Digital Image Enhancement in Spatial Domain Eng.

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Abstract:

The principal objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application. Image enhancement approaches fall into two broad categories: spatial domain methods and frequency domain methods. The term ***spatial domain*** refers to the image plane itself, and approaches in this category are based on direct manipulation of pixels in an image. ***Frequency domain*** processing techniques are based on modifying the Fourier transform of an image.
Keywords: Image processing, Filter , Mask and Image Type.

الخلاصة:

الهدف الرئيسي من تحسين الصورة هو العمل على جعل الصورة الجديدة أكثر ملاءمة من الصورة الأصلية لتطبيق معين. طرق تحسين الصورة تقسم إلى فئتين كبيرتين: طرق وأساليب المجال المكاني وطرق وأساليب المجال الترددي. مصطلح المجال المكاني يشير إلى مستوى الصورة نفسها وبالتالي فان التلاعب يكون بصورة مباشر على وحدات البكسل في الصورة. وتقوم تقنيات معالجة نطاق التردد على تعديل تحويل فورير من الصورة الى النتائج المطلوبة.
الكلمات المفتاحية: معالجة الصور ، المرشح و أنواع الاقنعة والصور .

1. Introduction

Images constitute a spatial distribution of the ***irradiance***at a plane. Mathematically speaking, the spatial irradiance distribution can be described as a continuous function of two spatial variables:

$$E(x_1,x_2)- E(x)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1.1)$$

Computers cannot handle continuous images but only arrays of digital numbers. Thus it is required to represent images as two-dimensional arras of points. A point on the 2-D grid is called a ***pixel***or ***pel***.Both words are abbreviations of the word picture element(S. M. Pizer, J. B. Zimmerman, and E. Staab, 1984). A pixel represents the irradiance at the corresponding grid position. In the simplest case, the pixels are located on a rectangular grid. The position of the pixel is given in the common notation for matrices. The first index, *m*, denotes the position of the row, the second, *n*, the position of the column (**Fig. 1**).

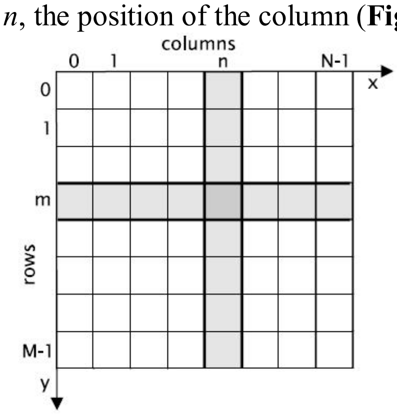


Figure 1:*Representation of digital images by arrays of discrete points on a rectangular grid. (2-D image)*

If the digital image contains *M* x *N* pixels, i.e., is represented by an *M* x *N* matrix, the index *n* runs from 0 to *N* - 1, and the index *m* from 0 to *M* - 1. *M* gives the number of rows, *N* the number of columns. In accordance with the matrix notation, the vertical axis (*y* axis) runs from top to bottom and not vice versa as it is common in graphs. The horizontal axis (*x* axis) runs as usual from left to right(D. J. Jobson, Z. Rahman, G. A. Woodell, G.D.Hines, 2006).

Each pixel represents not just a point in the image but rather a rectangular region, the elementary cell of the grid. The value associated with the pixel must represent the average irradiance in the corresponding cell in an appropriate way.

2. Basics of Spatial Filtering

Some neighborhood operations work with the values of the image pixels in the neighborhood *and* the corresponding values of a subimage that has the same dimensions as the neighborhood. The subimage is called a ***filter, mask, kernel, template,*** or ***window***, with the first three terms being the most prevalent terminology. The values in a filter subimage are referred to as ***coefficients***, rather than pixels(S. M. Pizer, J. B. Zimmerman, and E. Staab, 1984; E. Land, 1986)

The concept of filtering has its roots in the use of the Fourier transform for signal processing in the so-called ***frequency domain***. We use the term ***spatial filtering*** to differentiate this type of process from the more traditional frequency domain filtering.

