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Neural Network Method of Operative Linking of Airphoto Intelligence and Virtual Topographic Model

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Abstract: In this research, the method of operative linking of airphoto intelligence and virtual topographic model are described. This method begins with preprocessing step which is made using anti-aliasing algorithm including low frequency filtration and deblurring algorithm application (this algorithm is based on Tikhonov's filtration), contour detection step which is made using non-linear cellular artificial neural network and contour correlation step which is made using restricted Boltzmann machine.

Key words: Aerial photography, anti-aliasing, Tikhonov filter, non-linear cellular artificial neural network, restricted Boltzmann machine

INTRODUCTION

At the present time, many various social and economic, environmental, natural and other tasks are decided using the vector ground maps which contain information on the height of artificial and natural objects. To create a precise map material, it is need to use a software and hardware complex of automatic construction of detailed three-dimensional topographic models which includes an Unmanned Aerial Vehicle (UAV) capable of performing detailed imaging in different spectral channels. To form the image it is necessary to develop a specialized system of combined vision. The image is produced by combining data from television and infrared imaging cameras (multi-channel image B) installed in a flying machine and the virtual Terrain Model (TIM), received via digital map.

ALIGNMENT ALGORITHM

Currently existing algorithms do not allow to achieve maximum efficiency in task solution, making it impossible to use them in real-time (Akinin and Nikiforov, 2013a). This algorithm consists of the following steps:

- View generation of HMW by inaccurate coordinates and parameters of orientation obtained from on-board system of UAV and matrix generation of M-bitmap of view representation
- Denticulation elimination on bitmap view representation
- Contour detection on the satellite image using neural network algorithm based on the use of non linear cellular neural networks described by Akinin and Nikiforov (2013b)
- Contours filtration (because not all selected contours are necessary and suitable for further correlation alignment)
- Matching of images contours on the satellite image with boundaries of objects in TIM

A number of problems arise during the development of automatically alignment tasks solution. One of the problems is denticulation on the boundaries of linear and polygon objects while mapping a virtual model of the terrain when flying at low altitudes. Before the alignment it is necessary to smooth the boundaries of objects on HMW with a view to removing denticulations. The algorithm of smoothing of the HMW textures was developed to solve this problem.

ALGORITHM OF SMOOTHING OF THE HMW TEXTURES

This algorithm consists of the following steps:

Applying to images the low-frequency filters and the result is the intensive HMW image blurring. After the low-frequency filters, all lines are smoothed-out but the object basic information isn't lost. All information is just redistributed according to a certain law and may be restored with exception of small objects and thin lines which are not significant for further alignment:

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Deblurring is the process of removing blurring contours from images. When thin lines and small objects were removed from the image with the help of low-frequency filters, it is necessary to restore clear boundaries of large objects with deblurring algorithm based of Tikhonov's filtration. The choice of deblurring algorithm was discussed in details by Sokolova *et al.* (2014). During use of the deblurring algorithm it is supposed that the image was fuzzy by disturbing function based on Gaussian low-frequency filters.

GAUSSIAN FILTER

The low-frequency filters reduce the amplitude of high-frequency components in an image spectrum (Arkashian *et al.*, 2012). The Gaussian filter is based on use of the two-dimensional Gaussian function:

$$g(x, y) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

The parameter σ in Eq. 1 affects to the sharpness of the function peak (the smaller absolute value of parameter the peak is sharper and vice versa).

The Gaussian filter preserves the dominant influence of the pixel which falls in the center of the shot and also takes into account the values if neighboring pixels which leads to a slight blurring of the original image.

