GEODEZJA I KARTOGRAFIA
GEODESY AND CARTOGRAPHY
Vol. 53, No 2, 2004, pp. 99-113

The use of line moments of edge contour automatically detected with wavelet transform for surface matching

Luong Chinh Ke

Warsaw University of Technology
Institute of Photogrammetry and Cartography
1 Plac Politechniki, 00-661 Warsaw, Poland
e-mail: lchinhke@gazeta.pl

Received: 28 April 2003/Accepted: 18 March 2004

Abstract: The paper presents the line moments of edge contour detected in an image as the high level features which are useful for surface matching. It has been proved that line moments do not depend on scale and rotation in transformation and they are sensitive to small changes of line erroneously extracted. Therefore, line moments are the useful tools in the process of feature-based matching, which can be used for merging (comparing) two surfaces derived with different sensors for the same terrain scene. In order to receive a line in an image, the edge pixels of terrain contour have to be detected and then linked into a line. The paper also focuses on the problem of using wavelet transform for automatic detection of edge pixels.

The suggestion of 3-D line moments for surface matching has been presented in the section 5.

Keywords: Surface matching, wavelet transform, line moment, edge contour

1. Introduction

Feature-based matching is one of the three basic methods of image matching. Fundamental features are points and lines of interest. The group of line features may include normal, tangential vectors, curves and moments in given points of line. The line features are not only used in industry production for recognising and inspecting patterns but they are also widely applied in digital photogrammetry for matching images of the terrain. For recognition of partially occluded objects, the maximum curvature points have been applied (Ansari and Delp, 1991; Min-Hong and Dongsig, 1990). The line moments of object boundaries have also been utilised to recognise products manufactured and verify their quality (Wei and Lozzi, 1993). Terrain investigations of the line features become a suitable instrument in digital photogrammetry for performing the interior, exterior, relative and absolute orientation (Smith and Park, 2000).

Natural forms, such as roads, paths, fence lines, waterways, etc. are the interesting line features. Those features are easily visible on the images and often accessible on the ground. They could be extracted from individual images or models by different means, e.g. by manual, analytical or digital techniques. In the study line features will be obtained by means of the digital technique.

In order to obtain lines on an image, the edge pixels of interest have to be firstly detected and joined. The first method of edge pixel detection is based on the pixel gradients, which include operators proposed by Robert, Prewitt, Sobel, etc. It is called a gradient-based method. The second method is based on zero-crossings. It uses a cubic polynomial or B-spline as the fitting function (Ghen and Huang, 1995).

Recently, the wavelet transform technique has been considered a suitable instrument, for image processing. An image expressed in space domain is transformed to frequency domain. In the case of image compression the wavelet transform technique has more advantages than classical Fourier transform, and allows to reach the high effectiveness (Ueffing Merzhausen, 2001). The wavelet transform was already applied in detecting multiscale corner (Lee et al., 1995), haze in high resolution satellite images (Vacili, 2002), edge contour (Malat and Wen, 1992) and also for filtering a SAR speckle (Yunhan et al., 2000) etc.

The paper focuses on the ability of using the wavelet transform for detecting edge pixels. The wavelet transform technique is based on the convolution theory of two functions: a planar, linear function and a smoothing function. After detecting edge contour of terrain in an image with wavelet transform technique the line moments have been computed for the matching process. The 3-D line moments are suggested in section 5. They are projected into three planes *XY*, *XZ*, *YZ*. Thus, the formulae presented in section 3 and 4 can easily be applied.

2. Background of wavelet transforms for detecting edge contour

In the space domain a digital image is generally expressed as the grey function $f(x, y)$. Information contained in an image can be represented in other form through transformations, e.g. using the Fourier transform that tranforms an image from the space domain into the frequency domain. Other important transforms so-called wavelet transforms can also be used. The reducing noise during edge detection is the main advantage of wavelet transforms over the Fourier transform.

2.1. Fourier transform

Fourier complex integral that expresses the relation between value of f function at arbitrary point $x \in \Re$ and values of this function at all points of the interval $(-\infty, +\infty)$ is presented as follows (Leitner, 1995)

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} f(u)\, e^{-i\omega u} du \right] e^{i\omega x} d\omega \qquad x \in \Re \tag{1}$$

The integral in brackets expresses a certain function F of real variable ω. The formula (1) can thus be represented by a pair of functions

$$F(\omega) = \int_{-\infty}^{\infty} f(x) e^{-i\omega x} dx; \qquad f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{i\omega x} d\omega \qquad x, \omega \in \Re \tag{2}$$

where the first function corresponds to a direct Fourier transform (of function $f(x)$) and the second – an inverse Fourier transform (Fourier transform of function $F(x)$). The pair of functions

$$f(x) \Leftrightarrow F(\omega) \tag{3}$$

is called a pair of Fourier transforms.

