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Improvement of Bat Algorithm Classification Accuracy Using Image Fusion Techniques

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ABSTRACT

This paper investigates the pansharpening influence on satellite images-classification using Bat algorithm (BA). To this end, experiments are proceed using two fusion techniques: Brovey Transform and Intensity-Hue-Saturation transform, in order to merge the characteristics of images of the same area. Considering the classification as an optimization problem, BA can be applied on a fully-featured image. For this research, recent Landsat 8 panchromatic and multispectral images taken over the city of Oran (Algeria) are used to show the performance of BA and the benefit of using fusion techniques to improve classification. This paper shows improvement in the results when a fusion step is applied. Additionally, BA performance is compared against K-Means and Particle Swarm Optimization. From the obtained results, it can be concluded that BA can be successfully applied to solve unsupervised classification problems.

Key words: Bat Algorithm, Bio-inspired Algorithm, Image Fusion, Multiresolution Fusion Remote Sensing Image Classification, Pansharpening, Remote Sensed Image Processing.

1. INTRODUCTION

Thanks to the recent progress in satellite development, the vast majority of the remote sensing satellites can provide, at the same time, images with different resolutions such as panchromatic (PAN) and multispectral (MS) images [1]. The PAN images supply high spatial resolution and detailed information which are appropriate for identifying spatial characteristics of objects such as texture, objects, and shapes [2]. MS images supply rich and pertinent spectral information that become an increasingly important component for several remote sensing applications, as well as machine learning and land cover detection [3]. PAN and MS images can be used separately, but can possibly be more useful when combined together. The resulting image acquires the advantages of the two images used: the new image offers both a high spatial and spectral resolution Since 1998 and until now [5], researchers have shown an increased interest in using pansharpening, especially encouraged by the diffusion of high resolution images in products such as Google Earth and Bing Maps [6]. Moreover, pansharpening aims at enhancing images that constitutes a preliminary step for many remote sensing tasks [6], such as change detection [7] thematic classification [8] and visual image interpretation [9]. The impact of pansharpening is highly measured as shown by reviewing the recent literature, in which we can deduce that pansharpening can increase classification accuracy [5].

Image classification consists of affecting each pixel of an image to a thematic class or a group. The classified image is then composed of many regions; each region corresponds to a category such as “forest”, “sea”, or “grass”. In some instances, image classification can be an intermediate part of analysis for many areas such as image processing and pattern recognition. In other cases, the classification itself may be the aim of the process. For example, land classification uses satellite images in order to produce a thematic map as a final product. The classification techniques can be separated into two categories: supervised and unsupervised [10]. Supervised classification needs a training set of samples and considerable interaction with the analyst. On the other hand, unsupervised classification generates groups according to the similarity between pixels composing the image. This type of classification requires small to no interaction from the analyst.

This study aims to analyze the impact of pansharpening on the results given by bat algorithm classification. A comparison is performed between the results of the classification of original MS and the pansharpened MS images. To this end, two well-known pansharpening algorithms are used: Intensity-Hue-Saturation (IHS) [11] and Brovey Transform [12].

To adequately analyze the effects of pansharpening algorithms on Bat classification, several experiments were performed by applying the aforementioned algorithms to well-known images acquired by the Landsat 8 sensor on the city of Oran (Algeria). Using a known region gives us the advantage of being able to prepare a reliable reference image to evaluate the effectiveness of our classification approach. The evaluation is performed by using the kappa [13] and the overall accuracy values to determine whether this new approach gives better results or not. The results show that pansharpening gives higher classification accuracy and also improves the visual appearance by showing more details.

The rest of this paper is organized as follow: Section two presents a detailed description of the used pansharpening algorithms and of the original bat algorithm and how we adapted it for classification. Section three presents the studied area used to test our approach and assesses the experimental results. The last section presents the findings of our work and identifies the problems encountered for further research.

