A Fast Tracking Algorithm for Estimating Ultrasonic Signal Time of Flight in Drilled Shafts Using Active Shape Models

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Abstract—**Drilled shaft is an important substructure foundation in building construction. A drilled shaft needs to be placed precisely in high accuracy and satisfy the diameter precision requirement. In order to measure the verticality and the diameter of a shaft, the M-superimposed Gaussian Echoes Model (GEM) is used to estimate the time of flight (TOF) of ultrasound. Compared to the conventional threshold and cross-correlation based methods, GEM method has higher resolution and higher signal-to-noise ratio. However, the GEM method is computational expensive. In this paper, we propose an Active Shape Models (ASMs) tracking based algorithm to estimate the time of flight (TOF) of the ultrasound testing inside a cylindrical container. It extracts the pattern of the first several arriving peaks and troughs in a more flexible way with better efficiency than GEM.**

Keywords—Drilled Shaft, Ultrasonic Time of Flight, Active Shape Models

I. INTRODUCTION

Ultrasonic testing method is widely applied in drilled shaft testing, which depends on the accurate estimation of the ultrasonic time of flight (TOF). By estimating the diameter and verticality of the drilled shaft using TOF, deformation of the drilled shaft can be detected. Many existing works have been proposed to estimate the ultrasonic TOF, for instance, the threshold based method [1][2], the cross-correlation method [3] and the model based method [4]. Among these three methods, the model based method with Gaussian Echo Models (GEMs) achieves the highest resolution [4]. Expectation Maximization (EM) algorithm [5][6] or Quasi Maximum Likelihood [7] algorithm is used to estimate the GEM model parameters. However, these estimation algorithms require parameter initialization and heavier computational load than the conventional threshold or cross-correlation based methods.

The above-mentioned methods are all detector based algorithms, which assume the consecutive sample sequences are independent in generation and sampling. However, this may not be always true since the ultrasonic transducers are pulled up steadily from the bottom of a drilled shaft, and the property of slurry change slowly in specific depth. We here consider the correlation between consecutive sample sequences and propose a tracking based algorithm with Active Shape Models (ASMs) as template. It extracts the pattern of the first several arriving peaks and troughs in a more flexible way than GEMs.

The differences between our method and GEMs are as follows. First, we focus on the representative points of the ultrasound wave shape rather than the exact parameters of an ultrasonic signal. Second, we extract the first several peaks and troughs of the ultrasound waves rather than the entire observed data sequence. Third, we train a template to track frame-by-frame rather than analyzing each sample sequence independently.

The rest of this paper is organized as follows: Section II explains the training of ASMs, Section III describes the tracking algorithm of ultrasonic TOF using ASMs. Section IV introduces the experimental setup and Section V discusses the results, followed by the conclusions in Section VI.

II. TRAINING ACTIVE SHAPE MODELS OF ULTRASONIC SIGNAL

Under the assumption that the transducers are pulled up steadily from the bottom of the drilled shaft, the sample sequences of consecutive sampling depths share some similarities, especially in the first few peaks and troughs. This motivates us to explore the shape patterns of ultrasonic signal to estimate the TOF, and find a more effective model to describe the shape of ultrasound. Active Shape Model (ASM) was developed by Tim Cootes and Chris Taylor in 1995 and is widely used in computer vision applications. It is a kind of statistical model describing the object shapes. It iteratively deforms to fit an object template. The shapes are constrained by the point distribution model (PDM) and can vary only in ways which were recorded in the training data [8].

In our experiment, we collect ultrasonic signals with equipment mentioned in Section V and convert the ultrasound signal sequences into a series of consecutive 2D images by mapping the index of time and the voltage of the ultrasound signal to the pixel coordinate via linear transformation. After the conversion, representative points are extracted from the first few peaks and troughs to train an Active Shape Model. For a 2D image, we represent *n* representative points $\{x_i\}$, each point is (u_i, v_i) for a single point, forming a 2*n* element vector x where

$$x = (u_1, ..., u_n, v_1, ..., v_n)^T \tag{1}$$

By aligning a set of training shapes into a common coordinate frame and performing dimension reduction using Principal Component Analysis (PCA), we get the ASMs as follows

$$x = \bar{x} + Pb \tag{2}$$

$$\bar{x} = 1/N \sum_{i=1}^{N} x_i \tag{3}$$

$$S = \sum_i (x_i - \bar{x})(x_i - \bar{x})^T \tag{4}$$

$$P = [p_0, p_1, ..., p_{t-1}]^T \tag{5}$$

$$b = [b_0, b_1, ..., b_{t-1}]^T \tag{6}$$

P is the first t principle components of a covariance matrix S, and b is a vector of weight under the constraint that

$$|b_i| < 3\sqrt{\lambda_i} \tag{7}$$

λ_i is the corresponding eigenvalue.

In our work, we try different configurations to extract representative points, Fig.1 shows representative points from multiple sequences sampled at 17 positions uniformly distributed in the 2D image, and Fig.2 demonstrates the corresponding normalized mean shape. In the experiment, we also try different numbers of representative points as well as the different distributions of their positions in the shape contour.