In practice, observed or experimental data, coded values of image grey levels, etc. provide discrete information. Let $f(k)$ ($k = 0,1,2,3, ..., N-1$) be the discrete digital series in space domain, and $F(l)$ ($l = 0,1,2,3, ..., N-1$) is its discrete Fourier transform that represents the respective series in frequency domain. The 1-D discrete transform is given as follows (Wang, 1990)

$$\begin{aligned} F(l) &= \sum_{k=0}^{N-1} f(k) e^{-i2\pi \frac{kl}{N}} \\ f(k) &= \frac{1}{N} \sum_{l=0}^{N-1} F(l) e^{i2\pi \frac{kl}{N}} \end{aligned} \tag{4}$$

The dilation and convolution properties of the Fourier transform will be used in the next sections. A dilation $f_s(x)$ of $f(x)$ function by the scale factor s, is expressed by following formula

$$f_s(x) = \frac{1}{s} f\left(\frac{x}{s}\right) \Leftrightarrow \frac{1}{|s|} F\left(\frac{\omega}{s}\right) \tag{5}$$

where s is an arbitrary constant except $s \neq 0$.

The convolution of two functions $f(x)$ and $g(x)$ of the same variable is defined as

$$f(x) * g(x) = \int_{-\infty}^{\infty} f(u)\, g(x-u) du = F(\omega)\, G(\omega) \tag{6}$$

where $F(\omega)$, $G(\omega)$ are Fourier transforms of $f(x)$, $g(x)$, respectively. Function $g(x)$ is the smoothing function (low pass-filter) that smoothes the given function $f(x)$. Inversely, convolution of functions $F(\omega)$, $G(\omega)$ is

$$F(\omega) * G(\omega) = f(x)\, g(x) \tag{7}$$

Formulae describing Fourier transforms in 2-D could be found in (Leitner, 1995; Wang, 1990).

2.2. Detecting edge contours with the wavelet transform

Firstly, for detecting edge contours, the 1-D wavelet transforms have been determined. The edges of the different structures of ground or objects that appear in an image are characterised by intensity of sharp transitions where the gradient of the image intensity has the locally extreme value. Let $g(x)$ be a smoothing function which integral is not equal to zero. It can be viewed as an impulse response of a low-pass filter and also as a weighting function. Let $f(x)$ be any real function, which edges at the scale s are defined as local sharp variation points of the function $f(x)$, smoothed by $g_s(x) = \frac{1}{s} g\left(\frac{x}{s}\right)$ defined by (5). It will be shown how edges can be detected with the wavelet transform.

Let $\Psi^{(1)}(x)$, $\Psi^{(2)}(x)$ and $\Psi_s^{(1)}(x)$, $\Psi_s^{(2)}(x)$ be two pairs of wavelets (Malat and Wen, 1992) defined by

$$\begin{cases} \Psi^{(1)}(x) = \dfrac{dg(x)}{dx} \\ \Psi^{(2)}(x) = \dfrac{d^2 g(x)}{dx^2} \end{cases} \quad \text{and} \quad \begin{cases} \Psi_s^{(1)}(x) = \dfrac{dg_s(x)}{dx} \\ \Psi_s^{(2)}(x) = \dfrac{d^2 g_s(x)}{dx^2} \end{cases} \tag{8}$$

Basing on the convolution property the wavelet transforms can be defind with respect to each of these wavelets as follows

$$\begin{cases} W^1 f(s,x) = f(x) * \Psi_s^{(1)}(x) \\ W^2 f(s,x) = f(x) * \Psi_s^{(2)}(x) \end{cases} \tag{9a}$$

or

$$\begin{pmatrix} W^1 f(s,x) \\ W^2 f(s,x) \end{pmatrix} = \begin{pmatrix} s \dfrac{d}{dx} [f * g_s](x) \\ s^2 \dfrac{d^2}{dx^2} [f * g_s](x) \end{pmatrix} \tag{9b}$$

Wavelet transforms $W^1 f(s, x)$ and $W^2 f(s, x)$ (9b) are proportional to the first and second derivatives of $f(x)$, respectively, smoothed by $g_s(x)$. For the fixed scale s the extreme of $W^1 f(s, x)$ along the x-axis corresponds to zero-crossing of $W^2 f(s, x)$ and to the inflection points of $f(x) * g_s(x)$ that are represented in Fig. 1.

Fig. 1 shows that the edge can be detected by the extreme of wavelet transform $W^1 f(s, x)$. The local maxima or minima of the absolute values of the first derivatives are sharp variation points. For edges detection, only local maxima of $|W^1 f(s, x)|$ need to be calculated.

