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Abstract

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Optimal Filtering based Shift Estimation for Fringe Pattern Profilometry by Generalized Analysis Model

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Abstract—This paper presents a new algorithm for fringe pattern profilometry by utilizing generalized analysis model, called optimal filtering based shift estimation (OFSE) method, which provides much lower complexity compared with traditional methods. Meanwhile, as OFSE is derived based on the generalized analysis model, the reconstruction results will not be influenced by the nonlinearity of fringe pattern projection and acquisition system. The efficiency of the proposed OFSE method is confirmed by simulation results, which show that the accuracy of three-dimensional reconstruction using digital fringe pattern profilometry technique can be much improved and the computational complexity can be significantly reduced.

I. INTRODUCTION

Fringe pattern profilometry (FPP) is one of the most popular non-contact approaches to measuring three-dimensional object surfaces. With FPP, a Ronchi grating or sinusoidal grating is projected onto a three-dimensional diffuse surface, the height distribution of which deforms the projected fringe patterns and modulates them in phase domain. Hence by retrieving the phase difference between the original and deformed fringe patterns, three-dimensional profilometry can be achieved. In order to obtain phase maps from original and deformed fringes patterns, researchers contributed various analysis methods, including Fourier Transform Profilometry (FTP) [1], [2], Phase Shifting Profilometry (PSP) [7], Spatial Phase Detection (SPD) [10], Phase Locked Loop (PLL) [11] and other analysis methods [12], [13].

In recent years, because of the simplicity and controllability, digital projectors have been widely used to yield fringe patterns for implementing FPP [14]–[17]. However, when generating fringe patterns by using digital projectors, nonlinear distortions are unavoidably introduced and result in visible measurement errors [16], [17], which has been theoretically analyzed by Hu et al. [17]. In order to eliminate the reconstruction errors caused by nonlinear distortions, Guo et al. [16] proposed a gamma correction based method to recover the distorted fringes. However, with this method, the precondition is that the projection system strictly matches the gamma distortion model. Moreover, as gamma coefficient varies with projection systems, the correction coefficient has to be estimated for different systems or whenever the system condition changes. Hu et al. introduced a generalized analysis model, which revealed the essential relationship between the

projected and the deformed fringe patterns. This model does not depend on the nonlinear characteristics of projection systems [17]. Based on the mathematical model, Gradient-based Shift Estimation (GSE) algorithm [17] and inverse function analysis (IFA) method [18] have been presented to reconstruct accurate profiles from nonlinearly distorted fringe patterns.

However, with IFA algorithm, the performance of IFA highly depends on the degree of the polynomial selected for curve fitting and in order to achieve high accuracy, higher degree polynomials has to be used, which accordingly leads to higher computational complexity. On the other hand, with GSE method, the height distribution of the surface is calculated point-by-point, but not to simultaneously reconstruct the whole object profile. The height distribution of each point on the object surface has to be individually and independently measured, which results in substantial computation if the captured image has got relatively high resolution. In addition, although GSE has a very strong ability to obtain precise surfaces without prior-knowledge of projection system, for some points of the surface, it needs very small learning rates and accordingly many times of iterations to achieve desired accuracy.

In order to reduce computational complexity, in this paper, we present a novel shift estimation approach to fringe pattern profilometry based on the design of optimal filters, called optimal filtering based shift estimation (OFSE) algorithm. The proposed OFSE converts the original shift estimation problem into a new problem of estimating the parameters of a designed optimal filter. Thus, the parameter space can be significantly reduced and consequently economic computation can be achieved. Additionally, because of the use of generalized analysis model, same with GSE and IFA, proposed OFSE algorithm can be also utilized to accurately reconstruct object surfaces from nonlinearly distorted fringe patterns.

This paper is organized as follows. In Section II, we review the principles of FPP technique and generalized mathematical model for fringe pattern analysis. In Section III, we design a optimal filtering scheme to accurately reconstruct height distribution of object surfaces. Meanwhile, based on generalized analysis model, an algorithm of estimating the parameters of the filter is derived. Simulation results are demonstrated in Section IV. Section V concludes this paper.

