WAVELET -- BASED IMAGE MATCHING for DIFFERENT SENSOR

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ABSTRACT

In a general, different sensor images of the same scene have different gray characteristics. Simple algorithms such as those based on area correlation can not be used directly. Therefore, an edge feature-matching algorithm is pressed in this paper. The algorithm uses feature parameters of edges as matching primitives. An edge detection approach with wavelet is discussed in order to extract edges from images. The mathematical models of edge representation and matching algorithm based on line moments are developed. Results obtained from above methods are reported.

1 INTRODUCTION

In real-time matching for different sensor images during position and navigation of aerocraft, speed and precision are a challenging problem. The method that combined feature with image least square matching is an effective approach. The former may provide some credible initial values during the large-area searching procedure. The latter can realize exact sub-pixel matching. In feature matching, reliability of feature extraction and detection is the one of key points. For these, we present an efficient detection algorithm used gradient direction profile.

In real-time scene matching, another problem is that it maybe exist bigger rotation between the real-time scene and reference image. So we adopt the invariant-based line moment feature matching which is rotation-independent, and the constraints are introduced. According to these, The sub-pixel matching technique that combined feature with least square image matching is realized.

2 EDGE DETECTION BASED ON WAVELET TRANSFORM

In two-dimensional space, $\psi(x,y)$ is said to be wavelet function if and only if it satisfies.

$$\iint_{R^2} \psi(x,y)dxdy = 0$$

It is known that a two-dimensional smoothing function $\theta(x,y)$ whose integral is nonzero can be made as wavelet function using its partial derivatives along x and y directions respectively.

$$\left.\begin{aligned} \psi^1(x,y) &= \frac{\partial\theta(x,y)}{\partial x} \\ \psi^2(x,y) &= \frac{\partial\theta(x,y)}{\partial y} \end{aligned}\right\} \tag{1}$$

For any function $f(x,y) \in L^2(R^2)$ in dyadic scale 2^j, its two-dimensional dyadic wavelet transform is defined as the set of functions.

$$Wf = \{W^1_{2^j} f(x,y), W^2_{2^j} f(x,y)\}_{j \in z}$$

i.e.

$$\begin{bmatrix} W^1_{2^j} f(x,y) \\ W^2_{2^j} f(x,y) \end{bmatrix} = \begin{bmatrix} f * \psi^1_{2^j}(x,y) \\ f * \psi^1_{2^j}(x,y) \end{bmatrix} \tag{2}$$

The modulus and amplitude angle of gradient vector are defined according to formula (2) respectively as:

$$\left.\begin{aligned} M_{2^j} f(x,y) &= \sqrt{|W^1_{2^j} f(x,y)|^2 + |W^2_{2^j} f(x,y)|^2} \\ A_{2^j} f(x,y) &= \arg\tan(W^2_{2^j} f(x,y) / W^1_{2^j} f(x,y)) \end{aligned}\right\} \tag{3}$$

Choosing two-dimensional Gaussian or B-spline as smoothing function, from formulas (1), (2) and (3), we can obtain corresponding wavelets and obtain the modulus M_2^j f(x,y) and amplitude angle A_2^j f(x,y) of gradient vector in image f(x,y) respectively. Then, image gradient and direction map (g_map and d_map) can be generated from M_2^j f(x,y) and A_2^j f(x,y). This is the foundation for the gradient direction profile detection algorithm presented in this paper. First, the modulus whose absolute value is maximum is detected along gradient direction. Through tracing and connecting the points where the modulus and direction are the most approximate, the edge contours are obtained and expressed by chain code. Figure 1 shows the detection procedure.

Most matching algorithms are done in pyramid images. The pyramid images in this paper are generated using decomposition and reconstruction base on wavelet. The set of decomposition for image f can be given [Ying,1998.12],

$$\left.\begin{aligned} f^j &= H_c H_r f^{j-1} \\ d^{j,h} &= G_c H_r f^{j-1} \\ d^{j,v} &= H_c G_r f^{j-1} \\ d^{j,a} &= G_c G_r f^{j-1} \end{aligned}\right\} \tag{4}$$

