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The machine learning method of phase extraction in interferometry

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ABSTRACT

Phase extraction of interferometry is a crucial step of optical measurement. In this paper, a machine learning method is proposed to extract the phase from the interferometric signal with the least squares support vector machine, which eliminates the phase unwrapping procedure and enhances the phase measuring accuracy greatly when compared with traditional phase unwrapping methods. Furthermore, it can also work well in the undersampling situation to some extent. Our method is capable of extracting both linear and nonlinear phases. A Michelson interferometer was constructed to demonstrate the validity of the method proposed, which can be potentially applied in many significant fields.

1. Introduction

Interferometry is a widely used measuring method in many fields such as nanotechnology [1], biotechnology [2], and precision control [3]. The measurement can be realized in several ways, among which phase extraction is preferred as it has high precision and a simple process. However, most of the existing phase extraction methods are limited by phase modulation hardware or phase unwrapping algorithms, thereby resulting in low accuracy. For example, the Fourier transform (FT) and the wavelet transform (WT), most commonly applied at the current time, have several limitations. For the FT, the band filter needs to be built in many cases to enhance the signal-to-noise ratio (SNR); For the WT, the mother wavelet function and its scale parameter “a” and shift parameter “b” need to be found in advance to obtain better recovered phase information. To address these limitations, we proposed a machine learning method to extract phase from the interferometric signal, which provides high accuracy without the phase unwrapping procedure.

In recent years, machine learning algorithms have been developed rapidly, and the support vector machine (SVM) is representative of them as it has been used in many fields such as data mining [4], computer vision [5], natural language processing [6], and face recognition [7]. SVM has been used in some research on the interferometric signal’s phase [8–10]. However, all these studies used traditional methods to extract the phase from the interferometric signal, which has low accuracy.

In this paper, a machine learning method is proposed by using a multi-input and multi-output least squares support vector machine (LSSVM) model to extract the phase from the interferometric signal, which yields a deviation of about 10^{-5}(rad) in numerical simulations, much smaller than traditional methods, and also excludes the phase unwrapping process. We proved that this method is applicable to both linear and nonlinear motions’ interferometric signals and shows good performance in the undersampling situation to some extent. A Michelson interferometer was constructed to demonstrate our method and achieved a precious measurement result, representing an extensive application in actual technology.

2. Principles

2.1. Michelson interferometer

The interferometric signal is a type of cosine signal and the information on the object is contained in its phase. To obtain more accurate information about the object, such as displacement, velocity, and strain, the accuracy of the signal phase is required. We take a Michelson interferometer as an example to show how our method extracts the phase from the interferometric signal by LSSVM.

The structure of the Michelson interferometer is shown in Fig. 1. The laser beam emits from the laser and is incident to two polarizers that can adjust the light intensity. The beam is then expanded by the spatial filter and then divided into two beams by the beam splitter. One beam is incident to the reference mirror, reflected back to the beam splitter, and incident to the CCD as the reference arm. The other beam is incident straight, reflected at the object mirror, and then it returns to the beam splitter and is reflected to the CCD as the measuring arm. Two beams

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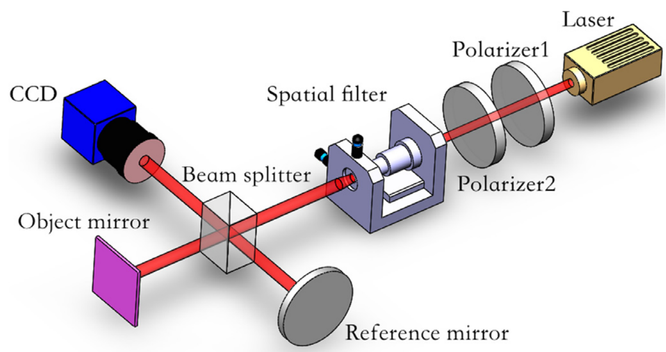

Fig. 1. The structure of the Michelson interferometer.

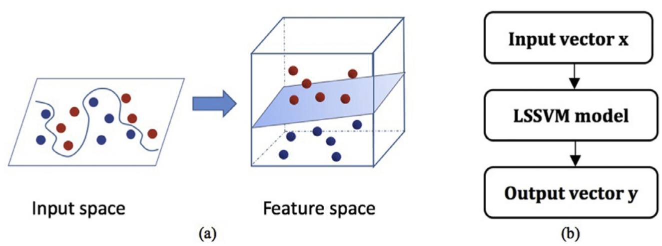

Fig. 2. (a) The vectors in input space and feature space; (b) The process of obtaining the output vector.

recombine and interfere at the CCD, thus becoming an interferometer signal.

