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Image Resolution Increasing using Segmentation

Zahra Ghanbari, Vahid Ghods*

Department of Electrical Engineering, Semnan Branch, Islamic Azad University, Semnan, Iran.

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*Corresponding Author's Email Address:
v.ghods@semnaniau.ac.ir

Abstract

Increasing the image resolution is very important and is used in various fields such as medicine, photography, and machine vision. It is possible to see more details of the image and analyze it better by increasing the image resolution. However, increasing the image resolution has also been associated with some challenges. Increase in noise, increase in artificial details, and high processing time are among the typical challenges. In addition, interaction with image complexities such as images with repetitive patterns and non-textured noises creates other challenges either. Image is divided into smaller parts using segmentation. Then, the images are combined with each other using the support vector regression algorithm and new images are created. A multi-stage process has been used to increase the image quality in this research and the pre-processing operation has been carried out in the first stage in order to improve the image quality. Three phases of training, testing, and parameter adjustment have been used after the pre-processing operation in order to increase the image quality. In the training section, the images are first converted to lower levels, and the color segmentation operation takes place at the lower levels. After the image classification operation in terms of color, the gradient is used to extract the image properties. The support vector regression algorithm was used to predict the image pixels, and this algorithm was improved by a meta-heuristic algorithm called whale algorithm. Evaluation parameters including PSNR and SSIM criteria have been used in this research that yielded promising results

Introduction

Photo resolution has become one of the most popular issues in the last decade. It is possible to record images with high resolution and more details as the technology of cameras, scanners, and image edit software advance [1]. Indeed, the resolution refers to the extent of accuracy and clarity of the image. The higher the image resolution, the more details can be seen in the image [2]. This issue is very important in many fields, including photography, graphic design, image medicine, as well as video and film production. The images are investigated and analyzed more accurately and it is possible to identify smaller details and more color and contrast differences due to the high resolution [3, 4]. This is very important in diagnosing diseases in medical images, analyzing scientific and research pictures, as well as designing websites and content production. The main goal is to reduce the blur (opacity) in central points and edge of the image in issues related to increasing resolution by using different algorithms [5].

More precisely, the points of the image whose quality has decreased during imaging can be recovered using this technique. Methods of increase in resolution or supper resolution are classified into two categories based on the type of process: resolution with the help of a single image and resolution with the help of multiple images [6 and 7]. A low-resolution image is used as input in resolution with the help of single image and a high-resolution and more accurate image is obtained by using complex algorithms and image processing techniques. This method is mostly used in cases where only a single low-resolution image is available, such as the ones taken by conventional cameras. Several low-resolution images are used as input in multi-image resolution. These images can be created by small changes in camera position or observation angle or by using multiple images taken gradually in higher quality.

Doi:

The high-resolution image and more details will be obtained using image processing techniques and algorithms. This method is mostly used in cases where a number of low-resolution images are available and a better-quality and high-resolution image is obtained by combining them. The classification of these two methods based on the type of process shows whether the process of increasing the resolution of images is conducted using only one single input image or requires the use of several images. In this research, quality enhancement is used using the photo itself. Therefore, this research will be in the category of resolution with the help of a single image. A high-resolution image is estimated from a lower-resolution image in order to perform this process and increase in quality of images. Therefore, the high-resolution image will be the output of the supper resolution process and the low-resolution image will be considered as the input of this process [8].

One of the challenges of the image resolution is noise and ambiguity in the image. Noise can result from various sources such as background light, camera sensor, image transmission and compression and can cause the reduction of image resolution and quality. In addition, ambiguity can occur due to lighting changes, camera movement, or moving objects in the scene and cause the reduction of the resolution accuracy of the image. Different methods can be used to solve the resolution challenges of photos. Noise removal algorithms such as average, median, and Gaussian filters can be used to reduce the noise and ambiguity in the image [9]. Also, the use of resolution algorithms such as unsharpening and sharpening filters can help improve the image resolution. Furthermore, the use of advanced imaging techniques such as high-pace photography and HDR photography can also help improve the resolution of images. Image stabilization techniques such as using electronic image stabilizers or mechanical stabilizers can be used to solve the challenge of camera movement and moving objects in the scene [10].

