# Development of effective procedures for automatic stereo matching

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## ABSTRACT

It is well known that the cross correlation stereo matching algorithms are still the basis of most of digital photogrammetric systems. This paper concerns the important problem of computational speed increasing for automatic stereo matching. Two techniques are presented. The first one is statistical approach for elimination of image parts with low information presence. The second is non-traditional implementation of computations using the "sliding window" technique.

**Keywords:** stereo matching, correlation technique, image information, fast implementation.

## 1. INTRODUCTION

It is well known that cross correlation stereo matching algorithms are the basis of most of digital photogrammetric systems. This paper describes two possibilities for reducing of computational burden. One of them is based on image informative characteristics. Another one uses the non-traditional implementation of computations in a sliding correlation window.

Our experience of operation with well known Russian TK-350 spaceborn images[1] shows, that they usually include some low-informative regions. Stereo matching of such regions is just a waste of time. Therefore there is a problem of selection of sample regions from the viewpoint of their selfdescriptiveness under the criterion of accuracy and probability of correct stereo matching. At use of correlation methods, a cross correlation coefficient is the best characteristic of a signal level inside template. The disadvantage of this characteristic that it is calculated during matching, while the index of signal level should be calculated before matching, indicating on those templates, which will have accurate matching. In the developed method an adaptive statistics of template brightness is used as an a priori evaluation of informative index, which is similar to the correlation coefficient. An advantage of this index is that it is calculated prior to the beginning of matching. This problem is considered in the section 2 of this paper.

Then the problem of reduction of computational time is considered concerning the automatic stereo matching based on the normalized correlation. The idea of acceleration of calculation of the convolution sums in a sliding window is well known (see, for example, paper[2]). The essence of this idea consists of storing the ready-made column sums and recursive subtracting and adding of the appropriate partial sums corresponding to the motion of a sliding window along the image row. It allows essentially reducing the amount of calculations in case of usual correlation convolutions, but not in case of stereo matching with separate convolution fields for all image points. In this work it is offered to bypass this problem by means of changing the order of calculations. It is proposed to implement the loop by disparities as an external loop, and the convolution loop as an internal one. In this case all calculations can be implemented in a manner of sliding window algorithm, and we obtain the required gain in productivity. This problem is considered in the section 3 of this paper.

## 2. ANALYSIS OF SELFDESCRIPTIVENESS OF IMAGE FRAGMENT

Fig. 2.1 demonstrates typical fragments of space born images used in our research. Images Fig.2.1.(a,b) were captured by TK-350 camera.*

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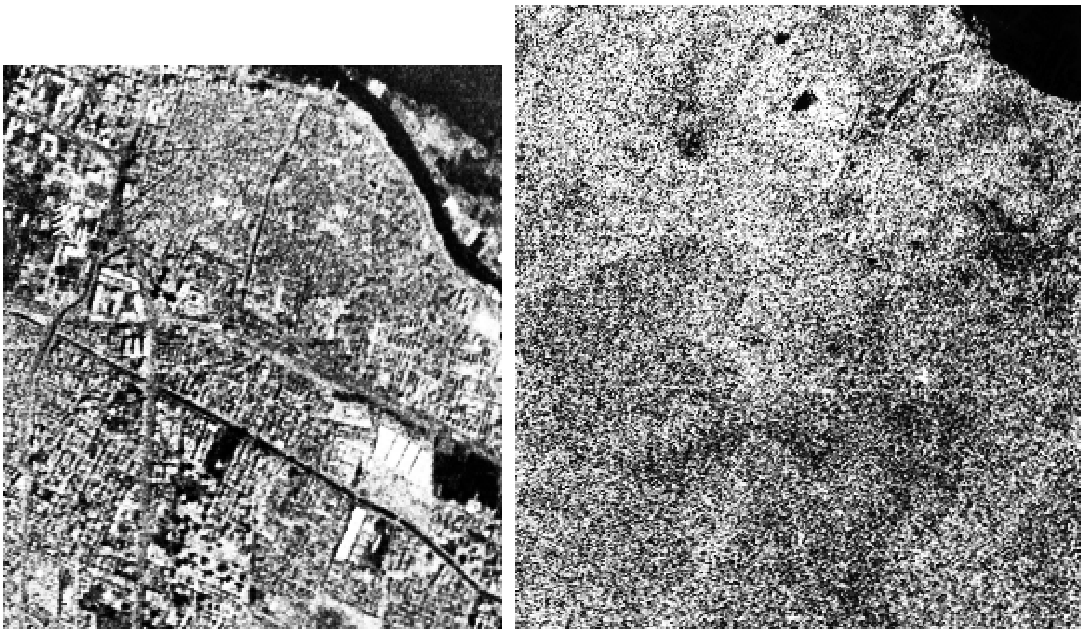


(a) (b)

Fig.2.2. Fragments of images tested: space born image of Cair city and neighborhood (a – part of town, b – desert region with low-informative parts).