The mechanics of spatial filtering process consists simply of moving the filter mask from point to point in an image (A. Hurlbert, 1986). At each point (x, y), the response of the filter at that point is given by a sum of products of the filter coefficients and the corresponding image pixels in the area spanned by the filter mask. The result (or response), R, of linear filtering with the filter mask at a point (x, y) in the image is

$$R = w(-1,-1)f(x-1, y-1) + w(-1,0)f(x-1, y) + \ldots + w(0,0)f(x, y) + \ldots + w(1,0)f(x+1, y) + w(1,1)f(x+1, y+1),$$

Which we see is the sum of products of the mask coefficients with the corresponding pixels directly under the mask. Note in particular that the coefficient $w(0, 0)$ coincides with image value $f(x, y)$, indicating that the mask is centered at (x, y) when the computation of the sum of products takes place.

For a mask of size $m\times n$, we assume that $m=2a+1$ and $n=2b+1$,where a and b are nonnegative integers (Z. Rahman, D. J. Jobson, and G. A. Woodell,1996). All this says is that our focus in the following discussion will be on masks of odd sizes, with the smallest meaningful size being 3×3 (we exclude from our discussion the trivial case of a 1×1 mask).

In general, linear filtering of an image f of size $M\times N$ with a filter mask of size m×n is given by the expression:

$$g(x, y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x+s, y+t) \qquad \textbf{(1)}$$

Where, from the previous paragraph, $a = (m-1)/2$ and $b = (n-1)/2$. To generate a complete filtered image this equation must be applied for $x = 0, 1, 2, \ldots, M-1$ and $y = 0, 1, 2, \ldots, N-1$. In this way, we are assured that the mask processes all pixels in the image. It is easily verified when $m=n=3$ that this expression reduces to the example given in the previous paragraph.

The process of linear filtering given in **Eq. (1)** is similar to a frequency domain concept called ***convolution***. For this reason, linear spatial filtering often is referred to as "convolving a mask with an image." Similarly, filter masks are sometimes called ***convolution masks***. The term ***convolution kernel*** also is in common use(N. Unaldi, P. Sankaran, K. V. Asari, Z. Rahman, 2008.).

When interest lies on the response, R, of an $m\times n$ mask at any point (x, y), and not on the mechanics of implementing mask convolution, it is common practice to simplify the notation by using the following expression:

$$R = w_1 z_1 + w_2 z_2 + \ldots + w_{mn} z_{mn} \qquad \textbf{(2)}$$
$$= \sum_{i=1}^{mn} w_i z_i$$

Where the w's are mask coefficients, the z's are the values of the image gray levels corresponding to those coefficients, and mn is the total number of coefficients in the mask(S. M. Pizer and E. P. Amburn, 1987 ; A. Hurlbert, 1986).

Nonlinear spatial filters also operate on neighborhoods, and the mechanics of sliding a mask past an image are the same as was just outlined. In general, however, the filtering operation is based conditionally on the values of the pixels in the neighborhood under consideration, and they do not explicitly use coefficients in the sum-of-products manner described in **Eqs. (1)** and **(2)**.

For example, noise reduction can be achieved effectively with a nonlinear filter whose basic function is to compute the median gray-level value in the neighborhood in which the filter is located. Computation of the median is a nonlinear operation(Y. Jin, L. M. Fayad, and A. F. Laine, 2001; S. M. Pizer, J. B. Zimmerman, and E. Staab, 1984).

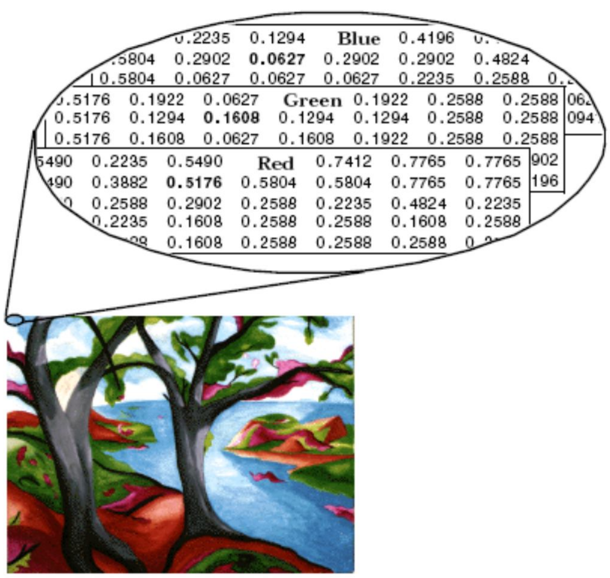


Figure 2: *Example of RGB type*

3. Applications of Digital Image Processing

Digital image processing techniques can be used to analyze a digital image or to process it to a new, improved image. Any situation requiring the enhancement, restoration, analysis, or creation of a digital image is a candidate for these techniques. Here are some of the major applications of digital image processing technology in use today:

Biological Research

Bio-research and bio-medical laboratories use digital techniques to visually analyse components of a biological sample. In some cases, digital image processing techniques provide totally automated systems for specimen analysis.

