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PYRAMID METHOD IN IMAGE PROCESSING

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Abstract- The image pyramid is continuous and forms array of pixels for high resolution imbedding for 3D object to mount and display. It is highly efficient tool for image enhancement and patterning of object. Various methods are used to resolve image processing. One of the important method is Pyramid method in image processing. It is highly efficient and remarkable in the filed of science and technology especially in medical science and Biotechnology, Genetic Engineering, Molecular Science and Pharmaceutical Industries.
Keywords- 3D object Image Tracker, Resolution Grid, Memory Segmentation, Pyramidal Object, Grading, Image Simulator, Graphic Enhancer.

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Introduction

The image pyramid offers a flexible, convenient multi resolution format that mirrors the multiple scales of processing in the human visual system. In image enhancement , for example, a variety of methods now exist for removing image degradations and emphasizing important image information, and in computer graphics, digital images can be generated, modified, and combined for a wide variety of visual effects. In data compression, images may be efficiently stored and transmitted if translated into a compact digital code [1]. In machine version, automatic inspection systems and robots can make simple decisions based on the digitized input from a television camera. The data structure used to represent image information can be critical to the successful completion of an image processing task. One structure that has attracted considerable attention is the image pyramid. This consists of a set of lowpass or bandpass copies of an
image, each representing pattern information of a different scale. A variety of pyramid methods improves image data compression, enhancement, analysis and graphics [2]. It is becoming increasing clear that the format used to represent image data can be as critical as in image processing as the algorithms applied to the data. A digital image is initially encoded as an array of pixel intensities, but this raw format is not suited to most tasks. Alternatively, an image may be represented by its Fourier transform, with operations applied to the transform coefficients rather than to the original pixel values [3]. This is appropriate for some data compression and image enhancement tasks, but inappropriate for others. The transformation representation is particularly unsuited for machine vision and computer graphics, where the spatial location of pattern elements is critical [4].

Recently there has been a great deal of interest in representations that retain spatial-frequency domain. This is achieved by decomposing the image into a set of spatial frequency bandpass component images. Individual samples of a component image represent image pattern information about a particular fineness of detail or scale. There is evidence that the human visual system uses such a representation, and multiresolution schemes are becoming increasingly popular in machine vision and in image processing in general [5].The importance of analyzing images at many scales arises from the nature of images themselves. Scenes in the world contain objects of many sizes, and these objects contain features of many sizes. Moreover, objects can be at various distances from the viewer. As a result, any analysis procedure that is applied only at a single scale may miss information at other scales. The solution is to carry out analysis at all scales simultaneously. Convolution is the basic operation of most image analysis systems, and convolution with large weighting functions is a notoriously expensive computation. In a multiresolution system one wish to perform convolutions with kernels of many sizes, ranging from very small to very large and the computational problems appear forbidding. Therefore one of the main problems is working with multiresolution representations is to develop fast and efficient techniques [6]. A Pyramid-based method is an approach to fundamental problems in image analysis, data compression, and image manipulation.

Image pyramids
Image Pyramids

The task of detecting a target pattern that may appear at any scale can be approached in several ways. Two of these, which involve only some convolutions, are illustrated in Fig 1.

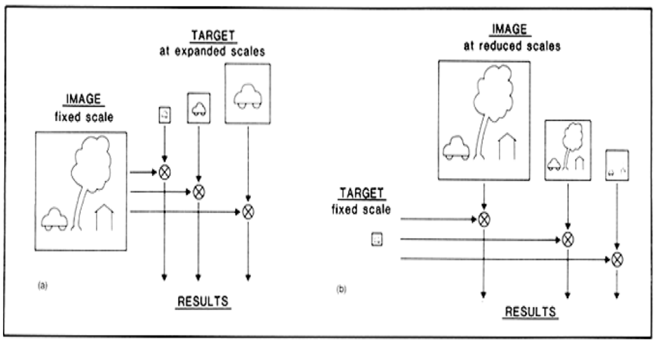

Fig. 1- Two methods of searching for a target pattern over many scales. In the first approach, (a). copies of the target pattern are constructed at several expanded scales, and each is convolved with the original image. In the second approach, (b), a single copy of the target is convolved with copies of the image reduced in scale. The target should be just large enough to resolve critical details. The two approaches should give equivalent results, but the second is more efficient by the forth power of the scale factor (image convolution are represented by 'O'

