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Super-Resolution Technique for MRI Images Using Artificial Neural Network

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Abstract-Image upscaling is an important field of digital image processing. It is often required to create higher resolution images from the lower resolution images at hand in computer graphics, media devices, satellite imagery etc. Upscaling is also referred to as 'single image super-resolution'. The process is a tradeoff between efficiency, time and the quality of output images obtained. Images with higher quality are needed and are essential in many areas like medical, astronomy, surveillance, satellite imaging etc. In medical imaging, images are obtained for medical investigative purposes and for providing information about the important diagnosis instrument to determine the presence of certain diseases. Many techniques like PET (Positron Emission Tomography), CT (Computed Tomography), MRI (Magnetic Resonance Imaging) in the medical field are used for detecting diseases. Generally, medical images suffer from low resolution, High level of noise and blur type of factors. In the present paper, a feed forward neural network using supervised training for image upscaling is proposed. The performance of a neural network is compared to different training function & measure PSNR.

Index Terms: *Up scaling, Neural Network, ANN, Super-Resolution.*

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I. INTRODUCTION

Super Resolution is a technique that is used for improving the resolution of a digital and electronic imaging system by converting an image into a high-resolution image from a set of low-resolution images. The high resolutions images are required in much application such as medical field, satellites, videos enhancements and various standard conversions of videos and remote sensing.

The Digital images are taken with the help of CCD (Charge Coupled Devices) and CMOS (Complementary metal oxide semiconductor) Sensors [7]. Super-resolution is a technique which can improve a resolution of imaging systems beyond their sensor and optics limit. Super-resolution can be done using two ways single frame and multi frames.

Images with higher quality are needed and are essential in many areas. Resolution of an image could be increased by either increasing the size of the chip or by reducing the size of the pixel or by another way we have to use a higher resolution sensor which in turn is expensive. Thus many kinds of new techniques are used for resolution enhancement. All imaging systems have an upper limit on resolution.

These limitations can arise in several ways:

- Diffraction of light limits resolution to the wavelength of the illumination light.
- Lenses in optical imaging systems truncate the image spectrum in the frequency domain.
- A sampling of images limits the maximum spatial frequency to a fraction of the sampling rate.

II. CONCEPT OF SUPER RESOLUTION

A. Super Resolution

Super-resolution (SR), also known as High-resolution (HR), means that pixel density within an image is high, and therefore an HR image can offer more details that may be critical in various applications. There are many applications, such as medical imaging, video surveillance, astronomy, etc. In the medical image for correct diagnosis, one needs to determine the presence of certain disease. Therefore, increasing the image resolution should significantly improve the diagnosis ability for corrective treatment and planning accuracy.

B. Super Resolution Approach used in Medical Images

Medical imaging is an important diagnosis instrument to determine the presence of certain diseases. Therefore, increasing the image resolution should significantly improve the diagnosis ability for corrective treatment.

Furthermore, a better resolution may substantially improve automatic detection and image segmentation results.

Medical images typically suffer from one or more of the following imperfections:

- Low resolution (in the spatial and spectral domains)
- High level of noise
- Low contrast
- Geometric deformations
- Presence of imaging artifacts
- Noisy & Blurred

C. Basics need of Image Up sailing

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

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

III. NEURAL NETWORK

An Artificial Neural Network (ANN) is an imitation of the way our biological neural network works. The nervous system contains numerous neurons that are linked to each other. These neurons play a key role in decision making and thought process.

An artificial neural network aims to mimic the neural activity at a much smaller scale. An ANN consists of artificial neurons. Information processing takes place via these neurons. Each neuron is connected to other neurons by means of directed communication links, each with an associated weight. The weights represent information being used by the net to solve a problem.

Neural networks can be applied to a wide variety of problems, such as storing and recalling data or patterns, classifying patterns, performing general mappings from input patterns to output patterns, grouping similar patterns, or finding solutions to constrained optimization problems.

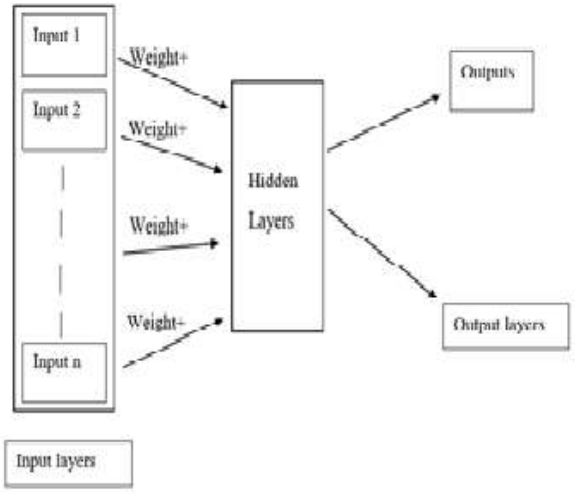

Figure 1: A simple Neural Network

A. Types of Artificial Neural Networks

There are two Artificial Neural Network topologies

– Feed Forward and Feedback.