Research Background

Chen et al. have used the image resolution method by means of a single image to increase the image resolution in 2022. The main goal of this research is to reconstruct a high-resolution image from a low-resolution image. The proposed method consists of two main steps. In the first stage, deep networks are used to generate high-resolution images from low-resolution images. The low-resolution images are given as input to the network using this method and the network generates high-resolution images using deep learning. This new method can significantly improve the resolution of images and increase their quality. In the second stage, they used the techniques such as combining resources and using information related to the image structure to improve the performance of the proposed method. They extracted more information about the high-resolution image by combining several low-resolution images together. Also, they used the information about the spatial relationships between pixels by investigating the image structure to improve the high-resolution image. This combined approach significantly caused the improvement of the images' resolution and increase in their resolution. The experimental results obtained from the available data support the effectiveness of the proposed method [11].

Eilers et al. have used the image resolution method by means of a single image to increase the image resolution in 2022. The proposed method uses a simple and fast algorithm to increase the resolution of images with exceptional singular image quality. This algorithm is based on penalized least squares regression method and two-dimensional complexity tensor structure. Two penalties (ridge and difference) get combined in this method. The ridge penalty is used to remove singularities and the difference penalty is used to remove ringing noise. Conjugate gradient algorithm has been used to avoid explicit matrix inversion. This algorithm processes the large images easily. The obtained experimental results show that the proposed method has been proficient in increasing the image resolution [12].

Jiang et al. used deep neural networks to increase the image resolution in 2021. In this research, the proposed method has used low-quality image resolution methods based on deep learning in a systematic way. The low-quality image resolution problem is explained briefly in the first stage of the proposed method and common evaluation criteria are introduced. Facial features and dataset are used in the resolution of the low-quality image in the second stage. Facial features are categorized in the last step according to the results obtained from the existing methods. The obtained experimental results show that the proposed method has been proficient in increasing the image resolution [13].

Kayo et al. have used deep neural networks in 2020 to increase the image resolution. The proposed method introduces a deep neural network called FDNN for low-quality image resolution. This network has two important advantages over existing SISR methods. The first advantage is that it improves network performance without increasing the depth or using complex structures. Its second advantage is that it replaces all convolution operations with deconvolution operations to perform effective reconstruction. In other words, the proposed FDNN only includes deconvolution layers and converts from low-quality images into high-quality ones. The obtained experimental results indicate that the proposed method is superior to other existing methods [14].

Proposed Method

The hierarchical process has been used to increase the image clarity in this research. Before stating the proposed method, it is necessary to state the existing challenges and goals in increasing the clarity of an image. The main goal in increasing the image clarity is to increase the image quality using low clarity to high one but there are challenges in this process that need to be addressed.
One of the main challenges in increasing the image clarity is the loss of real details of a low-resolution image because there is less detail in low-resolution images and detailed information about the details of the image is lost. Therefore, clarity-increasing algorithms should be able to recover these details and produce a high-resolution image with more details.
Another challenge in increasing the image clarity is maintaining the reality and naturalness of the image. When increasing the resolution, images should be created that do not have an inappropriate and artificial shape. Therefore, the resolution enhancement methods should be able to reasonably combine the new details with the details in the low-resolution image so that the final image is close to the image reality. Considering these challenges, the resolution enhancement methods should be able to significantly improve the resolution and quality of the image while maintaining the image features. Therefore, the process shown in Fig. (1) will be used in this research

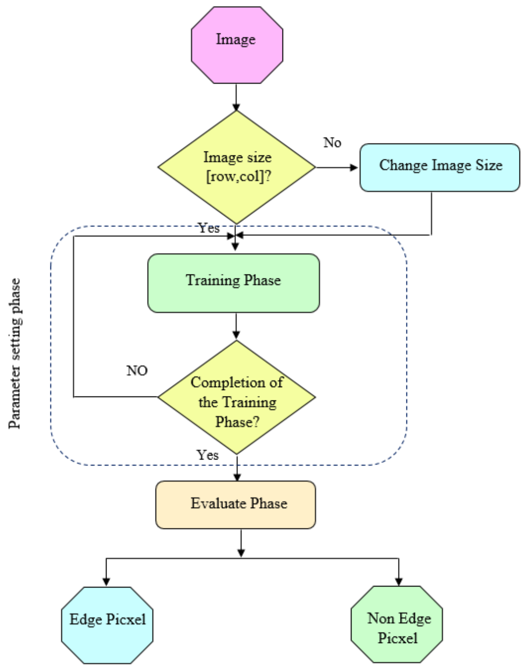

Fig. 1: Resolution process and image clarity enhancement

Fig. (1) shows the process of resolution and image clarity enhancement in the proposed method. The proposed method uses three phases of training, parameter adjustment, and test phase to increase the image clarity. Each of the desired sections will be explained in the following.

