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Adaptive image interpolation using probabilistic neural network

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ABSTRACT

This paper proposes an image interpolation model based on probabilistic neural network (PNN). The method adjusts automatically the smoothing parameters for varied smooth/edge image region, and takes into consideration both smoothness (flat region) and sharpness (edge region) characteristics at the same model. A single neuron, combined with PSO training, is used for sharpness/smoothness adaptation. Finally, we report the performance of these newly proposed methods in other image interpolation method.

1. Introduction

Image interpolation is a popular technique for image manipulation and processing. It is most common application is to provide better visual effect after resizing a digital image for display or printing. In recent years, due to the consumer multimedia products being in vogue, imaging and display device become ubiquitous, and image interpolation is becoming more and more important.

The size and resolution of image display device, like LCD, increase constantly. The display systems require full screen and high quality visual effect. The image interpolation becomes an important process. Besides, digital zooming of DSC (digital still camera) also relies on image interpolation technique.

Divers interpolation methods have been proposed. The simplest and fastest one is nearest-neighbor (NN) method in which the value of the pixel point the closest is given as the value at the interpolating position (Thevenaz, Blu, & Unser, 2000). This method is efficient, but its disadvantage is the blocking effect. Another generic method is bi-linear interpolation. The interpolative value is given by the weighting average of neighboring pixels. This method considers that the variation value between the neighbor pixels of image is always smooth, despite the shape features like edges in images. It conduce blurry effect on image visualization.

Better interpolative image quality can be produced by bi-cubic interpolation (Keys, 1981). Its principle is similar as bi-linear interpolation, but the linear spatial model is replaced by cubic-spline model. Consequently, it provides higher precision. Inevitably, it still has obvious artifact and blurry interpolative effect.

Aiming at above problems, some researchers proposed various methods to reduce blurry interpolative effect at edge region (Arandiga, Donat, & Mulet, 2003; Battiato, Gallo, & Stanco, 2002; Dao-Qing, Tsi-Min, & Foo-Tim, 1998; Thurnhofer & Mitra, 1996). These methods can be classified into two categories: one is to carry out edge detection or sharpness estimation before interpolation. This kind of interpolations consumes a great deal of computational resources. Besides, it may produce discontinuities at edge transition region and degrade therefore the visual quality of images. The category resides in the execution of edge enhancement after normal interpolation procedure. In addition to the consumption of extra computing time, it also has the drawback of introducing more noises as a result of twofold image processing stages.

An innovative approach of image interpolation is introduced in this paper. We propose an interpolative PNN (probabilistic neural network) model which is consisted of five layers of neurons: Euclidian layer, Gaussian layer, weighting layer, summation layer and division layer. During the interpolation, the interpolative PNN is adjusted by a sharpness-adaptation single neuron. This approach not only provides smooth interpolation but also preserves sharpness at edge region.

2. Formulations of interpolation PNN model

This section outlines the derivation of equations that define interpolation PNN model. Interpolation attempts to re-create a continuous signal from discrete samples.

Let $s(\zeta)$, $[\zeta \in R]$, be a continuous signal and $s(X_i)$, $[X_i \in R]$, be a signal consisting of uniformly spaced discrete samples from the $s(\zeta)$.

Interpolation of the original signal typically is implemented by convolving the signal $s(X_i)$ with a continuous interpolation kernel filter $f(\zeta)$, $[\zeta \in R]$. $r(X_i)$ is interpolation result.

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$$r(X_i) = \sum_{m=-\infty}^{\infty} s[m_i] * f(X_i - m) \tag{1}$$

Many popular image interpolation methods are defined in this way, including nearest-neighbor, bi-linear, bi-cubic, cubic-spline and cubic convolution.

However most of interpolation kernels have not parameter to adapt other constraints, likes flat region and edge region. PNN interpolation kernel has a sharpness-adaptation parameter to solve this program.

2.1. Probabilistic neural network

Specht(1988), (1992) has introduced a neural classifier architecture, named probabilistic neural network (PNN) that is well adapted to manipulate pattern recognition and classification problem. PNN is constructed on the basis of Bayes theorem and Parzen probability density function estimation.

Specht's PNN model is consisted of three layers of neurons. The middle layer is kernel function layer which uses Gaussian kernel. Fig. 1 shows the simplified kernel neuron. With input feature $X = (x_1, x_2, x_3, \ldots, x_n)$, the estimation of probability density function f for given category C is

$$f = P(X|C) = e^{\frac{E}{\sigma^2}} \tag{2}$$

where is smoothing factor.

