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Image Upscaling and Fuzzy ARTMAP Neural Network

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Abstract: *In Image upscaling, a higher resolution image is processed from an available low resolution image. There are numerous scenarios and applications where image upscaling is required and performed. The paper proposes a simple image scaling algorithm and implements it with a fuzzy variant of the supervised ART neural network, ARTMAP. The method has been compared with nearest neighbor interpolation, bilinear interpolation and bicubic interpolation, both objectively and subjectively. The present paper is an attempt at understanding the Adaptive Resonance Theory networks while proposing a simple linear upscaling method.*
Keywords: *ARTMAP, Artificial neural network, bilinear, nearest neighbor, Upscaling*

I. Introduction

Digital image processing is a field of computing that deals with processing and operations on digitally acquired images. Image processing entails various operations like enhancement, restoration, segmentation, feature extraction etc. Image upscaling is one of the various applications of the wide field of digital image processing. In upscaling, we aim to produce a high resolution replica of an image from the original low resolution image as shown in Fig. 1. The goal of image interpolation is to produce acceptable images at different resolutions from a single low-resolution image. The actual resolution of an image is defined as the number of pixels, but the effective resolution is a much harder quantity to define as it depends on subjective human judgment and perception[1]. It so happens, that we quite often come across situations when we have to deal with an image which is big enough spatially to view or observe the subject(s) comfortably or effectively. In such situations we need to obtain a bigger image, a higher resolution image, which is easier to work with. This is where image upscaling or up-sampling comes in. It takes a small image as input, performs some operations and gives a bigger replica. It should be noted however, that up-sampling the image will not add any more detail to the original image. A simple definition image is still simple definition, upscaling will only increase the spatial resolution; not enhance the definition or detailing to the image than it already has.

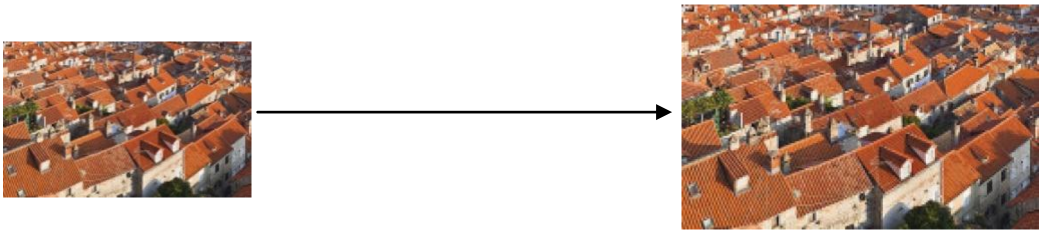

Fig 1: Original image to Upscaled image

The image upscaling problem is also referred to as 'single-image super-resolution' problem.

1.1 Need for Image Upscaling

Scaling of images from lower resolution to a higher resolution is needed because of the following reasons:

1) It's easier to analyze and study higher resolution images.
2) Available sensors have limitation in respect to maximum resolution[2] So we need upscaling to overcome some of the inherent resolution limitations of low-cost imaging sensors [3]
3) To produce images of high perceptual quality and produce visually appealing results
4) To keep the text and graphics as original as possible, while avoiding noise and artifacts in the image [4]
5) To preserve the nature and texture of image while enlarging it.
6) To allow for better utilization of the growing capability of High Resolution displays (e.g., HD LCDs). [3]

1.2 Applications of Image Upscaling

Image upscaling (and more generally image interpolation) methods are implemented in a variety of computer tools like printers, digital TV, media players, image processing packages, graphics renderers and so on.[4]. Some application areas of image upscaling/ single image super resolution are as follows:

1) **Printing:** To scale and print images according to canvas size while maintaining picture quality.

2) **Video playback:** Televisions use real time up scaling algorithms to display simple definition content on high-resolution displays.

3) **Mobile devices:** To scale graphics and videos onto varying display sizes for viewing and playback.
4) **Image processing packages:** Image processing software use scaling for viewing and resizing the image. [4]

5) **Satellite imaging:** Nowadays, satellite images are used in many applications such as geosciences studies, astronomy, and geographical information systems**.** [5]

6) **Computer Graphics:** Computers perform screen image scaling which includes web pages, text, graphics, game scenes etc. [6]

