Gray-level Morphological Operations for Image Segmentation and Tracking Edges on Medical Applications

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Summary

In this paper we mainly focused on grayscale images and how these images can be decomposed into number of peaks. This decomposition is called the peak analysis of grayscale images. Due its sensitive definition, there is a wide range of applications for peak analysis. The detection criterion expresses the fact that important edges should not be missed. It is of paramount important to preserve, uncover or detect the geometric structure of image objects. Thus morphological filters, which are more suitable than linear filters for shape analysis, play a major role for geometry based enhancement and detection.

A new method for image segmentation and tracking edges based on morphological transformation is proposed. This algorithm uses the morphological transformations dilation and erosion. A gradient determined grey level morphological procedure for edge increase and decrease is present. First, the maximum gradient, in the local neighborhood, forms the contribution to the erosion of the center pixel of that neighborhood. The gradients of the transformed image are then used as contributions to subsequent dilation of eroded image. The edge sharpening algorithm is applied on various sample images. Proposed algorithm segments the image by preserving important edges.

Key words:
Dilation, Erosion, Peak, Valley, Edge, Toggle contrast.

1. Introduction

Mathematical morphology stresses the role of "shape" in image pre-processing, segmentation and object description. Morphology usually divided into binary mathematical morphology which operates on binary images and gray-level images. The two fundamental operations are Dilation and erosion. Dilation expands the object to the closest pixels of the neighborhood. Dilation combines two sets using vector addition

$$X \oplus B = \{p\ \Sigma \in 2 : p = x + b,\ x \in X \text{ and } b \in B\}$$

Where X is Binary image, B is the Structuring element. Erosion shrinks the object. Erosion Θ combines two sets using vector subtraction of set elements and is the dual operation of dilation.

$$X\ \Theta\ B = \{p \in \Sigma\ 2 : p + b \in X \text{ and for every } b \in B\}$$

Where X is Binary image, B is structuring element. Extending morphological operators from binary to gray-level images can be done by using set representations of signals and transforming these input sets by means of morphological set operators. Thus, consider an image signal f(x) defined on the continuous or discrete plane ID=R^2 or Z^2 and assuming values in R=R U ($-\infty$, ∞). Shareholding *f* at all amplitude levels produces an ensemble of binary image represented by the threshold sets.

$$\Theta v(f) \equiv \{x \in ID : f(x) \geq v\},\ -\infty < v < +\infty.$$

The image can be exactly reconstructed from all its threshold sets

$$f(x) = \sup\{v \in R : x \in \Psi[\Theta v(f)]\}$$

Where "sup" denotes superman transforming threshold set of the input signal *f* by a set operator and viewing the transformed sets as threshold sets of a new image creates a flat image operator, whose output signal is

$$\Psi(f)(x) = \sup\{v \in R : x \in \Psi[\Theta v(f)]\}$$

For example if Ψ is the set dilation and erosion by B, the above procedure creates the two most elementary morphological image operators , the dilation and erosion of f(x) by a set

$$B: (f \oplus g)(x) \equiv \vee f(x-y),\ (f\ \Theta\ B)(x) \equiv \wedge f(x+y)$$

Where 'v' denotes supremum (or maximum for finite B) and '$\wedge$' denotes infimum (or minimum for finite B). Flat erosion (dilation) of a function f by a small convex set B reduce the peaks with minimum enhancement of the function and increases valleys with a maxima enhancement of the function. The flat opening

$f \circ B = (f\ \Theta\ B)\ \Theta\ B$ of f by B

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smoothes the graph of *f* from below by cutting down its peaks, whereas the closing

$$f \bullet B = (f \oplus B) \Theta$$

smoothes it from above by filling up its valleys. The most general translation-invariant morphological dilation and erosion of a gray-level image signal f(x) by another signal g are:

$(f \oplus g)(x) \equiv \vee\ f(x-y)+g(y)$

$(f\ \Theta\ g)(x) \equiv \wedge\ f(x+y)-g(y)$

Note that signal dilation is a nonlinear convolution where the sum of products in the standard linear convolution is replaced by a max of sums. Dilation or erosions can be combined in many ways to create more complex morphological operations that can solve a broad variety of problems in image analysis and nonlinear filtering. Their versatility is further strengthened by a theory outlined in that represents a broad class of nonlinear and linear operators as a minimal combination of erosions and dilations. Here we summarize the main results of this theory, restricting our discussion only to discrete 2-D image signals.