The edge can also be detected by the zero-crossing of wavelet transform $W^2 f(s, x)$. In other words, the phase $\psi(s, x)$ equals to $\pm\pi/2$ if $W^2 f(s, x) = 0$ (see Fig. 1). The zero-crossing indicates the location of a sharp variation point and singularity but more information on the decay of $|W^2 f(s, x)|$ in the vicinity of zero-crossing is needed.

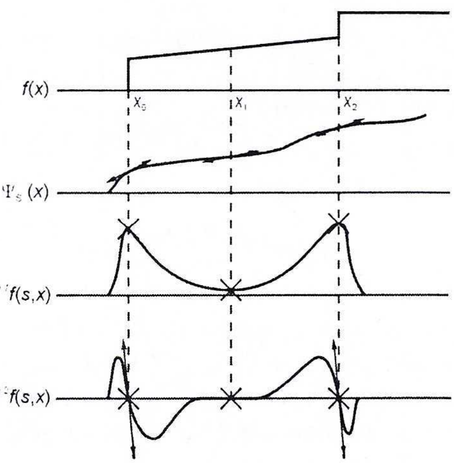

Fig. 1: The wavelet transform with extrema of $W^1 f(s, x)$ and zero-crossings of $W^2 f(s, x)$ (Malat and Wen, 1992)

With 2-D smoothing function $g(x, y)$ which double integral is not equal to zero, the wavelets are defined as

$$\Psi^{(1)} = \frac{\partial g(x, y)}{\partial x}, \quad \Psi^{(2)} = \frac{\partial g(x, y)}{\partial y}, \quad \Psi^{(3)} = \frac{\partial^2 g(x, y)}{\partial x^2},$$
$$\Psi^{(4)} = \frac{\partial^2 g(x, y)}{\partial x \partial y}, \quad \Psi^{(5)} = \frac{\partial^2 g(x, y)}{\partial y \partial x}, \quad \Psi^{(6)} = \frac{\partial^2 g(x, y)}{\partial y^2} \tag{10}$$

For any $f(x, y)$ function the wavelet transforms, defined with respect to $\Psi^{(\cdot)}(x, y)$, are

$$\begin{cases} W^1 f(s, x, y) = f * \Psi_s^{(1)}(x, y) \\ W^2 f(s, x, y) = f * \Psi_s^{(2)}(x, y) \end{cases}; \qquad \begin{cases} W^3 f(s, x, y) = f * \Psi_s^{(3)}(x, y) \\ W^4 f(s, x, y) = f * \Psi_s^{(4)}(x, y) \end{cases};$$

$$\begin{cases} W^5 f(s, x, y) = f * \Psi_s^{(5)}(x, y) \\ W^6 f(s, x, y) = f * \Psi_s^{(6)}(x, y) \end{cases}$$

or

$$\begin{pmatrix} W^1 f(s, x, y) \\ W^2 f(s, x, y) \end{pmatrix} = s \begin{pmatrix} \frac{d}{dx}[f * g_s](x, y) \\ \frac{d}{dy}[f * g_s](x, y) \end{pmatrix} = s\nabla(f * g_s)(x, y) \tag{10a}$$

and

$$\begin{pmatrix} W^3f(s,x,y) \\ W^4f(s,x,y) \\ W^5f(s,x,y) \\ W^6f(s,x,y) \end{pmatrix} = s^2 \begin{pmatrix} \frac{\partial^2}{\partial x^2}[f*g_s](x,y) \\ \frac{\partial^2}{\partial x \partial y}[f*g_s](x,y) \\ \frac{\partial^2}{\partial y \partial x}[f*g_s](x,y) \\ \frac{\partial^2}{\partial y^2}[f*g_s](x,y) \end{pmatrix} = s^2 \nabla^2 (f*g_s)(x,y) \qquad (10b)$$

The edges can be detected with a gradient vector ∇ of an image (10a, 10b). When the scale s varies over the dyadic sequence $(2^j)_{j\in Z}$ (Z = 0,1,2,...) only, where the 2-D dyadic wavelet transform of $f(x, y)$ determines the set of functions $[W^1f(2^j,x,y), W^2f(2^j,x,y)]_{j\in Z}$. The modulus of the wavelet transform $Mf(2^j,x,y)$ at the scale 2^j is

$$Mf(2^j,x,y) = \sqrt{|W^1f(2^j,x,y)|^2 + |W^2f(2^j,x,y)|^2} \qquad (11)$$

The angle $Af(2^j,x,y)$ between the gradient vector $\nabla(f*g_s)(x,y)$ and the horizontal plane is

$$Af(2^j,x,y) = arctg\left(\frac{W^2f(2^j,x,y)}{W^1f(2^j,x,y)}\right) \qquad (12)$$

The angle (12) indicates locally the direction of the sharpest variation of the pixels, i.e. the local orientation of the edge.

