Identification of fine tracking system for free space optical communications

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Abstract: The precise model of the fine tracking system (FTS) provides a crucial condition to study the control strategy, and find the key factors which impact the dynamic and static characteristics of FTS. The fine tracking identify system is designed in this paper which includes the fast steering mirror (FSM), the charge coupled device (CCD), the Digital to Analog Converter (DAC) and the associated electronics. Traditionally, the model of the FTS is considered as a second order model, a series of process such as the input and output data, the model class and the equivalent standards of the least square method is presented to obtain the model. In order to evaluate the performance of the least square identification method, the model is compared with the one obtained by the traditional frequency response method. The residual sum of squares between these two model outputs and the actual output are 8.20 and 89.52, respectively; while the correlation coefficients are 0.98 and 0.95, respectively. The results indicate that the model of the FTS obtained by the least squares identification method is more accurate than the one obtained by the frequency response method.

Key words: free space optical communications; fine tracking system; system identification; least square identification method; frequency response method

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自由空间光通信中精跟踪系统的辨识

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摘 要:精确的精跟踪系统模型为研究精跟踪的控制算法,找到影响其动态、静态性能的关键因素提供了重要的条件。设计了精跟踪辨识系统,该系统包括:快速倾斜镜、CCD、DA 以及相关的电子设备。精跟踪模型传统上被认为是一个二阶系统,通过输入输出数据、模型类和最小二乘等价准则等一系列过程确定精跟踪的模型。为了评估该辨识方法的性能,将最小二乘辨识法得到的模型与传统的频率响应法得到的模型做比较。通过验证发现,两种模型的输出与实际系统输出的模型残差平方和分别为 8.20 和 89.52,相关系数分别为 0.98 和 0.95。结果表明,最小二乘法得到的精跟踪模型比频率响应法得到的模型更准确地反映出实际系统的特性。

关键词:自由空间光通信; 精跟踪系统; 系统辨识; 最小二乘辨识法; 频率响应法

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0 Introduction

The advantages of the free space optical communications (FSO) over the radio frequency communications include a wider bandwidth, a larger capacity, lower power consumption, greater security against eavesdropping, and immunity from interference [1]. FSO has been used in the free space such as between the satellites and the terminals at the surface, between the satellites, between the airplanes, and so on [2-5]. For an earth orbit distance, the system should be able to track the receiving station within a few micro radians; otherwise, the system performance will be degraded severely. Because of the jitter and motion of the spacecraft platform, FSO requires accurate and stable pointing, acquiring and tracking (PAT) of a transmit laser beam to maintain high communication rate. Typically, the PAT contains two subsystems: the coarse tracking system and the FTS. The FTS is used to compensate the residual error of the coarse tracking system and tracks the laser beacon within the required tolerances, so it decides the accuracy and the bandwidth of the PAT. The FTS mainly includes the piezoelectric actuator (PZT), the CCD, the Field Programmable Gate Array (FPGA) and the DAC.

The system identification is to improve the overall performance of the FTS by the mathematical model. Recently several identification methods have been investigated. Men[6] presented to use the genetic algorithm optimized single -output three -layer back propagation neural network to identify Volterra series kemels. Wu [7] analyzed the issues of the subspace identification methods. Zhong [8] studied the problems of parameter estimation of state -space models. In this paper, the least square identification method is presented to identify the model of the FTS. The least square identification method belongs to the parameter identification, and its identification process adopts some optimization algorithms. The resulting models obtained by the least square identification method and the traditional frequency response method are analyzed and compared.

1 Fine tracking identification system

The structure diagram of the fine tracking identify system is shown in Fig.1. The signal generator outputs signals to the PZT driver, and the motion of the PZT is recorded by the CCD. The recorded data are processed by the FPGA, and then translated into the coordinates of the beam spot. There are two waveforms displayed on the oscilloscope (OSC), one is the output signal of the DA which is transformed from the coordinates of the beam spot and the other is the output single of the signal generator. According to these two waveforms, the phase frequency characteristics of the FTS can be obtained. In the process of identification, the FPGA, the DAC, the PZT and its driver are treated as the system plant and the CCD can be treated as the system delay.