2. MATERIALS AND METHODS

2.1 Pansharpening algorithm

Pansharpening refers to the merging of a high-resolution PAN (panchromatic image) and a low-resolution MS (multispectral image) acquired in the same area. This can be considered as a particular problem of data fusion, for the reason that it aims to merge the spatial details which are uniquely present in PAN with the spectral diversity of MS which is missed in PAN in order to create a new and unique product [6]. The merged image is not only useful for facilitating visual interpretation, but also for improving the results of classification [14]. In addition, a merged image provides a beautiful color image for image viewing applications [15]. In the following, two popular pansharpening algorithms used in our study are described: Intensity-Hue-Saturation and Brovey transform.

2.1.1 Intensity-Hue-Saturation algorithm

The Intensity-Hue-Saturation (IHS) can be applied for pansharpening [6] and is widely used in remote sensing image fusion to take advantage of both, panchromatic (PAN) and spectral (MS) bands. IHS fusion transforms an image from RGB space to the IHS space, hence the name. The IHS color space is very important because it is similar to how the human eye senses colors. Intensity corresponds to the brightness, whereas hue describes the average wavelength and saturation specifies the amount of white in the color [11]. There are many transformations to convert an image from the RGB color-space to the IHS color-space [16]. A very commonly used transformation is expressed by the equation based on a cylindrical color model [5] and was reported in [17]. It consists essentially to replace each intensity component in the IHS space with a newly calculated value from the corresponding PAN component and next converting back the new calculated hue and saturation components to the RGB space. To obtain a transformation from RGB space to IHS space, the standard procedure is described in the following steps [18]:

1. PAN and MS images do not have the same size and cannot be superposed as if. The MS image, which is the image with the lowest resolution, must be upsampled using linear interpolation to correspond to the size of the PAN image.
2. Transform the three bands of MS image from standard RGB space into IHS space by using equation (1)
3. From the results of equation (1), intensity component I is replaced by the corresponding value from PAN image
4. The resulting components are projected back into RGB data space using equation (2), to obtain the fused image.

$$\begin{pmatrix} I \\ v_1 \\ v_2 \end{pmatrix} = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ -\sqrt{2}/6 & -\sqrt{2}/6 & 2\sqrt{2}/6 \\ 1\sqrt{2} & -1\sqrt{2} & 0 \end{bmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \quad (1)$$

$$\begin{pmatrix} R_{\text{fused}} \\ G_{\text{fused}} \\ B_{\text{fused}} \end{pmatrix} = \begin{bmatrix} 1 & -1/\sqrt{2} & 1/\sqrt{2} \\ 1 & -1/\sqrt{2} & -1/\sqrt{2} \\ 1 & -\sqrt{2} & 0 \end{bmatrix} \begin{pmatrix} \text{PAN} \\ v_1 \\ v_2 \end{pmatrix} \quad (2)$$

R_{fused}, G_{fused} and B_{fused} correspond to the red, green and blue components of the multicolored fused image. v_1 and v_2 represent intermediate variables, which are needed in the transformation.

For simplified and efficient implementation of the IHS procedure we can write equation (3) as follow:

$$\begin{pmatrix} R_{\text{fused}} \\ G_{\text{fused}} \\ B_{\text{fused}} \end{pmatrix} = \begin{bmatrix} 1 & -1/\sqrt{2} & 1/\sqrt{2} \\ 1 & -1/\sqrt{2} & -1/\sqrt{2} \\ 1 & -\sqrt{2} & 0 \end{bmatrix} \begin{pmatrix} \text{I+(PAN} - I) \\ v_1 \\ v_2 \end{pmatrix} = \begin{bmatrix} 1 & -1/\sqrt{2} & 1/\sqrt{2} \\ 1 & -1/\sqrt{2} & -1/\sqrt{2} \\ 1 & -\sqrt{2} & 0 \end{bmatrix} \begin{pmatrix} \text{R+}\delta \\ \text{G+}\delta \\ \text{B+}\delta \end{pmatrix} \quad (3)$$

Where $\delta = PAN - I$.

With this simplification, the fused image can be easily obtained from the original RGB image, with only additions.