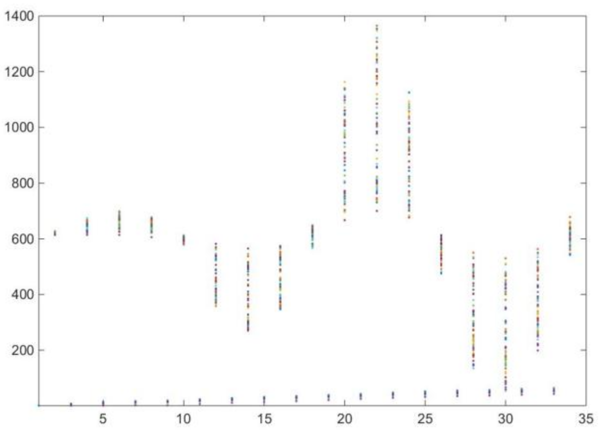

Fig.1 Representative points

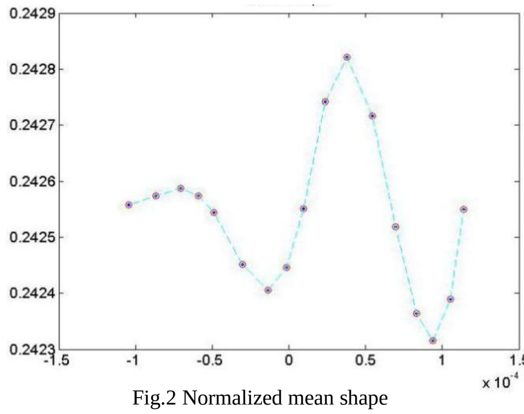

Fig.2 Normalized mean shape

III. TRACKING ULTRASONIC TOF USING ASMS

In contract to the detector based algorithms, our tracking based algorithm can perform faster and each sample sequence can be used as a reference for the subsequent sequences.

Before tracking, we first locate the potential starting point of each sample sequence, and extract the region that last for 300us to construct consecutive 2D images. Then the ASMs template is aligned to the image coordinate. Assuming X is the model instance in image, it is given by

$$X = T_{Xt,Yt,s,\theta}(\bar{x} + Pb) \tag{8}$$

$$|b_i| < 3\sqrt{\lambda_i} \tag{9}$$

$$T_{Xt,Yt,s,\theta}\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} s\cos\theta & -s\sin\theta \\ s\sin\theta & s\cos\theta \end{pmatrix}\begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} Xt \\ Yt \end{pmatrix} \tag{10}$$

The initial estimation of the pose parameters and shape parameters are achieved using the threshold based method. In the tracking step, we calculate the adjustment along a normal to the model boundary toward the strongest image edge by minimizing the term in (10), via modifying the pose parameters $p = (Xt, Yt, s, \theta)$, and the shape parameters b, the best location of the point set Y is found to match the model instance X.

$$\min \left\| Y - T_{Xt,Yt,s,\theta}(\bar{x} + Pb) \right\|^2 \tag{11}$$

Because of the time delay and attenuation of ultrasound in propagation, the position convergence of the representative points in the first peak is faster than the following peaks and troughs. This unbalanced convergence is shown in Fig.5. We simply multiply a weighted vector when calculating the Error of Shape (EOS) and place more importance on the first peak and trough, which is more important for estimating TOF. The tracking process is shown in Fig.3, where the red dots represent the previous position and the blue dots represent the estimated position by optimizing equation (10). Fig.4 is the contour of the boundary of the ultrasound when the tracking is converged. The first point of the ASMs model is corresponding to the point for estimating TOF. After tracking all the frames, we get a sequence of points to estimate TOF of different ultrasound sample sequence, which are represented as $\{k_0, k_1, ..., k_m\}$, that can be transferred into time coordinate to represent the TOF.