A. *Pre Processing*

The first step in the proposed method is the pre-processing operation. The sections shown in Fig. (2) are performed in this operation.

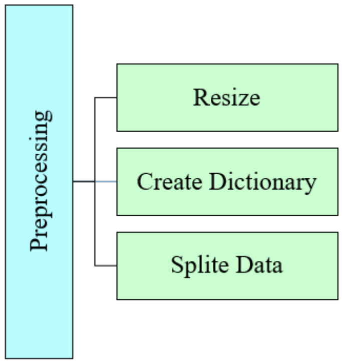

Fig. 2: Pre-Processing Operation

Resizing images before increasing the image clarity can have a significant impact on image enhancement. In addition to improving the image clarity, the image size can also affect the features extracted from the image. The larger the size of the images, the more features extracted from the image. Therefore, the size of the images should become identical for the size of the extracted features being identical.

Creating a dictionary plays an important role in increasing the image clarity. A dictionary is used as a set of patterns in this method that is attributed to low- and high-resolution images. This dictionary is usually taught using high- and low-resolution images. The purpose of creating a dictionary is to create patterns for the support vector regression algorithm. The support vector regression algorithm needs identification patterns to predict the image pixels. It takes the identification patterns from the patterns existing in the dictionary. The support vector regression algorithm is fully described in the next section. High-resolution images are used as a training set in the dictionary creation process. These high-resolution images are used as reference patterns. Then, a corresponding low-resolution representation (display) is trained for each pattern in the dictionary. These displays are produced using low-resolution images.

The aim of data segmentation is to classify them into training and testing groups. In this research, data means the images used. The aim of using the training data in enhancing the image resolution is to train algorithms and models for training and teaching with high-clarity data. Using the training data, we can train models and algorithms that can transform the low-resolution images into high-resolution ones. The training data is used to create the dictionary model and the test data is used to evaluate the model.

B. Training Phase Using Support Vector Regression

The proposed method uses the two phases of training and testing to increase the image clarity. The aim of the training section is to develop a model to increase the image clarity. In this step, the input image is first converted into two other images based on a reduction rate. In this case, we call the input image as the main image, and two other images named I1 and I2 are made out of this image, which are known as low-level images. The purpose of this operation is to produce an image as large as the input image, which is known as the high-level image, and we call it Ir. Now, the low-level images are used to recover the final image. Two-cube interpolation is used in order to create this transformation.

Two-cube interpolation is one of the widely-used methods in increasing the images' clarity. In this method, neighborhood information and existing pixels in the low-resolution image are used to generate new pixels in the high-resolution image. The low-resolution images are continuously converted into high-resolution ones using bicubic interpolation without creating dark lines at the edges. Using cubic functions to estimate new pixel values, this method provides better results than simpler methods such as linear interpolation. The bicubic interpolation method attempts to interpolate a surface within four points of a corner using a third-degree polynomial function. The values of intensity and the horizontal, vertical, and diagonal derivatives must be determined at the four points of the corner to calculate the bicubic interpolation. The interpolated surface, f_i (x,y), which is described by a third-degree polynomial, is obtained using Eq.1.

$$f_i(x,y) = \sum_{i=\text{۰}}^{\text{۳}} \sum_{j=\text{۰}}^{\text{۳}} a_{ij} * x^i y^j \qquad (1)$$

16 coefficients of a_ij must be specified to calculate the function in equation (1). Four coefficients of the intensity values in the four corners have been determined directly; eight coefficients are obtained from spatial derivative in horizontal and vertical direction and four coefficients are obtained from diagonal derivatives. Fig. (3) shows the bicubic interpolation operation.

