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A Literature Survey on Image Enhancement Based on Abstraction and Neural Network

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***Abstract* - Image abstraction is a method of enhancing or high lighting the visualization of main information contents of image and smoothing the other portion. It is quite important for many multimedia applications like cartooning and animation where symbolic presentation matters; hence it is an important part in the field of image processing. In this Paper we study a neural network based approach & also the other methods of Image Enhancement. A neural network based approach which not only abstract the image but also avoids the enhancement of noise. The algorithm uses the image abstraction technique for detecting the information density in different parts of image then accordingly operates the smoothing filter and after filtering the information's of edges are recombined with the filtered image. The technique also utilizes the Neural Network for filtering noise generated edge patterns. Hence the approach not only enhances the image but also avoids the enhancement of noise. After comparison with other enhancement techniques we conclude that it improves the perception; remove noise while maintaining the structure information intact it is also found that the Neural Network technique is quite fast.**

***Keywords* - Image Enhancement, Neural Network, Empirical Analysis.**

I. Introduction

There are many definitions available for the term image enhancement one of them is "Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing `better' input for other automated image processing techniques". On other words the objective of image enhancement is to modify its features according to the requirements of processing space. While considering the above mentioned things it is clear that enhancement techniques are very relevant to the field where the processed image to be used, because of this several techniques are available for enhancement of image depending upon the use (like human perceptions, medical imagery or very complex radar systems). Another problem with enhancement techniques is that most of the method required a properly de-noised image otherwise the noise generated artifacts could also get enhanced hence de-noising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient de-noising technique to compensate for such data corruption. Because of the characteristics of noise Image de-noising still remains a challenge for researchers because of nature of noise. This paper describes methodologies for noise reduction (or de-noising) giving an idea to soft computing algorithm to find the reliable estimate of the noise pattern in given degraded image.

As discussed above the noise modeling in images is greatly varies depending upon capturing instruments, data transmission media, image quantization and discrete sources of radiation. It is difficult to design a single mathematical model for all types of noise instead a soft computing based black box model could be a much better solution for noise model. This paper also considers information based processing depth for each part of image which not only reduces the processing time but also protects the information loss.[6]

II. Image Enhancement

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide `better' input for other automated image processing techniques. Image enhancement techniques can be divided into two broad categories: Spatial domain methods, which operate directly on pixels, and Frequency domain methods, which operate on the Fourier transform of an image. Unfortunately, there is no general theory for determining what 'good' image enhancement is when it comes to human perception. If it looks good, it is good! However, when image enhancement techniques are used as pre-processing tools for other image processing techniques, then quantitative measures can determine which techniques are most appropriate. The value of a pixel with coordinates (x,y) in the enhanced image $\hat{F}$ is the result of performing some operation on the pixels in the neighborhood of (x,y) in the input image, F. Neighborhoods can be any shape, but usually they are rectangular. The simplest form of operation is when the operator T only acts on a 1X1 pixel neighborhood in the input image, that is $F(x,y)$ only depends on the value of F at (x,y). This is a grey scale transformation or mapping. The simplest case is thresholding where the intensity profile is replaced by a step function, active at a chosen threshold value. In this case any pixel with a grey level below the threshold in the input image gets mapped to 0 in the output image. Other pixels are mapped to 255.Other grey scale transformations are outlined.[7]

III. Neural Network

An artificial neural network (ANN), usually called neural network (NN), is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a

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connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. Computational neurobiologists have constructed very elaborate computer models of neurons in order to run detailed simulations of particular circuits in the brain. As Computer Scientists, we are more interested in the general properties of neural networks, independent of how they are actually "implemented" in the brain. This means that we can use much simpler, abstract "neurons", which (hopefully) capture the essence of neural computation even if they leave out much of the details of how biological neurons work. People have implemented model neurons in hardware as electronic circuits, often integrated on VLSI chips. Remember though that computers run much faster than brains - we can therefore run fairly large networks of simple model neurons as software simulations in reasonable time. This has obvious advantages over having to use special "neural" computer hardware.