The proposed method for elimination of "empty places" is based on analysis of brightness statistical properties of the special "wedge" (Fig.2.2) also captured by this camera. The "wedge" here is an image with smoothed intensity changing from left to right border.

Analysis method contains the following steps:

1) Splitting the "wedge" image k(x,y) onto M non-intersected rectangular "strip" regions of N pixel width and the length of whole "wedge". For each i-th region (i=2...N), calculating functions $B_i(d)$ and MSE of intensity $D_i(d)$ along the "wedge":

$$B_i(d) = \frac{1}{N}\sum_{y=1}^{N} k(d,y) \quad D_i(d) = \frac{1}{N}\sum_{y=1}^{N} (k(d,y))^2 - (B_i(d))^2 \tag{2.1}$$

2) Because of the intensity in columns of "wedge" image should be constant, MSE of intensity should be equal to MSE of the noise. In practice there are essential variations of intensity in columns. So, performing the averaging by regions to obtain the mean values B(d) and MSE of D(d):

$$B(d) = \frac{1}{M}\sum_{i=1}^{M} B_i(d) \quad D(d) = \frac{1}{M}\sum_{i=1}^{M} D_i(d) \tag{2.1'}$$

Fig. 2.3 (c,a) demonstrates B(d) и D(d) correspondingly.

3) Smoothing of D(d) (Fig. 2.3 b, n=3):

$$D_*(d) = \frac{1}{2n+1}\sum_{k=-n}^{n} D(1+k),$$

4) Obtaining the dependence of noise MSE on intensity D(b). For this purpose one should create the inverse function

$$d = B^{-1}(b)$$

using the linear interpolation. The function

$$D(b) = D_*(B^{-1}(b)).$$

is shown on Fig.2.3. d.

Function $\sigma^2 = D(b)$ allows testing the signal presence in the image fragment.

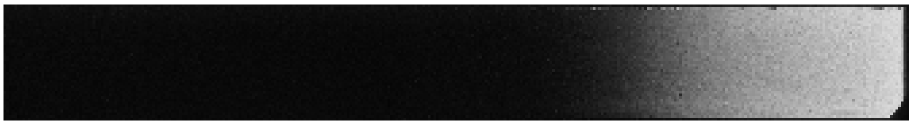


Fig.2.2. The optical "wedge" image.

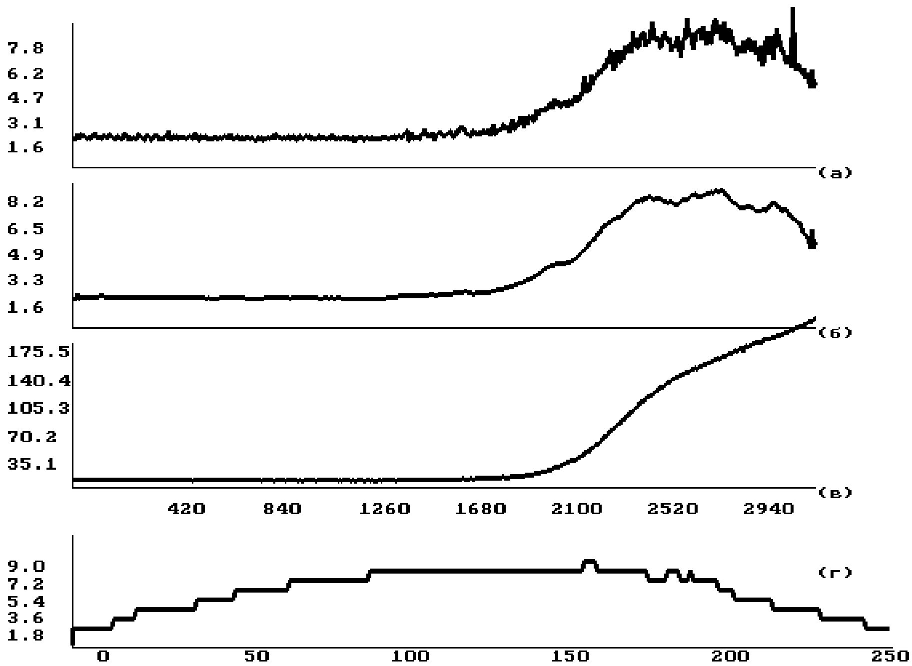



Fig.2.3. Analysis of statistical properties of noise by the "wedge" image: a – noise variance along the "wedge"; b – smoothed noise variance; c – changing of intensity along the "wedge" d – dependence of noise variance on intensity.