Defense / Intelligence

The military has made widespread use of digital image processing techniques for various applications like automated interpretation of earth satellite imagery to look for sensitive targets, military threats or military installations.

Document Processing

Acquisition and processing of documents and drawings have helped to automate many industries that were classically paper-driven, such as banking and insurance-claim processing.

Factory Automation

Vision systems in the manufacturing environment provide automated quality inspection and process monitoring. These systems free the human operator and inspector while improving overall process accuracy and reliability.

Law Enforcement Forensics

Law enforcement agencies process large volumes of images for mug shots, evidence and fingerprints. Various forms of digital enhancement, archiving and classification processing are part of the modern operation.

Medical Diagnostic Imaging

Medical radiological imaging looks at the internal components of the human body. X-ray imaging and computed tomography techniques make intensive use of digital image processing.

Photography

Digital image processing techniques have augmented and in some cases replaced methods used by the photographer for image composition and dark room processing.

Space Exploration / Astronomy

Digital image systems are used almost exclusively on board exploratory spacecraft and earth-bound telescopes. This equipment makes extensive use of digital image processing techniques to enhance, restore and analyse extra-terrestrial imagery.

Video / Film Special Effects

The video and film production industries use various digital image-processing techniques for creating and hiding artefacts of special visual effects. Methods of reducing the data size of images improve both video archiving and transmission processes. The television program distribution industries such as cable television, direct-broadcast satellite, and electronic video distribution can all benefit greatly from image compression techniques.

These above applications represent many of the uses for digital image processing and the opportunities remain endless. With declining costs of general computing equipment and of specific devices for digital image acquisition, processing and display, new applications merge daily. Digital image processing is and will be the key technology for many innovations yet to come (K. Rehm and W. J. Dallas, 1989).

4. Type of special enhancement

4.1 Histogram Equalization

The cure for contrast images is "histogram equalization". The histogram equalization smoothest out the image or selection's histogram so that it is more evenly distributed across the spectrum. This results in a histogram with a mountain grouped closely together to "spread out" into a flat or equalized histogram.

Histogram equalization does not operate on the histogram itself. Rather, histogram equalization uses the results of one histogram to transform the original image into an image that will have an equalized histogram (S. M. Pizer and E. P. Amburn, 1987).

- Let r represent the gray levels in the image to be enhanced and s is the enhanced output with a transformation of the form s=T(r).

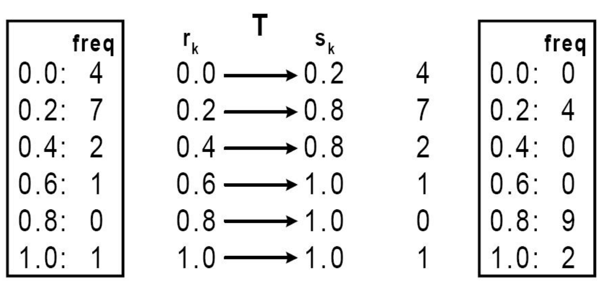
-Assumption:

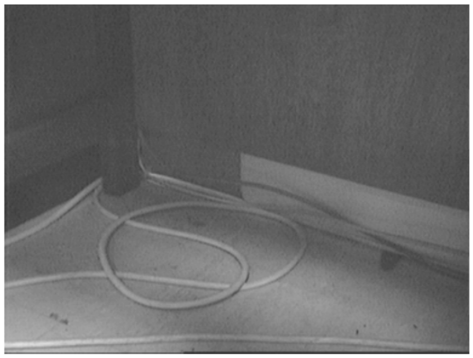
1. T(r) is single-valued and monotonically increasing in the interval [0,1], which preserves the order from black to white in the gray scale.
2. $0 \le T(r) \le 1$ for $0 \le r \le 1$, which guarantees the mapping is consistent with the allowed range of pixel values.
- If $P_r(r)$ and T(r) are known and $T^{-1}(s)$ satisfies condition (a), the pdf (probability-density function) of the transformed gray levels is