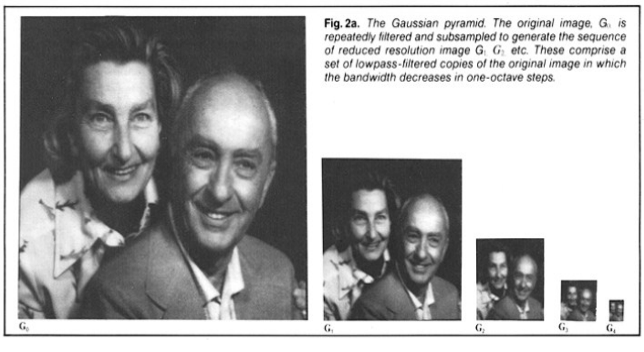

Fig. 2a. *The Gaussian pyramid. The original image, G_0 is repeatedly filtered and subsampled to generate the sequence of reduced resolution image G_1 G_2 etc. These comprise a set of lowpass-filtered copies of the original image in which the bandwidth decreases in one-octave steps.*

Fig. 2a-

Several copies of the pattern can be constructed at increasing scales. Each is convolved with the image. Alternatively, a pattern of fixed size can be convolved with several copies of the image represented at correspondingly reduced resolutions. The two approaches yield equivalent results, provided critical information in the target pattern is adequately represented. However, the second approach is mush more efficient a given convolution with the target pattern expanded in scale by a factor s will be s4 more arithmetic operations than the corresponding convolution with the image reduced in scale by a factor of s. This can be substantial for scale factors in the range 2 to 32, a commonly used range in image analysis.

The image pyramid is a data structure designed to support efficient scaled convolution to support efficient scaled convolution through reduced image representation. It consists of a sequence of copies an original image in which both sample density and resolution are decreased in regular steps. An example is shown in Fig. 2a. These reduced resolution levels of the pyramids are themselves obtained through a highly efficient iterative algorithm. The bottom, or zero level of the pyramid, G_0, is equal to the original image. This is low-pass-filtered and subsampled by a factor of two to obtain the next pyramid level, G_1. G_1 is then filtered in the same way and subsampled to obtain G_2. Further repetitions of the filter subsample steps generate the remaining pyramid levels. To be precise, the levels of the pyramid are obtained iteratively as follows.

For 0<l<N

$$G_l\ (i,j)\ \sum_m \sum_n w\ (m,n)\ G_{l-1}\ (2i+m, 2j+n)$$

However, it is convenient to refer to this

Fig. 2b-

Levels of the Gaussian Pyramid expanded to the size of the original image. The effects of lowpass filtering are now clearly apparent.

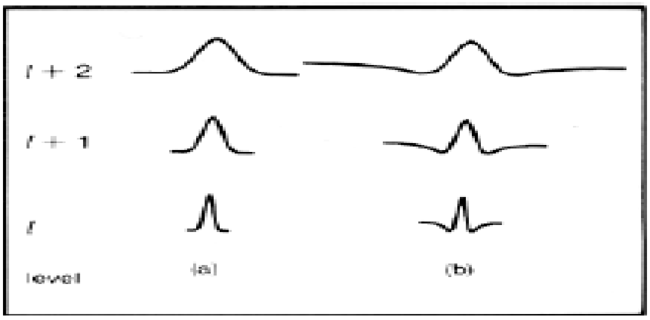

Fig. 3- Equivalent weighting functions. The process of constructing the Gaussian (lowpass) pyramid is equivalent to convolving the original image with a set of Gaussian-like weighting functions, then subsampling, as shown in (a). The weighting functions double in size with each increase in 1.

The corresponding functions for the Laplacian pyramid reassemble the difference of two Gaussians, as shown in (b).

Process as a standard REDUCE operation and simply write

$$G_l = \text{REDUCE}\ [G_{l-1}].$$

A weighting function w (m, n) the "generating kernel." For the reasons of computational efficiency this should be small and separable. A five-tap filter was used to generate the pyramid in Fig. 2a. Pyramid construction is equivalent to convolving the original image with a set of Gaussian-like weighting functions. These "equivalent weighting functions" for three successive pyramid levels are shown in Fig. 3a. The function doubles in width with each level. The convolution acts as a lowpass filter with the band limit reduced correspondingly by one octave with each level. Because of this resemblance to the Gaussian density function, the pyramid of low pass images defined as the "Gaussian pyramids."
Bandpass, rater than lowpass, images are required for many purposes. These may be obtained by subtracting each Gaussian (lowpass) pyramid level from the next lower level in the pyramid. Because these levels differ in their sample density it is necessary to interpolate new sample values between those in a given level before that level is subtracted from the next-lower level. Interpolation can be achieved by reversing the REDUCE process. This is an EXPAND operation. Let $G_{l,k}$ be the image obtained by expanding G_l k times. Then $G_{l,k}$ = EXPAND $[G\ G_{l,k-1}]$, or to be precise,

$G_{l,0} = G_l$ and for k>0,

$$G_{l,k}(i,j) = 4 \sum_m \sum_n G_{l,k-1}\left(\frac{2i+m}{2}, \frac{2j+n}{2}\right)$$

Here only terms for which (2i+m)/2 and (2j+n)/2 are integers contribute to the sum. The expand operation doubles the size of the image with each iteration, so that $G_{l,1}$, is the size of image with each iteration, so that $G_{l,1}$, is the size of $G_{l,1}$, and $G_{l,1}$, is the same size as that of the original image. Examples of expanded Gaussian pyramid levels are as shown in Fig. 2b.