Let $f_i$ – means the value of signal samples inside the fragment, i=1,...,(2N+1)(2N+1). It is required to test the hypothesis $H_0$ concerning the data set is homogeneous:

$$H_0: \quad f_i = u + n_i, \quad n_i \in N(0,\sigma^2(u)),$$

where u is the supposed constant brightness value on a fragment; $n_i$ – noise samples, $\sigma(u)$ –dependence of MSE on intensity, derived from the "wedge".

Hypothesis $H_0$ is equivalent for the following:

$$H_0: \quad f_i = \xi_i, \quad \xi_i \in N(u,\sigma^2(u))$$

For variance $\frac{1}{N}\sum_{i=1}^{N} f_i^2 - \left(\frac{1}{N}\sum_{i=1}^{N} f_i\right)^2$

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} f_i^2 - \left(\frac{1}{N}\sum_{i=1}^{N} f_i\right)^2 \qquad (2.2)$$

it is known, that the value $\frac{(N-1)\sigma^2}{\sigma^2(u)}$ satisfies to $\chi^2$ – distribution with (N-1) degrees of freedom. So, $H_0$ is equivalent to the following expression:

$$H_0: \quad s = \frac{(N-1)\sigma^2}{\sigma^2(u)} \in \chi^2(N-1), \tag{2.3}$$

The estimation of value is formed as follows:

$$u = \frac{1}{N}\sum_{i=1}^{N} f_i . \tag{2.4}$$

Then, since statistics are calculated, the criterion of signal presence is tested as follows:

If $s \geq \chi^2(N-1)$ then $H_0$ hypothesis to be rejected.

For N > 30 the quantile of $\chi_p^2$ distribution can be estimated by formula

$$\chi_p^2(m) = \frac{1}{2}\left(\sqrt{2m-1} + \alpha_p\right)^2,$$

where $\alpha_p$ - the quantile of normal distribution.

Thus, the decision rule has the form:

$$\frac{(N-1)\sigma^2}{\sigma^2(u)} \geq \frac{1}{2}(\sqrt{2(N-1)-1} + \alpha_p)^2 ,$$

which is equivalent to $\frac{\sigma}{\sigma(u)} \geq \frac{1}{\sqrt{2(N-1)}}(\sqrt{2(N-1)-1} + \alpha_p) \approx 1 + \frac{\alpha_p}{\sqrt{2(N-1)}}$ .

So, the decision rule takes the form:

If $\sigma \geq (1 + \frac{\alpha_p}{\sqrt{2(N-1)}})\sigma(u)$, then $H_0$ hypothesis to be rejected.

Because it is useful to process data sets with *N*>200, this criterion is applied in the following form:

$$\sigma \geq (1 + \frac{C}{\sqrt{N}})\sigma(u),$$

where $C = \frac{\alpha_{0995}}{\sqrt{2}} \approx 2.4$.

So, the thresholding becomes adaptive. It depends both on the testing set amount, and on the statistical properties of the signal inside the image fragment. If one use the informative function