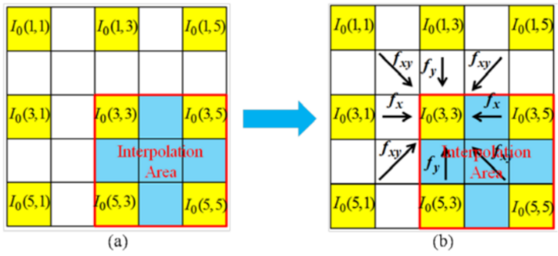

Fig. 3: Pre-Processing Operation

Bicubic interpolation usually causes the blurring (opaqueness) of the details and edges of the image. This is due to the use of third-order polynomial functions in the interpolation, which usually results in a more normal and well-developed transfer of detail. For this reason, the bicubic interpolation algorithm cannot accurately reconstruct fine details and sharp edges. We first segment the lowest level of the image, which is known as the I2 image, based on the appearance information of the matrix, which includes color and brightness in order to preserve the existing information of the edges. The resulting image is called 〖I'〗 _2 as a new image. Now, in this case, the image contains N parts, each of which has a single color. Now, we reconstruct the target image based on bicubic interpolation. The most important advantage of this method for interpolation is that the number of areas will be the same in all levels and the desired areas will be corresponding in all recovery levels, too. For example, the zoning of the Lena image is shown in Fig. (4).

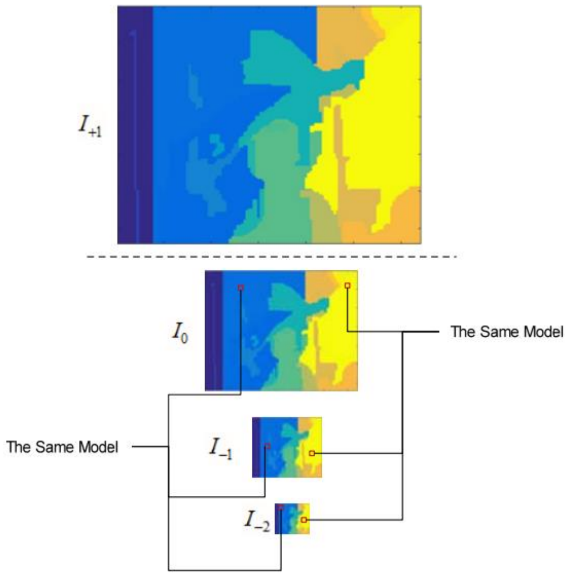

Fig. 4: Zoning of images based on two-cube interpolation method

In this research, the first and second-order gradients are used to predict the edge value. The overlapping method is used to calculate the gradient of the first and second order of a pixel. In this case, a 5x5 window is considered around the desired pixel so that the desired pixel is located in the center of the matrix. This window is the same for every image patch at different levels. Now, if we consider the vector G(i,j) as the feature vector of the first and second order gradients for pixel (i,j) in image I, then this matrix can be calculated as Eq. 2.

$$G(i,j) = \begin{bmatrix} I(i+1,j) - I(i-1,j) \\ I(i,j+1) - I(i,j-1) \\ I(i+2,j) - 2 * I(i,j) + I(i-2,j) \\ I(i,j+2) - 2 * I(i,j) + I(i,j-2) \end{bmatrix} \qquad (2)$$

In other words, we can reconstruct high-quality image pixels more accurately by using this algorithm. Also, the algorithm is able to recognize the patterns and structures in the image and perform better in the reconstruction process using the information in the trained lists. Having detailed information and the capability to make accurate estimations is an important advantage for the support vector regression algorithm in increasing the image clarity.

Support vector regression is a method derived from machine learning algorithm that we can develop a prediction model, which can provide accurate predictions for new data based on the training data, by using support vector regression methods. This algorithm operates based on the concept of vectors' support in which the training data are used as supports in the model.

The main goal in support vector regression is to optimize the regression problem using a kernel function. This kernel function allows the use of high-dimensional features space and makes support vector regression applicable to complex problems with non-linear data. Using the support vector regression algorithm, we can develop a robust prediction model that is capable of accurate and stable estimation for new data. The desired model is trained based on the values of the first and second order gradient vector. As stated above, the gradient features are calculated for each pixel and the image pixels are predicted using the gradient values and the model developed by the support vector regression. In this case, the image pixels for reconstruction are determined using the support vector regression. In other words, the input of the support vector regression in this case is the features extracted from the gradient and the output of the support vector is the predicted value of the image pixels.