We note that there are many versions of IHS in the literature, and this version is limited to three bands (RGB). To extend this we can use equation (4) [5].

$$\text{MS}_{\text{fused}}\text{i}=\text{MS}_i+\beta \quad (4)$$

Where β is the difference between the high-resolution PAN image and each individual multispectral band i of n number of bands. It is calculated by using equation (5).

$$\beta = (\text{PAN} - 1) \Big/ \left(n \sum_{\text{i}=1}^{n} \text{MS}_i \right) \quad (5)$$

2.1.2 Brovey Transform algorithm

Apart from Intensity-Hue-Saturation (IHS), Brovey Transform (BT) is one of the most popular techniques in remote sensing image fusion. This technique is also called color normalization transform because it involves an RGB color transform method [19]. It is a classical technique and one of the most successful methods, based on spectral modeling. It was originally developed to increase visual contrast, especially at both extremities of the histograms of the data [5].

The general principle of this algorithm consists of resampling bands of the multispectral image to the resolution of the panchromatic image using interpolation. Then, the weighted average of the spectral bands is calculated to obtain a pseudo panchromatic intensity. Finally, the MS bands are multiplied by a ratio of the real panchromatic intensity and divided by the sum of the MS bands [20]. The general BT fusion procedure can be calculated by equation (6):

$$\text{Ms}_{\text{fused}} = \left[\text{Ms}_i \Big/ \left(\sum_{i}^{n} \text{Ms}_i \right) \right] \text{Pan} \quad (6)$$

By using weights and three bands (RGB), BT formula can be adapted as described in equation (7).

$$(R_{\text{fused}},G_{\text{fused}},B_{\text{fused}})=\text{PAN} * \left(R\Big/\left(\sum_{i}^{3} w_i\,\text{MS}_i\right), G\Big/\left(\sum_{i}^{3} w_i\,\text{MS}_i\right), B\Big/\left(\sum_{i}^{3} w_i\,\text{MS}_i\right)\right) \quad (7)$$

2.2 Bat Algorithm

The Bat Algorithm (BA) is originally designed to resolve a multi-objective optimization problem. It was inspired by the echolocation phenomenon of the microbats [21]. While flying [22], microbats emit high-frequency ultrasound. Then, the echoes are returned to the bat by the different types of prey and obstacles. The bats hear the echoes and analyze them to know the position and the nature of the prey and obstacles. Furthermore, bats are able to find their way and capture their prey even in deep darkness. To solve an optimization problem, the author of BA models the echolocation behavior of bats based on the three following rules:

1. Due to echolocation, bats can obtain detailed information about their environment, such as the distance and the nature of prey and obstacles.
2. Bats move randomly with a velocity v_i at the position x_i with the initial frequency f_{min}, varying wavelength λ, and loudness A_0 to search prey. They can automatically adjust the frequency and the rate $r \in [0,1]$ of their emitted pulses according to the proximity of their target,
3. It is assumed that the loudness varies between the values A_0 and A_{min}, where A_0 is positive and A_{min} is a minimum constant value.

Each bat corresponds to a possible solution of the optimization problem. A new solution is calculated during each iteration of the algorithm, according to equations (8), (9) and (10).

$$f_i=\text{f}_{\min} + (f_{\max} - f_{\min})\beta, \quad (8)$$

$$v_i^t=\text{v}_i^{(t-1)} + (x_i^t - x_*)f_i, \quad (9)$$

$$x_i^t=\text{x}_i^{t-1}+\text{v}_t^i, \quad (10)$$

where $\beta \in [0, 1]$ is a random vector calculated from an uniform distribution. For simplicity, the BA's author recommends the following assumptions: $f_{min}= 0$ and $f_{max}= 1$.

A bat can be blocked at a specific position and will stop the search for better solution. To avoid this behavior, a new solution is generated around the best actual solution for each bat using equation (11).

$$x_{\text{new}}=\text{x}_{\text{old}} + \epsilon A^t \quad (11)$$

where ϵ is randomly chosen from values in [-1, 1], and $A^t = \langle A_i^t \rangle$, the average loudness of all the bats at a current iteration.