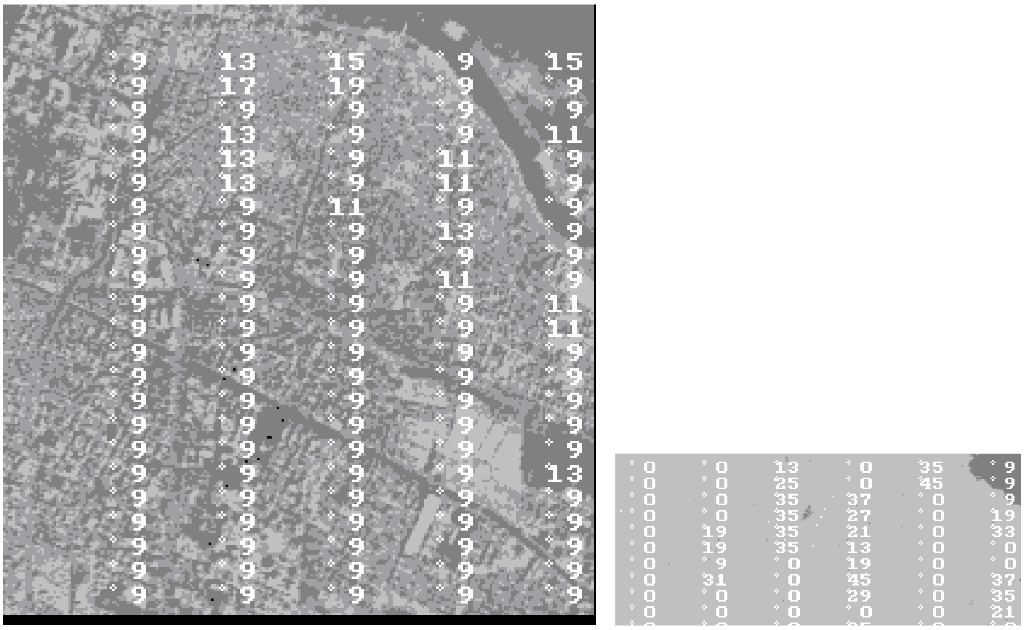
$$I(x_0,y_0,N) = \sigma(x_0,y_0,N),$$

then the threshold T is obtained as

$$T = (1 + \frac{C}{\sqrt{N}})\sigma(u) \tag{2.5}$$

Fig.2.4. demonstrates the result of application of algorithm of adaptive choice of image fragment. This algorithm starts the processing from the minimal size $N_{min}$=9 pixels. If at some step of size increasing the criterion $\sigma \geq T$ is satisfied, then the fragment size is fixed. If the size of fragment reached $N_{max}$=45 pixels, then the fragment is considered as non-informative.

Fig.2.4. demonstrates the fragment sizes (in pixels) for nodes of regular grid.



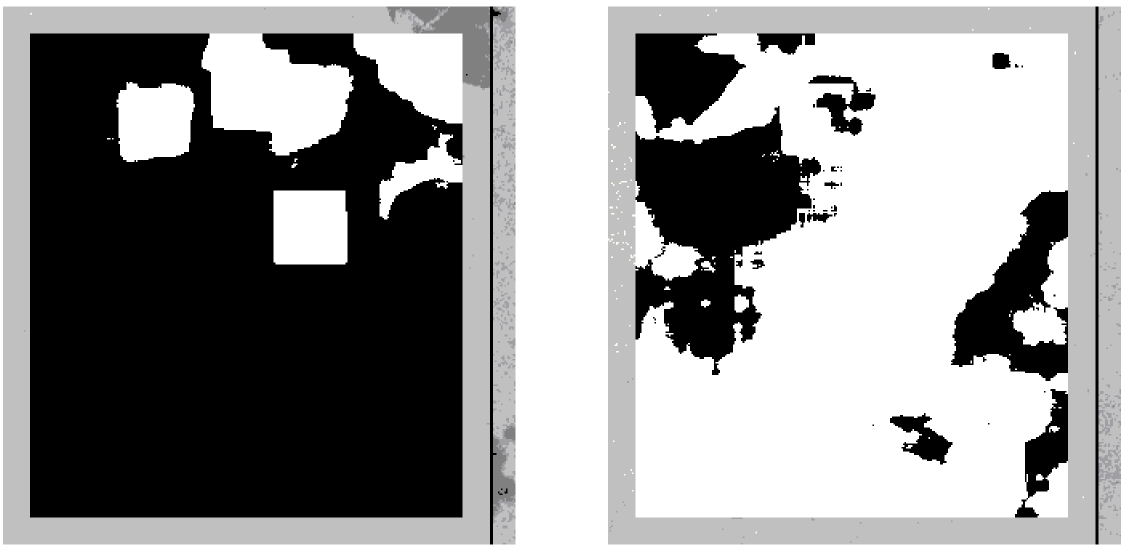
(a) (б)

Fig. 2.4. Sizes of informative fragments estimated based on signal/noise ratio for MSE.

Fig.2.5. demonstrates the example of estimation of informative fragments.

The each pixel of source image is considered as a center of 15x15 pixel fragment. For each fragment the informative criterion is tested. The resultant selfdiscriptiveness map is given at Fig.2.5.

This binary map is obtained as follows: $b(x,y) = 255$, if $I(x,y,15) \geq T$; $b(x,y) = 0$, if $I(x,y,15) < T$.



(a) (б)

Fig.2.5. The selfdiscriptiveness map. Informative regions are marked by white color.

## 3. ACCELERATED ALGORITHM FOR IMAGE STEREO CORRELATION

In this part of the paper the problem of reduction of computational time is considered concerning the automatic stereo matching based on the normalized correlation.

Let consider the following statement of stereo correspondence problem. Let we have two grayscale digital stereo images of 3D scene: $g_l(x,y)$ – intensity value for pixel $(x,y)$ on the left image; $g_r(x,y)$ – intensity value for pixel $(x,y)$ on the right image.

The following task is stated: for each pixel from the left image rectangle $\Omega = [left, right] \times [top, bottom]$ of size $M \times N$ $M = right - left + 1$, $N = bottom - top + 1$ (see fig.3.1) it is required to find the best corresponded pixels on the right image. Here «corresponded pixels» mean that both of them are the images (mappings) of the one 3D surface element of the scene.