C. Test Phase

The model evaluation operation takes place in this section. The process shown in Fig. (5) is used to evaluate the model. The process is described at below.

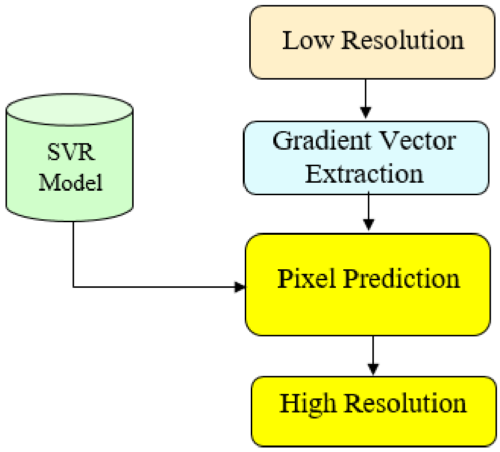

Fig. 5: Test phase to predict image pixels

Fig. (5) shows the pixel prediction operation for test data. At this stage, low-resolution images are first sent to the gradient vector section. In this section, gradient vectors are extracted based on the available pixels. The extracted gradient vectors are transferred to the support vector machine regression algorithm that was taught in the previous step. Now, the image pixels are predicted based on the gradient vector and the support vector regression model.

D. Parameter Adjustment Phase

One of the important parts of the proposed method is the one related to setting (adjusting) the parameters of the support vector regression algorithm. The whale algorithm has been used to set the parameter of the support vector regression algorithm in this research. Therefore, the input of the whale algorithm is the support vector regression parameters that are not optimized, and the output of the whale algorithm is the optimized parameters of the support vector regression. In other words, the input of the whale algorithm is in the form of a range of parameter values (a range of values is considered for each parameter), but the output of the whale algorithm is in the form of a single value (a value is considered for each parameter). The whale algorithm uses the process shown in Fig (6) to set (adjust) the desired parameters. This process is described at below.

Fig. 6: Algorithm parameter adjustment process

The support vector regression algorithm has several adjustable parameters that can be improved by using the whale algorithm. These parameters include C, Gamma, and kernel parameters. Parameter C is related to determining the tolerance level in the model training trend. Tolerance in the concept of support vector regression refers to the extent to which the data is allowed to fit the model or the error in data prediction. In other words, tolerance shows how well the model fits the training data, or in other words, how much it cares about the training data. As the value of C increases, the model fits the training data better and may cause an increase in overfitting. The whale algorithm can be used to optimize the appropriate value of C. The Gamma parameter is related to the influence of data points on other points in the model. A high gamma value makes the data points close to each other more influential in the model. An appropriate value can be considered for the gamma parameter using the whale algorithm. Selection of the correct kernel function for the given problem can also be improved by using the whale algorithm. The whale algorithm can check different combinations of kernel functions and determine the appropriate kernel function for the given problem.

Now, the initial population in the whale algorithm is set as follows based on the desired parameters, which is shown in Fig. (7).

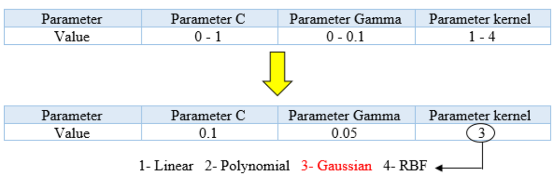

Fig. 7: Initial population

The fitness function used in this research is the SSIM function. This criterion calculates the similarity of the recovered image to the real image. The closer the value of this criterion is to one, the more similar the recovered image is to the original image. Therefore, the goal used in this research is maximal. The input of the fitness function is the original image and the recovered image and the output of the objective function is the degree of similarity of the recovered image relative to the original image. The original image is used to measure the efficiency of the proposed method. The most important reason to use the SSIM criterion is to measure the proposed method. If we want to supply the proposed system with the market, then the proposed system must be evaluated on a dataset. In this case, a high-quality and a low-quality image are available for each image and the high-quality image is determined as the main image and the low-quality one is determined as the input of the proposed algorithm in this case. The goal of the proposed algorithm is to create an image that is close to the high-quality one. The more the image created by the proposed method is to the original image (the high-quality image should be closer), the higher the value of the SSIM criterion will be. The fitness function is defined in Eq. 3.

$$SSIM = \frac{2 * \mu_I * \mu_{I'}}{{\mu_I}^2 + {\mu_{I'}}^2} * \frac{2 * \sigma_{II'}}{{\sigma_I}^2 + {\sigma_{I'}}^2} \quad (3)$$

In the above equation, μ_I indicates the average pixels of the original image, μ_I^') indicates the average pixels of the recovered image, σ_I indicates the variance of the original image , 〖σ_(I^')^2 indicates the variance of the recovered image, and σ_(II^') indicates the covariance of the images.

