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Hybrid image fusion scheme using self-fractional Fourier functions and multivariate empirical mode decomposition

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ABSTRACT

Image fusion has emerged as a promising area of research and a bivariate empirical mode decomposition based fusion scheme has recently been proposed in the literature. In this paper, a hybrid fusion scheme combining self-fractional Fourier function (SFFF) decomposition and multivariate empirical mode decomposition is proposed. In the proposed image fusion technique, images to be fused are decomposed into SFFF images. The SFFF images are further decomposed into intrinsic mode functions (IMFs) using multivariate empirical mode decomposition (MEMD). Corresponding IMFs of same decomposition level of SFFF images are fused using local variance based adaptive weight fusion rule to obtain fused IMF images. The fused image is obtained by applying inverse transformation on fused IMF images. The proposed technique provides flexibility in the number of functions in the SFFF decomposition, transform before SFFF decomposition, and the types of source images (real and complex) to be fused. Simulations are performed for fusion of test images with different SFFF decomposition levels and the results are compared with other existing methods. It is seen that the simulation results are comparable to the existing schemes.

1. Introduction

Image fusion is the process of combining multiple images into a single image to improve the information content of the resulting image [1,2]. The researchers have proposed various image fusion schemes in the spatial as well as transform domains with different fusion rules such as pixel averaging, weighted average, maximum value selection, region energy, region variance and so forth [1–17].

Several fusion approaches using multiscale transform such as the discrete wavelet transforms (DWT) [4,5], the Laplacian pyramid [6], the contrast pyramid [7] and the FFT [8] have been presented in literature. However, multiresolution transform based techniques do not allow image adaptive representation of local features and results in suboptimal image fusion [11,12].

Fractional Fourier transform (FRFT) is generalization of the FFT and it is used to perform signal analysis into intermediate domains. FRFT based fusion schemes provide additional degree of freedom in optimizing fusion quality due to additional free parameter. Image fusion combining FRFT and nonsubsampled contourlet transform (NSCT) has been presented in [17] to exploit the local feature representation capability of NSCT and intermediate time–frequency representation capability of FRFT.

Recently, an image fusion scheme based on image decomposition using self-fractional Fourier functions (SFFF) is reported in [16]. In this scheme, fusion quality of images is optimized by changing number of decomposition levels and by using some transform before SFFF decomposition. Similarly bivariate EMD (BiEMD) algorithm [28] has also been used for image fusion in [12].

However, BiEMD cannot be used when the two source images to be fused are complex or when more than two

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images are to be fused [14,19]. Multivariate empirical mode decomposition (MEMD) algorithm proposed in [29] is an extension of the BiEMD algorithm [28] which overcomes the limitations of BiEMD.

In this paper a hybrid image fusion scheme based on image decomposition using SFFF and MEMD is presented. The proposed scheme includes, it provides additional degree of freedom in using the transform before SFFF decomposition, number of SFFF decomposition levels and number of images to improve the fusion quality.

The motivation behind combining SFFF with MEMD is that the decomposed components may not be orthogonal to each other in other fusion techniques based on multi-scale transforms, but in case of SFFF they are orthogonal to each other and therefore carries independent information. Secondly, signals to be fused may not be bandlimited in conventional Fourier domain, but bandlimited in some FRFT domain. However, SFFF decomposition is not a data adaptive decomposition but, empirical mode decomposition (MEMD) is data adaptive decomposition and decomposing signal into nearly orthogonal (not completely orthogonal) intrinsic mode functions (IMFs). Therefore by combining SFFF decomposition with MEMD, the orthogonal signals are used for fusion algorithm and giving better fusion results from this combination [12–27].

The rest of the paper is organized as follows: In Section 2 background theory related to fractional Fourier transform, self-fractional Fourier functions, empirical mode decomposition and multivariate empirical mode decomposition is presented. In Section 3, the proposed fusion scheme is presented. Section 4 gives the simulation results and the conclusions are given in Section 5.