The two magnitudes $Mf(2^j,x,y)$ and $Af(2^j,x,y)$ are the basis for the profile detection algorithm. At first, their maxima are detected along the gradient direction. Then, through connecting, the edge contours are derived and coded in chain (in polygonal form). The conditions for connecting edge pixels into a line with modulus and direction of gradient vector smaller than the predefined thresholds, are

$$\begin{aligned} |Mf(2^j,x,y) - Mf(2^j,x\pm 1,y\pm 1)| &\le M_T \\ |Af(2^j,x,y) - Af(2^j,x\pm 1,y\pm 1)| &\le A_T \end{aligned} \qquad (13)$$

where (x, y) – the current pixel, $(x\pm 1, y\pm 1)$ – the neighbouring pixels around the pixel (x, y) in a search window.

The edges could also be detected using the algorithm based on (10b). The given pixel is the edge pixel only if the following equation system is fulfilled (Bronsztejn and Siemiendiajew, 2000)

$$\begin{cases} f(x, y) = 0 \\ D(x, y) = 0 \end{cases} \tag{14}$$

where

$$D(x, y) = \begin{vmatrix} W^3 f(x, y) & W^4 f(x, y) & W^1 f(x, y) \\ W^5 f(x, y) & W^6 f(x, y) & W^2 f(x, y) \\ W^1 f(x, y) & W^2 f(x, y) & 0 \end{vmatrix}$$

In addition, the signs of determinants D of neighbouring pixels $(x+1, y+1)$, $(x-1, y-1)$ and $(x-1, y+1)$, $(x+1, y-1)$ should be examined.

In practice, a smoothing function $g(x, y)$ can be the 2-D Gausian or a cubic polynomial (or a B-spline representation). The first is (Ying, 2000)

$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(x^2 + y^2)}{2\sigma^2}} \tag{15}$$

and the second is (Ghen and Huang, 1995; Salari and Balaji, 1991)

$$g(x, y) = k_0 + k_1 x + k_2 y + k_3 x^2 + k_4 xy + k_5 y^2 + k_6 x^3 + k_7 x^2 y + k_8 xy^2 + k_9 y^3 \tag{16}$$

where x, y – the current pixel co-ordinates, σ – the standard derivation, $k_o, k_1, k_2, ..., k_9$ – the coefficients of a cubic polynomial.

The edge contour has certain dominant points characteristic in terms of line curvature. They are crucial for shape recognition in the matching process. A planar (2-D) contour could be represented in a parametric form as $[x(t), y(t)] \in \Re^2$ by a set of points, where t is the path length along the contour. For this case, the wavelet is a smoothing function convolving $x(t)$ and $y(t)$, respectively, with 1-D Gausian filter (Ansari and Delp, 1991)

$$G(t, \omega) = \frac{1}{\sqrt{2\pi\omega}} e^{\frac{-(t/\omega)^2}{2}} \tag{17}$$

where ω is the width (spatial support) of the filter ($\omega \equiv \sigma$, see (15)).

The set of points $[X(t, \omega), Y(t, \omega)]$ is a result of convolution:

$$\begin{aligned} X(t, \omega) &= x(t) * G(t, \omega) \\ Y(t, \omega) &= y(t) * G(t, \omega) \end{aligned} \tag{18}$$

The curvature of smoothed contour at given point is

$$k(t, \omega) = \frac{X' Y'' - Y' X''}{(X'^2 + Y'^2)^{3/2}} \tag{19}$$

where X', Y', X'', Y'' are the first and second derivatives of the smoothed contour at given point.

Due to the discrete representation of the 2-D contour in a digital image, the parameter t is discrete. Thus, the first and second derivatives in (19) have been determined as (Ansari and Delp, 1991)

$$\begin{aligned} X' &= X(t+1) - X(t-1) \\ X'' &= X(t+1) + X(t-1) - 2X(t) \\ Y' &= Y(t+1) - Y(t-1) \\ Y'' &= Y(t+1) + Y(t-1) - 2Y(t) \end{aligned} \tag{20}$$

In the B-spline representation of a smoothing function (16) any point p on the line segment of edge contour is given by (Salari and Balaji, 1991)

$$p(t) = \sum_{i=0}^{n} C_i P_{ik}(t) \tag{21}$$

where C_i $(i = 0,1,...n)$ are the coefficients of $(n+1)$ points, P_{ik} are the $(k+1)$ degree blending functions (the order of orthogonal polynomial (B-spline)). In practice $(k+1)$ equals 3. Then (21) becomes (Salari and Balaji, 1991)

$$p(t) = C_0 P_{1,4}(t) + C_1 P_{2,4}(t) + C_2 P_{3,4}(t) + C_3 P_{4,4}(t) \tag{22}$$

$$P_{1,4} = \frac{1}{6}(-t^3 + 3t^2 - 3t + 1) \qquad P_{2,4} = \frac{1}{6}(3t^3 - 6t^2 + 4)$$

where

$$P_{3,4} = \frac{1}{6}(-3t^3 + 3t^2 + 3t + 1) \qquad P_{4,4} = \frac{1}{6}(t^2)$$

1-D smoothing functions (17) as well as (21) can easily be computed.