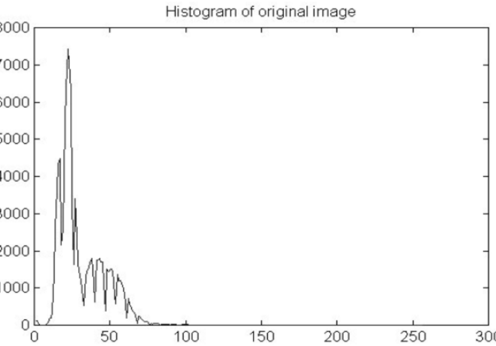
$$P_s(s) = P_r(r)\left.\frac{dr}{ds}\right|_{r=T^{-1}(s)}$$

- If $s = T(r) = \int_0^r P_r(w)dw$ for $0 \le r \le 1$ then we have $\frac{ds}{dr} = P_r(r)$ and hence Ps(s)=1 for $0 \le s \le 1$.
-Using a transformation function equal to the cumulative distribution of r produces an image whose gray levels have a uniform density, which implies an increase in the dynamic range of the pixels(K. Rehm and W. J. Dallas, 1989).
-In order to be useful for digital image processing, eqns. should be formulated in discrete form:
$P_r(r_k) = \frac{n_k}{n}$ and $s_k = T(r_k) = \sum_{j=0}^{k} \frac{n_j}{n}$, where k =0,1…L-1
- A plot of $P_r(r_k)$ versus r_k is actually a histogram.
Example: equalizing an image of 6 gray levels.

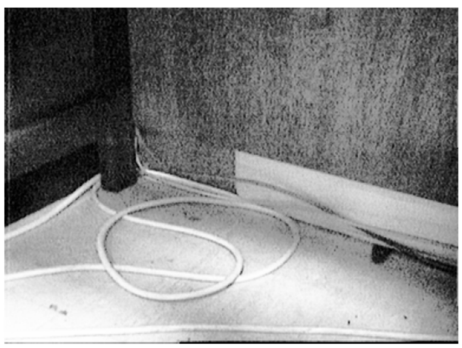
Index k	0	1	2	3	4	5
Normalized Input level, r_k/5	0.0	0.2	0.4	0.6	0.8	1.0
Freq. Count of r_k, n_k	**4**	**7**	**2**	**1**	**0**	**1**
Probability $P(r_k) = n_k/n$	4/15	7/15	2/15	1/15	0/15	1/15
$s_k = T(r_k) = \sum_{j=0}^{k} \frac{n_j}{n}$	4/15 = **0.27**	11/15 = **0.73**	13/15 = **0.87**	14/15 = **0.93**	14/15 = **0.93**	15/15 = **1.00**
Quantized s_k	0.2	0.8	0.8	1.0	1.0	1.0

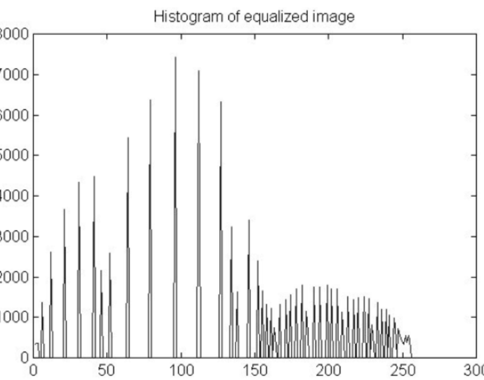






Original image Histogram





Equalized image Histogram

Figure 3: *Example of histogram equalization*

3. Smoothing Spatial Filters (Low-Pass Filters)

Smoothing filters are used for blurring and for noise reduction. Blurring is used in preprocessing steps, such as removal of small details from an image prior to (large) object extraction, and bridging of small gaps in lines or curves. Noise, reduction can be accomplished by blurring with a linear filter and also by nonlinear filtering (Z. Rahman, D. J. Jobson, and G. A. Woodell,1996).

(a) Smoothing Linear Filters

The output (response) of a smoothing, linear spatial filter is simply the average of the pixels contained in the neighborhood of the filter mask. These filters sometimes are called ***averaging filters***.

