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Contrast Enhancement Effect on High Dynamic Range Image Registration Using Mutual Information

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Abstract

Mutual Information (MI) is emerging as a very strong metric for image registration purposes in the literature. It has many applications from remote sensing to medical image registration. From this wide range of use of MI, images are mostly expressed in different numbers of bits (high dynamic range) especially in medical and satellite imaging. In such cases, contrast enhancement becomes inevitable before MI-based image registration since all the images should be in the same intensity range. The change in intensities in images will directly affect MI metric. Contrast enhancement methods also have a significant effect on the registration performance due to MI metric and this problem is not sufficiently addressed in the literature. In this paper, the effect of the outstanding contrast enhancement methods is examined on image registration performance. For this purpose, high dynamic range satellite images were used and Monte Carlo tests were performed. They are tried to be aligned with MI and constrained optimization by linear approximations (COBYLA) optimization algorithm. Consequently, it is found that contrast enhancement methods have an effect on MI-based image registration. It is concluded that Laplacian of Gaussian unsharp blending masks (LoGUnsarp), adaptive histogram equalization (AHE) and contrast limited adaptive histogram equalization (CLAHE) methods have better registration performance. They can be preferred in such registration purposes.

Keywords — contrast enhancement, image registration, mutual information, optimization.

Introduction

The main purpose of image registration is to find the most appropriate geometric transformation parameters that maximize the similarity between two or more images. Two main methods are proposed in order to find the optimal parameters; feature and region based methods [1]. In feature-based image registration, points, lines, edges, curves in the image are considered [2]. On the other hand the grayscale properties of images are taken into account in region-based methods and a similarity metric is defined. This similarity metric can be cross-correlation [3], cross power spectrum [4] or mutual information (MI) [5, 6]. In this study, MI which is accepted as the state-of-the-art technique [7] is used to show the effect of the contrast enhancement techniques on the performance of image registration.

The MI metric has been proposed for aligning two or more images in image processing. In cases where the transformation between images can be expressed by homography, the objects in the images are also aligned by image registration. In this way, more detailed analysis can be accomplished in multi-band images by examining them simultaneously. It is possible to define image registration algorithms with 3 basic components: transformation matrix, matching metric and optimization algorithm [8]. The transformation matrix contains the geometric transformation that allows the images to align with each other and is basically performed into two ways: rigid and non-rigid [9]. The similarity metric provides information about how well the two images overlap each other. Nevertheless, optimization algorithms aim to find the optimal transformation that gives the best matching metric by refreshing the transformation matrix cyclically, in general.

In recent years, it is clear that MI-based metrics are preferred in many studies for the registration of images [5, 10-12]. It has promising results in multi-modality image registration [6, 7, 13, 14]. The study in [6] gives experimental evidence of the power and the generality of the MI by presenting registration errors from various image modalities involving CT, MR and PET. It states that the MI criterion is highly data independent and allows for robust and completely automated registration of multimodal images. Implicit Similarity (IS) over MI proposed for the registration of significantly dissimilar images, acquired by sensors of different modalities in [7]. However, it reports that MI outperforms IS. In the survey in [13], MI is stated as a successful registration measure for many applications including multi-band images and it can undoubtedly be adapted and extended to aid in many more problems. The algorithm proposed in [16] has accomplished registration of multiband satellite images by extending use of MI metric with kernel convolution. Multimodal and multiband images from different sensor do not always have the same dynamic range. For instance, thermal images are usually expressed in 14-16 bits while visible band images represented in 8-bits on a single channel. This situation makes the step of contrast enhancement or tone mapping necessary before image registration. The problem of how such techniques affects image registration performance with MI metric is not addressed in the literature. In this study, the effect of prominent contrast enhancement techniques on MI-based image registration is examined and registration quality of them is compared. The results reveal the necessity of such an analysis due to the observation that contrast enhancement method applied as a preprocessing step before MI-based image registration significantly affects the registration performance.

The remainder of the paper is organized as follows: The MI metric is described in section II and the contrast enhancement techniques tested are mentioned in section III. The contrast enhancement methods followed in this study are presented in section IV. Finally, in section V the results are discussed by supplying experimental results.