II. PRINCIPLES OF FPP AND GENERALIZED ANALYSIS MODEL

A schematic diagram of a typical FPP system is shown in Fig.1. For simplicity, we consider a cross section of the object

Fig. 1. Schematic diagram of fringe pattern profilometry (FPP) system

surface for a given y coordinate. Hence, the intensity of fringe patterns captured by CCD camera and the height distribution function can be expressed as a function with single variable x . Thus we use $s(x)$ and $d(x)$ to denote the intensity of the projected and deformed fringe pattern respectively and use $h(x)$ to represent the height distribution of the object surface.

Conventional fringe pattern analysis methods are based on Fourier expansion and fundamental component analysis, which is sensitive to nonlinear distortions and highly depends on the performance of filters and the characteristics of the profile.

In order to solve this problem and accurately reconstruct three-dimensional surfaces from nonlinearly distorted fringe patterns, Hu et al. presented a generalized analysis model to explain the principle of FPP technique [17], [18]:

$$d(x) = s(x - u(x)) \quad (1)$$

$$h(x) = \frac{l_0 u(x)}{d_0 + u(x)} \quad (2)$$

where $u(x)$ represents the shift between the fringe patterns captured on the reference plane and the surface of the object, which varies with x coordinates. Eq.(1) reveals that the deformed signal $d(x)$ is a shifted version of $s(x)$, and the shift function $u(x)$ can be used to determine the object height distribution by Eq.(2). Therefore, the key to reconstructing three dimensional surface is to retrieve the shift function $u(x)$ from $s(x)$ and $d(x)$. In addition, because of its simplicity and generality, in following sections of this paper, the generalized model will be used for our algorithm derivation.

III. OPTIMAL FILTERING BASED SHIFT ESTIMATION (OFSE) ALGORITHM

As theoretically analyzed in [17], nonlinear distortions of the projected and captured fringe pattern will unavoidably introduce measurement errors into the height distribution $h_p(x)$

calculated by FTP or PSP algorithm. On the other hand, although FTP and PSP can not make an accurate reconstruction when nonlinear distortion exists, either of them is still capable of roughly measuring a profile of an object. Therefore, $h_p(x)$ can be still employed as a pre-estimation of the theoretical value of the height distribution $h(x)$. Corresponding to $h_p(x)$, $u_p(x)$ denoting the pre-estimated shift signal can be calculated by simply inverting Eq.(2). Obviously, compared to the theoretical shift distribution $u(x)$, $u_p(x)$ is not accurate either. Thus, we can regard the errors as a sort of noise and further eliminate it by a well-designed digital filter. Hence, the shift estimation problem can be converted into a new problem of designing a filter to make its output be a precise estimation of the theoretical value of the shift distribution. Certainly, the design of the optimal filter should be based on the generalized model given by Eqs.(1) and (2). Additionally, as the number of the filter parameter is usually much fewer than the number of sample points of the shift distribution $u(x)$, the parameter space will be significantly reduced, so that less computational complexity and faster convergence can be achieved.

A. Notation and representation

Generally, after the pre-estimated signal $u_p(x)$ has been filtered by a $2K + 1$ order spatial filter $p(k)$, the output signal $u(x)$ can be expressed as:

$$u(x) = \sum_{k=-K}^{k=K} u_p(x + k)p(k) \quad (3)$$

Obviously, we are expecting that the output $u(x)$ can satisfy the generalized model give by Eq.(1). Hence, as $u_p(x)$ has been known, our task becomes to estimating the parameters of the spatial filter p based on the generalized model.