To switch to the exploitation stage, the loudness A_i and the pulse rate r_i are varied during iterations when necessary. Therefore, as soon as the bat finds its prey, it reduces the pulse emission rate. So, $A_i \in [A_{min}, A_{max}]$ where $A_{min}= 0$ means that the bat has stopped temporarily emitting any sound because it has just found the prey. Under these assumptions, A_i^{t+1} *and* r_i^{t+1} can be calculated as follow:

$$A_i^{t+1}=\alpha A_i^t, \quad (12)$$

$$A_i^{t+1}=\alpha A_i^t, \quad (12)$$

$$r_i^{t+1}=\text{r}_i^0[1 - \exp(-\gamma t)], \quad (13)$$

Where α and γ are constants. For any $0 < \alpha < 1$ and $\gamma > 0$, we have $A_i^t \to 0$, and $r_i^t \to r_i^0$, as $t \to \infty$

For the standard bat algorithm, the simplest case assumes that $\alpha = \gamma$.

The principles steps of a standard bat algorithm are described in Figure (1).

```
Define the objective function: f(x), x=(x1,…,xd)T
Initialize the parameters: population size (N),
maximum number of iterations (nb_iter), α, γ, fmin,
fmax
Randomly initialize the population of bat: xi,vi
and fi
Initialize the pulse rate ri and the loudness Ai
Evaluate the fitness of each bat and initialize x*
with the bat which have the best fitness
set t=0
while (t<nb_iter)
  For each bat do
    Generate new solutions by adjusting frequency,
updating velocities, and location/solutions using
equation (8), (9) and (10)
    if (rand > ri)
      Generate a new solution surrounding the
selected best solution by using equation (11)
      Evaluate its fitness
    end if
    if (rand < Ai & f(xi) < f(x*))
      Accept the new solution
      Increase ri and reduce Ai
    end if
Evaluate the bats and calculate the current best x*
End while
Display results
```

Figure 1: Original Bat Algorithm

2.3 Proposed image classification Bat Algorithm

One aim of our study is to adapt the bat algorithm for remotely sensed image clustering (unsupervised classification). We use the bat algorithm to find the best centers of the groups composing a satellite image. The bat algorithm is simple to implement and it produces good results for clustering [23]. To use the bat algorithm for image clustering we consider the following elements:

2.3.1 The objective function

The goal of the bat algorithm is to find the centers of groups with the minimum dispersion from their centers. The mean square-error function [24] is used as an objective function. It is calculated by using the Euclidean distances between each pixel and a group center. The Euclidean distance is calculated as shown in equation (14). The point is affected to the group that gives the lowest value for the objective function.

$$\text{f}=\frac{1}{N}\sum_{\text{j}=1}^{k}\sum_{\text{i}=1}^{N} z_{\text{nk}}\left(d(p_i,\text{c}_j)\right) \quad (14)$$

Where, z_{nk} is an indicator variable, such that z_{nk} = 1 if the n[th] pixel p_i belongs to the cluster c_k and z_{nk} = 1 otherwise, $d(p_i, c_i)$ represents the distance between pixel p_i and a cluster center c_j. There are different distances that can be used such as Euclidean, Average, and Manhattan distance [25]. In this study, we have chosen the recognised Euclidean distance defined as [26] in equation (15).

$$d(P_i - P_j) = \sqrt{\sum_{\mathrm{d}=1}^{m} \left(p_i^d - p_j^d\right)^2} \qquad (15)$$

Where $d(p_i - p_j)$ is the distance between p_i and p_j, and m is the dimension of the data point. In our case, p corresponds to pixel and m to the number of bands.

2.3.2 The population of bats

In the proposed algorithm, each bat in the population corresponds to a candidate solution and is represented by a vector of dimension $k \times m$ as following : $x_i = (c_{11}, c_{12}, \ldots, c_{1m}, c_{2m}, c_{22}, \ldots, c_{k1}, c_{k2}, \ldots, c_{km})$, where k is the number of clusters, c_1 represents the first cluster's centroid, and c_k represents the k^{th} cluster centroid.