DEBLURRING

The operation of applying the disturbing function to another function (to the image in this case) is the pixel-by-pixel convolution which is for each pixel is calculated a weighted sum of its neighborhood. Applying of the disturbing function h to the image f can be described as:

$$\begin{aligned} & f = \left[f_{xy}\right]; x = \overline{1, M}; y = \overline{1, N}; \\ & h = \left[h_{\mu ?}\right]; \mu = \overline{1, m}; \kappa = \overline{1, n}; \\ & g(x, y) = h \times f(x, y) = \\ & \sum_{i=-a}^{a} \sum_{j=-b}^{b} h(a+i+1, b+j+1) f(x+i, y+j); \\ & a = \frac{m-1}{2}; b = \frac{n-1}{2}, \end{aligned} \quad (2)$$

Where:

M, N = Image sizes
m, n = Sizes of disturbing filter
g(x, y) = Disturbing image

Deconvolution: There is a convolution theorem which states that the convolution in spatial domain is equivalent to regular multiplication in the frequency domain (and the element by element multiplication, not matrix). Consequently, the process of disturbing (Eq. 2) can be written like this:

$$G(u, v) = H(u, v)F(u, v)$$

where, G(u,v), H(u,v), F(u,v) the fourier transform of the disturbing image, disturbing function and also the original image. The task of rebuilding the disturbing image is to find the best approximation f'(x, y) of the original image.

TIKHONOV'S FILTRATION

To restore the image we need to solve the problem of finding the extremum (minimum) of some of the smoothing functional. In the method based on Tikhonov's filtration (Gonzalez and Woods, 2005) as a functional C[f], you can use the square of the norm of the Laplacian:

$$C[f] = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left(\nabla^2 f(x, y)\right)^2 \quad (3)$$

With an additional constraint:

$$\left\|g - H\hat{f}\right\|^2 = \|\eta\|^2 \quad (4)$$

Where:

$\hat{f}$ = Unknown of undistorted image
η = Noise

So, in this algorithm the external noise is absent and artificial image blurring is happened and η = 0 (Eq. 4) we can rewrite:

$$\left\|g - H\hat{f}\right\| = 0 \quad (5)$$

The solution of the optimization problem (Eq. 3) subject to Eq. 5 in the frequency domain is given by the equation:

$$F(u, v) = \left(\frac{H^*(u, v)}{|H(u, v)|^2 + \gamma |P(u, v)|^2}\right) G(u, v)$$

Where:

$H^*(u, v)$ = Complex conjugation of disturbing function H(u, v) (frequency-domain representation)
$|H(u, v)|^2$ = The unit square equals to the product of a complex number on the complex conjugate
γ = The regularization parameter that must be chosen to fulfill the Eq. 5
P(u, v) = A Fourier transform of the function

$$p(x, y) = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

i.e., to the function which determines the Laplasian operator; G(u, v) Fourier transform of disturbing image.

CONTOUR CORRELATOR

There are several approaches to the problem of contour correlation alignment as shown by Akinin and Nikiforov, the most effective from the point of view of execution time and required computational resources and allows to obtain with high precision the result is an approach based on using neural network associative memory based on Restricted Boltzmann Machine, RBM) (Aksenov and Novoseltsev, 2006).

Let $G_B = \{g_B\}$ is set of contour descriptions g'_B detailed on the image B ($|G_B| = N_B$); $G_M = \{g_M\}$ is set of contour descriptions g_M of objects, present in the image view BMM M ($|G_M| = N_M$).

The vector length g_B and g_B are the same and equal to S_{SZ}. The algorithm of the correlator consists of the following steps:

1) Training of the correlator on the many G_B with algorithm CD-k (Contrastive Divergence), described by Hinton;
2) Correlator pass for every g_M and the formation of pairs of descriptions of the contours $(g'_B, g_M) \in G_{pair}$ such for contour g_M contour g'_B is the best from the point of view of the correlator
3) Formation of many pairs of coincident points P for a number of G_{pair}
4) Calculation for a set of pairs of coincident points P final conversion of the match

A key element of the presented algorithm is the correlator based on the use of restricted Boltzmann machine.