For simplicity, we denote a discrete signal $u(x)$ as a column vector $\mathbf{u} = (u(1), u(2), \dots, u(N))^T$ (N is the length of the signal $u(x)$ and $(\cdot)^T$ represents transpose operation). Similarly, the spatial filter $p(k)$ will be represented as a column vector $\mathbf{p} = (p(-K), p(-K+1), p(-K+2), \dots, p(0), p(1), \dots, p(K-1), p(K))^T$. Thus, Eq.(3) can be expressed in the form of matrix and vectors as:

$$\mathbf{u} = \mathbf{U}_p \times \mathbf{p} \quad (4)$$

where $\mathbf{U}_p$ is a $N \times (2K + 1)$ matrix defined as

$$\mathbf{U}_p = (u_{ij})_{N \times (2K+1)} \quad (5)$$

where $i = 1, 2, \dots, N$ and $j = 1, 2, \dots, 2K + 1$ and

$$u_{ij} = \begin{cases} u_p(i + j - K - 1), & (K + 1 < i + j \leq N + K + 1) \\ 0, & (\text{others}) \end{cases} \quad (6)$$

Hence, as $\mathbf{U}_p$ is known, the estimated result $\mathbf{u}$ only depends on the parameters of the designed filter $\mathbf{p}$. As mentioned above, the number of the parameters of $\mathbf{p}$, $2K + 1$ is usually much fewer than the dimension of the original vector $\mathbf{u}$, which implies we can use fewer parameters to express $\mathbf{u}$.

B. Derivation of OFSE algorithm

According to the representation method mentioned in Section III-A, instead of directly calculating $\mathbf{u}$, we can estimate $\mathbf{p}$ before retrieve $\mathbf{u}$. Therefore, in order to estimate $\mathbf{p}$, we define the mean square error between $s(x)$ and $d(x)$ as an objective function.

$$J = E(e^2) = E([d(x) - s(x - u(x))]^2) \quad (7)$$

where $e = d(x) - s(x - u(x))$, $E(\cdot)$ denotes the expectation and recall $u(x)$ is the x -th element of $\mathbf{u}$. Similarly, in the following of this paper, for a vector $\mathbf{v}$, we use $\mathbf{v}(q)$ to denote the q -th element of the vector $\mathbf{v}$. Meanwhile, for a matrix $\mathbf{A}$ we use $\mathbf{A}(q)$ to denote the q -th row vector of matrix $\mathbf{A}$. Hence, Eq.(7) can be expressed as:

$$J = E([d(x) - s(x - \mathbf{u}(x))]^2) \quad (8)$$

Substituting Eq.(4) into Eq.(8), we can have

$$\begin{aligned} J(\mathbf{p}) &= E([d(x) - s(x - (\mathbf{U}_{\mathbf{p}} \times \mathbf{p})(x))]^2) \\ &= E([d(x) - s(x - \mathbf{U}_{\mathbf{p}}(x) \times \mathbf{p})]^2) \end{aligned} \quad (9)$$

By minimizing this object function with respect to the parameter vector $\mathbf{p}$, $\hat{\mathbf{p}}$, the estimation of $\mathbf{p}$ can be estimated in sense of least mean square error. In order to minimize J , we use gradient-based method to obtain the estimation of $\hat{\mathbf{p}}$ in an iterative way:

$$\hat{\mathbf{p}}_{m+1} = \hat{\mathbf{p}}_m - \eta \cdot \nabla_{\mathbf{p}} J(\hat{\mathbf{p}}_m) \quad (10)$$

where $\nabla_{\mathbf{p}} J(\cdot)$ represents the gradient of function $J(\cdot)$ regarding to variable $\mathbf{p}$, η is the learning rate and the subscript m denotes the m -th time iteration. By using LMS algorithm, we can replace $\nabla_{\mathbf{p}} J(\hat{\mathbf{p}}_m)$ with $\hat{\nabla}_{\mathbf{p}} J(\hat{\mathbf{p}}_m)$, the estimation of the gradient $\nabla_{\mathbf{p}} J(\hat{\mathbf{p}}_m)$, for simplifying calculation. Namely,

$$\hat{\mathbf{p}}_{m+1} = \hat{\mathbf{p}}_m - \eta \cdot \hat{\nabla}_{\mathbf{p}} J(\hat{\mathbf{p}}_m) \quad (11)$$