Any translation invariant set operator Ψ is uniquely characterized by its kernel

$$(\Psi) \equiv \{X \in Z^2 : 0 \in \Psi(X)\}$$

The kernel representation requires an infinite number of erosions or dilations. A more efficient representation uses only substructure of the kernel, its basis Bas (Ψ), defined as the collection of kernel elements that are minimal with respect to the partial ordering. If Ψ is also increasing and upper semi continuous, then Ψ has a nonempty basis and can be represented exactly as a union of erosions by its basis sets:

$$\Psi\ (X) = \bigcup\ A\ \in\ \mathrm{Bas}\ (\Psi)\ X\ \Theta\ A$$

The morphological basis representation has also been extended to gray-level signal operators, that is translation invariant and commutes with threshold.

2. Existing Techniques:

Edge-based methods center around contour detection: their weakness in connecting together broken contour lines make them, too, prone to failure in the presence of blurring. The main disadvantage of these edge detectors is their dependence on the size of objects and sensitivity to noise

Further, since conventional boundary finding relies on changes in the grey level, rather than their actual values, it is less sensitive to changes in the grey scale distributions over images as against region based segmentation

The existing techniques for morphological transformations are dilation (⊕) and erosion (Θ).The dilation ⊕ combines two sets using vector addition. The erosion Θ combines two sets using vector subtraction of set of elements and is the dual operator of dilation.

Erosion and dilation are not inverse transformations, an image is eroded and then dilated, the original image is not re-obtained. To over come this, we used new techniques that is: Opening and Closing .The Erosion followed by dilation an important morphological transformation called **Opening** ∘. Dilation followed by erosion is called **Closing** •.

3. Proposed Techniques:

3. 1 Proposed Technique for segmentation

New algorithm for image segmentation can be proposed based on different existing techniques and finally a new one is proposed that only to perform the segmentation with help of addition of rows and subtraction of column values. It is easy to remember and implement.

Algorithm for segmentation

1. Take the raw image as input image
2. Read the input image, store the image in array and convert into character values
3. int i,j,max,k,count=0,z,e,sum,X,Y,Z,U;
4. Initialize the "for" loop values

```
for(i=0;i<=64;i++)
 {
 for(j=0;j<=64;j++)
  {
 ch=getc(fp);
 a[i][j]=(int)ch;
 sum=sum+a[i][j];
  }  }
  avg=sum/(64*64);
  for(i=0;i<64;i++)
  {
  for(j=0;j<64;j++)
  {
  if(a[i][j]>=avg)
  n=255;
  else
```

```
 n=0;
 putpixel(100+j,100+i,n);
   }}
 for(i=0;i<62;i++)
{
 for(j=0;j<62;j++)
 {
 X=abs(a[i][j]-a[i][j+1]);
 Y=abs(a[i][j]-a[i+1][j]);
 Z=abs(a[i][j]-a[i+1][j+1]);
 U=abs(a[i][j]-a[i+1][j-1]);
 if(X>=45 || Y>=45 || Z>=50 || U>=45)
 n=255;
 else
 n=0;
 putpixel(200+j,320+i,n);
} }
outtextxy(180,300," segmented image");
getch();
 fclose(fp);
 closegraph();
}
```

5. Print the segment image as out put

Based on above morphological operations we proposed new techniques that are **Peak** and **Valley**. These two techniques define based on opening and closing respectively.

3.2 Morphological Peak future Detection:

Peak analysis is defined as the process of the iterative extraction of TP (*f*) from *f* until it contains no top-hat peaks. Following is description of the process.

Residual between openings or closings and original image offer an intuitively simple and mathematically formal way for peak or valley detection. Specifically, subtracting from an input image *f* its opening by a compact convex set B yields an output consisting of the image peaks whose support cannot contain B. This is top-hat transformation,

$$\text{Peak } (f) = f - (f \circ B),$$

Which has found numerous applications in geometric feature detection. It can detect bright blobs, i.e. regions with significantly brighter intensities relative to the surroundings. The shape of the detected peaks support is controlled by the shape of B, where as the scale of the peak is controlled by the size of B.