3. 2-D line segment moments of the edge contour

For any line segment, expressed by $f(x, y) = 0$, with the density distribution function $\rho(x, y)$, the x_c, y_c co-ordinates of its centroid are (Wei and Lozzi, 1993)

$$\begin{aligned} x_c &= \frac{1}{l} \int_{f(x,y)} x\rho(x,y)\,dl \\ y_c &= \frac{1}{l} \int_{f(x,y)} y\rho(x,y)\,dl \end{aligned} \tag{23}$$

where $$l = \int_{f(x,y)} dl$$

dl – is the length of a line segment element.

The $(p+q)$ order geometric central moments with respect to the centroid (x_c, y_c) of the line segment, having the density distribution function $\rho(x, y)$ are defined as

$$\mu_{p,q} = \int_{-\infty}^{\infty} (x - x_c)^p (y - y_c)^q \rho(x, y) dl \tag{24a}$$

Taking $x_c = y_c = 0$ for the simplicity of description, the central moments $\mu_{p,q}$will be expressed as

$$\mu_{p,q} = \int_{-\infty}^{\infty} x^p y^q \rho(x, y) dl \tag{24b}$$

The moment invariants I_1, I_2, I_{max}, I_{min}, in terms of second order moments $\mu_{2,0}$, $\mu_{0,2}$, $\mu_{1,1}$ given as

$$I_1 = \mu_{2,0} + \mu_{0,2} \qquad I_{max} = \frac{I_1 + I_2}{2}$$

$$I_2 = \pm\sqrt{(\mu_{2,0} - \mu_{0,2})^2 + 4(\mu_{1,1})^2} \qquad I_{min} = \frac{I_1 - I_2}{2} \tag{25}$$

are independent of the scale and rotation transformation parameters. They have been determined for any line segment of the edge contour and used as the line features for the matching method.

For a polygonal line segment $f[x(t), y(t)] = 0$ with M vertices, the parametric equations of the line between two vertices $(i$-1) and i are

$$x_i(t) = x_i + \frac{x_i - x_{i-1}}{t_i - t_{i-1}}(t - t_i) \tag{26}$$

$$y_i(t) = y_i + \frac{y_i - y_{i-1}}{t_i - t_{i-1}}(t - t_i)$$

It is assumed that the density distribution function $\rho(x, y) = 1$. Thus (24) becomes

$$\mu_{p,q} = \sum_{i=1}^{M} \int_{t_{i-1}}^{t_i} x_i^p(t) y_i^p(t) \sqrt{x_i'^2(t) + y_i'^2(t)} dt \tag{27}$$

where $x_i'(t), y_i'(t)$ – the first order derivatives of $x(t)$, $y(t)$.

Substituting (26) to (27) gives

$$\mu_{1,0} \equiv m_{1,0} = \sum_{i=1}^{M} \Delta l_i \left(x_i - \frac{1}{2}\Delta x_i \right)$$

$$\mu_{0,1} \equiv m_{0,1} = \sum_{i=1}^{M} \Delta l_i \left(y_i - \frac{1}{2}\Delta y_i \right)$$

$$\mu_{1,1} = \sum_{i=1}^{M} \Delta l_i \left(x_i y_i - \frac{1}{2}\Delta y_i x_i - \frac{1}{2}\Delta x_i y_i + \frac{1}{3}\Delta x_i \Delta y_i \right) \tag{28}$$

$$\mu_{2,0} = \sum_{i=1}^{M} \Delta l_i \left(x_i^2 + \frac{1}{3}\Delta x_i^2 - \Delta x_i x_i \right)$$

$$\mu_{0,2} = \sum_{i=1}^{M} \Delta l_i \left(y_i^2 - \frac{1}{3}\Delta y_i^2 - \Delta y_i y_i \right)$$

where: $\Delta x_i = x_i - x_{i-1};\ \Delta y_i = y_i - y_{i-1};\ \Delta l_i = \left(\sqrt{\Delta x_i^2 + \Delta y_i^2}\right)$

The edge contour may be divided into more line segments between two dominant points, defined by the breakpoints or points with extreme curvatures. For every line segment the moments are determined again basing on (28).