where

$$\begin{aligned} \hat{\nabla}_{\mathbf{p}}(J(\hat{\mathbf{p}}_m)) &= \nabla_{\mathbf{p}}([d(x) - s(x - \mathbf{U}_{\mathbf{p}}(x) \times \hat{\mathbf{p}}_m)]^2) \\ &= \nabla_{\mathbf{p}} e_m^2 = 2e_m \nabla_{\mathbf{p}} e_m = -2e_m \nabla_{\mathbf{p}} s(\hat{\mathbf{p}}_m) \\ &= -2e_m \nabla_{\mathbf{p}} s(\hat{u}_m(x)) \cdot \nabla_{\mathbf{p}} \hat{u}_m(x) \end{aligned} \quad (12)$$

where $u(x) = \mathbf{U}_{\mathbf{p}}(x) \times \mathbf{p}$ and $\hat{u}_m(x) = \mathbf{U}_{\mathbf{p}}(x) \times \hat{\mathbf{p}}_m$. So

$$\begin{aligned} \hat{\nabla}_{\mathbf{p}}(J(\hat{\mathbf{p}}_m)) &= -2e_m \times \frac{s(x - (\hat{u}_m(x) + 1)) - s(x - (\hat{u}_m(x) - 1))}{(\hat{u}_m(x) + 1) - (\hat{u}_m(x) - 1)} \\ &\quad \times \nabla_{\mathbf{p}} \hat{u}_m(x) \\ &= -e_m (s(x - \hat{u}_m(x) - 1) - s(x - \hat{u}_m(x) + 1)) \\ &\quad \times \mathbf{U}_{\mathbf{p}}(x) \\ &= -[d(x) - s(x - \mathbf{U}_{\mathbf{p}}(x) \times \hat{\mathbf{p}}_m)] \\ &\quad \times [s(x - \hat{u}_m(x) - 1) - s(x - \hat{u}_m(x) + 1)] \\ &\quad \times \mathbf{U}_{\mathbf{p}}(x) \\ &= -[d(x) - s(x - \mathbf{U}_{\mathbf{p}}(x) \times \hat{\mathbf{p}}_m)] \\ &\quad \times [s(x - \mathbf{U}_{\mathbf{p}}(x) \times \hat{\mathbf{p}}_m - 1) - s(x - \mathbf{U}_{\mathbf{p}}(x) \times \hat{\mathbf{p}}_m + 1)] \\ &\quad \times \mathbf{U}_{\mathbf{p}}(x) \end{aligned} \quad (13)$$

Because every point contains efficient information of parameter vector $\mathbf{p}$, we can sequentially and cyclically use all the point from 1 to N until the algorithm has converged. Namely, for the m -th time iteration, we can use the point at $x = (m-1)\%N + 1$, where $\%$ is the modulus operator, to calculate the gradient by using Eq.(13). Therefore, the derived OFSE algorithm can be expressed as:

$$\begin{aligned} \hat{\mathbf{p}}_{m+1} &= \hat{\mathbf{p}}_m + \eta \cdot [d(x) - s(x - \mathbf{U}_{\mathbf{p}}(x) \times \hat{\mathbf{p}}_m)] \\ &\quad \times [s(x - \mathbf{U}_{\mathbf{p}}(x) \times \hat{\mathbf{p}}_m - 1) - s(x - \mathbf{U}_{\mathbf{p}}(x) \times \hat{\mathbf{p}}_m + 1)] \\ &\quad \times \mathbf{U}_{\mathbf{p}}(x) \end{aligned} \quad (14)$$

For initialization, we can simply let $\mathbf{p}_1 = (p_1(-M), p_1(-M+1), p_1(-M+2), \dots, p_1(0), p_1(1), \dots, p_1(M-1), p_1(M))^T$, where

$$p_1(m) = \begin{cases} 1, & m = 0 \\ 0, & \text{others} \end{cases} \quad (15)$$

which corresponds to the case where there is no filtering operation on the pre-estimated signal $u_p(x)$.

