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Adaptive Algorithm in the Application of Visual Measurement System

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Abstract

Focus on the problem that noise is existing in the input signals and output signals of visual measurement system , if calculate via the classic least mean square algorithm or recursive least square , it would generate the larger errors ; Or calculate directly , the calculation work loading is too complex . So the solution of weight vector could be as the limited best optimization solution of Rayleigh Quotient of augmentation input vector self correlation matrix , take iteration estimation to the augmentation input vector and set up the function relationship between step factor and error ; The simulation analysis experiment results indicate the standard tolerance of proposed adaptive total least squares algorithm is 0.0375mm ; but the one of normal total least squares algorithm is only 0.0598mm . Obviously , the proposed algorithm has more high precision than normal total least squares algorithm , and its structure is simple , the calculation speed is faster .

Keywords: Adaptive Algorithm; Visual Measurement; Total Least Squares ;

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1. Introduction

In the application of visual measurement system of single camera , the characteristic point is as the target to the measured point . Generally , to achieve the coordinate of measured points via the measurement to the characteristics point . The advanced defined coordinate of the characteristic point is marked as input matrix A , the measurement result of the characteristic point is as output matrix b , then the transition matrix x between A and b could be calculated by linear simultaneous equations $A \cdot x = b$ .During the data processing of visual measurement system of single camera , the least square solution of linear simultaneous equations $A \cdot x = b$ has been the general requirement . But only when the noise or error of vector b is 0 , the error's sum of squares is minimum , the least squares estimation would be close to the best optimization solution . But the error is existing in vector A and b , the least squares estimation is not the best optimization . In this case , the best way is total least squares (TLS)[1-3]. But in more cases , the TLS algorithm is batch mode based on direct singular value decomposition , it needs to take singular value decomposition for $N \times N$ matrix , its calculation is too complex and in the case of N is too large , it's very difficult to do . Focus on this point , the scientific research workers in domestic and oversea make a lot of research analysis , SUYKENS J. et al., 1999 present Least squares support vector machine classifiers [4]; SANCHEZ A. et al., 1995 presents Robustization of a learning method for RBF net-works [5]; KRUGER U. et al., 2008 present Robust partial least squares regression: part I algorithmic developments [6] . Summary the above research analysis results , to propose one kind of method which is to achieve step length recursion formula of TLS algorithm based on the cost function gradient .

2. Normal Total Least Sqares Algorithm

For the solution of linear simultaneous equations $A \cdot x = b$, due to the input matrix A and the output matrix b are get by actual visual measurement system , so the noise interference error is always existing , least squares estimation is not the best optimized in the statistics viewpoint , its covariation would be increased due to noise interference error . Define the disturbance matrix E and vector e to calibrate the interference error of matrix A and b . So :

$$(A+E) \cdot x = (b+e) \tag{1}$$

$$([A,-b]+[E,-e]) \cdot \begin{bmatrix} x \\ 1 \end{bmatrix} = 0 \tag{2}$$

Define $A' = [A,-b], E' = [E,-e]$, then , $(K' + E')x = 0$.

Restrain x is a vector of unit norm. Define $A'x = -E'x$, $-E'x$ could be as the error vector of least square solution x . Total least square solution x is the least square solution which sum of error squares is minimum the least square solution [7].

Define the singular value decomposition of augmented matrix A' is :

$$A' = U \cdot Diag(a_1, \cdots, a_i) \cdot V^H \tag{3}$$

The diagonal element $a_1 \geq a_2 \geq \cdots \geq a_i \geq 0$; and opposite singular value vector are $v_1, v_2, \cdots, v_i$.

The least square solution of $A'x = 0$ is the right singular vector oppositing to minimum singular value a_i .

So the least square solution of $A \cdot x = b$ should satisfy :

$$x = \frac{1}{v_1}[v_2, \cdots, v_i]^T = [v_1', \cdots, v_{i-1}'] \tag{4}$$

Finally , the least square solution should be as below :

$$x = \frac{\sum_{i=1}^{n} \frac{v'_i}{v'_{i+1}}}{n} \tag{5}$$

But TLS algorithm is batch mode based on direct singular value decomposition , it needs to take a long time to have singular value decomposition , its calculation is too complex and it's very difficult to calculate much times , so to present the application in adaptive total least squares algorithm .

3. Adaptive Total Least Sqares Algorithm

Define input and output data separately is $X_I(k)$ and $Y_O(k)$, so :

$$X_I(k) = x(k) + u_I(k) \tag{6}$$

$$Y_O(k) = y(k) + u_O(k) \tag{7}$$

Among it , $k = 1,2,...,n$; $x(k)$ and $y(k)$ are the valid data , $u_I(k)$ and $u_O(k)$ is the interference error of input and output data . Define the weight vector of system is :

$$H(k) = [h_1(k), h_2(k),..., h_n(k)]^T \tag{8}$$

Define the augmentation input vector and weight vector separately are :

$$Z(k) = [X^T(k), Y^T(k)]^T \tag{9}$$

$$W(k) = [H^T(k), -1]^T \tag{10}$$

So output error is :

$$e(k) = Z^T(k)W(k) \tag{11}$$

Define the cost function is the sum of Rayleigh Quotient and the last element's constrain of the augmentation weight vector :

$$f(W(k),\eta) = \frac{W(k)^T R(k)W(k)}{\|W(k)\|_2^2} + \eta(-1 - W(k)^T e_{n+1}) \tag{12}$$