Mutual Information Metric

In information theory, the metric that measures the relationship between two random variables X and Y is called mutual information (MI). This metric actually measures how much a random variable contains the other. MI can be expressed as in (1) using Shannon entropy [15].

$$I(X,Y) = H(X) - H(Y|X) = H(X) + H(Y) - H(X,Y) \quad (1)$$

where H denotes entropy and I is the MI metric between given random variables X and Y. Assume that X and Y random variables represents two separate images. In this case, *H(X)* and *H(Y)* are entropy values of first and second image respectively and *H(X, Y)* is the joint entropy value between the two and these are defined as in (2) and (3), respectively. Since images are characterized as discrete signals, distributions are represented with probability mass function (PMF).

$$H(X) = -\sum_i \ p_x(i) \log(p_x(i)) \quad (2)$$

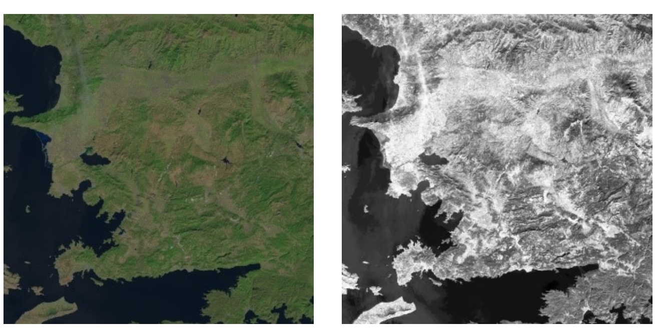
$$H(X,Y) = \ -\sum_{i,j} p_{xy}(i,j) \log(p_{xy}(i,j)) \quad (3)$$

In the equations (2) and (3), p_x is the marginal PMF of the random variable X, while p_{xy} denotes the joint PMF of the random variables X and Y. Given a set of observations for any random variable X, several methods have been proposed for estimating PMF. The most common techniques for estimating PMF of images are based on histogram [6, 16, 8] and kernel (i.e. Parzen window) [17, 18, 19] approaches. In this study, both methods are utilized to evaluate MI metric. In histogram based approaches, PMF is taken as histogram of the image. On the other hand, in kernel-based approaches, a kernel K as in (4) and (5) is used for PMF estimations.

$$p_x = \frac{1}{m} \sum_{i=1}^{m} K(x_i, x) \quad (4)$$

$$p_{x,y} = \frac{1}{m} \sum_{i=1}^{m} K(x_i, x) \, K(y_i, y) \quad (5)$$

where m represents number of samples and K is the kernel function. In this study, well-known method called Parzen window [17] is used for PMF estimation. It estimates PMF by taking samples randomly from the image. If sample size is too low, then estimated PMF will be far away from the actual PMF of the image. Thus this value is important for producing accurate MI metric. The third MI metric proposed in [16] is the combination of histogram-based and kernel density estimation methods. It divides the samples data all over the histogram bins instead of discretely assigning them to a specific bin. This method referred as hybrid-MI throughout this paper.

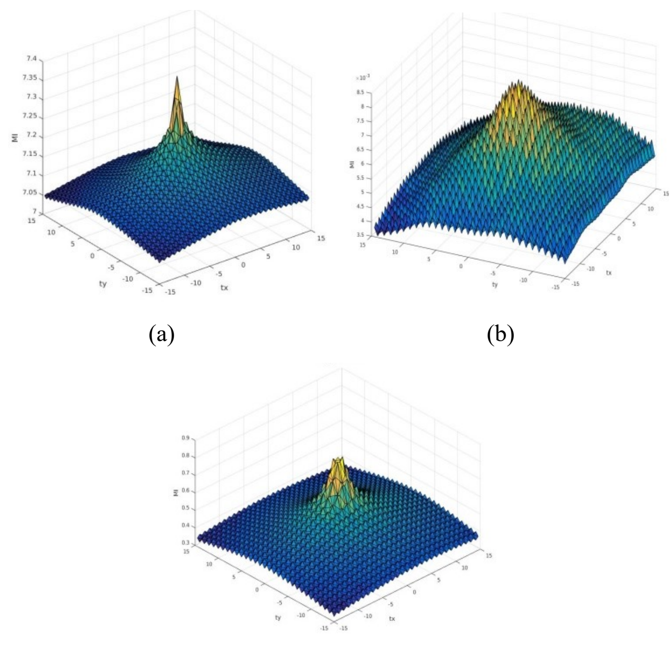


(a) (b)

Figure 1. (a) Visible band image and (b) 8-bit thermal image [29] which is converted from 16-bit using Min-Max Scaling)

The MI metric considers the intensity of the brightness values of the images as well as the joint probability distribution at the same time. The more the *X* and *Y* random variables depend on each other, the lower joint entropy value is obtained. As the joint entropy value gets lower, MI metric will be higher from (1) when *H(X)* and *H(Y)* are constant. Therefore, the MI metric is expected to produce the maximum value when two images are perfectly aligned. Typical visible and thermal band images used in this study are shown in Fig. 1.