The principal steps of the bat algorithm for unsupervised image classification are described in Figure (2):

```
Initialization of all parameters of bat algorithm and the population of bat (assign a random pixel for each bat)
The classification of the image is performed according to the initial population. We obtain several classified images (each image corresponds to one bat
Evaluate the fitness value and find the current global best
As long as the number of iterations is not reached do:
  Move each bat by using equations (8), (9) and (10), so we obtain new position for each bat
  Evaluate the new solution and modify the best solution if the new solution is better,
  Generate a new local solution surrounding the selected best  solution by using equation (11) and evaluate its fitness
  if (rand > ri)
    Accept the new solution, increase ri, and reduce Ai if (rand < Ai & f(xi)<f(x*))
    evaluate the bats and find current best bat (corresponding to the best classification)
Increment the number of iteration
Classify the image with the best bat
```

Figure 2: Unsupervised image classification with Bat Algorithm

3. RESULTS AND DISCUSSION

To study the effect of image pansharpening on classification, panchromatic (PAN) and multispectral (MS) images of the same region from the Landsat 8 satellite are fused by both algorithms: Intensity-Hue-Saturation and Brovey Transform. The fused images are then classified by Bat unsupervised classification. Finally, the quality of the classified images is evaluated.

3.1 Study area

To assess the impact of image pansharpening on bat algorithm clustering, a high multispectral and panchromatic Landsat imagery of the Algerian city of Oran was used, which was acquired on 2020-02-06. A Landsat 8 image has 11 bands, one of which is panchromatic (PAN). In our experiments, we used the PAN image with a resolution of 15 meters and the three R, G, and B multispectral (MS) images with a resolution of 30 meters. The imagery covers a diversified area of land, particularly challenging for our study. Figure (3) represents a true color (a combination of RGB bands) and panchromatic images of the experimental area.

Mediterranean Sea is not particularly interesting. Consequently, the image is cropped to focus on two interesting areas, mixing several types of grounds. Figure (4) illustrate the cropped images Clip 1 and Clip 2. Clip 1 contains six regions: sea, vegetation, forest, urban, ground, and crop fields whereas Clip 2 contains five regions: vegetation, forest, urban, ground, and crop fields.

Figure 3: Oran, Algeria, Landsat 8 image collected on February 6, 2020, MS and PAN images respectively

Figure 4: Cropped images: Clip1 and Clip2


Figure 5: Clip 1: original image, IHS and Brovey Transform pansharpened images

3.2 Pansharpening

The aim of our study is to analyze the effects of pansharpening on the classification of satellite images by the bat algorithm. With this objective in mind, we applied the two pansharpening algorithms described before to multispectral and panchromatic images of our study area. We obtained two different pansharpened images, each one is composed of three different images (each one corresponds to one band). The final images are illustrated in Figure (5) and Figure (6) are used for classification.

3.3 Definition of parameters of Bat Algorithm

As described before, the Bat Algorithm (BA) highly depends on several parameters such as the frequencies or the attenuation. Choosing adequate values is relevant since it will impact the algorithm efficiency thus, the clustering. In our implementation, random numbers used in the algorithm are generated using the Mersenne Twister pseudo-random number generator [27] as implemented in the C++ standard library. As with every pseudo-random number generator, the generation is initialized using a seed. Thus, the generation behavior can be fixed using the same seed across each execution. After fixing the random aspect of the algorithm, we can repeat the execution while changing the parameters to find the most efficient configuration giving the best classification. Table (1) describes the experimentation intervals and the retained values of each parameter of the BA.

Every algorithm used in this paper is written in C++ and executed on Linux Manjaro using an Intel i5-8250U CPU and 8 GB of RAM. The proposed algorithm was run many days for fixing the appropriate parameters for clustering.

Once the best parameters were determined, the algorithm was run ten times to produce the results described later.