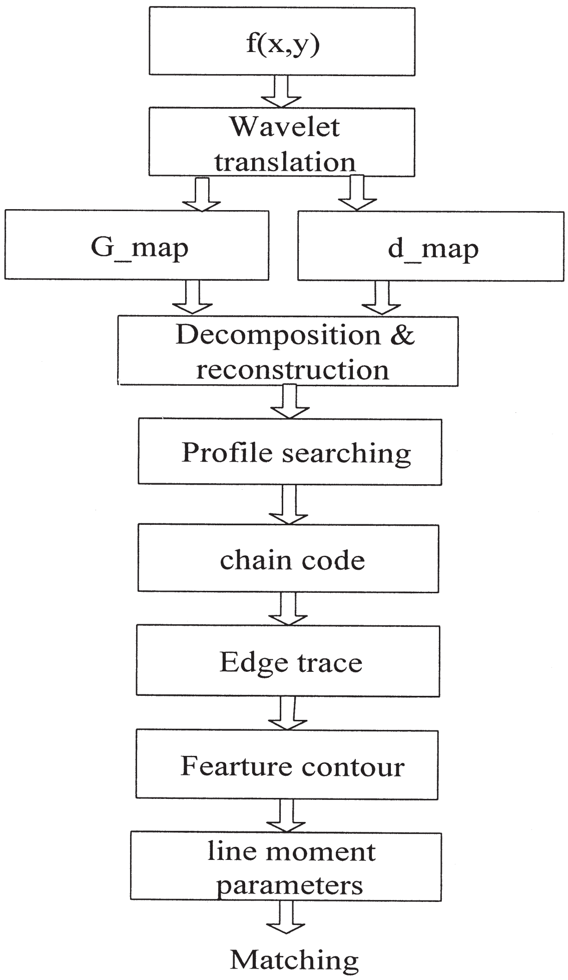


Fig.1: Edge Detection Procedure

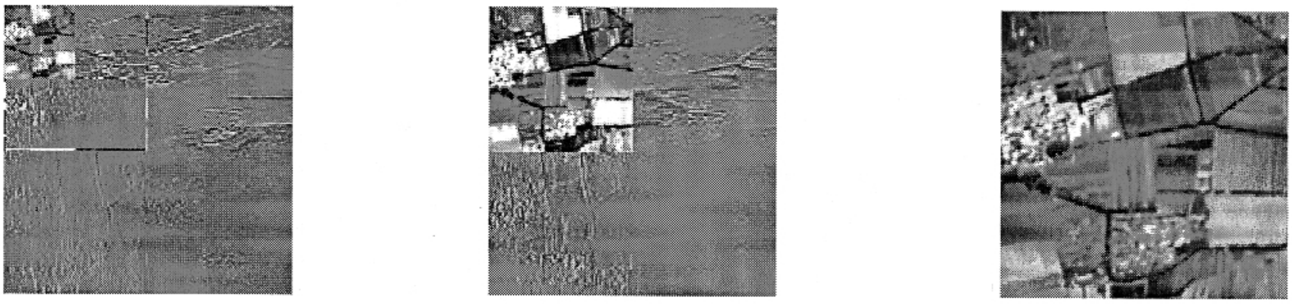
The set of reconstruction can be written

$$f^{j-1} = \overline{H}_c \overline{H}_r f^j + \overline{G}_c \overline{H}_r d^{j,h} + \overline{H}_c \overline{G}_r d^{j,v} + \overline{G}_c \overline{G}_r d^{j,a} \tag{5}$$

The results of decomposition and reconstruction are expressed as figure 2.

A remarkable property of wavelet Transform is its ability to characterize the local regularity of functions.The regularity indicates a singularity of image feature and can be often measured with **Lipschitz** exponents α . Mallat[1992] have demonstrated that the maximum of modulus for wavelet translation must satisfy,

$$M_{2^j} f(x,y) \le A(2^j)^\alpha$$



2^2 2^1 2^0

Fig. 2: Decomposition and reconstruction base on wavelet

i.e

$$\log_2(M_{2^j} f(x,y)) \le j\alpha + \log_2(A) \tag{6}$$

In this paper, three different scale images are adopted to solve **Lipschitz** α and the status of a edge is detected according to following formulas,

$$\left.\begin{aligned} &\alpha = 0: && \textit{discontinuity} \\ &\alpha < 0: && \textit{noise} \\ &\alpha > 0: && \textit{signal} \end{aligned}\right\} \tag{7}$$

1 LINE MOMENT DESCRIPTION OF EDGE CONTOUR

The edges detected can be expressed with direction chain code[Lide Wu,1993]. Edge contour length l and centroid coordinates $\bar{x}$, $\bar{y}$ which describe contour characteristic would be written as moment[Ying,1998.4].