1.3 Methods for image upscaling

There are many ways of upscaling via image interpolation. Some methods are adaptive and some are non-adaptive.
Linear or Non-adaptive methods: The non-adaptive methods are quicker. The non-adaptive approach applies same operations on all the pixels of the image, without taking into account any of its characteristics.
Non-linear or Adaptive methods: The performance of conventional approaches is only acceptable for small upscaling factors[7].The adaptive methods rely on the assumption that, in natural images, frequency components are not all equally probable [8]. The adaptive methods perform a little better but have the downside to being too complex and higher processing times. The adaptive methods apply operations depending upon certain characteristics and features like presence of curves, edges, the image quality etc.
Adaptive algorithm basically uses some of the image features and improves interpolation result. Adaptive algorithm works based on different intensity present and local structure of image. Many adaptive interpolation algorithms have been proposed which enhance edges in images. Local gradient information can also be used to enhance non adaptive interpolation algorithm. Normal problem with interpolation technique is blurring and blocking artifacts. This can be solved using directional interpolation. For example, Edge directed interpolation, NEDI (New Edge Directed Interpolation), SAI (Soft decision adaptive Interpolation).

II. Artificial Neural Networks

An artificial neural network is an information processing paradigm that is inspired by and tries to mimic the biological nervous system. In a biological nervous system, the decision making process is facilitated by neurons and neural pathways that fire upon stimuli and transfer the desired signal to the brain. In the same way, the artificial neural network tries to mimic the decision making process and information transfer abilities of the biological nervous system. In an artificial neural network the nodes represent the neurons of a nervous system, the interconnections between neurons are imitated by the use of weights and biases over the inter-connections among the neurons.

The artificial neural network or ANN can be a single layer network or a multiple layered network. A single layered neural network does not have hidden layers in between the input and output layers. Usually multi-layered neural networks are implemented and they have more than one hidden layers in between the input and output layers. Each hidden layer is connected to others via weights. The higher the number of layers in a network, the more complex operations can be performed by the ANN.

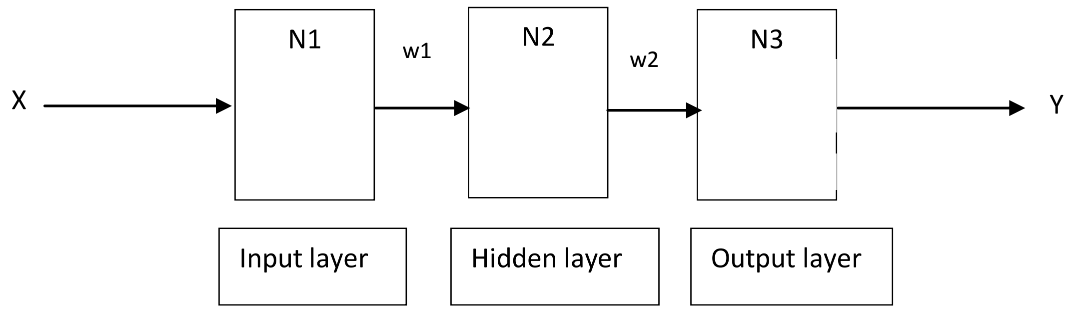

Fig 2: A simple neural network

The Fig. 3 shows an example of a simple neural network. Where X is the input to the network. N1, N2, N3 are the input, hidden and output layers of the neural network respectively. The intermediate connections between the layers are represented by weighted connections w1 and w2.

2.1 Artmap Neural Network

ARTMAP neural network is a supervised form of ART neural network. ART neural network has an inherently un-supervised approach to learning, which may be unsuitable for certain situations and applications. The supervised nature of an ARTMAP network makes it more reliable and better at learning. ARTMAP is among the family of neural networks that are capable of fast supervised, incremental learning and prediction. A number of variants of the network are available, like distributed ARTMAP, fuzzy ARTMAP, default ARTMAP, probabilistic ARTMAP etc.

The fuzzy ARTMAP network has integrated the fuzzy ART which enables it to process both analog and binary-valued input patterns. This neural network is simple and has been designed with the ability to perform supervised learning. In supervised learning mode, the sequential learning process grows the number of recognition categories according to a problem's complexity. [11]

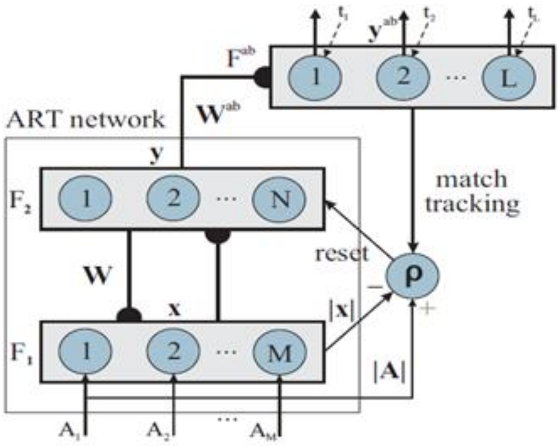

Fig 3: An ARTMAP structure [9]

The Fig.3 above shows a basic ARTMAP structure, where A is the input to the network. F1, F2 are its layers. And the ART subsystem is connected to the Map Field via weights $W^{ab.}$ The Map Field determines whether the prediction of the network is equal to what was desired by the network.