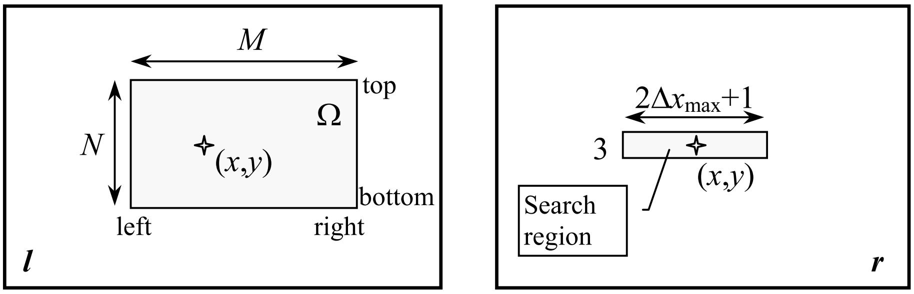



Fig.3.1. Regions for searching of stereo corresponded pixels.

Standard solution of stereo correspondence problem by means of stereo correlation method uses the normalized correlation measure of closeness of pixels $(x_l, y_l)$ and $(x_r, y_r)$ of the form:

$$corr(x_l, y_l; x_r, y_r) = \frac{\overline{(g_l - \overline{g_l}) \cdot (g_r - \overline{g_r})}}{\sqrt{\left(\overline{g_l^2 - \overline{g_l}^2}\right) \cdot \left(\overline{g_r^2 - \overline{g_r}^2}\right)}} = \frac{\overline{g_l g_r} - \overline{g_l} \cdot \overline{g_r}}{\sqrt{\left(\overline{g_l^2} - \overline{g_l}^2\right)\left(\overline{g_r^2} - \overline{g_r}^2\right)}} = \tag{3.1}$$

$$= \frac{\sum_{x=-a}^{a}\sum_{y=-b}^{b} g_l(x_l+x, y_l+y) g_r(x_r+x, y_r+y) - \sum_{x=-a}^{a}\sum_{y=-b}^{b} g_l(x_l+x, y_l+y) \cdot \sum_{x=-a}^{a}\sum_{y=-b}^{b} g_r(x_r+x, y_r+y)}{\sqrt{\left[\sum_{x=-a}^{a}\sum_{y=-b}^{b} g_l^2(x_l+x, y_l+y) - \left(\sum_{x=-a}^{a}\sum_{y=-b}^{b} g_l(x_l+x, y_l+y)\right)^2\right] \cdot \left[\sum_{x=-a}^{a}\sum_{y=-b}^{b} g_r^2(x_r+x, y_r+y) - \left(\sum_{x=-a}^{a}\sum_{y=-b}^{b} g_r(x_r+x, y_r+y)\right)^2\right]}},$$

where $(2a+1) \times (2b+1)$ – the size of correlation region (see. fig.3.2).

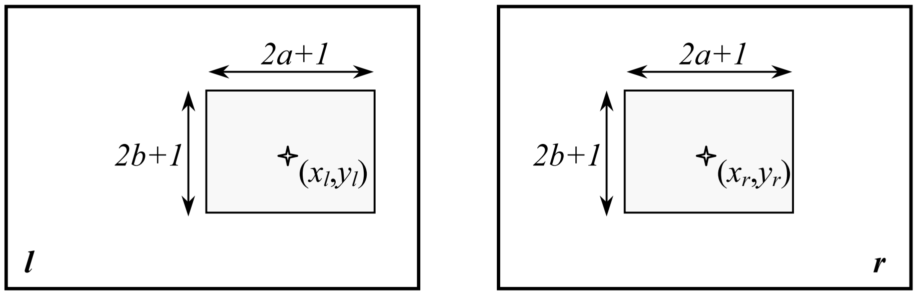



Fig.3.2. Correlation regions for pixels $(x_l, y_l)$ and $(x_r, y_r)$

For the best matching it is necessary to find:

$$(x_r(x_l, y_l), y_r(x_l, y_l)) = \mathop{\arg\max}_{|x_l - x_r| \le \Delta x_{\max}, |y_l - y_r| \le \Delta y_{\max}} corr((x_l, y_l);(x_r, y_r)) \quad (3.2)$$

### 3.1. Conventional stereo correlation algorithm

Usual method (3.2) for stereo correspondence determination based on the normalized coefficient (3.1) can be implemented as follows.