4. Optimisation-based line matching

The line matching used is based on the invariant moments of line segments defined by (25). Every i^{th} segment of the edge contour is described with four parameters x_{ic}, y_{ic}, l_i, θ_i where (x_{ic}, y_{ic}) are the co-ordinates of the centroid of segment, l_i – the length of the segment, θ_i – the angle between the positive x-axis and the principle axis of the segment, with respect to which the second order moment of the contour segment is maximum (Fig. 2).

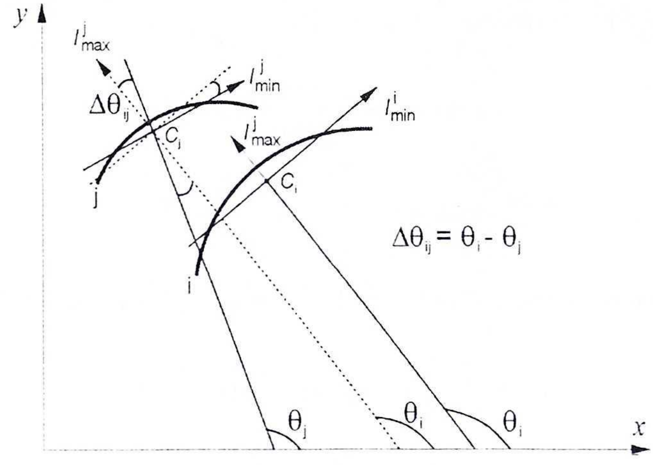

Fig. 2. The elements C_i, C_j, l, θ of line segments i, j and their relations

Its value can be calculated as follows

$$tg2\theta = \frac{2\mu_{1,1}}{\mu_{2,0} - \mu_{0,2}} \tag{29}$$

The three parameters of the i^{th} segment $I_{max(i)}, I_{min(i)}, I_{2(i)}$ describe its shape. The distances D_k between the i^{th} segment of a *reference image* (O) and the j^{th} segment of a *real-time image* (R) are defined as

$$\begin{aligned} D_1(i,j) &= \frac{|I^o_{max(i)} - I^r_{max(j)}|}{|I^o_{max(i)} + I^r_{max(j)}|} \\ D_2(i,j) &= \frac{|I^o_{min(i)} - I^r_{min(j)}|}{|I^o_{min(i)} + I^r_{min(j)}|} \\ D_3(i,j) &= \frac{|I^o_{2(i)} - I^r_{2(j)}|}{|I^o_{2(i)} + I^r_{2(j)}|} \end{aligned} \tag{30}$$

Best matching of two images (O), (R) is performed when the sum of distances D_k is minimum

$$\sum_{k=1}^{3} D_k(i,j) = \min \quad i.e. \quad \begin{aligned} D_1(i,j) &\le \delta_1 \\ D_2(i,j) &\le \delta_2 \\ D_3(i,j) &\le \delta_3 \end{aligned} \tag{31}$$

where δ_1, δ_2, δ_3 – are the predefined thresholds.

Matching performed under the minimum condition (31) is, the so-called, optimisation-based matching or the minimum weight matching (Min-Hong and Dongsig, 1990). The goal of the matching process is to determine transformation parameters as well as the scale, rotation and translation between two edge contours of a reference and a real-time image. To determine the most likely transformation parameters, a Hough transformation has been used (Adamos and Faig, 1992; Wei and Lozzi, 1993; Habib et al., 2000; Yun et al., 2000). For every i^{th} segment of a *reference image* and every j^{th} segment of a *real-time image*, the scale $k_{i,j}$, rotation difference $\Delta\theta_{i,j}$, and translation parameters $\Delta x_{c(i,j)}$, $\Delta y_{c(i,j)}$ have been computed using (32) (Fig. 2).

$$\begin{cases} k_{i,j} = \dfrac{l^o_i}{l^r_j} \\ \Delta\theta_{i,j} = \theta^o_i - \theta^r_j \\ \begin{cases} \Delta x_{c(i,j)} = x_{ci} - x_{cj} \\ \Delta y_{c(i,j)} = y_{ci} - y_{cj} \end{cases} \end{cases} \tag{32}$$

To find a consistent set of $\Delta\theta_{i,j}$, $k_{i,j}$ using Hough transformation, the accumulator arrays A_r, A_k are indexed by θ (rotation) and k (scale), respectively, and then the search for mutual identities of line segments is performed using simple statistical tools. The θ values determined using (32) are indexed into accumulator A_r and incremented by 1. The accumulator A_k is incremented in a similar way. The procedure is repeated for each possible pair of the contour segments of a real-time and a reference image. Indices of the peak in data series investigated identify best rotation and scale value in the accumulator arrays A_r, A_k, respectively. Once the scale and rotation are known, the translation $\Delta x_{c(i,j)}$, $\Delta y_{c(i,j)}$ may be found.