Because this neural network architecture has a small number of parameters and requires no problem-specific system crafting or choice of initial weight values, it is also easy to use. In an ARTMAP network, an epoch is defined as one cycle of training on an entire set of input examples [10]. The fuzzy ARTMAP algorithm is discussed in the Fig.4 below.

- Fuzzy ARTMAP algorithm

```
Initialization();
{
All weight values initialized to 1.
Intialise learning rate and vigilance parameter
}
Input patterns();
{
normalize input
}
Learn();
{
Input pattern propagated to layer F1
Apply weights
Propagate to layer F2
F2 produces a pattern J.
J is propagated back to F1
Compare for match against vigilance parameters
If test matches condition, node stays active, else reset and calculate again
Pattern fed to the map field
Map field test pattern against vigilance parameter
If mismatch, vigilance parameter is raised.
If match occurs, weight updated with node J
}
Repeat for next input
```

Fig. 4: The fuzzy ARTMAP algorithm

III. Proposed Method

The proposed method aims to upscaleimages by gradually increasing or decreasing the intensity values between the existing pixels in order to interpolate new pixel values. The method avoids interpolation by taking average of the intensity values. Fig.5 discusses the algorithm.

```
Proposed Algorithm for scaling
Input image();
Pre-processing();
{
//conversion to grayscale, size reduction, blurring.
}
Start_scaling();
{
Create matrix with 2x rows and 2x columns
Assign existing values to new matrix
For rows{
Check intensity difference between nearest pixels.
gradually increase/decrease intensity value and assign to empty pixels.
}
Repeat for columns
}
Post-processing();
}
Write output to disk
```

Fig. 5: The proposed algorithm

IV. Results And Discussion

The work has been implemented using MATLAB version R2014a. The system had the following configuration

1. Processor - AMD ® A8-6410APU
2. RAM - 8.00 GB (6.95 GB usable)
3. Operating System – Windows 8.1, 64-bit.

This section compares the outputs of the three existing methods and the proposed method both objectively and subjectively. The subjective analysis compares the output images of the algorithms. Objective analysis compares the performance evaluation parameters obtained after the implementation of the respective methods.

Results of the existing methods and the proposed method with ARTMAP are evaluated on the basis of the following performance evaluation parameters:

1. Peak Signal to Noise Ratio (PSNR)
2. Mean Square Error (MSE)
3. Structural similarity index (ssim)

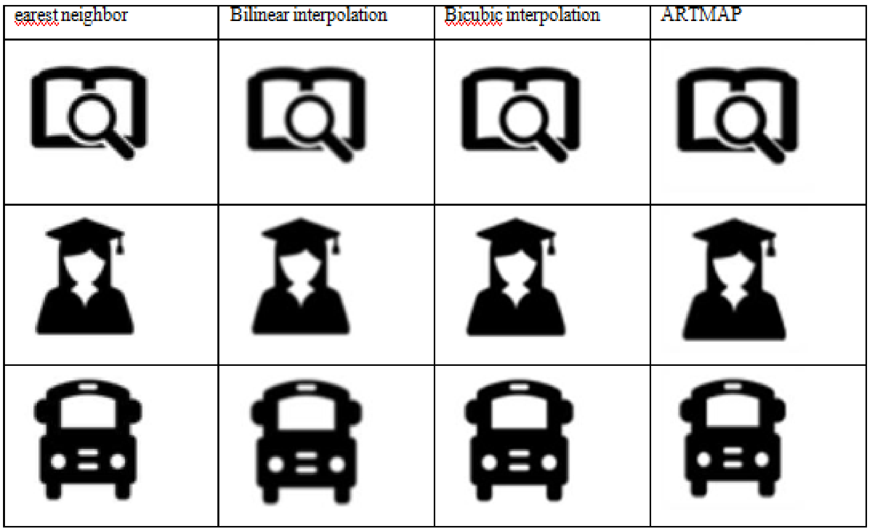

Fig. 6: Some examples of outputs of existing methods and ARTMAP implementation

Table 1 (a),(b),(c),(d) : Calculated PSNR, MSE, SSIM and RMSE values of some outputs