**Algorithm 1:**

1) Create three digital arrays of size $M \times N$:
   $Corr(x_l, y_l)$ – maximal correlation value for pixel $(x_l, y_l)$ of left image;
   $\Delta x(x_l, y_l)$ – x-parallax value ($\Delta x(x_l, y_l) = x_r(x_l, y_l) - x_l$);
   $\Delta y(x_l, y_l)$ – y-parallax value ($\Delta y(x_l, y_l) = y_r(x_l, y_l) - y_l$).
2) Fill all elements of $Corr(x_l, y_l)$ by value $-1$.
3) Perform steps 4-13 in a loop by all pixels $(x_l, y_l) \in \Omega$.
4) Perform steps 5-13 in a loop by $\Delta x = -\Delta x_{\max}, ...0, ...\Delta x_{\max}$ and $\Delta y = -1,0,1$.
5) Reset variables $s_l$, $s_r$, $s_{ll}$, $s_{lr}$, $s_{rr}$ by 0.
6) Perform steps 7-11 in a loop by $x = -a, ...0, ...a$, $y = -b, ...0, ...b$.
7) Increment $s_l$ by $g_l(x_l + x, y_l + y)$.
8) Increment $s_r$ by $g_r(x_l + \Delta x + x, y_l + \Delta y + y)$.
9) Increment $s_{ll}$ by $g_l^2(x_l + x, y_l + y)$.
10) Increment $s_{rr}$ by $g_r^2(x_l + \Delta x + x, y_l + \Delta y + y)$.
11) Increment $s_{lr}$ by $g_l(x_l + x, y_l + y) \cdot g_r(x_l + \Delta x + x, y_l + \Delta y + y)$.

12) Compute *corr* as $corr = \frac{s_{lr} - s_l \cdot s_r}{\sqrt{(s_{ll} - s_l^2) \cdot (s_{rr} - s_r^2)}}$.

13) If $corr > Corr(x_l, y_l)$, then $Corr(x_l, y_l)$ asssign $corr$, $\Delta x(x_l, y_l)$ assign current $\Delta x$, $\Delta y(x_l, y_l)$ assign current $\Delta y$.

As a result we obtain the arrays $Corr(x_l, y_l)$, $\Delta x(x_l, y_l)$, $\Delta y(x_l, y_l)$ filled by corresponded optimal values. So, the task is solved:

$$x_r(x_l, y_r) = x_l + \Delta x(x_l, y_l),\ y_r(x_l, y_l) = y_l + \Delta y(x_l, y_l),\ (x_l, y_l) \in \Omega. \tag{3.3}$$

Let us estimate the computational complexity of simple stereo correlation algorithm.

Take the complexity of one addition operation as a unit of computational complexity. Let one multiplication is equivalent to $k_*$ additions, one division operation – $k_/$ additions, one calling of 2D array element - $k_0$ additions, one square root extraction – $k_{\sqrt{}}$ additions.

*Note*. For modern processors all these *k* values are in the range from 1 to 10.

Then we will not account the loop organization efforts (it does not create the strong incorrectness, because $M$, $N$, $\Delta x_{\max}$, $a$ and $b$ are much greater than 1).

Under the assumptions made, the computational complexity of simple stereo correlation algorithm can be estimated as

$$\left[(5 + 3k_* + 2k_0)(2a+1)(2b+1) + 3 + 4k_* + k_/ + k_{\sqrt{}}\right] \cdot 3 \cdot (2\Delta x_{\max} + 1) \cdot M \cdot N. \tag{3.3}$$

Taking in account the fact that in practice one usually applied the neighborhoods of size $15 \times 15$ pixels (i.e. $a = 7$ and $b = 7$, $(2a+1)(2b+1) = 225 >> 10$), the expression (3.3) may be reformulated as follows:

$$24(5 + 3k_* + 2k_0) \cdot a \cdot b \cdot \Delta x_{\max} \cdot M \cdot N. \tag{3.4}$$

So, we found the complexity of algorithm to be linear by all region sizes: $M$, $N$, $a$, $b$, $\Delta x_{\max}$.

**3.2. Fast algorithm for stereo correlation based on a "sliding window" method.**

It is easy to see that the algorithm described in the previous paragraphs performs some computation more than one time. To improve this situation we can use the "sliding window" algorithm like analogous sliding window algorithms for sum accumulation described by Huang[2].

Let consider this "sliding window" method.

$$s_l(x_l, y_l) = \sum_{x=-a}^{a} \sum_{y=-b}^{b} g_l(x_l + x, y_l + y),\ (x_l, y_l) \in \Omega. \tag{3.5}$$

If one computes this sum directly by formula, it requires about

$$(1 + k_0) \cdot (2a+1) \cdot (2b+1) \cdot N \cdot M \approx 4(1 + k_0) \cdot a \cdot b \cdot N \cdot M \tag{3.6}$$

of operations.

The idea is to memorize the current result and recurrently use it for computation of each next result. The special 1D array of current sum is introduced:

$$sum(i) = \sum_{y=-b}^{b} g_l(x_l + x_i, y_l + y),\ \ i = 0,...2a \cdot \quad (3.7)$$

Then, during the motion by $x$ from left to right, in the $sum(i)$ array the elements are sequentially substituted (see fig.3.3).