Results

The evaluation criteria of the proposed method are given in this section and these criteria include the following, which are described at below.

$$\text{PSNR} = 10 * \log_{10} \frac{Max^2}{MSE} \quad (4)$$

Max represents the maximum pixel value, which is equal to 255, in the above equation. In addition, the standard dataset used in the reference paper has been used in this research to evaluate the proposed method and these images are shown in Fig. (8).

Fig. 8: The set of desired images to evaluate the proposed method

The results of the proposed method are given based on PSNR and SSIM criteria in this section. The criteria are given in Table (1).

Table (1): The results of the proposed method

Picture Name	Picture	PSNR	SSIM
Tree		31.12	**0.92**
Lena		38.25	**0.965**
House		35.45	**0.9320**
Susan		36.75	**0.9685**
Peppers		37.75	**0.9415**
Boat		34.33	**0.9125**
Airplane		35.85	**0.9710**
Baboon		32.65	**0.8535**

Table (1) shows the results of the proposed method for test images. Fig. (9) shows a comparison between the results obtained by the PSNR criterion by the proposed method.

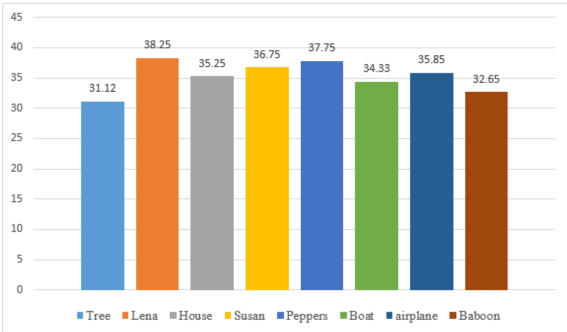

Fig. 9: Comparison of results based on PSNR criterion

The PSNR criterion is used to measure the quality of images. This criterion calculates the signal-to-noise ratio by comparing the difference between the original image and the post-recovery image. Using the PSNR criterion to compare the two images can be used in two different fields. First, we can compare the quality of the recovered image with the original one in the field of image recovery by calculating the PSNR. As the PSNR value increases, the recovered image quality is closer to the original image. This criterion can help us compare and evaluate the image recovery algorithms. Secondly, the PSNR criterion can be used to compare the quality of images after applying filters, color changes, resizing, etc. in the field of image processing. We can see how much the changes applied to the image have caused the quality loss by calculating the PSNR value. In general, using the PSNR criterion to compare two images helps us better understand the image quality and the changes applied to it. This criterion can be used to evaluate and improve algorithms and image recovery and processing methods. The higher the value of this criterion, the higher the quality of the image. Fig. (10) shows the comparison of the results of the proposed method based on the SSIM criterion.

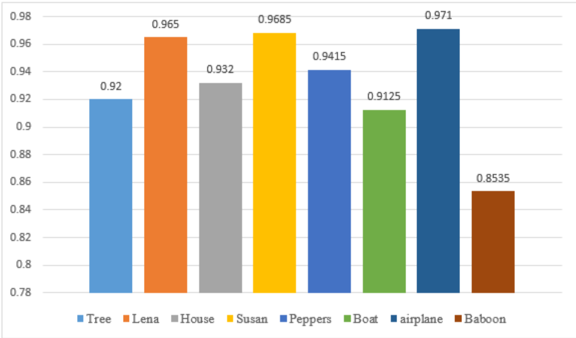

Fig. 10: Comparison of results based on PSNR criteria

The SSIM criterion is used to measure the structural similarity between two images. This criterion provides an accurate assessment of image quality changes according to the structure and details of the images. The value of SSIM is between 0 and 1, with the highest value being 1. A high SSIM value indicates the similarity between two images. In other words, the closer the SSIM value is to 1, the more structural similarity between the two images. The SSIM value shows how similar the test image (post-recovery image) is to the reference (original) image. Whenever the value of SSIM is close to 1, it indicates the preservation of the structure and details of the image, and its high value indicates the high quality of the image. Therefore, a high SSIM value in comparing two images is a sign of high similarity and high quality in the test image relative to the reference image. In practice, high SSIM values are usually considered to be 0.9 and higher that mean the preservation of very good detail and structure in the image. As the SSIM value increases, the structural similarity and image quality improve. The results of the proposed method with other evaluation methods stated in the reference paper are given based on the PSNR and SSIM criteria in the following and these results are shown in Table (2).