After determining the transformation parameters, the real-time image is transformed into the reference image system. The image transformed this way is considered as a similar image that can once again be pre-processed using the least-square matching (Heipke, 1992), in order to improve the sub-pixel accuracy.

Basing on the exterior orientation given an Inertial System or analytically computed exterior orientation elements, the spatial co-ordinates of terrain points of the real-time image, obtained after the least-square matching, are determined. Then, accuracy analysis based on the terrain point co-ordinates obtained from the reference sensor (image), could be provided.

5. 3-D ground line segment moments

Basing on the two point sets of the same terrain model, derived with "the reference" sensor (O) and "the real-time" sensor (R), the spatial (3-D) line features will be extracted by means of the digital technique. The corresponding ground line will be co-ordinated in three dimensions, by a suitable the sensor. Then the spatial line features of (O) and (R) sensors are automatically matched to get the best mutual fit. Finally, the co-ordinate transformation of the model (R) to the model (O) will be performed using the transformation parameters obtained in the discussed matching process.

Basing on (24) the geometric spatial line moments of $(p+q+r)$ order of density distribution function $\rho(X, Y, Z)$ can be defined as

$$\mu_{p,q,r} = \int_{-\infty}^{\infty} X^p Y^q Z^r \rho(X, Y, Z) dL \qquad (33)$$

where X, Y, Z – the model co-ordinates of points on the line; dL – the differential of ground line; p, q, $r = 0,1,2,\ldots$

To simplify calculations and to make use of the formulae presented in the sections 3 and 4, spatial moments of line segment are projected into three planes XY, XZ, YZ. Their three components are

$$\mu_{p,q} = \int_{-\infty}^{\infty} X^p Y^q \rho_{XY}(X, Y) dL_{XY}$$

$$\mu_{p,r} = \int_{-\infty}^{\infty} X^p Z^r \rho_{XZ}(X, Z) dL_{XZ} \tag{34}$$

$$\mu_{q,r} = \int_{-\infty}^{\infty} Y^q Z^r \rho_{YZ}(Y, Z) dL_{YZ}$$

Line matching is performed in each plane with determination of three transformation parameters (scale, rotation, translation). Rotation angle in plane XY is considered equal to the turning angle χ; in the XZ plane it is a longitude tilt angle φ and in the YZ plane it is a lateral tilt angle ω. Three scale factors computed in three planes XY, XZ, YZ determine the scale factors (k_X, k_Y, k_Z) of the affine transformation. Translations in three X, Y, Z directions will be the average values of translations in three planes XY, XZ, YZ, respectively. The final spatial transformation of point coordinates of a set from sensor (R) into sensor (O) will be taken. The accuracy of matching process can be estimated basing on the co-ordinate differences of the corresponding spatial points.

Conclusions

Nowadays, data on the same terrain could be obtained with different sensors in the imagery or as a set of point co-ordinates from GPS, SAR, InSAR, LIDAR, digital mapping combined with DTM. In general, obtained data is recorded by various systems that differ in scale and rotation parameters. The problem of data integration is one of the main directions of investigation. In order to solve this problem, the surface matching technique has to be carried out to simultaneously implement two tasks: image matching and transformation.

Basing on the theory of the second order moments of two variables, the defined moment invariants of 2-D line segment, automatically extracted with the wavelet transform, are used as the features for matching process. The property of the wavelet transform of the convolution of two functions of the same variables is used. Application of smoothing functions in the Gaussian filter or the B-spline representation has been proposed. The main advantage of the wavelet transform technique is that edge pixels can be detected and extracted in images characterised by large noise. The longer time of computations needed is, however a disadvantage of the method.

This paper focuses on the use of line segment moments of an edge contour as the high level features that play the major role in the matching process.

The 3-D line segment moments have been proposed for the case when data has been recorded by a set of spatial point co-ordinates. It is convenient to project 3-D line segment moments into three planes XY, XZ, YZ, in which 2-D line segment moments can be used for the simplicity of performing the following computations.

Introduction of edge pixels, which have been automatically detected with the wavelet transform technique, into the matching process using 2-D or 3-D line segment moments, opens a potential possibility of the automatic data processing of relative and absolute orientation.

Acknowledgments

The author would like to express warmest thanks to the authorities of the Institute of Photogrammetry and Cartography, the Warsaw University of Technology as well as to Prof. R. Kaczynski from the Institute of Geodesy and Cartography, Warsaw, for helpful consultations and suggestions.

References

Adamos C., Faig W., (1992): *Hough transform in digital photogrammetry*, Int. Arch. Phot. Rem. Sens., Washington 1992, Vol. 31, part B3, pp. 250-253.