The levels of the bandpass pyramid, L_0, L_1 ...., L_N, may now be specified in terms of the lowpass pyramid level as follows:

$$L_l = G_l - \text{EXPAND}\,[G_{l+1}]$$

$$= G_l - G_{l+1,1}$$

The first four levels are shown in Fig. 4a.
Just as the value of each node in the Gaussian pyramid could have been obtained directly by convoluting a Gaussian-like equivalent weighting function with the original image, each value of this bandpass pyramid could be obtained by convolving a difference of two Gaussian with the original image. These functions closely resemble the Laplacian operators commonly used in image processing (Fig. 3b). For this reason the bandpass pyramid is called as "Laplacian pyramids."
A Laplacian pyramid is a complete image representation: the steps used to construct the pyramid may be reserved to recover the original image exactly. The top pyramid level L_N, is first expanded and added to L_{N-1} to form G_{N-1} then this array is expanded and added to L_{N-2} to recover G_N and so on. Alternatively,

$$G_0 = \sum L_{l,l}$$

The pyramid has been introduced is adapt structure for supporting scaled image analysis. The same structure is well suited for a variety of other image processing tasks. Applications in the data compression and graphics, as well as in image analysis are main constituent in image processing. The pyramid-building procedures have significant advantages over other approaches to scaled analysis in terms of both computation cost and complexity. The pyramids levels are obtained with repeated REDUCE and EXPAND operations than is possible with the standard FFT.

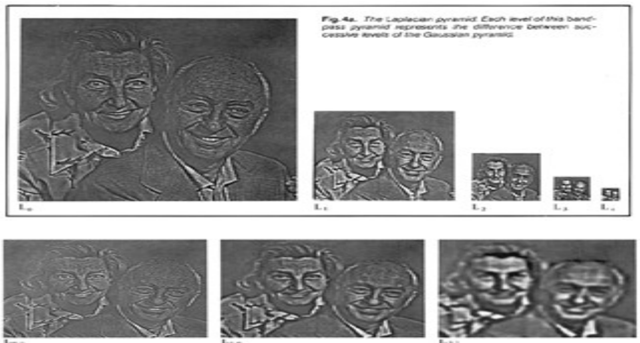

Fig. 4a & 4b-
Levels of the Laplacian pyramid expanded to the size of the original image. Edge and bar features are enhanced and segregated by size.
Furthermore, direct convolution with large equivalent weighting functions requires 20- to 30-bit arithmetic to maintain the same accuracy as the cascade of convolutions with the small generating kernels using just 8-bit arithmetic.

Compact code
The laplacian pyramid has been described as a data structure composed of bandpass copies of an image that is well suited for scaled-image analysis. But the pyramid may also be viewed as an image transformation, or code. The pyramid nodes are then considered code elements and the equivalent weighting functions are sampling functions that give node values when convolved with the image.
There are two reasons for transforming an image from one representation to another: the transformation may isolate critical components of the image pattern so they are more directly accessible to analysis or the transformation may place the data in a more compact form so that they can be stored and transmitted more efficiently. The Laplacian pyramid serves both of these objectives.

Fig. 5-
Pyramid data compression. The original image represented at 8 bit per pixel as shown in (a). The node values of the Laplacian pyramid representation of this image were quantitized to obtain effective data rates of 1 b/p and ½ b/p. reconstructed images (b) and (c) show relatively little degradation.

Image Analysis

Pyramid methods may be applied to analysis in several ways. Important three parameters are: The first concerns pattern matching to locate a particular target pattern that may occur at any scale within an image. The pattern is convolved with each level of the image pyramid. All levels of the pyramid combined contain just one third more nodes that there are pixels in the original image. Thus the cost of searching for a pattern at many scales is just one third more than that of searching the original image alone.

Second Important Image Analysis concerns the estimation of integrated properties within local image regions. Another important Image Analysis is Pattern Scale for both the convolution and integration stages.

