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Creation of Parallel Realizations for Image-Recognizing Algorithms[1]

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Abstract

The material of this report deals with some problems of image noise clearing. Due to high computing complexity of the algorithms in question, a parallel modification without the reducing of counting precision is suggested.

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General Terms: noise reduction, parallel computing
Additional Key Words and Phrases: image noise clearing, image revision, hyperspace, algorithm optimization

1. INTRODUCTION

Image noise clearing plays the important role before the processing of image recognition and analyzing. The noise source can be in the transmission devices, imperfection of optical equipment or the analyzed object surface defects. The goal of the digital revision of the image is to reduce the influence of the noise and preserve the quality outline of the image.

The most noticeable image revision process is the revision of strongly noised images, when the energy of the initial picture is comparable with the energy of the image noise. A method of decomposition of initial picture into the segments and analyzing these segments is described below.

This method lets find the less exposed to noise image segments and then interpolate image signal to the mostly noised segments. Though the algorithm of this method needs a lot of resources and has a very high computing complexity we suggest its parallel modification without the reducing of counting precision.

2. HYPERSURFACE BUILDING

Consider the image as a surface in a 3-dimension space, or as a 2-dimension vector F.

$$F=\{f_{ij}>0, n>0, m>0, i=0..n, j=0..m\}, \quad (1)$$

where f_{ij} - is an amplitude of the image in the point $[i;j]$, n,m - the size of the image.

We bring in the set of Λ vectors:

$$\Lambda=\{\lambda^{p1,p2,q1,q2}, n>p2>p1, m>q2>q1\};$$
$$\lambda_{ij}^{p1,p2,q1,q2}=\begin{pmatrix}1, i\in[p1..p2]\wedge j\in[q1..q2]\\ 0, i\notin[p1..p2]\vee j\notin[q1..q2]\end{pmatrix}, \quad (2)$$

where $p1,p2,q1,q2$ - are indexes, $\lambda_{ij}^{p1,p2,q1,q2}$ - 2-dimension vector with n x m sizes.

The vectors from the Λ set are a range of characteristic functions for various rectangular areas of image vector F.

We bring in to Λ function $L(\lambda^{p1,p2,q1,q2})=(p2-p1)\times(q2-q1)$.

Let $\lambda^{p11,p12,q11,q12}$ и $\lambda^{p21,p22,q21,q22}$ - are the two unconditioned vectors Λ.

Let us evaluate the value of quantity $L(\lambda^{p11,p12,q11,q12}+\lambda^{p21,p22,q21,q22})$ with various values of $p11,p12,q11,q12$ and $p21,p22,q21,q22$, i.e. with various values of rectangles $T1$ and $T2$ characteristic functions $\lambda^{p11,p12,q11,q12}$ and $\lambda^{p21,p22,q21,q22}$. As the vectors $\lambda^{p11,p12,q11,q12}$ and $\lambda^{p21,p22,q21,q22}$ are unconditioned, there are 3 variations to explore:

let $T1$ cross $T2$, but not belongs to $T2$, then

$$L(\lambda^{p11,p12,q11,q12}+\lambda^{p21,p22,q21,q22})<L(\lambda^{p11,p12,q11,q12})+L(\lambda^{p21,p22,q21,q22}) \quad (3)$$

let $T1$ belong to $T2$, then

$$L(\lambda^{p11,p12,q11,q12}+\lambda^{p21,p22,q21,q22})<L(\lambda^{p11,p12,q11,q12})+L(\lambda^{p21,p22,q21,q22}) \quad (4)$$

let $T1$ and $T2$ do not cross, then

$$L(\lambda^{p11,p12,q11,q12}+\lambda^{p21,p22,q21,q22})=L(\lambda^{p11,p12,q11,q12})+L(\lambda^{p21,p22,q21,q22}) \quad (5)$$

Therefore, from (3), (4), (5), we draw a conclusion, that

$$\begin{aligned}&\forall\lambda^{p11,p12,q11,q12},\lambda^{p21,p22,q21,q22}\in\Lambda\Rightarrow\\&L(\lambda^{p11,p12,q11,q12}+\lambda^{p21,p22,q21,q22})\le L(\lambda^{p11,p12,q11,q12})+L(\lambda^{p21,p22,q21,q22})\end{aligned} \quad (6)$$

Let us consider the set of G vectors like

$$\begin{aligned}&G=\{g^{p1,p2,q1,q2},n>p2>p1,m>q2>q1\};\\&g_{ij}^{p1,p2,q1,q2}=f_{ij}\times\lambda_{ij}^{p1,p2,q1,q2}\end{aligned} \quad (7)$$

where f_{ij} - the elements of vector F, $\lambda^{p1,p2,q1,q2}$ - the vectors from the set Λ.