In the utilized dataset [29], the images are initially aligned (see Fig. 1). In order to see the effectiveness of MI metric for image alignment, thermal image is translated on both x and y-axes with 0.5-pixel steps in the range of [-15, +15]. MI between translated image and visible image is calculated and the surface in Fig. 2 is obtained for all these cases. Bin number is chosen as 64 for histogram based MI metric. In kernel (Parzen window) based MI metric, standard deviation is taken as 0.4 and sample size is chosen as 0.05% of image dimensions (width*height). In hybrid MI, kernel size is 5, number of observation is 300 and bin width is 4. Since the images are aligned at the beginning, the maximum MI value is occurred at (0, 0). As it is clear from Fig. 2, MI is a powerful metric to deduce the quality of image registration.



(a) (b)

(c)

Figure 2. (a) Histogram based and (b) Parzen window kernel based and (c) hybrid MI metric distribution generated from translating thermal image in the range of ±15 pixels on both x and y-axes over visible

Contrast Enhancement Techniques

Details or the information in an image may disappear when high dynamic range images represented by more than 8-bits are displayed on standard 8-bit screens. For this purpose, it is necessary to reduce the number of bits preserving details as much as possible by using contrast enhancement techniques. This can be accomplished in in two ways in two ways, in spatial [20] and frequency domain [21]. In general spatial domain methods employ spatial location information of pixels and manipulate them. On the other hand, frequency domain methods utilize Fourier transform of an image to enhance mostly edges. The algorithm proposed in [20] computes the spatial entropy of pixels using spatial distribution of pixel in gray levels. On the other hand in [21], curvelet transform is used to enhance edges on noisy images.

Contrast enhancement is preferred to improve the visual quality of the image and the accuracy of computer vision applications. This process will affect the MI metric between the two images as it changes the brightness values in the image. In this study, the effect of contrast enhancement techniques is examined on the performance of MI-based image registration.

Min-Max Scaling

One of the easiest way to increase the contrast of an image is to apply linear min-max scaling as in (6). In this method, linear scaling parameters a and b can be found as the parameters that map the minimum and maximum intensity values of the image to 0 and 255 respectively if 8-bit representation is considered.

$$y = ax + b \tag{6}$$

$$0 = ax_{min} + b \tag{7}$$

$$L = ax_{max} + b \tag{8}$$

where x_{min} and x_{max} minimum and maximum intensity values in given high dynamic range image L is the maximum intensity level that image pixel can reach (i.e.255 for 8-bit representation).

Global Histogram Equalization

Histogram equalization (HE) is one of the best known techniques used to increase contrast in images. It performs good results especially in image data with close contrast values such as backgrounds and foregrounds that are both bright or both dark. Through this adjustment, the histogram of the entire image is uniformly distributed in the light and dark intensity levels. Histogram equalization can be performed as follows:

$$h(i) = round\left(\frac{cdf(i) - cdf_{min}}{M*N - cdf_{min}}\right) * I_{max} \tag{9}$$

where M, N are the image dimensions, I_{max} is the maximum intensity level (for 8-bit representation it is 255) and cdf is cumulative distribution function defined using the following relation.

$$cdf(X) = P(x \leq X) = \sum_{i<X} p_x(i) \tag{10}$$

Since the probability distributions are calculated in a global manner, this technique is called global histogram equalization.

Adaptive Histogram Equalization

Adaptive histogram equalization (AHE) is another image processing method proposed for enhancing the contrast in an image based on histogram equalization; however, it is applied locally contrary to global histogram equalization. It computes several histograms for each corresponding to a distinct section of the image and it transforms intensity using these histograms [22]. Although AHE is quite effective, in some cases it has a tendency to amplify noise in the image.

Contrast Limited Adaptive Histogram Equalization

Contrast limited AHE (CLAHE) enhances contrast locally like AHE and is a variant of AHE. The difference between AHE and CLAHE lies in its limitation of the slope of the transformation function. AHE has a tendency to overamplify noise while CLAHE prevents this by clipping histogram at a predefined value before CDF computation; therefore, it limits the slope of CDF [23].