$$l = \mu_{0,0} = m_{0,0} = \int_c dl = n_e + \sqrt{2} n_o$$

$$\left.\begin{aligned} \bar{x} &= \frac{\int_c x\,dl}{\int_c dl} = \frac{m_{1,0}}{l} \\ \bar{y} &= \frac{\int_c y\,dl}{\int_c dl} = \frac{m_{0,1}}{l} \end{aligned}\right\}$$

where: n_e and n_o indicate pixel number which chain code are even or odd respectively. m indicates original moment of an edge contour.

$$\left.\begin{aligned} m_{1,0} &= \sum_{i=1}^{n} \Delta l_i \left(x_{i-1} + \frac{1}{2}\Delta x_i \right) \\ m_{0,1} &= \sum_{i=1}^{n} \Delta l_i \left(y_{i-1} + \frac{1}{2}\Delta y_i \right) \end{aligned}\right\}$$

Central moments $\mu_{p,q}$ of a contour can be derived from its chain code.

$$
\left.\begin{aligned}
\mu_{1,1} &= \sum_{i=1}^{n} \Delta l_i \left((x_{i-1} + \Delta x_i)\left(y_{i-1} + \frac{1}{2}\Delta y_i \right) - \Delta x_i \left(\frac{1}{2} y_{i-1} + \frac{1}{6}\Delta y_i \right) \right) \\
\mu_{2,0} &= \sum_{i=1}^{n} \Delta l_i \left((x_{i-1} + \Delta x_i) x_{i-1} + \frac{1}{3}\Delta x_i^2 \right) \\
\mu_{0,2} &= \sum_{i=1}^{n} \Delta l_i \left((y_{i-1} + \Delta y_i) y_{i-1} + \frac{1}{3}\Delta y_i^2 \right)
\end{aligned}\right\} \tag{8}
$$

Where, Δ l, Δ x and Δ y could be soluted by chain code; x and y indicate centralized coordinates.

The scale moment invariant, which has been normalized, can be expressed as:

$$
\eta_{p,q} = \frac{\mu_{p,q}}{\mu_{0,0}^{p+q+1}}
$$

i.e.

$$
\eta_{p,q} = \frac{\mu_{p,q}}{l^{p+q+1}}
$$

Then the following scale and rotation invariant line moments can be derived to be,

$$
\left.\begin{aligned}
\phi_1 &= \eta_{20} + \eta_{02} \\
\phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2
\end{aligned}\right\}
$$

Wei Wen and A.Lozzi[1993] also presented two important invariant line moments. They could be used as matching primitives. Considering scale invariance and change them to:

$$
\left.\begin{aligned}
\phi_{\max} &= \frac{\phi_1}{2} + \frac{\sqrt{\phi_2}}{2} \\
\phi_{\min} &= \frac{\phi_1}{2} - \frac{\sqrt{\phi_2}}{2}
\end{aligned}\right\} \tag{9}
$$

2 MATCHING AND CONSTRAINTS

In order to obtain a correct matching between different sensor images (reference image b and real-time image r), following vector spatial distances would be selected. And the measurement criterion is that the total of these vector spatial distances is minimum.

$$
\sum_{k=1}^{n} D_k(i,j) < MIN \tag{10}
$$

$$
\left.\begin{aligned}
D_1(i,j) &= \frac{\left|\phi_2^b(i) - \phi_2^r(j)\right|}{\left|\phi_2^b(i) + \phi_2^r(j)\right|} \\
D_2(i,j) &= \frac{\left|\phi_{\max}^b(i) - \phi_{\max}^r(j)\right|}{\left|\phi_{\max}^b(i) + \phi_{\max}^r(j)\right|} \\
D_3(i,j) &= \frac{\left|\phi_{\min}^b(i) - \phi_{\min}^r(j)\right|}{\left|\phi_{\min}^b(i) + \phi_{\min}^r(j)\right|}
\end{aligned}\right\} \tag{11}
$$

where: Parameters i and j indicate the ith and the jth edge in image b and r respectively.

The constraints derived from feature chain is expressed as:

$$\left.\begin{aligned} & c_{br} = \frac{1}{n}\sum_{j=0}^{n-1}\cos\left(\frac{\pi}{4}\left|\left(a_j - avg_a\right) - \left(b_j - avg_b\right)\right|\right) \Rightarrow \max \\ & 0 < |davg| < T_a \end{aligned}\right\} \tag{12}$$

$$\left.\begin{aligned} & c_{br} = \frac{1}{n}\sum_{j=0}^{n-1}\cos\left(\frac{\pi}{4}\left|\left(a_{n-1-j} - avg_a\right) - \left(b_{n-1-j} - avg_b\right)\right|\right) \Rightarrow \max \\ & (T_a - 4) < |davg| < T_a + 4 \end{aligned}\right\} \tag{13}$$