Algorithm for Peak:

1. Take the raw image as input image
2. Read the input image, store the image in array and convert into character values
3. int i,j,max,k,count=0,z,e,sum;
4. Initialize the "for" loop values

```
for(i=0;i<=64;i++)
 {for (j=0; j<=64;j++)
  {
   ch=(int)getc(fp);
   a[i][j]=ch;
  } }
for(i=0;i<=62;i++)
  {for(j=0;j<=62;j++)
   {     g[i][j]=(a[i][j]-z[i][j]);
     sum2 +=g[i][j];
   }  }
   avg2=sum2/(62.0*62.0);
  for(i=0;i<=62;i++)
  {for(j=0;j<=62;j++)
   {
   if(g[i][j]>=avg2)
    t=255;
    else
    t=0;
   putpixel(300+i,300+j,t);
   }   }
  outtextxy(300+i,300+j,"image after peak");
```

5. Print the peak image as out put.

3.3 Morphological Valley future Detection:

Similarly, to detect dark blobs, modeled as image intensity valleys, we can use the valley detector,

$$\text{Valley}(f) = (f \bullet B) - f$$

The morphological peak/valley detectors are simple, efficient, and have some advantages over curvature-based approaches. Their applicability in situations in which the peaks or valleys are not clearly separated from their surroundings is further strengthened by generalizing them in following way. The conventional opening is replaced by a general lattice opening such as an area opening or opening by reconstruction. This generalization allows more effective estimations of the image background surroundings around the peak and hence a better detection of the peak.

Algorithm for Valley

1. Take the raw image as input image
2. Read the input image, store the image in array and convert into character values
3. int i,j,max,k,count=0,z,e,sum;
4. Initialize the "for" loop values

```
for(i=0;i<=64;i++)
 {for(j=0;j<=64;j++)
  {  ch=(int)getc(fp);
   a[i][j]=ch;
```

```
  } }
for(i=0;i<=62;i++)
  {for(j=0;j<=62;j++)
    {g[i][j]=(f[i][j]-a[i][j]);
    sum2 +=g[i][j];
    } }
    avg2=sum2/(62.0*62.0);
  for(i=0;i<=62;i++)
  {for(j=0;j<=62;j++)
    { if(g[i][j]>=avg2)
     t=255;
     else
     t=0;
   putpixel(250+i,250+j,t);
    } }
```

5. Print the valley image as out put.

4. Edge enhancement:

4.1 Morphological Gradients:

Consider the difference between the flat dilation and erosion of an image f by a symmetric disk like set b containing the origin whose diameter diam (B) is very small:

$$\text{Edge } (f) = (f \oplus B) - (f \Theta B) / diam(B).$$

If f is binary, edge (*f*) extracts its boundary. If *f* is gray level, the above residual enhances its edges by yielding an approximation to $\| \nabla f \|$ which is obtained in the limit of equation as diam (b) -> 0. Further, thresholding this morphological gradients leads to binary edge detection. The symmetric morphological gradient is the average of two symmetric ones: the erosion $f - (f \oplus B)$ and the dilation gradient $(f \oplus B) - f$. The symmetric or asymmetric morphological edge-enhancing gradients can be made more robust for edge detection by first smoothing the input image with a linear blur. These hybrid edge-detection schemes that largely contain morphological gradients are computationally more efficient and perform comparably or in some cases better than several conventional schemes based only on linear filters.

Algorithm for Gradient:

1. Take the raw image as input image
2. Read the input image, store the image in array and convert into character values
3. int i,j,min,k,count=0,z,e,sum2=0,avg=0,g;
4. Initialize the "for" loop values

```
for(i=0;i<=64;i++)
 { for(j=0;j<=64;j++)
   {ch=(int)getc(fp);
     a[i][j]=ch;
   } }
for(i=0;i<=62;i++)
  {for(j=0;j<=62;j++)
    {g[i][j]=(f[i][j]-z[i][j])/3;
    sum2 +=g[i][j];
    }}
    avg2=sum2/(62.0*62.0);
  for(i=0;i<=62;i++)
  {for(j=0;j<=62;j++)
    { if(g[i][j]>=avg2)
     t=255;
     else
     t=0;
   putpixel(400+i,400+j,t);
     } }
     outtextxy(400+i,400+j,"gradients");
```