Sr. no.	PSNR			
	Nearest	Bilinear	Bicubic	ARTMAP
1	71.10197	71.30628	72.6959	71.40239
2	66.55557	67.87013	68.96156	67.90918
3	67.35772	68.18001	69.3893	68.19185
4	68.10709	68.69197	69.89344	68.78284
5	67.59357	68.12016	69.39655	68.13071
6	67.29575	67.51184	68.8711	67.59819

Sr. no.	MSE			
	Nearest	Bilinear	Bicubic	ARTMAP
1	0.005045	0.004813	0.003495	0.004708
2	0.014372	0.010619	0.008259	0.010524
3	0.011948	0.009887	0.007484	0.00986
4	0.010055	0.008788	0.006664	0.008606
5	0.011317	0.010025	0.007472	0.01
6	0.01212	0.011532	0.008433	0.011305

Sr. no.	SSIM			
	Nearest	Bilinear	Bicubic	ARTMAP
1	0.924353	0.912687	0.944587	0.932728
2	0.834904	0.845701	0.892429	0.863879
3	0.851171	0.844353	0.894801	0.870758
4	0.89615	0.890866	0.922956	0.901667
5	0.870651	0.864665	0.908753	0.884181
6	0.875515	0.861271	0.904668	0.876414

Sr. no.	RMSE			
	Nearest	Bilinear	Bicubic	ARTMAP
1	0.071029958	0.069378679	0.05912146	0.068615258
2	0.11988412	0.10304661	0.09087867	0.102584336
3	0.109308553	0.099435112	0.086511793	0.099299645
4	0.100273331	0.093743635	0.081633443	0.092767966
5	0.106380415	0.100122562	0.086439613	0.100001048
6	0.110091194	0.107386142	0.091830156	0.106323868

4.

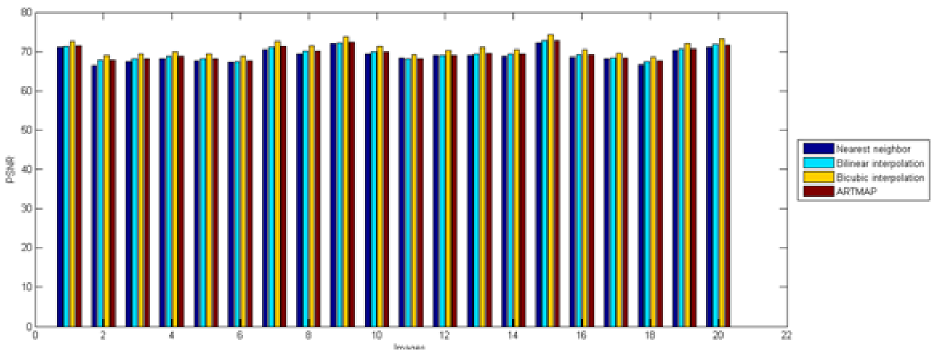

Fig. 7: Graph comparing the peak signal to noise ratio.

From left to right, the bars represent nearest neighbor, bilinear, bicubic interpolation and the ARTMAP implementation.