The idea behind smoothing filters is straightforward. By replacing the value of every pixel in an image by the average of the gray levels in the neighborhood defined by the filter mask, this process results in an image with reduced "sharp" transitions in gray levels (D. J. Jobson, Z. Rahman, G. A. Woodell, G.D.Hines, 2006).

Because random noise typically consists of sharp transitions in gray levels, the most obvious application of smoothing is noise reduction. However, edges (which almost always are desirable features of an image) also are characterized by sharp transitions in gray levels, so averaging filters have the undesirable side effect that they blur edges (E. Land and J. McCann, 1971)

$$\frac{1}{9}\times\begin{array}{|c|c|c|}\hline 1 & 1 & 1\\ \hline 1 & 1 & 1\\ \hline 1 & 1 & 1\\ \hline\end{array} \qquad \frac{1}{16}\times\begin{array}{|c|c|c|}\hline 1 & 2 & 1\\ \hline 2 & 4 & 2\\ \hline 1 & 2 & 1\\ \hline\end{array}$$

a b

FIGURE 4: *Two 3×3 smoothing (averaging) filter masks. The constant multiplier in front of each mask is equal to the sum of the values of its coefficients, as is required to compute an average.*

A major use of averaging filters is in the reduction of "irrelevant" detail in an image. By "irrelevant" we mean pixel regions that are small with respect to the size of the filter mask.

Fig.4 shows two 3×3 smoothing filters. Use of the first filter yields the standard average of the pixels under the mask. This can best be seen by substituting the coefficients of the mask into **Eq. (2)**:

$$R=\frac{1}{9}\sum_{i=1}^{9} z_i$$

Which is the average of the gray levels of the pixels in the 3×3 neighborhood defined by the mask. Note that, instead of being 1/9, the coefficients of the filter are all 1's.The idea here is that it is computationally more efficient to have coefficients valued1.

At the end of the filtering process the entire image is divided by 9.An $m\times n$ mask would have a normalizing constant equal to $1/mn$. A spatial averaging filter in which all coefficients are equal is sometimes called a ***box filter***.

The second mask shown in **Fig. 4 (b)** is a little more interesting. This mask yields a so-called ***weighted average***, terminology used to indicate that pixels are multiplied by different coefficients, thus giving more importance (weight) to some pixels at the expense of others.

In the mask shown in **Fig.4 (b)** the pixel at the center of the mask is multiplied by a higher value than any other, thus giving this pixel more importance in the calculation of the average. The other pixels are inversely weighted as a function of their distance from the center of the mask.

The diagonal terms are further away from the center than the orthogonal neighbors (by a factor of $\sqrt{2}$) and, thus, are weighed less than these immediate neighbors of the center pixel. The basic strategy behind weighing the center point the highest and then reducing the value of the coefficients as a function of increasing distance from the origin is simply an attempt to reduce blurring in the smoothing process. We could have picked other weights to accomplish the same general objective.

However, the sum of all the coefficients in the mask of **Fig. 4 (b)** is equal to 16. With reference to **Eq. (1)**, the general implementation for filtering an
$M\times N$ image with a weighted averaging filter of size m×n (m and n odd) is
given by the expression

$$g(x,y) = \frac{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t) f(x+s, y+t)}{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t)} \quad \textbf{(2)}$$

The effects of smoothing as a function of filter size are illustrated before, which shows an original image and the corresponding smoothed results obtained using square averaging filters of sizes n=3, 5, 9, 15, and 35 pixels, respectively(Z. Rahman, D. J. Jobson, and G. A. Woodell,1996).

(b) Order-Statistics Filters

Order-statistics filters are nonlinear spatial filters whose response is based on ordering (ranking) the pixels contained in the image area encompassed. The filter, and then replacing the value of the center pixel with the value determined by the ranking result.

The best-known example in this category is the ***median filter***, which, as its name implies, replaces the value of a pixel by the median of the gray levels in the neighborhood of that pixel (the original value of the pixel is included in the computation of the median).

Median filters are quite popular because, for certain types of random noise, they provide excellent noise-reduction capabilities, with considerably less blurring than linear smoothing filters of similar size.

Median filters are particularly effective in the presence of ***impulse noise***, also called ***salt-and-pepper noise*** because of its appearance as white and black dots superimposed on an image (E. Land, 1986; J. B. Zimmerman,1989).