Techniques with Unsharp Blending Masks

Some hybrid algorithms are proposed in contrast enhancement literature for concretizing edges in the images. Although MI is not a feature based metric, it is also investigated whether such techniques have an impact on image registration or not. The algorithm proposed in [24] is using GHE and unsharp masking based methods (UMBM) together for enhancing local contrast in infrared images. This method is called as HybirdUMBM in this study.

Laplacian of Gaussian (LoG) has a wide usage for edge detection purposes in image processing. Thus in order to enhance local details, LoG is adapted to HybridUMBM algorithm instead of UMBM and this method is referred as LoG-Blending throughout this study. In this method, image is smoothed with Gaussian kernel given in (11) to suppress the noise before using Laplace for edge detection. The second derivative of the Gaussian kernel gives LoG equation as in (12).

$$G_\sigma(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left(-\frac{(x^2+y^2)}{2\sigma^2}\right)} \tag{11}$$

$$LoG(x, y) = \frac{\partial^2}{\partial x} G_\sigma(x, y) + \frac{\partial^2}{\partial y} G_\sigma(x, y) \tag{12}$$

where σ refers to standard deviation.

Experimental Method

In the study, the effect of 6 different contrast enhancement algorithms, mentioned in Section-III, are analyzed in terms of MI-based image registration. Test images are obtained from NASA's official website (https://earthexplorer.usgs.gov) and a section covering Aegean and Mediterranean coasts is used. The images are 16-bit thermal and 8-bit 3-channel (RGB) satellite images of Landsat8. The images are initially aligned (see Fig. 1).

The steps performed in the Monte Carlo test are standard for each contrast enhancement method and are mainly as follows:

I. 8-bit 3 channel visible band image is converted to grayscale. 16-bit thermal image is converted to an 8-bit gray level image with tested contrast enhancement method.

II. Random rotation in the range [-5°, +5°] according to image center and random translation in the range of [-20, +20] pixels on both x and y-axes are applied to the 8-bit thermal image.

III. The random thermal image obtained in the previous step is tried to be aligned with the visible band image using constrained optimization by linear approximations (COBYLA) algorithm [25, 26] and defining MI metric as a cost function.

IV. Mean square error (MSE) is found between the initial thermal image (aligned with the visible band image) and the thermal image transformed using the estimated transformation matrix.

V. Step I has repeated once for each contrast enhancement method; II, III, IV are repeated 2000 times for the current contrast enhancement method. For each step, following results are saved for the analysis registration:

   a. Randomly introduced rotation and translation parameters

   b. Rotation and translations parameters found by optimization algorithm

   c. MSE

   d. Run-time in milliseconds

Image Coordinate Transformation

The optimization algorithm searches for a coordinate transformation that will maximize the MI metric in the search space. Although the transformation between the thermal and visible band coordinate axes can be expressed by affine or homography, an affine transformation is preferred in order to express the transformation matrix parametrically [9]. The matrix that performs the coordinate transformation contains the rotation and translation parameters (i.e. rigid transformation) and can be written as in (13) using homogeneous coordinates.

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta & t_x \\ sin\theta & cos\theta & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{13}$$

where θ is the angle of rotation, t_x and t_y represent the amount of translation in the x and y axes respectively. *x, y* and *x', y'* are the image coordinates before and after the transformation.

Contrast Enhancement and Optimization Parameters

Some of the contrast enhancement methods utilized in the experiments have several parameters. These parameters are determined as a result of some subjective tests that seek for the most visually pleasant images in terms of the level of details. These parameters are summarized in the following table.

Table 1: Contrast enhancement methods and its parameters

AHE [22]	SigmaS = 10, SigmaR =10
CLAHE [23]	Ctx:16, Cty=16, Number Of Bins=256, Cliping Limit=0.4
GHE [30]	Threshold: 5.0
Hybrid UMBM [24]	Kernel Size =3, Gain=200, Alpha=0.2
LoG-Blending (Propsed)	Laplace Kernel Size: 3 Gauss Kernel Size: 3

COBYLA is used as the optimization algorithm from the open-source NLOpt library [27]. The algorithm is a derivative of Powell's implementation [25, 26] and can be utilized to find local minimum or maximum. In this study, MI metric (cost function) is tried to be maximized as in (14) by updating transformation parameters. The library can handle numerical derivative operations and therefore there is no need to find the analytical derivative of the cost function. Function tolerance of the optimization algorithm is set to 1e-8 and maximum number of iterations is adjusted as 1500.

$$p^* = \arg\max_p \; I\,(I_1, T(I_2, p))) \tag{14}$$

where I is MI between visible image I_1 and warped thermal image I_2. T is transformation function (13) which takes parameter vector p composed of rotation (θ) and translation (t_x, t_y). Finally, p^* is estimated transformation parameters achieving maximum alignment.