2. Background theory

2.1. Fractional Fourier transform

The fractional Fourier transform (FRFT) is a generalization of the conventional Fourier transform and the FRFT domains can be interpreted as intermediate domains between spatial and frequency domains [21]. The 2D-FRFT with angles α and β of a signal $f(x, y)$, denoted as $\mathcal{F}^{\alpha,\beta}(u,v)$, is defined as [21]

$$\mathcal{F}^{\alpha,\beta}(u,v) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)K_{\alpha,\beta}(x,y,u,v)dx\,dy, \tag{1}$$

where $0<|\alpha|<\pi$ and $0<|\beta|<\pi$ and the inverse 2D-FRFT is given by [21]

$$f(x,y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \mathcal{F}^{\alpha,\beta}(u,v)K^{*}_{\alpha,\beta}(x,y,u,v)du\,dv, \tag{2}$$

where the 2D-FRFT transform kernel $K_{\alpha,\beta}(x,y,u,v)$ is defined as

$$K_{\alpha,\beta}(x,y,u,v) = \begin{cases} \frac{\sqrt{1-j\cot\alpha}\sqrt{1-j\cot\beta}}{2\pi} e^{j\left\{(u^2+x^2)/2\right\}\cot\alpha - jux\csc\alpha}\, e^{j\left\{(v^2+y^2)/2\right\}\cot\beta - jvy\csc\beta} & \text{if } \alpha=\beta\neq N\pi,\ N \text{ is integer} \\ \delta(x-u)\delta(y-v) & \text{if } \alpha=\beta=2N\pi,\ N \text{ is integer} \\ \delta(x+u)\delta(y+v) & \text{if } \alpha=\beta=(2N+1)\pi,\ N \text{ is integer} \end{cases}$$

In (2) the superscript $*$ denotes complex conjugation. The 2D-FRFT reduces to the conventional Fourier transform, when $\alpha,\beta=\pi/2$.The 2D-FRFT can be computed by 1D-FRFT using the separability property of it.

2.2. Self-fractional Fourier functions

Self-fractional Fourier function (SFFF) is a function, which is invariant under the fractional Fourier transformation for some angle α [21]. SFFFs are Eigen functions of the corresponding FRFT operator. A function from the Hilbert space of finite energy signals can be represented as a sum of M SFFFs, for an angle $2\pi/M$ [21–25].

The SFFF, signal $F(x)$ of rational order $\alpha=N/M$ is defined as [22–25],

$$F(x) = [F+\cdots+F^{(N/M)}+\cdots+F^{(k-1)N/M}]g(x), \tag{3}$$

where $g(x)$ be any generator function, N and M are integers, and F^{α} is the FRFT operator corresponding to angle α. We can represent $g(x, y)$ through the sum of M orthogonal SFFFs of order M as [18,22,23]

$$g(x,y) = \sum_{L=0}^{M-1} F(x,y)_{L,M}, \tag{4}$$

where

$$F(x,y)_{L,M} = \frac{1}{M}\sum_{k=1}^{M} \exp\left(\frac{j2\pi L(k-1)}{M}\right)\left[R^{(\alpha,\alpha)}g(u,v)\right](x,y). \tag{5}$$

The signal $F(x,y)_{L,M}$ is an SFFF, and $\alpha=2\pi(k-1)/M$, and $R^{(\alpha,\alpha)}$ represents a 2D-FRFT operator with angle α along x and y directions.

2.3. EMD and MEMD

Empirical mode decomposition (EMD) proposed in [26] is a fully data driven technique for multiscale decomposition of a nonlinear and nonstationary signal into finite set of oscillatory components. These oscillatory components are natural frequency components of the signal, called intrinsic mode functions (IMFs) and the coarsest component is termed as residue [26,27]. The IMFs of a given signal are extracted using a process called sifting algorithm [26].

Using the EMD, the input signal $f(x, y)$ is decomposed as [26]

$$f(x,y) = \sum_{j=1}^{n} C_j(x,y)+r(x,y), \tag{6}$$

where $C_j(x,y)$ $j=1,2,....,n$, represent intrinsic mode functions (IMFs), and $r(x, y)$ represent the residue signal.

The details of the EMD algorithm to decompose a signal are available in [26,27]. Because of its capability to separate spatial frequencies and to represent local features intuitively, recently a lot of work has been done for image fusion using EMD [9–15].