The median, ξ, of a set of values is such that half the values in the set are less than or equal to ξ, and half are greater than or equal to ξ. In order to perform median filtering at a point in an image, we first sort the values of the pixel in question and its neighbors, determine their median, and assign this value to that pixel.

For example, in a 3×3 neighborhood the median is the 5th largest value, in a 5×5 neighborhood the 13th largest value, and so on. When several values in a neighborhood are the same, all equal values are grouped. For example, suppose that a 3×3 neighborhood has values (10, 20, 20, 20, 15, 20, 20, 25, 100). These values are sorted as (10, 15, 20, 20, 20, 20, 20, 25, 100), which results in a median of 20. Thus, the principal function of median filters is to force points with distinct gray levels to be more like their neighbors. In fact, isolated clusters of pixels that are light or dark with respect to their neighbors, and whose area is less than $n2/2$ (one-half the filter area), are eliminated by an $n \times n$ median filter. In this case "eliminated" means forced to the median intensity of the neighbors. Larger clusters are affected considerably less.

Although the median filter is by far the most useful order-statistics filter in image processing, it is by no means the only one. The median represents the 50th percentile of a ranked set of numbers, but the reader will recall from basic statistics that ranking lends itself to many other possibilities.

For example, using the 100th percentile results in the so-called ***max filter***, which is useful in finding the brightest points in an image. The response of a 3×3 max filter is given by R=max $\{zk \mid k=1, 2,\dots, 9\}$.The 0th percentile filter is the ***min filter***, used for the opposite purpose.

The superiority in all respects of median over average filtering in this case is quite evident. In general, median filtering is much better suited than averaging for the removal of additive salt-and-pepper.

4. Sharpening filters (High-pass filters)

The principal objective of sharpening is to highlight fine detail in an image or to enhance detail that has been blurred, either in error or as a natural effect of a particular method of image acquisition.

Uses of image sharpening vary and include applications ranging from electronic printing and medical imaging to industrial inspection and autonomous target detection in smart weapons.

We saw that image blurring could be accomplished in the spatial domain by pixel averaging in a neighborhood.

Since averaging is analogous to integration, it is logical to conclude that sharpening could be accomplished by spatial differentiation. This, in fact, is the case, and the discussion in this section deals with various ways of defining and implementing operators for sharpening by digital differentiation.

The sharpening filters dividing in tow main categories: ***basic high-pass spatial filters*** and ***derivative filters*** (A. Hurlbert, 1986).

a) Basic high-pass spatial filters

The shape of the impulse response needed to implement a high-pass spatial filter indicates that the filter should have a form were A large coefficient generally appears in the center of the mask, surrounded by smaller positive and negative coefficients. Three common high-pass filter masks are:

-1	-1	-1
-1	9	-1
-1	-1	-1

Mask 1

0	-1	0
-1	5	-1
0	-1	0

Mask 2

1	-2	1
-2	5	-2
1	-2	1

Mask 3

The filtering output pixels might be of a gray level exceeding [0,255]. But the high-pass filter operation can produce results that are less than 0 or greater than 255. In these underflow and overflow cases, the resulting values are forced to 0 or 255, whichever is closest.

b) Derivative filters

Differentiation can be expected to have the opposite effect of averaging, which tends to blur detail in an image, and thus sharpen an image and be able to detect edges.

The most common method of differentiation in image processing applications is the gradient.

For a function f(x,y), the gradient of f at coordinates (x,y) is defined as the vector

$$\nabla f(x,y) = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{df}{dy} \end{bmatrix}$$

The magnitude of this vector is approximately

$$\text{Mag}(\nabla f(x,y)) = \left[\left(\frac{df}{dx}\right)^2 + \left(\frac{df}{dy}\right)^2\right]^{\frac{1}{2}}$$

Similar results are obtained by taking absolute values as follows:

$$\text{Mag}(\nabla f(x, y)) = \left|\frac{\partial f}{\partial x}\right| + \left|\frac{\partial f}{\partial y}\right|$$

Its magnitude can be approximated in a number of ways, which result in a number of operators such as ***Roberts***, ***Prewitt*** and ***Sobel*** operators for computing its value. These operators are use in ***Edge detection***.

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