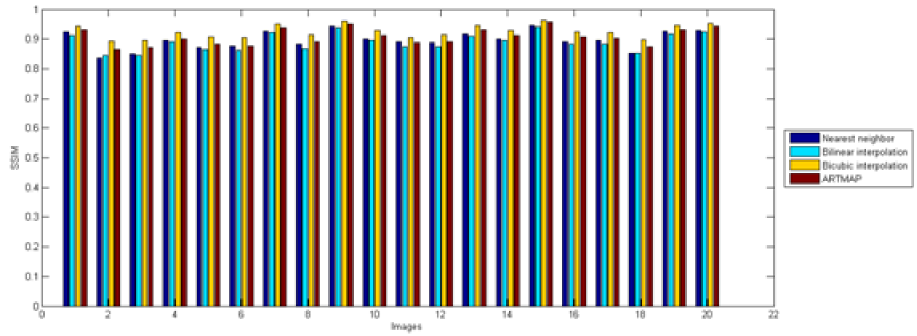

Fig. 8: Graph comparing the structural similarity of outputs

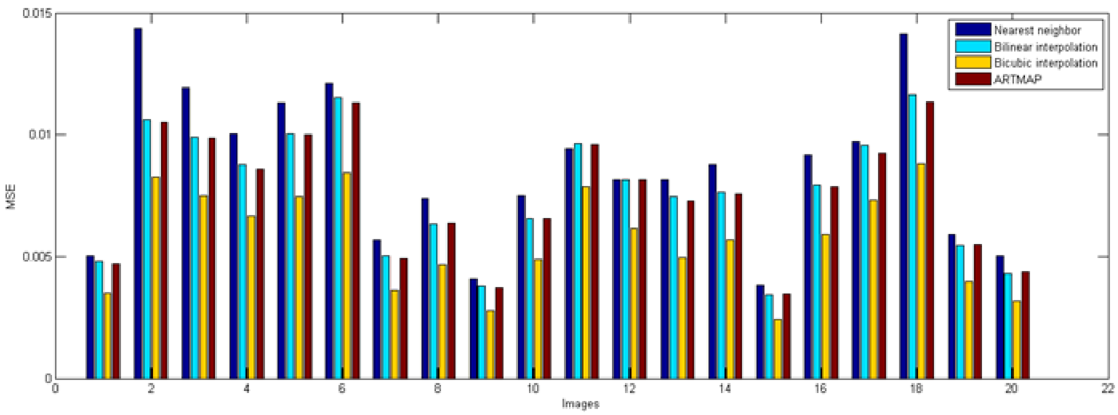

Fig. 9: Graph comparing the Mean square error values of outputs

From left to right, the bars represent nearest neighbor, bilinear, bicubic and implemented ARTMAP methods respectively.

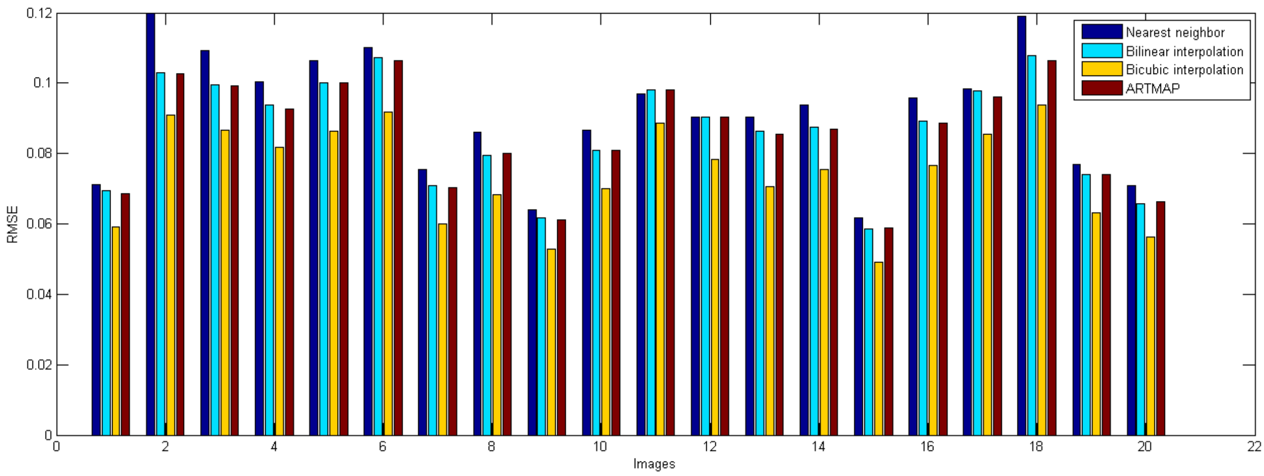

Fig 10: Comparison of RMSE values of ARTMAP and existing methods

V. Conclusion And Future Scope

The proposed algorithm is still in its early stages and has proved to be better than nearest neighbor interpolation and bilinear interpolation in all manners. It's also subjectively good when compared with images produced by bicubic interpolation.

The proposed method was able to improve on the problem of rough, jagged edges in images and too much blurring of images. The proposed upscaling algorithm still has some room for improvement in terms of performance parameters. Also the neural network can be upgraded in the future to work with grayscale and colored images as well, making it more useful.

Based on the obtained values and results, we make the following conclusions. Advantages of training ARTMAP with proposed algorithm:

- Better PSNR values than nearest neighbor
- Better MSE values than Nearest neighbor
- Structural similarity and RMSE are also satisfactory

Even though the proposed method scores lower than bicubic interpolation during objective evaluation, subjectively its output quality is quite good. It also deals with the too much blurring and ringing artifacts in the images to a large extent.

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