Satellite Image Fusion Using Maximization of Non-Gaussianity

A. M. El Ejaily 1, F. Eltohamy 2, M. S. Hamid 3 and G. Ismail 4

1Libyan Armed Force
2,3,4 Egyptian Armed Force
1 ejaily54@yahoo.com; 2 Ftohamy72@yahoo.com; 3 mshamid24@hotmail.com; 4 dr_gouda80@yahoo.com

Abstract—Image fusion is a technique for combining images from different sources to obtain a single image with enhanced information content. This paper proposes an image fusion method to merge panchromatic (PAN) and multispectral (MS) remote sensing satellite images using genetic algorithm to maximize the nongaussianity of the independent components of ICA. The genetic algorithm evolves the mixing matrix of the independent components of the MS image by maximizing the kurtosis. The proposed method is applied to Quickbird, Ikonos, and Worldview satellite image data. Performance evaluation of the proposed method is compared with that of IHS, PCA, and ICA based image fusion methods. Experimental results show optimum performance of the proposed method in terms of spatial resolution and color preservation of the fused images with the three different types of satellite image data.

Keywords—Image fusion; multispectral image MS; Panchromatic image PAN; Independent Component Analysis ICA; Genetic Algorithm GA

I. INTRODUCTION

Fusion of a panchromatic (Pan) image having high spatial and low spectral resolutions with multispectral (MS) image having low spatial and high spectral resolutions improves the quality of remotely sensed images for better classification and feature extraction and consequently increasing satellite image data usage [1]. The importance of image fusion in the field of remote sensing motivates the researchers to develop image fusion techniques that enhance the quality of the fused image.

The most common form of image fusion methods are based on intensity-hue-saturation (IHS) [2], principal component analysis (PCA) [3], discrete wavelet transform (DWT) [4, 5], and independent component analysis (ICA) [6]. ICA based image fusion technique has an advantage over other image fusion techniques because of its ability of using higher-order statistical properties in eliminating the redundancy between different image data.

The estimation of the data model of independent component analysis is usually performed by formulating an objective function and then minimizing or maximizing it. Therefore, the
properties of the ICA method depend on both the objective function and the optimization algorithm.

In this paper, genetic algorithm (GA) [8] uses kurtosis as a fitness function for evolving the best solution due to the fact that the obtained components should have a nongaussian distribution to be independent and the kurtosis is often used as a quantitative measure of nongaussianity [7]. The proposed fitness function reaches its maximum value when the obtained components have a nongaussian distribution, so the maximization of the fitness function ensures the independency of these components. The method is applied to Quickbird, Ikonos, and Worldview satellite image data. Objective measures and visual inspection are used to assess the quality of the fused images. The results are compared with that obtained from other image fusion methods.

II. INDEPENDENT COMPONENT ANALYSIS

ICA is a computational method for separating multivariate signal into additive components supposing the mutual statistical independence of the non-Gaussian source signals [7]. The components should be statistically independent. This means that the value of any one of the components gives no information about the values of the other components.

In fact, if data is Gaussian, it is simple to find components that are independent, because for Gaussian data, uncorrelated components are always independent. In practical situations, however, the data often does not follow a gaussian distribution, Hence, we cannot in general find a representation where the components are really independent, but we can at least find components that are as independent as possible.

Assume that there is an M-dimensional zero mean vector \( S = (S_1, S_2, ..., S_M)^T \), whose components have mutually independent distribution. We can write the multivariate joint probability density function (pdf) of the vector as the product of the marginal independent distributions:

\[
p(s) = \prod_{i=1}^{M} p_i(S_i)
\]  

A data vector \( X = (X_1, X_2, ..., X_N)^T \) is an observed vector such that

\[
S = AX
\]

where, \( A \) is an unknown scalar matrix which is called mixing matrix.

The goal of the ICA is to find the right linear transformation of the correlative input that makes the outputs as independent as possible.

III. GENETIC ALGORITHM

Genetic algorithm [8-10] is a sub area of the more general topic of evolutionary algorithms (EA). Genetic algorithm uses evolution as an optimization tool for engineering problems in a manner similar to the biological evolution. In the natural world there is a population of organisms, the life cycle of these organisms represent the fitness function, so the nature itself will select the best organism for the next generation. GA evolves a population of candidate
solutions to a given problem, using operators inspired by natural genetic variation and natural selection.

The function of the genetic algorithm is to search for the desired solution of engineering problem among a collection of candidate solutions. The set of candidate solutions represent the population of organism, each solution represent a chromosome. To evolve good solutions and to implement natural selection, we need a measure with a set of parameters involved for selecting good solutions from available solutions. This measure is so-called fitness function and the parameters are encoded to vectors, each vector represents a chromosome (possible solution). Once the problem is encoded in a chromosomal manner and a fitness measure has been chosen, GA starts to evolve the chromosomes of the search problem using a population of initial solutions through crossover and mutation operations until a predefined stopping criterion is reached.

