed into its directional edge representation using directional derivative filter

III. CONCLUSION

In this paper, the performance evaluation of image fusion using copulas has been presented. Gaussian copula density function has been used to estimate the mutual information,Tsallis and Renyi divergence based information have beenstudied, and their performance for image fusion is assessedbased on the fusion factor and fusion symmetry measures. Experiments show that Fusion symmetry measure is much better than Fusion Factor measure and that the Tsallis divergence offers improved ability to discriminate by adjusting its parameter (*a*). An Approach to choosing the optimal values of the parameter will be researched in the future. The results of experiment also provide the copula density as an alternative and robust way which can deal with any marginal distributions, to calculate the mutualinformation, and the Tsallis and Renyi divergence based information for the performance evaluation of image fusion.

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