[1]Feed Forward ANN

The information flow is unidirectional. A unit sends information to another unit from which it does not receive any information. There are no feedback loops. They are used in pattern generation/recognition/classification. They have fixed inputs and outputs. In this Paper Feed Forward ANN is used. Feed forward ANN is worked as supervised learning.

[2]Feed Back ANN

The information flow is bidirectional. They have used in content addressable memories. Basically, this type of ANN is typical & its take more time.

B. Machine Learning Functions

ANNs are capable of learning and they need to be trained. There are several learning strategies –

[1]Supervised Learning – It involves a teacher that is the scholar than the ANN itself. For example, the teacher feeds some example data about which the teacher already knows the answers.

[2]Unsupervised Learning – It is required when there is no example data set with known answers. It learned by itself. There is no teacher like supervised learning.

[3]Reinforcement Learning – this strategy built on observation. The ANN makes a decision by observing its environment.

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Here in this paper, Present functions are second order derivatives. While first-order techniques like standard back propagation only use the first derivatives. A second order technique generally finds a better way to a (local) minimum than a first order technique, but at a higher computational cost.

- Trainbr- Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the linear combination so that at the end of training the resulting network has good generalization qualities.

- Trainrp- The purpose of the resilient back propagation (Rprop) training algorithm is to eliminate these harmful effects of the magnitudes of the partial derivatives. Only the sign of the derivative can determine the direction of the weight update; the magnitude of the derivative has no effect on the weight update. The size of the weight change is determined by a separate update value.

- Trainscg- Scale Conjugate Gradient is a supervised learning algorithm for feed forward neural networks, and is a member of the class of conjugate gradient methods. trainscg can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate derivatives of performance perf with respect to the weight and bias variables X.

Training stops when any of these conditions occur:

- The maximum number of epochs (repetitions) is reached.

- The maximum amount of time has been exceeded.

- Performance has been minimized to the goal.

- The performance gradient falls below mingrad.

- Validation performance has increased more than max_fail times since the last time it decreased (when using validation).

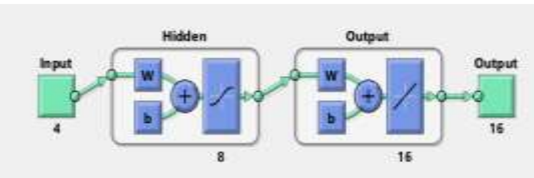

Fig2: Neural network training (nntrain tool)

C. Steps for the proposed method

For implementing the neural network to upscale images, these network training parameters have been taken.

- Input image=128x128 size image

- Target image=256x256 up scaled image

- Type of neural network used=newff (feed forward networks)

- Type of learning used=supervised learning

- Learning function= traingscg (scale conjugate gradient) & trainrp (resilient back propagation) & trainbr (Bayesian Regularization Back propagation)

- Cost function= PSNR (Peak Signal to Noise Ratio)

- Given below image PSNR trainscg= 30.9832dB,trainbr=28.2966dB,trainrp=30.98dB.

Fig3: Neural network training (nntrain tool)

Here the given fig is neural network training (nntraintool). This gives epoch, time, performance & also performance plot.

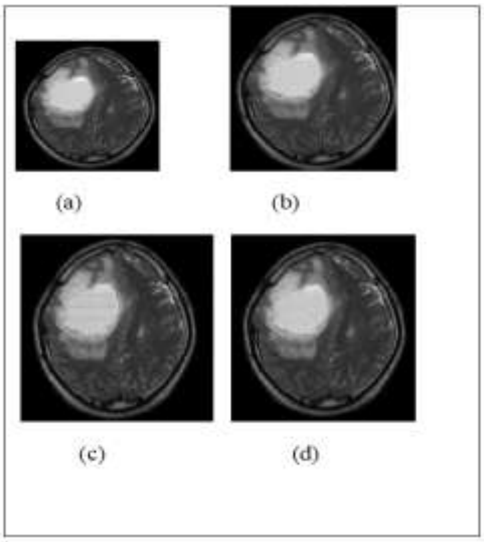

Fig4. Test & Train MRI brain tumor images (a) 128x128 brain tumor input image (b)256x256 output image using trainscg (c) 256x256 output image using trainbr (d) 256x256 output image using trainrp.

TABLE 1: Comparison of Medical image super-resolution using Neural Network

Training Function trainbr(Bayesian Regularization Backpropagation) PSNR (dB)	Training Function trainrp (Resilient Backpropagation) PSNR(dB)	Training Function trainscg(Scale Conjugate Gradient) PSNR (dB)
27.8054	29.6750	30.3772
25.3970	31.4173	32.0872
28.8364	33.3251	34.6405
28.2966	30.9472	30.9832
19.6213	28.8265	29.1888

Here in the table given the comparison between the different training functions.

IV. CONCLUSION

This paper mentions that the trained neural network was able to reproduce higher resolution images from low-resolution images. Neural feed forward network applied on MRI Brain Tumor images & this gives different PSNR value using trainscg, trainbr, traibrp. The implementation of the simple neural network has improved the good image output quality. The trainscg function gives better result for super-resolution than trainrp & trainbr.

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