Among it , $R(k) = E\{Z(k)Z(k)^T\}$ is the autocorrelation matrix of augmentation input vector . Formula (12) relative to $W(k)$ take partial derivative, and use the steepest descent method :

$$W(k+1) = W(k) - \sigma(k)\frac{\|W(k)\|_2^2 R(k)W(k) - W(k)^T R(k)W(k)W(k)}{(\|W(k)\|_2^2)^2} \tag{13}$$

Among it, $\sigma(k)$ is iteration step . To suppose $W(k)$ is convergence , known according to the Rayleigh Quotient property , its solution is corresponding standardization feature vector of smallest eigenvalue of $R(k)$,that is total least-squares solution. Generally, define $Z(k)Z(k)^T$ is instantaneous estimate of $R(k)$, and use the nonlinear function relation between step and instantaneous estimate to achieve the iteration update of step . But in fact it's only effective for specified single's operating environment , the accuracy of convergence is not perfect . Used the new estimate mode : $\tau R(k-1) + Z(k)Z(k)^T$, and it's more extensive adaptability relative to nonlinear function iteration , based on the step iteration rules of cost function gradient. Define the formula of step iteration is :

$$\sigma(k) = \sigma(k-1) - \delta\nabla f(k) \tag{14}$$

So :

$$\nabla f(k)\big|_{\sigma(k-1)} = \{\frac{\partial f(k)}{\partial W(k)}, \frac{\partial W(k)}{\partial \sigma(k-1)}\} \tag{15}$$

Among it ,

$$\frac{\partial f(k)}{\partial W(k)} = \frac{\|W(k)\|_2^2 R(k)W(k) - W(k)^T R(k)W(k)W(k)}{(\|W(k)\|_2^2)^2} ;$$

$$\frac{\partial W(k)}{\partial \sigma(k-1)} = -\frac{\partial f(k-1)}{\partial W(k-1)} .$$

4. The experimental results and data analysis

In order to validate the performance of the proposed adaptive total least square algorithm , so compare the proposed adaptive total least square algorithm with the normal total least square algorithm . Apply adaptive total least square algorithm in visual measurement system of single camera to calculate the attitude of optical characteristics points . Define the parameters of measurement system is as below: the focus of the camera is 12.026mm;The size of the imaging plane is $8.12mm \times 6.28mm$;Locate 5 optical characteristics points in CMM, their coordinates could be measured directly by CMM. And define randomly the position of fifty determinands , use separately the normal total least-squares algorithm and adaptive total least-squares algorithm to calculate the attitude of their optical characteristics points. Then compare the results calculated by every algorithm with the actual coordinate measured by CMM .

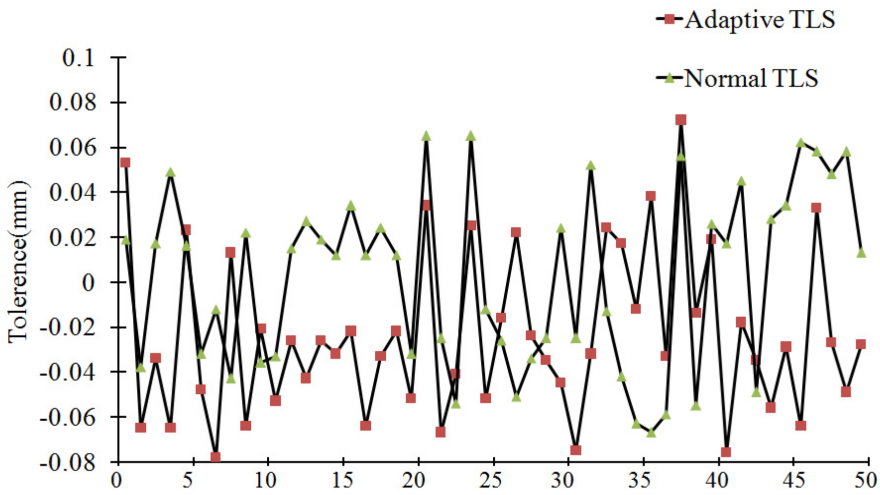

Fig. 1. The curve of measurement tolerance along X,Y,Z of CMM

The experiment results indicate the standard tolerance calculated by normal total least-squares algorithm is 0.0598mm, and the one done by adaptive total least-squares algorithm is 0.0375mm. Compared with normal total least-squares algorithm , the tolerance calculated by adaptive total least-squares algorithm is less .

In order to further validate the calculation speed of the adaptive total least square algorithm , set up the experiment environment : CPU：Intel core i7 3770，RAM：4G，Operation system : Windows xp，Matlab7.0 . The experiment used the normal total least square algorithm and adaptive total least square algorithm to continue calculating 10^6 times , separately records the time of five times experiment for every algorithm , shown as Table 1.

Table.1 The comparison between the time consumption

	Time(s)				
Normal TLS	1.38	1.66	1.15	1.56	1.31
Adaptive TLS	0.86	0.77	0.89	0.83	0.92

The results of Table. 1 indicate the calculation speed of adaptive total least square algorithm is better than the one of normal total least square algorithm .

Conclusion

In order to decrease the error tolerance when the noise is existing in both input signals and output signals of visual measurement system , and get the best optimization solution of the relative to the attitude conversion between optical characteristics points and camera , present the method of adaptive total least square algorithm . Firstly , introduce the function expression of normal total least squares algorithm; Then , based on the Rayleigh Quotient property to get the final equation of adaptive total least squares algorithm. Finally , make the simulation comparison experiment , the standard tolerance calculated by normal total least square algorithm is 0.0598mm ; But the one done by adaptive total least square algorithm is 0.0375mm ; The experiment results prove adaptive total least square algorithm has high precision , and calculation speed is better than normal total least square algorithm .

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