Results and Conclusion

The aim of this study is to analyze the effect of contrast enhancement methods on high dynamic range image registration using MI metric. For this purpose, histogram-based MI, kernel-based MI (Parzen window estimation) and hybrid MI metrics are utilized in the tests. In order to compare the quality and performance of image registration, random rotations and translations, estimated rotations and translations, MSE values and run-times are saved for each step. As a result, it is observed that contrast enhancement methods significantly affect the quality of high dynamic range image registration.

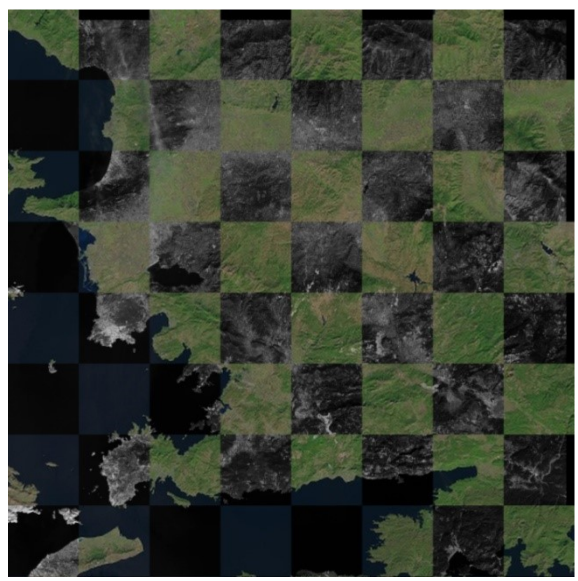
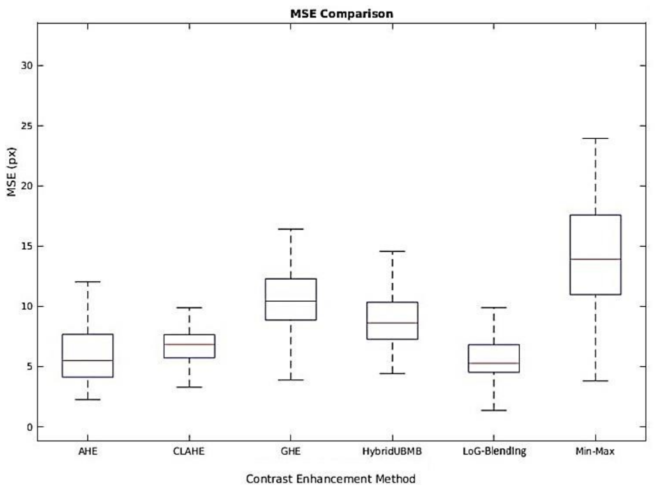
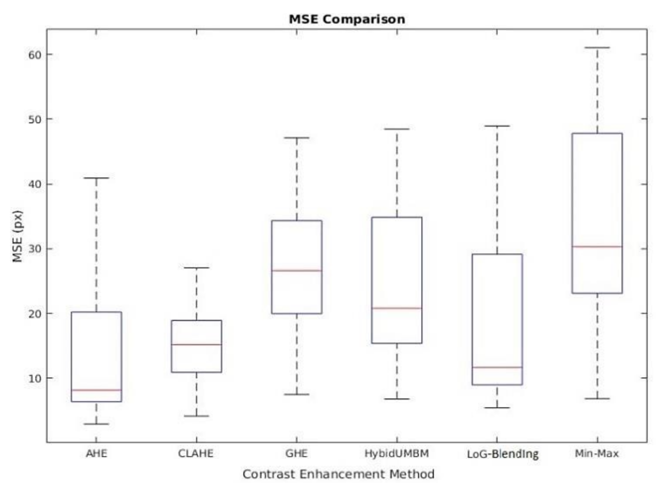