IV. SIMULATION AND COMPARISON

For simulations, we use a paraboloid object whose maximum height is 160mm, which is shown in Fig.2(d). Considering the second order harmonic usually has the

Fig. 2. Simulated fringe patterns and object

strongest power in harmonics [17], the projected fringe pattern is generated from a cosinusoidal signal with the second order harmonic introduced, which is expressed as:

$$s(x) = 128 + 100 \cdot \cos(2\pi f_0 x) + 10 \cdot \cos(2\pi \cdot (2f_0)x) \quad (16)$$

where f_0 is the spatial frequency of the fringe pattern, which is assumed to be 10/meter in our simulation. i.e. the spatial period of the fringe pattern is assumed to be 100mm. Meanwhile, we assume l_0 and d_0 in Fig.1 equal to 5 meters and 2 meters respectively. The spatial resolution of the captured image is assumed to be 1 pixel/mm. Note for the projected fringe pattern given by Eq.(16), the second order harmonic only has -20db of power compared with the fundamental component.

Further we assume when $s(x)$ is captured by CCD camera, it is distorted again by a nonlinear function:

$$\zeta(s) = 128 \frac{\tanh(\frac{3s}{128} - 3)}{\tanh(3)} + 128 \quad (17)$$

which is a nonlinear function mapping the values from range[0,256] to range [0,256]. The function is plotted in Fig.2(a). Thus, the captured fringe pattern of $s(x)$ is:

$$\hat{s}(x) = \zeta(s(x)) \quad (18)$$

Corresponding to Eq.(16), the deformed fringe pattern and its captured version can be respectively expressed as:

$$\begin{aligned} d(x) = & 128 + 100 \cos(2\pi f_0 x + \phi(x)) \\ & + 10 \cos(2\pi \cdot (2f_0)x + 2\phi(x)) \end{aligned} \quad (19)$$

where $\phi(x)$ is the phase shift caused by the object surface. And

$$\hat{d}(x) = \zeta(d(x)) \quad (20)$$

The projected fringe pattern on the reference plane is shown in Fig.2(b), and the fringe patterns deformed by the paraboloid is shown in Fig.2(c). Additionally, for clarity of comparison, we will use the central cross section of the paraboloid to demonstrate reconstruction result.

Because of the nonlinear distortion of the fringe pattern, FTP algorithm is only able to work out a roughly reconstructed height distribution result represented by solid line in Fig.3(a) and dashed line is the true value of the height distribution. Corresponding to the roughly estimated height distribution, the

Fig. 3. Reconstruction results by using FTP and OFSE

pre-estimated shift u_p can be calculated by inverting Eq.(2). In our simulation, we use $K = 30$ to perform our reconstruction. From the initial vector p_1 , we can adjust the parameter vector p by our proposed algorithm expressed by Eq.(14) until the algorithm converges to $\hat{p}_{opt}$, the optimal estimation of p , and at the same time an accurate reconstruction result can be obtained as shown in Fig.3(b) by solid line. In Fig.3(b), same with Fig.3(a), dashed line is the true value of the height

distribution. We can see that the reconstruction result is almost identical with the true value. Meanwhile, it provides much more accurate and smoother surface compared with the result calculated by FTP algorithm. This result also confirms the proposed OFSE algorithm precisely converges to the optimal value. Additionally, as we only use a 61-dimensional vector to express the profile signal, compared with directly estimating the elements of vector u with $N = 1000$ dimensions, the parameter space has been significantly reduced. That is why the proposed OFSE algorithm can achieve much faster convergence.

V. CONCLUSIONS

This paper has presented a novel shift estimation method, called optimal filtering based shift estimation (OFSE) for digital projection based fringe pattern profilometry. Because of using generalized analysis model, both OFSE and GSE can accurately reconstruct three-dimensional surfaces from nonlinearly distorted fringe patterns. However, the proposed OFSE can significantly reduce computational complexity compared with GSE and has much faster convergence speed. Moreover, because of the fast convergence and the reduced dimension of the parameter vector, OFSE is more suitable for realtime profilometry. Simulation results show that OFSE is a much faster, more efficient and reliable algorithm for fringe pattern profilometry.

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