IV. THE PROPOSED GA-BASED IMAGE FUSION METHOD

Many of image fusion algorithms based on genetic algorithm have already been published. In [11,12], the fused images were obtained by Weighted average of the input images and the genetic algorithm used to estimate the weights. A new optimized image is obtained from the average method using the optimized weights. In this paper, GA based independent component analysis is used for the fusion of PAN and MS satellite images. GA is used to estimate the best value of a mixing matrix which gives the best approximation of the source signals according to equation (2). The population of initial solutions is generated randomly. Each individual solution (mixing matrix) is encoded to a binary vector that represents a chromosome.

The candidate solution is used to generate the independent components according to equation (2) and GA is used to evolve the best solution (mixing matrix) by maximizing the fitness function. The fitness of the candidate solution is calculated by maximizing the kurtosis of the independent components according to the following function:

\[
\text{Fitness} = E(y^4) - 3 (E(y^2))^2 \tag{3}
\]

A maximum value of the fitness function indicates that the obtained components have a nongaussian distribution, so the components are independent. The best solution is used to generate the independent components of the MS image. The third independent component is replaced by the PAN image and then the new combination is multiplied by the inverse of the mixing matrix to obtain the fused image.

The size of the training images is 256 × 256 which is almost 1/16 of the total size of the satellite image data. This training image data is used for evolving the best solution (mixing matrix). Parent selection is accomplished by using the Binary Tournament Selection algorithm [10] with elitism. The evolution process is carried out using uniform crossover and bit mutation. The values of the parameters of the GA are selected to be 32 for the population size, 0.8 for the crossover probability, 0.03 for the mutation probability, and 100 for the total number of generations.

The maximum value of the fitness function is achieved when obtained components have large nongaussianity which means that they are highly independent. The proposed genetic algorithm based image fusion method has an advantage of low computational complexity because of the simplicity of the fitness function. However the main problem with this method is the dependence of the final solution on the initial population of the GA. This is solved by controlling the initial seed of the random number generator used with the GA.
V. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

- **Data set used**
  For experimental work and performance evaluation of the proposed method, three different image data sets acquired by QuickBird, Ikonos, and Worldview satellite sensors are considered. Table I summarizes the specifications of remote sensing satellite data being used.

- **Pre-processing steps**
  In order to perform the fusion process, the raw multispectral images have been resampled to be of the same size of the panchromatic images.

- **Fusion of test data**
  The size of the training data of the genetic algorithm is selected to be $256 \times 256$ pixels. Figures (1-3) demonstrate the training data and the evolution of the value of the fitness function in each generation for the Quickbird, Ikonos, and Worldview satellite images respectively. A normalized version of the best obtained fitness and the best mixing matrix for the three types of satellite image data are given in Table II. In addition to the proposed method, the IHS, PCA, and ICA methods are also applied to the same satellite image data. The ICA-fusion method uses principle component analysis and whitening for the estimation of the independent components. Figures (4-6) show the input and the obtained fused images corresponding to the Quickbird, Ikonos, and Worldview satellite respectively.

- **Image quality metrics and performance evaluation**
  In this paper, three image quality metrics HPC, MSE, and UQI are used for the evaluation of the objective quality of the fused images. High Pass Correlation (HPC) parameter [13] measures the spatial quality of the fused image. The higher the HPC value the better the spatial resolution of the fused image. Mean Square Error (MSE) [14] and Universal Quality Index (UQI) [15] measure the spectral quality of the fused image. The higher the UQI and lower the MSE the higher the spectral quality of the fused image.

  The results demonstrated in Table.III show that the proposed method outperforms the IHS in terms of spatial resolution. The visual inspection of the fused images demonstrated in Figure.4 reveal superior performance of the proposed method in terms of perceptual quality and color preservation.

  The results demonstrated in Table.IV show that the proposed method outperforms the IHS in terms of spatial resolution and the ICA method in terms of color preservation. The visual inspection of the fused images demonstrated in Figure.5 reveal superior performance of the proposed method in terms of perceptual quality and color preservation.

  The results demonstrated in Table.V show that the proposed method outperforms the three other methods in terms of color preservation. The visual inspection of the fused images demonstrated in Figure.6 reveal superior performance of the proposed method in terms of perceptual quality and color preservation.

  The results show that the proposed image fusion method demonstrates an optimum performance in terms of spatial resolution and color preservation of the fused images with different types of satellite image data.

### Table I

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Data Satcomination</th>
<th>MS Image</th>
<th>PAN Image</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bands combination</td>
<td>Size [Pixel]</td>
<td>Spatial Resolution [m]</td>
</tr>
<tr>
<td>Quickbird</td>
<td>(4,3,1) False color</td>
<td>1000x1000</td>
<td>2.44 m</td>
</tr>
<tr>
<td>Ikonos</td>
<td>(3,2,1) True color</td>
<td>1000x1000</td>
<td>4 m</td>
</tr>
<tr>
<td>Worldview</td>
<td>(3,2,1) True color</td>
<td>1000x1000</td>
<td>2 m</td>
</tr>
</tbody>
</table>

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VI. CONCLUSION

Fused image quality refers to both the spatial and spectral quality of the fused image. The goal of image fusion is to increase the spatial resolution of the MS images while preserving their spectral information content. In this paper, a genetic algorithm-based ICA image fusion method is proposed. The method is applied to Quickbird, Ikonos, and Worldview remote sensing satellite image data. The genetic algorithm evolves the mixing matrix of the independent components of the MS image by maximizing the kurtosis. The proposed method is compared to three other image fusion methods. The experimental results reveal that the proposed image fusion method demonstrates an optimum performance in terms of spatial resolution and color preservation of the fused images with different types of satellite image data.