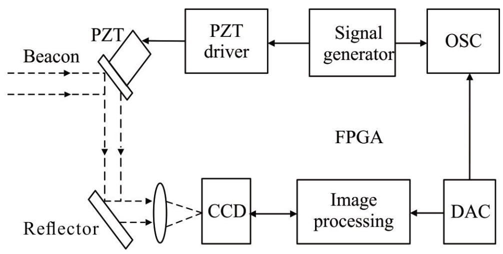

Fig.1 Structure diagram of fine tracking identify system

2 Model identification of FTS

2.1 Least square identification method

There are three key factors in the process of the least square identification method: the input and output data; the model class; the equivalent standards.

2.1.1 Input signal

If the model structure is correct, the accuracy of identification depends on the input signal. In order to achieve a high accuracy of identification, the input signal should be the persistently exciting signal of order $2n$, where n is the order of model [9]. Theoretical analysis indicates that the white noise is an ideal input signal, which can ensure achieve a good identification performance, but it is not easy to realize practically. Fortunately, the M sequence, which is easier to be generated, has some common characteristics with the white noise. So, it is used as the input signal of the identification system, as shown in Fig.2.

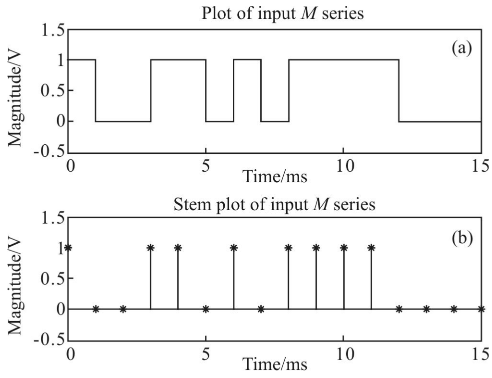

Fig.2 Plot and stem plot of M sequence

2.1.2 Model structure identification

The Akaike´s information criterion (AIC) can overcome the subjective influence and objectively determine the model order [10]. What´s more, the AIC uses the maximum likelihood parameter estimation to determine the model order and makes the probability distribution of the model output to approach the probability distribution of the actual output. Hence the AIC is used to determine the model order in this paper. The AIC is given as [11]

$$AIC=\lg\left\{\det\left[\frac{1}{M}\sum_{i=1}^{M}\varepsilon(i,\theta)\varepsilon^{T}(i,\theta)\right]\right\}+\frac{k}{M} \qquad (1)$$

where M, θ and k are the measured data set, the identification parameter set, and the number of the identification parameters, respectively. The input and measured output signals of the fine tracking identification system are shown in Fig.3.

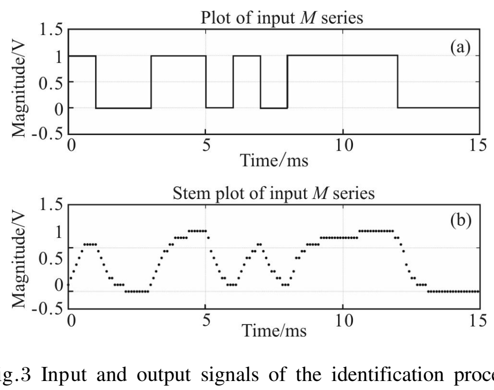

Fig.3 Input and output signals of the identification process

In one cycle of the M sequence, 31 sampling points are selected at regular intervals as the identification data. Table 1 shows the values of the AIC criterion obtained by equation (1). $m-1$ is the order of the numerator polynomial, and n is the order of the denominator polynomial. Akaike proved that the smaller the value of the AIC is, the more reasonable the order is [12]. However, if the model order was large, the model would be complex and difficult to be analyzed. Therefore, when (n, m) is equal to $(2, 3)$, the order is chosen as the suitable model order for the FTS.

Tab.1 AIC criterion values

n	m		
	1	2	3
1	1.031 4	−1.804 4	−1.936 1
2	0.696 7	−2.028 7	−2.172 1
3	0.584 7	−2.170 3	−2.129 4

2.1.3 Parameters identification of least-square method in discrete system

The FTS is an input and output system, the system model as shown in Fig.4.