in which: avga, avgb and davg are the directions of contour chain a,b (i.e. the average of corrected chain code [Ying, 1998.4]) and their rotation angle, T_a is threshold of rotation angle, generally not over 22.5° The cos is to make correlation coefficient C_{br} less than 1. Formula (12) shows that correct matching is available if C_{br} approach to maximum while the direction of contour start point is same as that of the end point in real-time scene and reference image. While davg is near to 4, it maybe exists a rotation of approximately 180° between two contour ,or start point is right-about to end point. Then using formula (13) could avoid false matching. While they are homologous features , right matching would be attainable from (13), though start point is right-about to end point.

When above conditions are satisfied, a reliable matching with one pixel precision can be obtained. According to the result, an enough accurate initial value is provided for least square image matching to realize sub-pixel matching. After finishing the above initial matching, a series of centroid coordinates(x_i,y_i) and(x_j.y_j) could be attainable. Therefore, corresponding between two different sensor images would be got. Meantime, rotation angles between two images could be determined.

$$k = \overline{avg}_b - \overline{avg}_a \tag{14}$$

According to this rotation relationship, we can preprocess real-time scene , and make its coordinate system homologous to reference image. Finally, least square matching between two images could be done as follows [Ying, 1998.4].

$$\left.\begin{aligned} & V = AX - L \quad p \\ & A = \begin{bmatrix} \frac{\partial g_x^b}{\partial x} & \frac{\partial g_x^b}{\partial x}x_0^b & \frac{\partial g_y^b}{\partial y} & \frac{\partial g_y^b}{\partial y}y_0^b \end{bmatrix} \\ & X = \begin{bmatrix} dx^b & df_x^b & dy^b & df_y^b \end{bmatrix}^T \end{aligned}\right\}$$

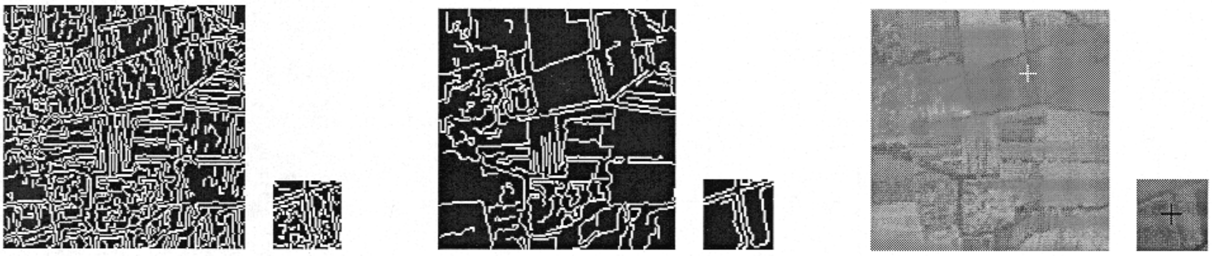
$$\hat{X} = \left(A^T PA\right)^{-1}\left(A^T PL\right) \tag{15}$$

3 EXPERIMENT RESULTS AND PRELIMINARY CONCLUSIONS

In this paper, matching experiments have been made by several SPOT digital images and low altitude CCD images. All of these have gained favorable effect. Fig.3 is one example of them.

In experiments, three pyramid images were used to do matching and edge detection. In order to improve efficiency and reliability of edge detection, gradient map must be preprocessed before detection . For this goal ,a histogram filter was used so that a great lot of non-characteristic information was removed [Ying,1998.4]. The contour feature with and without filter are shown in fig.3.

During feature matching, several candidate positions that satisfy formula (10) were obtained in top pyramid. Sequentially,image least square matching was done in ground pyramid, so that sub-pixel result was obtained.The mean square error of matching was less than 0.5 pixel.



SPOT image CCD image SPOT image CCD image SPOT image CCD image

a feature without filter b feature with filter c matching result

Fig 3 Feature extraction and matching result

Experiment results demonstrate:

a. The applications of Wavelet transform for matching between different sensor images have brought about the good effect. Specially, using **Lipschitz** exponents is propitious to reduce noise during edge Detection.

b. Edge direction profile detection method makes two dimension problems to one dimension processing. It is simple and efficient.

c. Line moment is independent to scale and rotation. Initial matching using moment parameters and available rigorous constraints could provide enough accurate initial value for least square image matching. Finally exact sub-pixel results would be attainable by least square matching.

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