If we use the addition of every vector element and multiplication of every vector element by number then it is obvious that G is a linear space [5].

Let us bring in norm ϕ to set G, like this

$$\phi(g^{p1,p2,q1,q2})=(1+L(\lambda^{p1,p2,q1,q2}))\times(\sum_{i=p1}^{p2}\sum_{j=q1}^{q2}g_{ij}^{p1,p2,q1,q2}), \quad (8)$$

where $g^{p1,p2,q1,q2}$ - vector of set G, $\lambda^{p1,p2,q1,q2}$ - vectors of set.

Considering (6), we have

$$\begin{aligned}&\forall g^{p11,p12,q11,q12},g^{p21,p22,q21,q22}\in G\Rightarrow\\&\phi(g^{p11,p12,q11,q12}+g^{p21,p22,q21,q22})\le\phi(g^{p11,p12,q11,q12})+\phi(g^{p21,p22,q21,q22})\end{aligned} \quad (9)$$

therefore, ϕ is a norm on set G.

Considering $[0..n]\times[0..m]\underset{\phi}{\Rightarrow}[0..n]\times[0..m]\times[0..n]\times[0..m]$, consider hypersurface, maked by ϕ values from $p1,p2,q1,q2$ parameters, parting in forming vectors g of set G.

3. HYPERSURFACE ANALYZING

Let us consider this hyperspace defined in 5d space and name reference axis like $p1, p2, q1, q2, z$. Hyperspace formed by ϕ values shows the energy image distribution F in space coordinates. Coordinates $p1, p2, q1, q2$ define rectangular area, where the image lies. Coordinate on axis $p1$ defines the beginning of interval on axis x, coordinate on axis $p2$ – the end of interval on axis x, coordinate on axis $q1$ defines the beginning of interval on axis y, coordinate on axis $q2$ – the end of interval on axis y, and coordinate z defines the value of norm $\phi(g^{p1,p2,q1,q2})$ of energy of initial image F, included in this rectangular area.

Let us consider points of this surface: we can get the initial picture by working with points that $p1 = p2$ and $q1 = q2$. I.e. point of surface $\phi(10,10,15,15)$ is a point of image $F(10,15)$, so, any point of surface $\phi(i,i,j,j)$ is a point of image $F(i,j)$. Neighboring points of surface are the middle values of energy of an image in the neighboring areas. Point of surface $\phi(10,20,15,25)$ is a middle value of energy of an image in area $i\in[10..20], j\in[15..25]$. So, any point of surface $\phi(i1,i2,j1,j2)$ is a middle value of energy of an image in area $i\in[i1..i2], j\in[j1..j2]$.

Let us consider the hypersurface in solving the problem of noise reduction. The influence of noise is strong in the small area of an image, while the values of noise of the whole image are nearly similar to the values of noise of the initial image.

The described surface lets us analyze the image using the benefits of two algorithms of noise reduction. Let us build the scheme of noise reduction:

$$\forall i,j \;\; \exists i1, j1, i2, j2 : (f[i,j] - \varphi[i1, j1, i2, j2] = \min) \tag{10}$$

where f_{ij} - the elements of vector from (1), $i; j, i1, j1, i2, j2$ - indexes, with $i1 < i < i2$, $j1 < j < j2$, ϕ - surface from (8), min - minimum value.

Property (10) is based on the fact that the image consists of the segments that are similar in their color characteristics and have a gradual alteration of color.