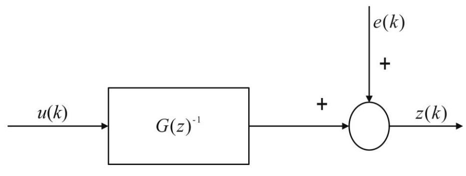

Fig. 4 Model diagram of FTS

In Fig.4, $u(k)$, $z(k)$, $G(z^{-1})$ and $e(k)$ are the input signal, the output signal, the model of FTS and the noise, respectively. The equation of the discrete system is shown as:

$$z(k)+\alpha_1 z(k-1)+\ldots\alpha_{n_a} z(k-n_a)=b_0 u(k)+$$
$$b_1 u(k-1)+\ldots b_{n_b} u(k-n_b)+e(k) \qquad (2)$$

The least square form of the FTS can be given as:

$$z(k)=h^{T}(k)\theta+e(k) \qquad (3)$$

where $h(k)$ is the sample set, and θ is the identification parameter set.

The criterion function[13] can be described as

$$J(\theta)=\sum_{k=1}^{\infty}[e(k)]^2=\sum_{k=1}^{\infty}[e(k)-h^{T}(k)\theta]^2 \qquad (4)$$

When $J(\theta)$ is the minimum, the estimate value of the least square identification method can be obtained. Because the order of the fine tracking model is determined, the discrete model of the FTS can be obtained by Equations (2) to (4). The discrete model of the FTS can be given as

$$H(z)=\frac{5.584z^{-1}-1.742z^{-2}}{1-0.519z^{-1}+0.093^{-2}} \tag{5}$$

In order to analyze the model conveniently, the discrete model is transform into a continuous model by the bilinear transformation formula [14]. The continuous model of the FTS is shown as

$$H(\mathrm{s})=\frac{1.0\times10^{4}s+1.115\times10^{7}}{s^{2}+2\,378s+1.717\times10^{6}} \tag{6}$$

2.2 Frequency response method

As shown in Fig.1, when the sinusoid signals of different frequencies are the input signals of the identification system, the values of the amplitude and phase frequency characteristic can be recorded. According to the recorded data, the bode diagram of the FTS is drawn as the measured data in Fig. 5.

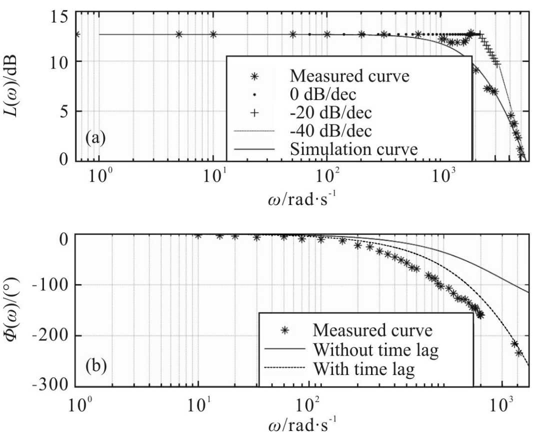

Fig.5 Bode diagram of FTS

A second order linear time invariant model is derived by fitting the open loop data of the FTS in both the amplitude and the phase [15]. The logarithmic amplitude frequency characteristic curve of the second order system is similar to the line whose slope is 0 dB/dec in low frequency bandwidth and 40 dB/dec in high frequency bandwidth. Three asymptotic lines whose slope respectively is 0 dB/dec, −20 dB/dec and −40 dB/dec are used to fit the recorded data of the amplitude frequency characteristic, as shown in Fig.5 (a). The values of the corner frequencies are 2 500 and 3 800, which are corresponding to the zeros or the poles of model [16]. The preliminary form of the transfer function is shown as

$$G(s)=\frac{4.3}{\left(\frac{s}{2\,500}+1\right)\times\left(\frac{s}{3\,800}+1\right)} \tag{7}$$

According to equation (7), the curves of the amplitude and phase frequency characteristics are plotted, as shown in Fig.5. The phase frequency characteristics curve without time lag is close to the measured data in the low frequency range, but the phase lag is increase as the increase of the frequency. Hence there is a time lag in the system. The change of the phase as the frequency can be used to determine the lag time. Finally, the transfer function of the FTS can be given as

$$G(s)^{-\tau s}=\frac{4.3}{\left(\frac{s}{2\,500}+1\right)\times\left(\frac{s}{3\,800}+1\right)}\mathrm{e}^{-8.10+10^{-4}s} \tag{8}$$

Using equation (8), the phase frequency characteristics curves have been drawn again. As shown in Fig.5(b), the phase frequency characteristics curve with the time lag is more close to the measured data.