Table (2) shows a comparison between the proposed method and the methods stated in the reference paper based on the PSNR criterion. The results of the proposed method are superior to the method of the reference paper since the support vector regression algorithm is used to predict the pixels of the final image and this algorithm is improved by the whale algorithm in the proposed method in addition to segmenting the areas. Therefore, the efficiency of the proposed method is higher than the results of the reference paper. Table (3) shows a comparison between the proposed method and reference paper methods based on SSIM criteria.

Conclusion

Three phases of training, testing, and parameter improvement have been used for the image resolution in this research. The images are first classified into smaller areas in the training phase. The classification of images is based on the image color. The characteristics of each patch are calculated after classifying the images based on the area based on the gradient algorithm. Finally, the support vector regression algorithm is used to predict the pixels of the image. The most important challenge of the support vector regression algorithm is to determine the algorithm parameters. The whale algorithm has been used to predict the regression parameters of the support vector in this research. The whale algorithm consists of four processes to predict the parameters: initial population, fitness, population improvement, and stoppage condition. After introducing the evaluation criteria, test images are given to evaluate the proposed method, which include tree, Lena, house, Susan, peppers, boat, airplane, and baboon. The results of the proposed method for the above images for the PSNR criteria are 31.12, 38.25, 35.45, 36.75, 37.75, 34.33, 35.85 and 32.65, respectively, and these results for the SSIM criteria are reported to be 0.92, 0.965, 0.9320, 0.9685, 0.9415, 0.9125, 0.9710, and 0.8535.

Table (2): Comparison of the results of the proposed method and the reference paper based on the PSNR criteria

Picture Name	PSNR							
	Reference							Our Method
	Bicubic	SlSR	LLE	ScSR	LsSR	SlNE	SR_Segment	
Tree	28.39	26.94	25.82	29.12	27.39	28.50	29.64	**31.12**
Lena	35.44	33.65	33.49	36.24	33.88	35.73	36.63	**38.25**
House	32.21	30.92	29.49	32.72	31.02	33.13	33.46	**35.45**
Susan	34.71	33.75	31.84	35.37	32.10	35.74	35.57	**36.75**
Peppers	33.17	31.71	30.64	33.59	31.39	33.82	34.65	**37.75**
Boat	29.94	29.79	24.27	30.64	30.27	28.56	32.18	**34.33**
Airplane	36.68	31.15	29.68	33.35	31.66	33.05	34.20	**35.85**
Baboon	24.96	23.38	22.94	25.49	23.65	25.29	25.70	**32.65**

Table (3): Comparison of the results of the proposed method and the reference paper based on SSIM criteria

Picture Name	SSIM							
	Reference							Our Method
	Bicubic	SlSR	LLE	ScSR	LsSR	SlNE	SR_Segment	
Tree	0.8730	0.8410	0.8257	0.8887	0.8122	0.8779	0.8988	**0.92**
Lena	0.9317	0.8986	0.9056	0.9380	0.9062	0.9346	0.9425	**0.965**
House	0.9034	0.8693	0.8446	0.9079	0.8841	0.9088	0.9159	**0.9320**
Susan	0.9466	0.9290	0.9239	0.9480	0.9391	0.9510	0.9538	**0.9685**
Peppers	0.9024	0.8660	0.8669	0.9046	0.7924	0.9195	0.9131	**0.9415**
Boat	0.8541	0.8334	0.6214	0.8714	0.8461	0.8709	0.8905	**0.9125**
Airplane	0.7255	0.9211	0.9122	0.9484	0.9242	0.9472	0.9561	**0.9710**
Baboon	0.8852	0.6854	0.6630	0.7809	0.6663	0.7555	0.7886	**0.8535**

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