5. Print the gradient image as out put.

4.2 Toggle Contrast filter:

Consider a gray level image *f*[x] and small size symmetric disk like structuring element B containing the origin. The following discrete nonlinear filter can enhance the local contrast of *f* by sharpening its edges

$$\psi(f)[x] = (f \oplus b)[x]$$

$$\text{If } (f \oplus b)[x] - f[x] \le f[x] - f(\Theta B)(f \oplus b)[x]$$

$$(f \oplus B)[x] - f[x] > f[x] - (f \Theta B[x])$$

At each pixel x, the output value of this filter toggles between the value of the dilation of *f* by b at x and the value of its erosion by B according to which is closer to input value *f*[x].The toggle filter is usually applied not only once but is iterated .the more iterations, the more contrast enhancement. Further, the iterations converge to a limit (fixed point) reached after a finite number of iterations.

Algorithm for Toggle Contrast:

1. Take the raw image as input image
2. Read the input image, store the image in array and Converted into character values
3. int i, j,min,k,count=0,z,e,sum;
4. Initialize the "for" loop values

```
for(i=0;i<=64;i++)
 {for(j=0;j<=64;j++)
   {ch=(int)getc(fp);
     a[i][j]=ch;
   }}
for(i=0;i<=62;i++)
  {for(j=0;j<=62;j++)
    {
    if(abs(z[i][j]-a[i][j])<=abs(a[i][j]-f[i][j]))
```

```
        g[i][j]=z[i][j];
        else
        g[i][j]=f[i][j];
        sum2 +=g[i][j];
        } }
        avg2=sum2/(64*64);
     for(i=0;i<=64;i++)
  {  for(j=0;j<=64;j++)
    { if(g[i][j]>=avg2)
        n=255;
        else
        n=0;
        putpixel(300+i,300+j,n);
        } }
outtextxy(300+i,300+j,"toggle contrast");
```

5. Print the toggle image as out put.

5. Experimental results.

As an application of proposed segmentation, peak and valley algorithms, we have taken medical images like spinal chord and skull (64 x 64), and for gradient and toggle contrast, we taken Lincon and Mona Lisa images (64 x 64) respectively. For segmentation, we increase column and store image in array and can perform operation on given image. The peak operation can be obtained by using differentiation between original image and opening image, the valley operation can be obtained by using differentiation between closing image and original image respectively. The gradient operation can be obtained by using differentiation between dilation and erosion and by using diameter value of structuring element B, gradient operation can be obtained by using differentiation between dilation and erosion is used to obtain contrast.

ORIGINAL IMAGES IMAGES SEGMENTED

IMAGE OPENING PEAK (PROPOSED)

IMAGE CLOSING VALLEY (PROPOSED)

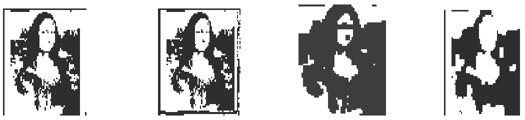

IMAGE DILATION (PROPOSED) ERODE CONTRAST

IMAGE DILATION (PROPOSED) EROSION GRADIENT

Conclusion

The proposed work will lead to several experiments based on the algorithms introduced, which improve the quality based on the peak analysis and valley analysis on given images. The techniques developed are mainly problem oriented. The edges in the images are thickly marked and are better visible than that of primitive operations. In morphology, the Dilation is performed if the central value of the kernel is less than ‘n’ and if it is greater than ‘n’ Erosion is performed, based on erosion and dilation. We achieve two contradictory edge enhancement algorithms that are gradient and toggle contrast, and the resultant images require an in-depth study.

The algorithm for image segmentation has been implemented using morphological transformations. The edge enhancement operator illustrates that it can be useful to consider edges as two-dimensional surface. This allows the combination of gradient direction and magnitude information. Edge sharpening is useful for extraction of phase regions. It does not have much effect, when implemented on diagonal edges. Sharp edges have been detected by this algorithm. This algorithm has been tested on various images and verified the result.

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