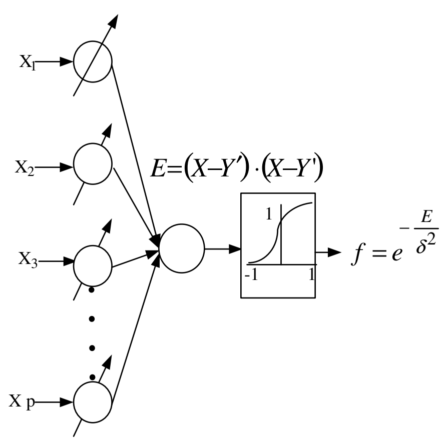

Fig. 1. The simplified PNN model.

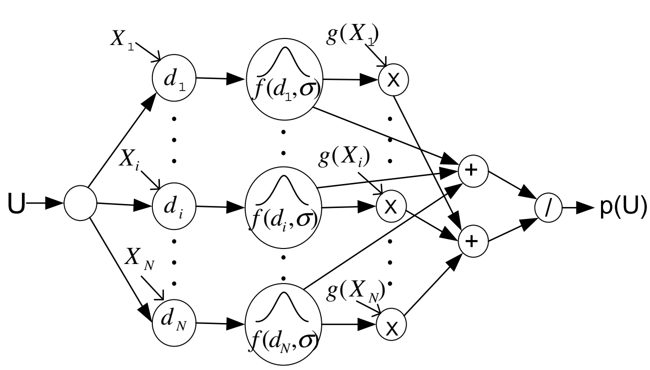

Fig. 2. Proposed interpolative PNN.

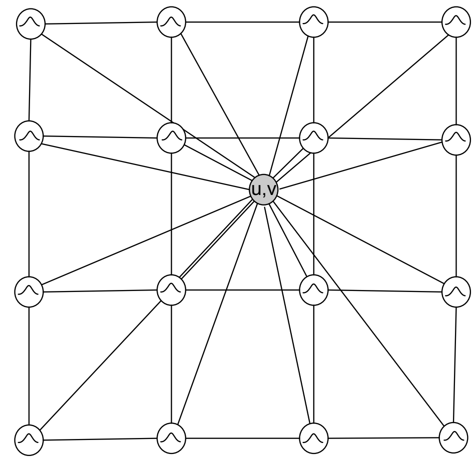

Fig. 3. Interpolative PNN with 16 neighbor pixels.

2.2. Interpolative PNN model

The interpolative PNN model that we propose is shown in Fig. 2. It is consisted of five layers neurons: Euclidian layer, Gaussian layer, weighting layer, summation layer and division layer.

In Fig. 2, the Euclidian distance

$$d_i = ||U_i - X_i|| \tag{3}$$

U is interpolation position. $X = \{(X_1, X_2, \ldots, X_N) | i \in N_U\}$, N_U are neighboring points of interpolation position U. $g(X_i)$ denotes signal value at X_i, $p(U)$ is interpolated value.

For an interpolative position U, the positions X_i, i = 0,...,N, of N neighbor points in N_U are adopted as connection weights of Euclidian layer. The output is then feed-forward to Gaussian neuron for obtaining the probability density function $f(d, \sigma)$. The value of neighbor point is used as weighting coefficient in weighting layer. Finally the resulting interpolated value is obtained by rule of gravity center:

$$P(U) = \frac{\sum_i g(U)^* f(d,\sigma)}{\sum_i f(d,\sigma)}, i \epsilon N_U \tag{4}$$

$$f_i(d,\sigma) = \exp\left(\frac{-d^2}{\sigma^2}\right) \tag{5}$$

Fig. 3 shows a case of interpolative position and its 16 neighbor pixels.

Let us consider the one-dimensional case for simplicity. Fig. 4 shows the interpolation result.

We can adjust Gaussian kernel, parameter σ, to adapt other constraints.

3. Sharpness adaptation in interpolative PNN

Due to the adoption of Gaussian function as kernel function of interpolative PNN, the interpolation will produce good smoothing result in flat image region. But at edge region, it may cause undesired blurring effect.

3.1. Estimation of smoothing parameter by single neuron

To overcome this blurring effect, we have elaborated a mechanism to make interpolative PNN adapt the region smoothing/sharpness. We use a single neuron (Ching-Han, 1998) to adjust the parameter σ of interpolative PNN. The edge feature at each pixel is measured as input vector of single neuron, and the output of neuron is smoothing parameter σ.