The principle of the Michelson interferometer signal is

$$I = I_1 + I_2 + 2\sqrt{I_1 I_2} \cdot \cos\left(\frac{4\pi}{\lambda} \cdot s + \varphi_0\right), \tag{1}$$

where I is the light intensity on the detector, I_1,I_2 are the light intensity of the reference arm and the measuring arm, respectively, λ is the wavelength of the laser source, s is the displacement of the object, and φ_0 is the initial phase.

2.2. Least squares support vector machine

The support vector machine is a supervised model to solve the problems such as classification and regression, proposed by Vapnik in 1995 [11]. In order to improve the training efficiency of the SVM, the least squares support vector machine (LSSVM) was proposed by Suykens in 2002, which uses the square of the training error instead of the slack variable in the SVM and the equality constraint instead of the inequality constraint [12]. Therefore, the training process only requires us to solve a set of linear equations and avoids a convex quadratic programming (QP) problem. As shown in Fig. 2a, it maps the input vectors of the training set into a high-dimensional feature space and attempts to find an optimal hyperplane that represents the relationship between inputs and outputs.

Suppose that there is an input vector x_i and, via a LSSVM model, an output vector y_i is produced. The process of obtaining the output vector is shown in Fig. 2b. To obtain the LSSVM model, first, a number of samples of input and relevant output $D\{(x_i, y_i)|i = 1, 2, \dots, m\}$ is needed to prepare, where x_i are the input vectors, y_i are the output vectors, and m is the number of samples. Then, we train these samples with LSSVM and obtain the LSSVM model. Finally, we input a test vector and the output vector is obtained through the model trained before with the function we estimate.

2.3. Phase extraction using LSSVM

While the object is moving, a series of interferograms are collected by the CCD at a constant sampling speed. We randomly select a pixel and obtain the intensity I recorded by it as the test input intensity. Then we set some normalized interferometric signals and the corresponding phase as training samples. The input vectors x_i are normalized light intensity, and the output vectors y_i are the corresponding phase.

As is shown in Fig. 3a, it maps the input vector light intensity into a high-dimension feature space and tries to find the optimal hyperplane, which represents the maximum distance between each support vector in the margin [13]. The points on the (hard) margin is called support vectors.

Suppose that the hyperplane's expression is

$$f(x) = \omega^T \phi(x) + b, \tag{2}$$

where $\omega^T = (\omega_1, \omega_2, \dots, \omega_d)$ is the normal vector of the hyperplane $f(x)$, b is the distance between the origin point and hyperplane, and $\phi(x)$ is the mapping of input light intensity x in feature space (eigenvector).

The distance between support vectors in two sides of the margin is

$$r = \frac{2}{\parallel \omega \parallel}. \tag{3}$$

To obtain the optimal hyperplane, the distance between two margins needs to be maximized, which means maximizing $\frac{1}{\|\omega\|}$. Maximizing $\frac{1}{\|\omega\|}$ is equal to

$$\min \frac{1}{2} \parallel \omega \parallel^2. \tag{4}$$

To avoid the LSSVM training incorrectly with some samples, we suppose that the error borne between the hyperplane $f(x)$ to output y (signal's phase) is ε and only calculate the loss when the error is larger than ε, as is shown in Fig. 3b.

Thus, the formula (4) is changed into

$$\min \frac{1}{2} \parallel \omega \parallel^2 + C \sum_{i=1}^{m} l_\varepsilon \left(f\left(x_i\right) - y_i\right), \tag{5}$$

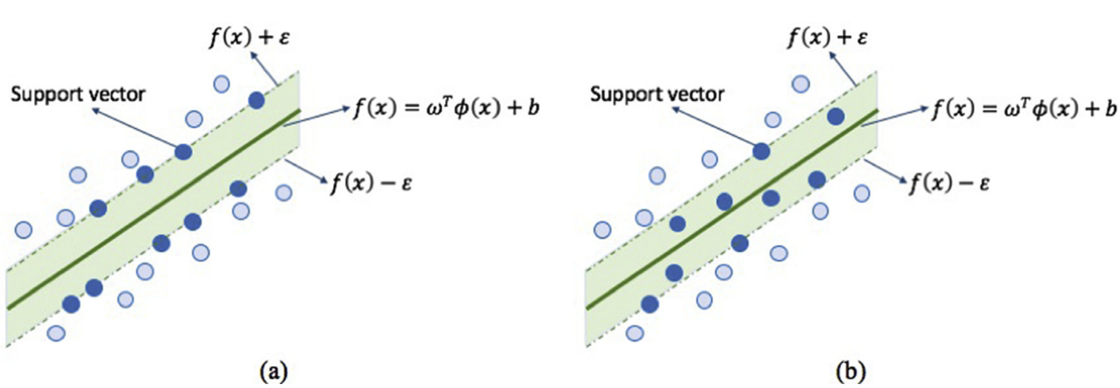

Fig. 3. (a) The feature space with hard margin; (b) The feature space with soft margin.