These areas let us interpolate the "gradual" values into the areas of noise with the help of the size- and form-changing window on the base of the clear-color information but not on the base of the noise-area information:

$$f[i,j] = \varphi[i1, j1, i2, j2]) \quad (11)$$

where f_{ij} - the element of vector (1), ϕ - surface fom (8), $i; j, i1, j1, i2, j2$ - indexes defined in accordance with conditions of (10).

So we evaluate an energetic contribution of point to the surface it belongs to. If the point is a point of noisement in any "gradual" area of an image then its contribution to the area is less than the contribution of other non-noised points and the value of this point is interpolated by the most probable value for this area.

4. OPTIMIZATION

The computing of the values of the hypersurface.

Listing 1. The analyzed fragment of an algorithm.

```
for (i1 = 0; i1 <= h-1; i1++)
{
    for (j1 = 0; j1 <= w-1; j1++)
    {
      for (i2 = i1+1; i2 <= h-1; i2++)
      {
        for (j2 = j1+1; j2 <= w-1; j2++)
        {
          sum = 0;
          for (i3 = i1; i3 <= i2; i3++)
          {
            for (j3 = j1; j3 <= j2; j3++)
```

```
                    {
                       sum = sum + f_image[i3][j3];
                    }
                 }
                 sum = sum/((i2-i1+1)*(j2-j1));
                 f_surface[i1][j1][i2][j2] = sum;
              }
           }
        }
    }
```

It is obvious that this algorithm needs a lot of resources. The graph [7] of this algorithm is a sequence of linked junctions from the cycle with the variable j2and because of this its parallel execution is impossible.

Let us bring in these signs:

$$S_{i1,j1,i2,j2} = \varphi[i1, j1, i2, j2])$$
$$r_{i1,i2,n1} = \sum_{i1}^{i2} f_{i,n1}$$
$$c_{j1,j2,n2} = \sum_{j1}^{j2} f_{n2,j} \qquad (12)$$

where f_{ij} - the elements of vector from (1), ϕ - surface from (8), $i; j, i1, j1, i2, j2, n1, n2$ - indexes.

Let c and r – be the partial sums, and S - be the sum. Notice, that

$$S_{i1,j1,i2+1,j2} = S_{i1,j1,i2,j2} + c_{j1,j2,i2+1}$$
$$S_{i1,j1,i2,j2+1} = S_{i1,j1,i2,j2} + r_{i1,i2,j2+1} \qquad (13)$$

Therefore, i and j sums can be calculated via partial sums.

If the calculation sums p values of neighboring variables (for example, $j1, j2$), in one pace, using the vector processors [2] for counting, then the quantity of the steps is:

$$N = y \cdot \left(\frac{x}{g \cdot k} \cdot \log_2 k + \frac{x}{2 \cdot g \cdot k} \cdot \log_2 k + \frac{x}{4 \cdot g \cdot k} \cdot \log_2 k + \ldots + \frac{x}{h \cdot g \cdot k} \cdot \log_2 k\right) \quad (14)$$

where x - the width, y - the height of an image, k - the quantity if the processors, g - capacity of the processor summator, i - index, h - like $2^h = \frac{x}{g \cdot k}$.

If $x >> g \cdot k$, (it is frequently in fact) then the real efficiency of the system tend to maximum.

5. PRACTICAL RESULTS

This method has been used in the analyzing of the videoimages of the sapphire-laid laser-signing. It is described in detail in [8].

One of the special features of this problem is a necessity of image analyzing of different sapphire plates images and with different reflection properties.

Besides this, the laser-signing often changes after the post-processing in case of physical influence. In its turn this influences the contrast of the laser-signing, and the optical elements can not transmit the clear picture to the recognition module.

Figure 1a shows the laser signing of a good quality. Figure 1b shows the laser-signing after the post-processing got in unfavorable conditions. Figure 1c shows the result of using our noise reduction method.

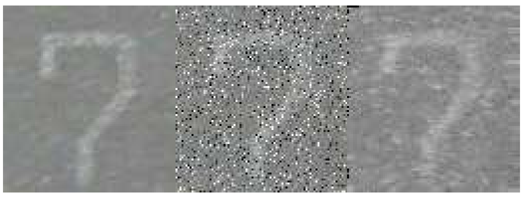

Fig. 1. a b c

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