Fig. 1 The training images and the evolution of the value of the fitness function for Quickbird image data: (a) PAN image; (b) MS image; (c) the value of the maximum obtained fitness in each generation.
Fig. 2 The training images and the evolution of the value of the fitness function for Ikonos image data: (a) PAN image; (b) MS image; (c) the value of the maximum obtained fitness in each generation.
TABLE II
NORMALIZED VALUES OF THE BEST FITNESS VALUE AND CORRESPONDING MIXING MATRIX.

<table>
<thead>
<tr>
<th></th>
<th>Best Fitness</th>
<th>Mixing matrix(A)</th>
</tr>
</thead>
</table>
| **Quickbird data** | 2.13         | \[
0.3805 & 0.2761 & -0.7620 \\
0.5112 & -0.1024 & -0.5415 \\
0.9980 & 0.9971 & 0.9951
\] |
| **Ikonos data**  | 5.2045       | \[
0.5112 & -0.6098 & 0.0634 \\
-0.6322 & 0.5854 & 0.1073 \\
0.9980 & 0.9971 & 0.9951
\] |
| **Worldview data** | 4.4174      | \[
0.3252 & -0.6348 & 0.3232 \\
-0.2051 & 0.2773 & -0.0908 \\
0.9990 & 0.9971 & 0.9901
\] |

Fig. 3 The training images and the evolution of the value of the fitness function for Worldview image data: (a) PAN image; (b) MS image; (c) the value of the maximum obtained fitness in each generation.
TABLE III
THE RESULTS OF SPATIAL AND SPECTRAL QUALITY ASSESSMENT (QUICKBIRD IMAGES).  

<table>
<thead>
<tr>
<th>Method</th>
<th>HPC</th>
<th>MSE</th>
<th>UQI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R</td>
<td>G</td>
<td>B</td>
</tr>
<tr>
<td>IHS</td>
<td>0.9726</td>
<td>0.9444</td>
<td>0.9420</td>
</tr>
<tr>
<td>PCA</td>
<td>0.8773</td>
<td>0.9556</td>
<td>0.8988</td>
</tr>
<tr>
<td>ICA</td>
<td>0.9825</td>
<td>0.9887</td>
<td>0.9894</td>
</tr>
<tr>
<td>Proposed method</td>
<td>0.9334</td>
<td>0.9688</td>
<td>0.9681</td>
</tr>
</tbody>
</table>

Fig. 4: Quickbird image data: (a) PAN image; (b) MS image; fused image by (c) IHS method; (d) PCA method; (e) ICA method; (f) proposed method.
TABLE IV
THE RESULTS OF SPATIAL AND SPECTRAL QUALITY ASSESSMENT (IKONOS IMAGES).

<table>
<thead>
<tr>
<th></th>
<th>HPC</th>
<th>MSE</th>
<th>UQI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R</td>
<td>G</td>
<td>B</td>
</tr>
<tr>
<td>IHS</td>
<td>0.9960</td>
<td>0.9934</td>
<td>0.9870</td>
</tr>
<tr>
<td>PCA</td>
<td>0.9910</td>
<td>0.9962</td>
<td>0.9938</td>
</tr>
<tr>
<td>ICA</td>
<td>0.9959</td>
<td>0.9987</td>
<td>0.9996</td>
</tr>
<tr>
<td>Proposed method</td>
<td>0.9965</td>
<td>0.9963</td>
<td>0.9939</td>
</tr>
</tbody>
</table>

Fig. 5. Ikonos image data: (a) PAN image; (b) MS image; fused image by (c) IHS method; (d) PCA method; (e) ICA method; (f) proposed method.
### Table V

The results of spatial and spectral quality assessment (Worldview images).

<table>
<thead>
<tr>
<th></th>
<th>HPC</th>
<th>MSE</th>
<th>UQI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R</td>
<td>G</td>
<td>B</td>
</tr>
<tr>
<td>IHS</td>
<td>0.9553</td>
<td>0.9798</td>
<td>0.9859</td>
</tr>
<tr>
<td>PCA</td>
<td>0.9049</td>
<td>0.9030</td>
<td>0.8568</td>
</tr>
<tr>
<td>ICA</td>
<td>0.9912</td>
<td>0.9944</td>
<td>0.9940</td>
</tr>
<tr>
<td>Proposed method</td>
<td>0.9387</td>
<td>0.9549</td>
<td>0.9425</td>
</tr>
</tbody>
</table>

Fig. 6. Worldview image data: (a) PAN image; (b) MS image; fused image by (c) IHS method; (d) PCA method; (e) ICA method; (f) proposed method.
REFERENCES