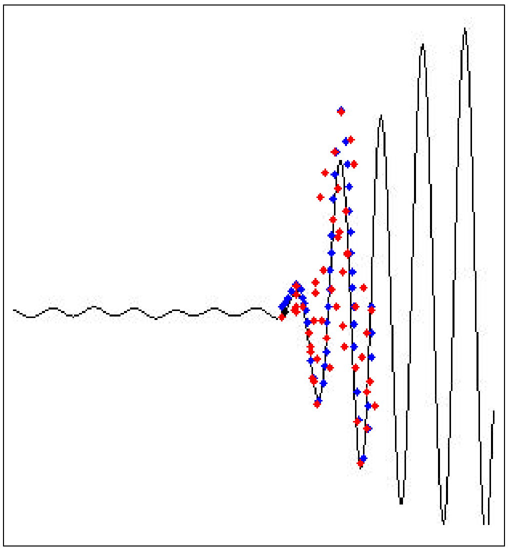

Fig.3 Tracking process

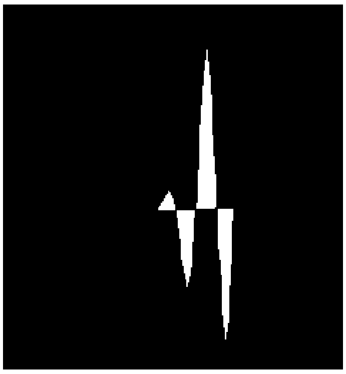

Fig.4 Contour of the ultrasound boundary

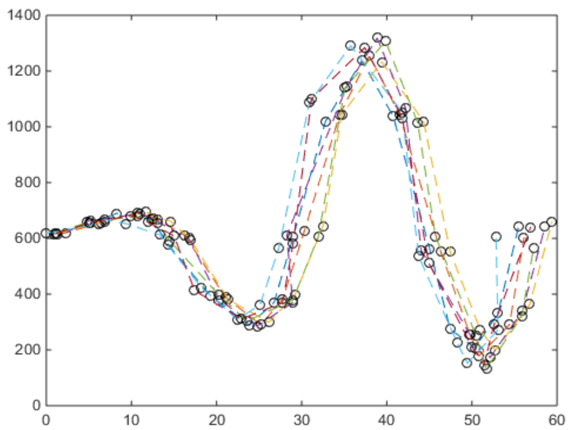

Fig.5 Unblanced convergence

IV. Experimental Setup

The experimental system consists of an ultrasonic transducer set with a center frequency of about 40kHz. Our NI DAQ equipment including Analogy to Digital Convector (ADLINK PXIe 9848) with the sampling frequency up to 10MHz, a signal generator (NI PXI 5412) for triggering the emitting transducer, and a I2C to USB (NI8541) convertor to collect the signal from electronic compass LSM303DLH. The test was performed inside a 1.5m height bucket with a diameter of 80cm to simulate a drilled shaft underground.

By manually pulling up the transducers set in height, the depth counter triggers the signal generator to emit the ultrasonic transducer. The ultrasonic wave is reflected from the wall of the bucket and received by an 8-direction receiver.

V. Results and Discussion

We first do a single pulse test mainly focusing on the accuracy of TOF by placing the transducer set outside the bucket, and using a wall to do the test on each channel separately. Then we do tests on consecutive sequences by continuously pulling up the transducers set vertically. A laser Distance Meter (CEM LDM-35) with the resolution of ±1.5mm used to generate the ground truths. We further compare the results with the ASMs based, threshold based, as well as the GEMs based method.

As GEMs are formulated to describe a smooth curve, in order to gain a comparable value describing the performance of estimated shape between the ASMs based and GEMs based method, we extract a number of corresponding points in the estimated ultrasound curves estimated by GEMs method, which have the same index with the representative points in ASMs. Table I is the comparison of each method, where E refers to the absolute error of TOF, Ɛ refers to the relative error, N refers to the average number of required iterations and EOS denotes the sum of Euclidean distance of representative points between the estimated shape and the ground truth.

Because we only extract limit representative points to describe the shape, some information of the received ultrasound signal is ignored, and the EOS of ASMs method is about twice of that of GEMs. Nonetheless, as we only focus on the first representative point of the ASMs, whose position in x axis of the pixel coordinate can be translated back to time for TOF estimation, we can see that the relative error of TOF is about 2.11%, while that of threshold based method and GEMs based method are about 3.22% and 1.27% respectively.

The average error of TOF of ASMs is higher than that of GEMs. By transferring the coordinate in image of the representative point into distance metric, the average error of distance of GEMs is 6.12mm while that of ASMs is 10.22mm. Both satisfy the range of industrial specifications 50mm [9] [10] [11]. Therefore, the ASMs tracking based method can perform faster than GEMs based method with a slightly lower resolution but calculation still meets the requirement of current industrial specification.

TABLE I. COMPARISON OF EACH METHOD

	Single Sequence			Consecutive Sequences (Vertical wall)			Consecutive Sequences (Tilting wall)		
	TS[a]	***GEMs***	***ASMs***	***TS***	***GEMs***	***ASMs***	***TS***	***GEMs***	***ASMs***
TOF E(us)	46.5	18.5	32.8	48.2	18.5	29.5	47.5	19.1	30.9
TOF Ɛ (%)	3.2	1.3	2.2	3.3	1.3	2.01	3.2	1.3	2.1
N	1	152	42	1	147	34	1	143	37
EOS	*	42	83	*	34	89	*	39	87

a. Threshold based method

VI. CONCLUSION

In this paper, we focus on the ultrasonic testing methods of drilled shaft and propose the tracking based Active Shape Models (ASMs) method to estimate the ultrasonic time of flight (TOF) inside a cylindrical capacity. By focusing on the representative points, and configuring their distribution and number, we train a template within the ASMs framework to track the TOF of ultrasonic signal. We compared our tracking based ASMs algorithm with the simplex threshold based method and GEMs model based method. Result shows that our method can provide a faster estimation of TOF than GEMs method and a slightly higher resolution than the threshold based algorithm, which is suitable and efficient for current industrial specification.

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