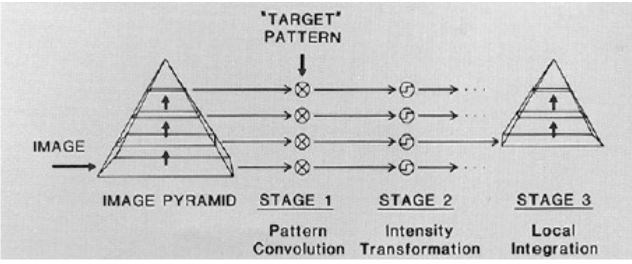

Fig. 6-

efficient procedure for computing integrated image properties at many scales. Each level of the image pyramid is convolved with a pattern to enhance an elementary image characteristic, step1. Sample value in the filtered to enhance elementary image characteristics.

Image enhancement

The image is first decomposed into its laplacian pyramid (bandpass) representation. The samples in each level are then passed through a coring function where small values are set to zero, while larger values are retained, or “peaked”. The final enhanced image is then obtained by summing the levels of the processed pyramids.

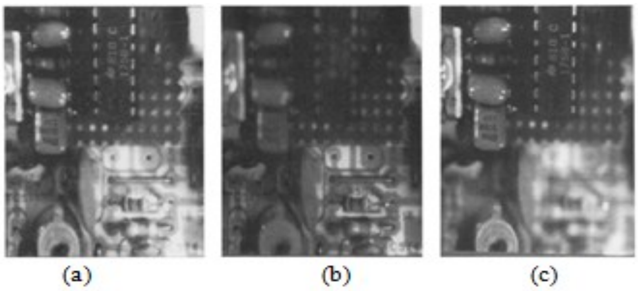

Fig. 7-

Multifocus composite image. The original images with limited depth of field are shown in (a) and (b). These are combined digitally to give the image will an extended depth of filed in ©.

Conclusions

The pyramid offers a useful image representation for a number of tasks. It is efficient to compute indeed pyramid filtering is faster than equivalent filtering done with a fast Fourier transform.

The left half of image (a) is catinated with the right half of image (b) to give the mosaic in (c). Note: The boundary between regions is clearly visible. The mosaic in (d) was obtained by combining images separately in each spatial frequency band of their pyramid representations then expanding and summing these bandpass mosaics.

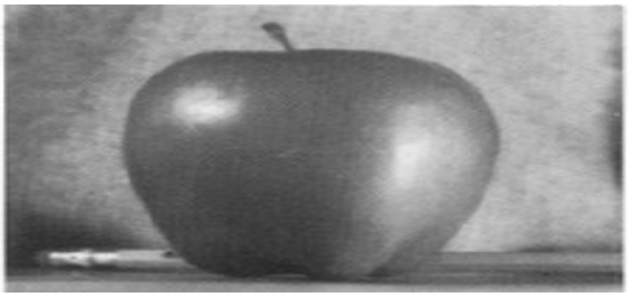

Fig. 8a-

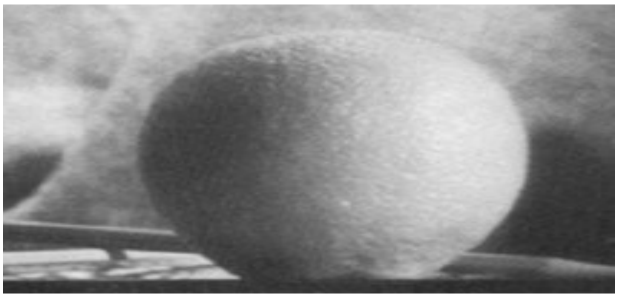

Fig. 8b-

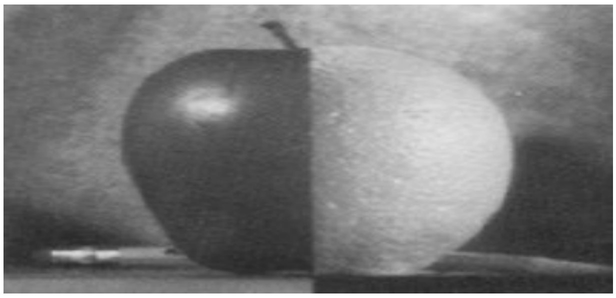

Fig. 8c-

Fig. 8d- Image mosaics.

The information is also available in a format that is convenient to use, since the nodes in each level represent information that is localized in both space and spatial frequency. Substantial data compression can be achieved by pyramid encoding combined with quantization and entropy coding. Tasks such as texture analysis can be done rapidly and simultaneously at all scales. Several different images can be combined to form a seamless mosaic, or several images of the same scene with different planes of focus can be combined to form a single sharply focused image. It offers a flexible, convenient multiresolution format that matches the multiple scales found in the visual scenes and mirror the multiple scales of processing in the human visual system.

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