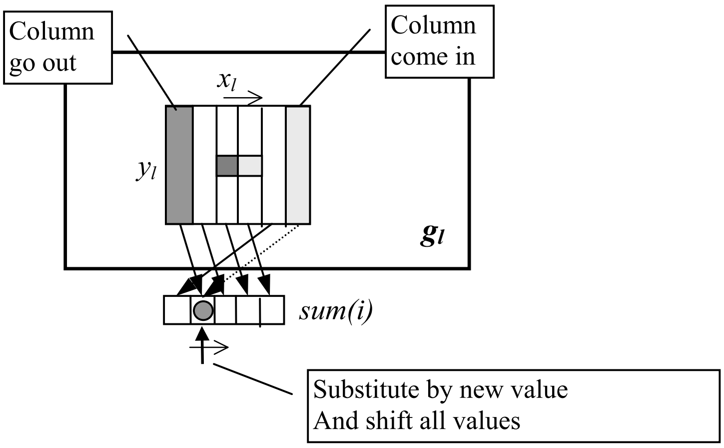



Fig.3.3. Filling of current sum array in the “sliding window” algorithm.

The computational complexity of such algorithm is about

$$(1+k_0)\cdot(2b+1)\cdot(N+2a)\cdot M \approx 2(1+k_0)\cdot b\cdot N\cdot M \quad (3.8)$$

of operations (because $N >> a >> 1$). So, it provides the computational gain in *2a* times.

In order to apply this idea to normalized stereo correlation computation, let rewrite the expression (3.1) with the following additional notetion:

$$s_{ll}(x_l, y_l) = \sum_{x=-a}^{a}\sum_{y=-b}^{b} g_l^2(x_l + x, y_l + y), \quad (3.9)$$

$$s_r(x_r, y_r) = \sum_{x=-a}^{a}\sum_{y=-b}^{b} g_r(x_r + x, y_r + y), \quad (3.10)$$

$$s_{rr}(x_r, y_r) = \sum_{x=-a}^{a}\sum_{y=-b}^{b} g_r^2(x_r + x, y_r + y), \quad (3.11)$$

$$s_{lr}(x_l, y_l; x_r, y_r) = \sum_{x=-a}^{a}\sum_{y=-b}^{b} g_l(x_l + x, y_l + y) g_r(x_r + x, y_r + y), \quad (3.12)$$

whre $(x_l, y_l) \in [left, right] \times [top, bottom]$ and $(x_r, y_r) \in [left - \Delta x_{\max}, right + \Delta x_{\max}] \times [top - 1, bottom + 1]$. Then

$$corr(x_l, y_l; x_r, y_r) = \frac{s_{lr}(x_l, y_l; x_r, y_r) - s_l(x_l, y_l) s_r(x_r, y_r)}{\sqrt{\left(s_{ll}(x_l, y_l) - s_l^2(x_l, y_l)\right)\cdot\left(s_{rr}(x_r, y_r) - s_r^2(x_r, y_r)\right)}}. \quad (3.13)$$

It is easy to see, that $s_l(x_l, y_l)$, $s_{ll}(x_l, y_l)$, $s_r(x_r, y_r)$, $s_{rr}(x_r, y_r)$ can be previously computed by sliding window algorithm (fig.3.3) before the main loop is started. These previous computation require about

$$2(2+k_0+k_*)\cdot b\cdot N\cdot M + 2(2+k_0+k_*)\cdot b\cdot(N+2a)\cdot(M+2) \approx 4(2+k_0+k_*)\cdot b\cdot N\cdot M \quad (3.14)$$

of operations.

However, it is not enough for essential acceleration of stereo correlation because the computation of $s_{lr}(x_l, y_l; x_r, y_r)$ still require $O(a \cdot b \cdot \Delta x_{\max} \cdot M \cdot N)$ of operation. To accelerate this stage, let transform the formula (3.12) as follows:

$$\tilde{s}_{lr}(x_l, y_l; \Delta x, \Delta y) \equiv s_{lr}(x_l, y_l; x_l + \Delta x, y_l + \Delta y) = \sum_{x=-a}^{a} \sum_{y=-b}^{b} g_l(x_l + x, y_l + y) g_r(x_l + \Delta x + x, y_l + \Delta y + y) =$$

$$= \sum_{x=-a}^{a} \sum_{y=-b}^{b} g_l(x_l + x, y_l + y) \tilde{g}_r(x_l + x, y_l + y; \Delta x, \Delta y), \quad (3.15)$$

where $\tilde{g}_r(x_l + x, y_l + y; \Delta x, \Delta y) = g_r(x_l + x + \Delta x, y_l + y + \Delta y)$. From (3.15) one can see, that under the fixed $\Delta x$ and $\Delta y$ values $\tilde{s}_{lr}(x_l, y_l; \Delta x, \Delta y)$ for $(x_l, y_l) \in \Omega$ can be computed by the "sliding window" algorithm approximately by

$$2(2 + k_0 + k_*) \cdot b \cdot N \cdot M \quad (3.16)$$

of operations.