Table 1: Parameters setting in BA algorithm

Parameters	Value	Retained
Population size	From 20 to 70	20
Number of iterations	From 10 to 300	30
Minimal frequency (f_{min})	[0, 18]	2
Maximal frequency (f_{max})	[0, 18]	15 (if number of groups = 5) 18 (if number of groups = 8)
Attenuation coefficient of loudness (α)	[0, 1[	0.95
Increasing coefficient of pulse emission (ɣ)	]0, 1[	0.05
Updating solution coefficient (ε)	[1, 150]	100
Number of groups	[5, 8]	5 or 6

3.4 Evaluation method

To assess an unsupervised classification approach, comparing a classified image with a ground truth image is still the most used evaluation method. For this, we proceeded in two steps. First, we have prepared a reference image by manually classifying the studied area using our knowledge about the region and cartographic information available on Google Maps. Second, we have calculated a confusion matrix: a matrix that shows the correspondence between the classification result and a reference image. From this matrix, we can calculate two important metrics: kappa and the overall accuracy [13].


Figure 6: Clip 2: Original image, IHS pansharpened and Brovey Transform pansharpened images

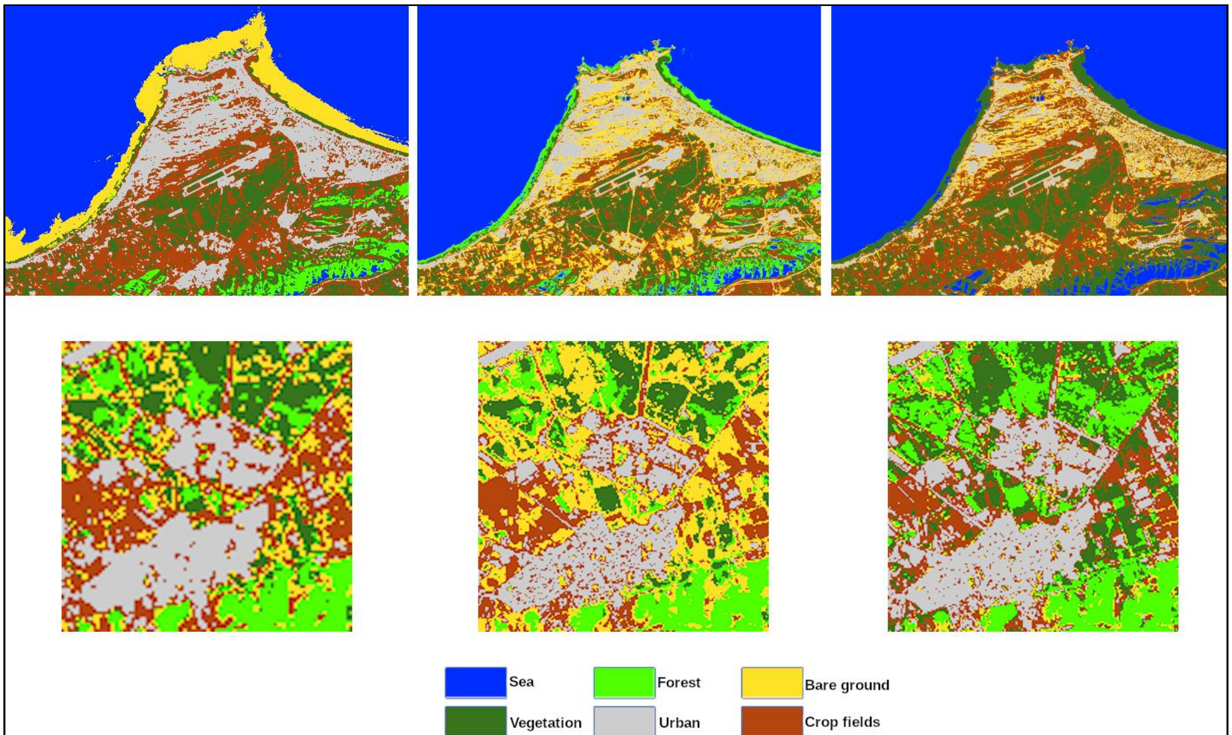

Figure 7: Clip 1 and Clip 2 classification: original, Intensity-Hue-Saturation pansharpened, Brovey pansharpened images