Ansari N., Delp E.J., (1991): *On detecting dominant points*, Pattern Recognition, Vol. 24, No 5, pp. 441-451.

Bronsztejn I.N., Siemiendiajew K.A., (2000): *Matematyka – Poradnik encyklopedyczny*, PWN.

Ghen F.S., Huang T.S., (1995): *Invariant matching and identification of curve using B-spline curve representation*, IEEE Transaction of Image Processing, Vol. 4, No 1, pp. 1-10.

Habib A., Kelley D., Asmamaw A., (2000): *New approach to solving matching problem in photogrammetry*, Int. Arch. Phot. Rem. Sens., Vol. 33, part B2, pp. 257-264, Amsterdam.

Heipke C., (1992): *A global approach for least squares image matching and surface reconstruction in object space*, Photogram. Eng. Remote Sens., 58(3).

Lee J-S., Sun Y.N., Chen C-H., (1995): *Multiscale corner detection by using wavelet transform*, Vol. 4, No 1, pp. 100-104.

Malat S., Wen L.H., (1992): *Singularity detection and processing with wavelets*. IEEE Transaction on Information Theory, Vol. 38, No 2.

Min-Hong H., Dongsig J., (1990): *The use maximum curvature point for the recognition of partially occluded object*, Pattern Recognition, Vol. 23, No 1/2, pp. 21-33.

Salari E., Balaji S., (1991): *Recognition of partially occluded objects using B-spline representation*, Pattern Recognition, Vol. 24, No 7, pp. 653-660.

Smith M.J., Park D.W.G., (2000): *Absolute and exterior orientation using linear features*, Int. Arch. Phot. Rem. Sens., Vol. 33, part B3, pp. 850-857, Amsterdam.

Ueffing Merzhausen C., (2001): *Wavelets based ECW image compression*, Week'01, Wichmann, 2001.

Vacili A., (2002): *Haze detection and removal in high resolution satellite image with wavelet analysis*, IEEE Transaction on Geoscience and Remote Sensing, Vol. 40, No 1, pp. 210-216.

Wang Z., (1990): *Principle of photogrammetry (with Remote Sensing)*, Press of Wuhan Technical University of Surveying and Mapping, Beijing.

Wei W., Lozzi A., (1993): *Recognition and inspection of manufactured parts using line moments of their boundaries*, Pattern Recognition, Vol. 26, No 10, pp. 1461-1471.

Ying C., (2000): *Wavelet-based image matching for different sensor*, Int. Arch. Phot. Rem. Sens., Vol. 33, part B3, pp. 177-182, Amsterdam.

Yun K.H., Sohn H.G., Yu K., Jeong S., (2000): *Hough transform for interior orientation in digital photogrammetry*. Int. Arch. Phot. Rem. Sens., Vol. 33, part B3, pp. 692-696, Amsterdam.

Yunhan D., Milne A.K., Forster B.C., (2000): *A SAR speckle filtering algorithm towards edges sharpening*, Int. Arch. Phot. Rem. Sens., Vol. 33, part B1, pp. 89-95, Amsterdam.

Zastosowanie momentów linii konturów automatycznie wydzielanych metodą przekształcenia wavelets dla dopasowania powierzchni

Luong Chinh Ke

Politechnika Warszawska
Instytut Fotogrametrii i Kartografii
Plac Politechniki 1, 00-661 Warszawa
e-mail: lchinhke@gazeta.pl

Streszczenie:

W ostatnich latach zgromadzony został ogromny zasób danych informatycznych o terenie w postaci zdjęć lotniczych, satelitarnych, SAR, IFSAR (InSAR), LIDAR, DTM terenu itd., otrzymanych różnymi sposobami i przy użyciu różnych sensorów. Integracja danych jest jednym z głównych kierunków badań. Linie konturowe powierzchni terenu na zdjęciu należą do podstawowych cech, które są wykorzystywane w procesie dopasowania metodą FBM (Feature-Based Matching).

Niniejsza praca przedstawia propozycję zastosowania niezmienników momentów linii konturowych, zwanych cechami wysokiego poziomu, do dopasowania powierzchni. Linie konturowe w pierwszym etapie muszą być rozpoznane i wydzielone. Dla realizacji tego celu zastosowano transformatę wavelets.

Połączenie automatycznie wydzielanych za pomocą transformaty wavelets linii konturowych wraz z wyznaczanymi ich momentami w 2-D (na zdjęciu) lub w 3-D (przestrzenne linie) wykorzystywanymi w procesie dopasowania powierzchni umożliwia pełną automatyzację procesu wykonania wzajemnej i absolutnej orientacji pary zdjęć, jak również wykonanie orientacji wewnętrznej i zewnętrznej poszczególnych zdjęć.