Thus, if we change the order of loops by $x_l$, $y_l$ (step 3 of Algorithm 1) and $\Delta x$, $\Delta y$ (step 4 of Algorithm 2) and use the "sliding window" method, we obtain the following algorithm:

**Algorithm 2:**

1) Fill two 2D arrays using the "sliding window" algorithm:
   $s_l(x_l, y_l)$, $s_{ll}(x_l, y_l)$, $x_l = left,...right$, $y_l = top,...bottom$.
2) Fill two 2D arrays using the "sliding window" algorithm:
   $s_r(x_r, y_r)$, $s_{rr}(x_r, y_r)$, $x_r = left - \Delta x_{\max},...right + \Delta x_{\max}$, $y_r = top - 1,...bottom + 1$.
3) Create three digital arrays of size $M \times N$:
   $Corr(x_l, y_l)$ – maximal correlation value for pixel $(x_l, y_l)$ of left image;
   $\Delta x(x_l, y_l)$ – x-parallax value ($\Delta x(x_l, y_l) = x_r(x_l, y_l) - x_l$);
   $\Delta y(x_l, y_l)$ – y-parallax value ($\Delta y(x_l, y_l) = y_r(x_l, y_l) - y_l$).
4) Fill all elements of $Corr(x_l, y_l)$ by value $-1$.
5) Perform steps 6-23 in a loop by $\Delta x = -\Delta x_{\max},...0,...\Delta x_{\max}$ and $\Delta y = -1,0,1$.
6) Perform steps 7-23 in a loop by $y_l = top$ to $bottom$.
7) Assign $s = 0$.
8) Perform steps 9-12 for $i = 0$ to $2a-1$.
9) Assign $sum(i) = 0$.
10) Perform step 11 for $y = -b$ to $b$.
11) Increment $sum(i)$ by $g_l(left - a + i, y_l + y) g_r(left - a + i + \Delta x, y_l + y + \Delta y)$.
12) Increment $s$ by $sum(i)$.

13) Assign $sum(2a) = 0$.

14) Assign $i = 2a$.

15) Perform steps 16-23 for $x_l = left$ to $right$.

16) Decrement $s$ by $sum(i)$.

17) Assign $sum(i) = 0$.

18) Perform step 15 for $y = -b$ to $b$.

19) Increment $sum(i)$ by $g_l(x_l + a, y_l + y) g_r(x_l + a + \Delta x, y_l + y + \Delta y)$.

20) Increment $s$ by $sum(i)$.

21) Compute: $corr = \dfrac{s - s_l(x_l, y_l) \cdot s_r(x_l + \Delta x, y_l + \Delta y)}{\sqrt{(s_{ll}(x_l, y_l) - s_l^2(x_l, y_l)) \cdot (s_{rr}(x_l + \Delta x, y_l + \Delta y) - s_r^2(x_l + \Delta x, y_l + \Delta y))}}$.

22) If $corr > Corr(x_l, y_l)$, then assign $Corr(x_l, y_l) = corr$, $\Delta x(x_l, y_l) = \Delta x$, $\Delta y(x_l, y_l) = \Delta y$.

23) Increment $i$ by (1 mod ($2a + 1$)).

The complexity of this algorithm can be estimated as:

$$4(2 + k_0 + k_*) \cdot b \cdot N \cdot M + \lfloor 2b \cdot (2k_0 + k_* + 1) + 3 + 4k_* + k_/ + k_{\sqrt{}} \rfloor \cdot N \cdot M \cdot 3 \cdot 2\Delta x_{\max} \approx$$

$$\approx 12(2k_0 + k_* + 1) \cdot b \cdot N \cdot M \cdot \Delta x_{\max} \qquad (3.17)$$

of operations (supposing that $\Delta x_{\max} >> 1$).

Comparing expression (3.4) and expression (3.17) we obtain the result that the computational complexity of Algorithm 2 is less than complexity of Algorithm in $2a$ times.

It is also important that the algorithm described can be easily implemented at any parallel architecture.

## 4. CONCLUSIONS

The problem of computational speed increasing for automatic stereo matching is an important issue for designing low cost photogrammetric systems on PC-compatible computers. In this paper the solution for this problem is proposed based on a priory image informative characteristics analysis and non-traditional implementation of computations in a sliding correlation window.

Both useful described techniques allows obtaining the economy of computational time up to 20-25 times while processing of typical Russian TK-350 spaceborn images, and could be used for another data processing schemes.

## REFERENCES

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