Restricted Boltzmann machine belongs to the class of artificial neural networks implementing of the associative memory. Training of Boltzmann machine is reduced to the memorization of the input set of vectors, then the input machine is fed some input vector and the machine performs a number of iterations until the outputs of the neurons in its input layer does not reach a steady state which is the vector from training set, restored for the given input vector. Restricted Boltzmann machine structure scheme is on Fig. 1. RBM consists of two neuron layers:

- Layer of visible neurons, vector of weights $W_{visible,\ q}$ where q neuron index:

$$|W_{visible\ q}| = |g_B| = |g_M| = S_{sz}$$

- Layer of visible neurons, vector of weights $W_{hidden,\ q}$

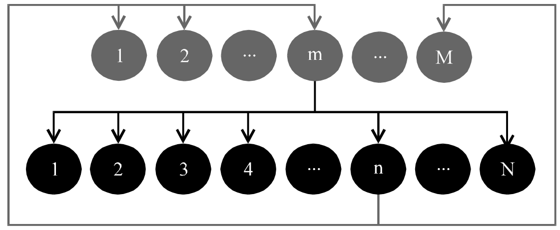

Fig. 1: Restricted Boltzmann machine structure scheme

The vectors of the weights of the neurons of each layer form matrix $W_{visible}$ and W_{hidden} number of rows $S_{visible}$ and S_{hidden} is a number of neurons in the visible and invisible neuron layers.

So, the restricted Boltzmann machine is the fully connected inertial navigation system, so $|W_{hidden\ q}| = S_{visible}$ and $|W_{hidden\ q}| = S_{hidden} = S^2_{SZ}$. The algorithm of inertial navigation system work of contour g_M to contour g'_B consists of following stages:

1) Original vector g_M comes to entry RBM: $g_{visible} = g_M$
2) $g_{visible\ prev} = g_{visible}$
3) Vector is calculated $\overline{g_{hidden}} = \{g_{hidden\ q}\}$ where $g_{hidden\ q} = W_{visible\ q}\, g^T_{visible};\ q = \overline{1, S_{visible}}$ each neuron calculates the sum of its entries (vector $g_{visible}$), weight by their synapsis (vector $W_{visible\ q}$)
4) Vector is calculated $\overline{g_{visible}} = \{g_{visible\ q}\}$ where $g_{visible\ q} = W_{hidden\ q}\, g^T_{hidden};\ q = \overline{1, S_{hidden}}$
5) Average squared difference of this vector is calculated $g_{visible}$ from this vector at the previous iteration ($g_{visible}$ prev):

$$\delta g_{visible} = \sqrt{\frac{\sum_{q=1}^{S_{visible}} \left(g_{visible\ q} - g_{visible\ prev\ q}\right)^2}{S_{visible}}}$$

6) If $\delta g_{visible} \leq \xi$, we done a stop of algorithm (vector $g_{visible}$ achieve a stable condition) or we do the step 3

Upon completion of the algorithm execution of the next vector $g_{visible}$ is taken as an approximation $\hat{g}'_B$ to vector g'_B.

Threshold amount $\xi > 0$ is the maximum allowable deviation of another vector $g_{visible}$ from the appropriate vector at the previous iteration at which the algorithm stops and te inertial navigation system is considered to have reached steady state. As $\hat{g}'_B$ vector $\hat{g}'_B \in G_B$ is chosen as nearly as possible to $\hat{g}'_B$ as Euclidean distance measure.

EXPERIMENT

The aim of this experimental study was the comparison of time indexes and quality factors of the alignment of the offered alignment algorithm and existing alignment algorithms. This experimental study was conducted using cluster computing, organized by the technology of Message Passing Interface (MPI) with the use of the software complex OpenMPI. To reduce the time spent on the experimental study each host used the power of the video processor available as part of a suitable computing system for additional parallelization part of calculations using the GPGPU technology. Estimated output parameters of the experiment were:

- Alignment (without considering training time of the model) with accurate to 1 msec
- The quality of the alignment E, the standard deviation of datum points on the test data accurate to 1 m was taken as the measure

SUMMARY

The offered alignment algorithm shows the result, best in 1.6 times of quality and 1.5 times of time, than the existing methods and algorithms of airphoto alignment and HMW.

CONCLUSION

The results of the experimental study demonstrate the feasibility of using the offered alignment algorithm the operational data analysis of airphoto in the process of solution of various applied tasks such as: automatic control of the UAV, the construction and refinement of three-dimensional topographic model and some other tasks.

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