Figure 3. Typical registration result with CLAHE method

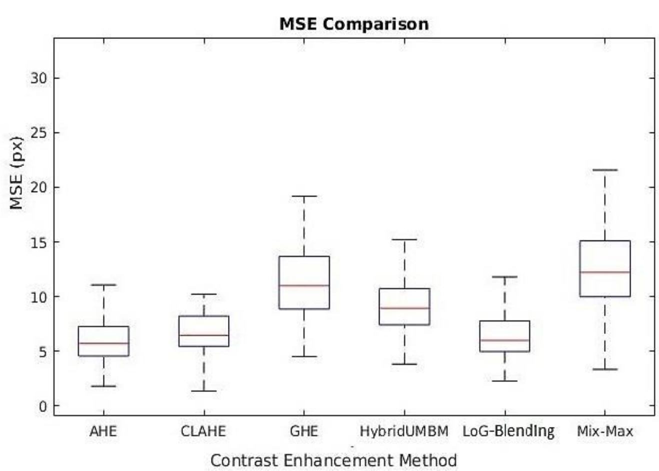
Typical registration result for CLAHE method is depicted in Fig. 3 in a checkerboard view. Boxplots in Fig. 4 show minimum, 1st quartile (%25 of samples), median, 3rd quartile (%75 of samples) and maximum MSE values from bottom to top for each contrast enhancement method respectively. It is also possible to make registration quality comparison between various MI types by looking at this figure. LoG-Blending, AHE and CLAHE methods are top 3 methods that have promising registration quality on each MI metric types. Min-max scaling has the worst performance on registration quality; however, it has acceptable errors with 15



(a)



(b)



(c)

Figure 4. MSE comparison in boxplot view for (a) histogram based, (b) kernel based and (c) hybrid MI-based image registration. AHE, CLAHE, LoG Unsharp methods have promising results in all MI type registration

pixels on average in histogram based and hybrid MI type registrations. In kernel-based MI (Parzen), registration quality is drastically decreased in some of the steps. The reason for relatively bad registration is that Parzen window cost function (see Fig. 2) is not as smooth as that of other MI types and has many local maximums. Since we have used local optimization algorithm (COBYLA), it is fitted to the local maxima in some of the steps in the test. If the sample size is increased for estimating PMF in kernel-based method, the cost function will be smoother but this time running time will increase due to random access to each pixel in the image.

We also save run-time for each registration step to figure out whether contrast enhancement methods affect also run-time and make registration faster or not. According to mean and variance values in Table 2 for running-times, AHE has the best running-time performance with lowest variance in histogram based and hybrid MI-based registration while CLAHE has the best in kernel-based MI (Parzen window estimation). Note that, tests performed on a laptop with following properties:

- Intel Core i7-4700HQ, 2.40GHz
- 16 GB of RAM
- Ubuntu 16.04 64-bit Operating System (OS)

The sizes of satellite images are 1024x1024.

Table 2: Average running-time for each contrast enhancement method for image registration and their variances. Rows in each method belong to histogram based MI, kernel-based MI (Parzen window estimation) and hybrid MI respectively

Method	Avg. run-time (s)	Variance (s)
Min-Max Scaling	19.209	98.075
	12.828	49.042
	28.724	168.497
GHE	18.727	83.665
	12.327	38.412
	22.719	113.611
Hybrid UMBM	22.636	96.177
	12.654	47.716
	26.539	140.684
LoG-Blending	19.777	58.940
	14.261	59.854
	24.061	127.548
AHE	**15.869**	**49.912**
	13.765	51.815
	19.127	**83.492**
CLAHE	17.864	80.711
	10.128	**13.781**
	21.050	96.185

In this paper, the effect of the contrast enhancement techniques on MI-based image registration is analyzed using satellite images having different dynamic ranges. According to the experimental tests performed, contrast enhancement methods have an impact on registration quality. LoG-Blending, AHE and CLAHE have stable and promising results for all MI types. These methods can be preferred for such image registration purposes. The worst contrast enhancement method is found as Min-Max scaling with the highest MSE values it produced (see Fig. 4). In addition to the registration accuracy, the selection of contrast enhancement technique affects convergence rate significantly. CLAHE and AHE methods have the fastest convergence rate in optimization (see

Table 2). It is also noted that histogram based MI and hybrid MI outperform Parzen window based MI with provided parameters for MI metrics in this study. If the sample size is increased in Parzen window estimation, it may produce better results.

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