3 Model validation and analysis

To assess the accuracy of the system model, two aspects should be considered. One is whether the actual system characteristics can be described by the system model accurately or not, and the other is the similarity of the model and the actual system [17]. Because the persistently exciting characteristic of the M sequence, it is used as the input signal of the model validation. According to Fig.1, the amplitude response data of the fine tracking identify system is measured. Using equation (6) and equation (8), the predictive output can also be obtained. The actual and predictive output curves of the FTS are drawn in Fig.6.

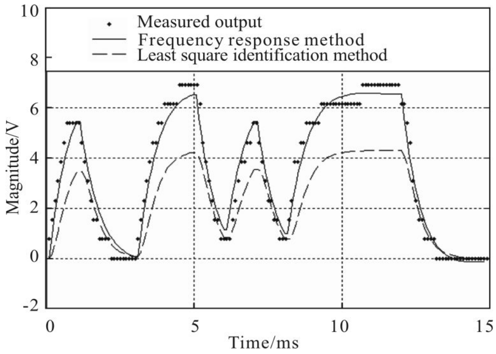

Fig.6 Actual and predictive outputs of FTS

The residual sum of the squ res and the correlation coefficient between the mathematical models and the actual system are used to validate the model of the FTS. When the input signals are the same, the model residuals are defined as the difference between the predictive output and the actual output of the system. Let the input data is $u(k)$ and the output data is $z(k)$, the model class of the FTS is described as

$$z(k)=G(z^{-1})u(k)+N(z^{-1})v(k) \quad (9)$$

The estimators of the transfer function are defined as and $\hat{G}(z^{-1})$, and $\hat{N}(z^{-1})$ the model residuals can be given as.

$$\varepsilon(k)=\hat{N}^{-1}(z^{-1})[z(k)-\hat{G}(z^{-1})u(k)] \quad (10)$$

In one cycle, the validation data are selected at regular intervals, and they are given in Tab.2, where SP, LMS and FRM are the sampling points, the model residual values of the least square identification method and the model residual values of the frequency response method, respectively.

The residual sum of the squares is described as

$$E\{\varepsilon(k)\}=\sum_{K=1}^{L}\varepsilon(k)^2 \quad (11)$$

Using the equation (11), the residual sum of squares by the frequency response method is 89.52 and the residual sum of squares by least square identification method is 8.20.

The similarity between the actual output of FTS and the model outputs can be measured by the correlation coefficient [18]. The correlation coefficient between the model output obtained by the frequency response method and the actual output is 0.95. While using the least square identification method, the correlation coefficient is 0.98. Therefore, the model obtained by the least square identification method is more close to the actual fine track system than the one obtained by the frequency response method.

Tab.2 Model residual values

SP	1	2	3	4	5	6
LMS	0.77	0.95	−0.08	−1.06	−0.33	−0.37
FRM	0.77	2.68	1.93	−0.56	0	−0.24
SP	7	8	9	10	11	12
LMS	−0.06	−0.23	0.76	0.72	0.40	0.13
FRM	−0.07	1.89	2.69	2.89	2.70	0.74
SP	13	14	15	16	17	18
LMS	−0.37	−0.47	0.15	−1.15	−0.43	0.86
FRM	−0.07	1.26	2.04	−0.60	−0.19	2.45
SP	19	20	21	22	23	24
LMS	0.39	0.19	−0.28	−0.41	0.34	0.36
FRM	2.27	2.25	1.95	1.88	2.63	2.63
SP	25	26	27	28	29	30
LMS	0.38	−0.33	−0.53	−0.35	0.03	0.14
FRM	2.62	0.26	−0.29	−0.34	−0.10	−0.02

4 Conclusion

In this paper, the least square identification method is used to identify the model of FTS. In order to validate the performance of the least square identification method, the resulting model is compared with the one obtained by the frequency response method. The results indicates that the model obtained by the frequency response method can just approximately perform the characteristics of system and it can′ t fulfill high precision requirement, and the model obtained by the least squares identification method can precisely describe the actual system.

The limitations of frequency response method as follow: (1) the inadequacy of data, the inconsistent data and the imperfections of the processing method; (2) the fine tracking model was empirically derived from a second order linear time invariant model that ignores some system characteristics. However, the least squares identification method firstly adopts the M sequence as the input signal of the identification system, it means that the frequency spectrum of the input signal can cover the process frequency spectrum. Secondly, AIC criterion uses the maximum likelihood parameter estimation to objectively determine the model order. Finally, the model parameters are ascertained by the classical least squares method. The process ensures the objectivity and precision of the model.

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