Our basic computational element (model neuron) is often called a node or unit. It receives input from some other units, or perhaps from an external source. Each input has an associated weight *w*, which can be modified so as to model synaptic learning. In principle, back prop provides a way to train networks with any number of hidden units arranged in any number of layers. (There are clear practical limits, which we will discuss later.) In fact, the network does not have to be organized in layers - any pattern of connectivity that permits a partial ordering of the nodes from input to output is allowed. In other words, there must be a way to order the units such that all connections go from "earlier" (closer to the input) to "later" ones (closer to the output). This is equivalent to stating that their connection pattern must not contain any cycles. Networks that respect this constraint are called feed forward networks; their connection pattern forms a directed acyclic graph or dag.

IV. Previous Work

Previous work in image-based stylization and abstraction systems varies in the use of scene geometry, video-based vs. static input, and the focus on perceptual task performance and evaluation. Among the earliest work on image-based NPR was that of Saito and Takahashi [1990] who performed image processing operations on data buffers derived from geometric properties of 3D scenes. Our own work differs in that we operate on raw images, without requiring underlying geometry. To derive limited geometric information from images, Raskar et al. [2004] computed ordinal depth from pictures taken with purpose-built multi-flash hardware. This allowed them to separate texture edges from depth edges and performs effective texture removal and other stylization effects. Our own framework does not model global effects such as repeated texture, but also requires no specialized hardware and does not face the technical difficulties of multi-flash for video. Several video stylization systems have been proposed, mainly to help artists with labor-intensive procedures [Wang et al. 2004; Collomosse et al. 2005]. Such systems extended the mean-shift based stylization approach of DeCarlo and Santella [2002] to computationally expensive three-dimensional video volumes. Difficulties with contour tracking required substantial user correction of the segmentation results, particularly in the presence of occlusions and camera movement. Our framework does not derive an explicit representation of image structure, thus limiting the types of stylization we can achieve. In turn, we gain a framework that is much faster to compute, fully automatic, and temporally coherent. Fischer et al. [2005] explored the use of automatic stylization techniques in augmented reality applications. To make virtual objects less distinct from the live video stream, they applied stylization effects to both virtual and real inputs. Although parts of their system are similar to our own, their implementation is limited in the amount of detail it can resolve, and their stylized edges tend to suffer from temporal noise. Recently, several authors of NPR systems have defined task-dependent objectives for their stylized imagery and tested these with perceptual user studies. DeCarlo and Santella [2002] use eye tracking data to guide image simplification in a multi-scale system. In follow-up work, Santella and DeCarlo [2004] found that their eye-tracking-driven simplifications guided viewers to regions determined to be important. They also considered the use of computational salience as an alternative to measured salience. Our own work does not rely on eye-tracking data, although such data can be used. Our implicit visual salience model is less elaborate than the explicit model of Santella and DeCarlo’s later work, but can be computed in real-time. Their explicit image structure representation allowed for more aggressive stylization, but included no provisions for the temporal coherence featured in our framework. Gooch et al. [2004] automatically created monochromatic human facial illustrations from Difference-of-Gaussian (DoG) edges and a simple model of brightness perception. We use a similar edge model and evaluation study to Gooch et al. but additionally address color, real-time performance and temporal coherence.

Many people proposed algorithms to reduce time on the basis of reduced search, which reduces the compatible block search using some type of grouping but this can reduce only a part of time which is involved in searching of blocks but the time to calculate error matrix does not change. So the way is to neglect the error matrix which saves time but causes degradation in image quality because in reduced levedomain image, it is not always possible to find exact matching block matching blocks. Hence at that case it will produce an image of quality inferior than normal methods.

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V. Conclusion

The Neural Network algorithm works on detection and enhancing the important information of an image while suppressing the noise generated false information contents this method has advantage that it does not dissolve the impulsive noise but eliminate it. This is particularly useful where the original image having possibility of being distorted by noise. The Neural Network algorithm is iterative and incremental, and therefore the level of abstraction is intuitively controlled. Optionally, simple user masking can be incorporated into the algorithm to selectively control the abstraction speed and to protect particular regions. After studying many of methods we conclude that results of image enhancement using neural networks were quite fast & promising.

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