3.5 Discussion

3.5.1 Evaluation of bat unsupervised classification

To analyze and understand separately Bat Algorithm and its influence on image classification, we tested it on several types of images and compared it with K-Means. To illustrate the results, we have chosen the five most significant results out of ten. As shown in the graphs in Figure (8) and Figure (9), there is a considerable distinction between our approach and K-Means. Bat algorithm always gives the best values of kappa and overall accuracy. From this, we can deduce that using Bat Algorithm in unsupervised classification is better.

3.5.2 Evaluation of Pansharpening and classification

Figure (7) reports the classified images for both Clip 1 and Clip 2. We compare the accuracy obtained by using the original Multispectral (MS) images without fusion and the ones yielded using the proposed pansharpening techniques. The comparison clearly shows that, from a visual point of view, the use of pansharpening algorithms can show more details than non-pansharpened images. A more deep analysis of the accuracy is illustrated in Table (2). As the table shows, using pansharpening techniques significantly increases the values of kappa and classification accuracy.

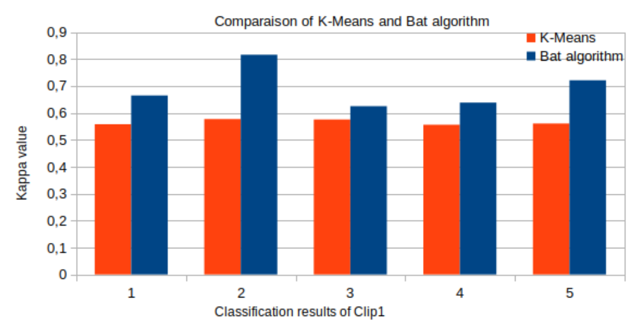

Figure 8: Comparison of Bat algorithm and K-Means (Clip 1)

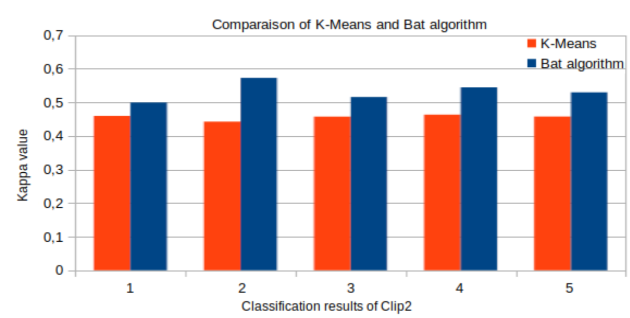

Figure 9: Comparison of Bat algorithm and K-Means (Clip 2)

Table 2: Kappa value and overall accuracy of non and pansharpened images

	Clip1			Clip 2		
	Fitness	**Overall accuracy**	**Kappa**	**Fitness**	**Overall accuracy**	**Kappa**
MS image	1.78	0.73	0.61	3.85	0.62	0.51
Pansharpened image (IHS)	0.48	0.90	0.86	1.32	0.67	0.57
Pansharpened image (Brovey)	0.67	0.80	0.71	1.99	0.9	0.86

4. CONCLUSION

The study of this paper consists of investigating the influence of fusion algorithms applied before using Bat Algorithm (BA) for classification. During this research, we used two different fusion algorithms (IHS and Brovey Transform). Panchromatic and multispectral Landsat 8 images are used to demonstrate the efficiency of the proposed approach. To determine the interest of using fusion algorithm before applying BA, the process is done on multispectral image only, then on the image obtained from the fusion. The results are evaluated using two classification quality metrics calculated from confusion matrix. Furthermore, the new approach is compared with K-Means.

The obtained results have shown that the classification is better when the fusion step is applied. Indeed, the aggregation of the panchromatic and spectral images results in a fully featured image containing more information at once. Visually, the resulting images have an increased contrast and therefore improve classification and interpretation. Furthermore the overall efficiency for BA is significantly higher than K-Means.

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