Neural network approximation of nonlinearity in laser nano-metrology system based on TLMi

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Abstract. In this paper, an approach based on neural network (NN) for nonlinearity modeling in a nano-metrology system using three-longitudinal-mode laser heterodyne interferometer (TLMi) for length and displacement measurements is presented. We model nonlinearity errors that arise from elliptically and non-orthogonally polarized laser beams, rotational error in the alignment of laser head with respect to the polarizing beam splitter, rotational error in the alignment of the mixing polarizer, and unequal transmission coefficients in the polarizing beam splitter. Here we use a neural network algorithm based on the multi-layer perceptron (MLP) network. The simulation results show that multi-layer feed forward perceptron network is successfully applicable to real noisy interferometer signals.

1. Introduction
A nano-metrology system can include length or size measurements, (where dimensions are typically given in nanometers and the measurement uncertainty is often less than 1nm), as well as measurement of force, mass, electrical and other properties like thin films layers and surfaces, carbon nano-tubes, inorganic nano-tubes, and nano-wires [1-3]. Precise control of dimensions of objects is the key issue of nanotechnology and the science of nano-objects. The measurement techniques developed for conventional materials in many cases cannot be simply applied to nanostructures. Nano-metrology has a crucial role in order to produce nanomaterials and devices with a high degree of accuracy and reliability. With development in semiconductor industry to make devices and circuits in nanometer size such as nano-electro-mechanical systems (NEMS), semiconductor nanosensors, and nanoelectronics is asking for improved resolution and reached the high accuracy of nano-metrology systems [1, 4]. Non-contact, absolute-distance measurement system with high resolution and an extending range is essential for a number of applications like semiconductor manufacture, calibration, precision cutting, lattice constant measuring, robotic systems, and controlling the gap of liquid crystal display (LCD) panels [1-4]. The laser heterodyne interferometer has special benefits for accurate length/speed measurements because it allows very precise measurements with nanometer resolution based on phase measurement [5-7].

Interferometers are typically influenced by polarization ellipticity or non-orthogonality of the laser beams. Even perfect optical components can also contribute to this nonlinearity. Furthermore, the misalignment of the interferometer seriously affects the nonlinearity of a heterodyne interferometer. This cyclic nonlinearity exists in all laser interferometers. This error can be worse under certain conditions. The nonlinearity errors happen mainly from two factors: polarization-mixing and frequency-mixing [8]. In a three-longitudinal-mode laser heterodyne Doppler interferometer (TLMi),
the phase is detected with some electronic sections [9]. The periodic nonlinearity in this nanometerology system is arising from polarization effects, frequency mixing, intermodulation distortion, phase detection uncertainty, and electrical cross-talk. However, the periodical nonlinearity property is an obstacle to improve the high measurement accuracy in nanometer scale [9]. In order to minimize the nonlinearity error of the heterodyne interferometer, it is important to model the nonlinearity and distinguish it from actual phase.

Quenelle [10] and Sutton [11] performed investigations of periodic error in heterodyne Michelson interferometers. Specific efforts have included to measure periodic error under various conditions, frequency domain analyses [12], analytical modeling techniques [13], and Jones calculus modeling methods [14]. Artificial Neural Networks are a programming paradigm that seek to emulate the microstructure of the brain, and are used extensively in artificial intelligence problems from simple pattern-recognition tasks, to advanced symbolic manipulation. Li et al. have first modeled and corrected the nonlinearity in the homodyne interferometers based on the multi-layer perceptrons neural networks in 2003 [15]. Then, Heo et al. employed a combined algorithm, which adopts recursive least square error (RLS) method and a neural network back-propagation algorithm to compensate the nonlinearity in the heterodyne interferometer in 2007 [16]. Olyaee et al. have modeled the nonlinearity resulting from non-ideal polarized light of a modified high-resolution laser heterodyne interferometer by using multi-layer perceptrons and radial basis function as single neural networks, and stacked generalization method by combination of neural networks [17].

By replacing a three-mode laser heterodyne interferometer the requirement for high resolution about less than 1 nanometer is achieved [14]. Yokoyama et al. have first analyzed periodic nonlinearity error in TLMI [18]. Then Olyaee et al. used Jones matrices and plane wave methods to predict and simulate nonlinearity originating from errors in optical alignment and polarization states of the components of nano-metrology system based on TLMI [7-9, 14]. But all of these methods need a lot of time and computational analysis.

The polarization-mixing in the TLMI commonly happens within elliptically polarized laser beams, non-orthogonally polarized laser beams, rotational error in the alignment of laser and beam splitter, rotational error in the alignment of the mixing polarizer, and unequal transmission coefficients in the polarizing beam splitter [14].

In this paper, we propose a simple algorithm using an artificial intelligence method which is set up in front of the detectors in the interferometer. The ability to learn and generalize is fundamental to any learning machine. Artificial neural networks (ANNs) use inductive learning to find general concepts from their concrete examples [19]. The feed forward neural network trained by back-propagation predicts the nonlinearity error and difference with the reference signal. In this paper, sections 2 and 3 introduce the principals of the optical setup and analysis of nonlinearity error, respectively. In section 4, the simulation results are presented. And finally conclusions are drawn in section 5.

2. Principals

In the TLMI, three orthogonally polarized beams with a split frequency of approximately 500MHz generated within the He-Ne laser first pass through a non-polarizing beam splitter (BS). One part is led to a linear polarizer (LP) in the base arm, the orthogonally polarized fields of the three modes are combined with the polarizer, and then, it is focused on the avalanche photodiode (APD) to generate a reference signal. The other part of emerged light is led to the measurement system (interferometer). There are two paths namely reference and target paths, which the incident light is separated in two orthogonal orientations with the polarizing beam splitter (PBS). In a three-longitudinal-mode laser heterodyne Doppler interferometer (TLMI) the phase is detected with some electronic sections [14].

By using the super-heterodyne phase detection circuit in the following of base and measurement avalanche photodiodes (APDb) and (APDm), the base and measurement signals are respectively concluded as [14]:

\[ V_{ob} = g \cos(\omega_0 t + \Phi_{n_0}) \]  \( \text{(1)} \)

\[ V_{om} = g \cos(\omega_0 t - 2\Delta\Phi + \Phi_{n_m}) \]  \( \text{(2)} \)
where $g$ is the total transfer gain of the signal conditioner, $\omega_3 = |\omega_{H} - \omega_{L}|$ is the secondary angular beat frequency, $\omega_{H} = \omega_{1} - \omega_{2}$ and $\omega_{L} = \omega_{2} - \omega_{1}$ are the higher and lower intermode angular beat frequencies, respectively. Here $\Phi_{nl_b}$ and $\Phi_{nl_m}$ are the phase nonlinearities in the base and measurement arms, respectively.

In the above formula, $\Delta \Phi = (4n \pi / \lambda_c) \Delta z$ is the phase shift due to the optical path difference $(\Delta z)$ [8], where $n$ is the refractive index and $\lambda_c$ is the wavelength of the central mode. Finally total nonlinearity phase is concluded as:

$$\psi_{nl-total} = \Phi_{nl_m} - \Phi_{nl_b}$$

(3)

3. Neural network approximation of nonlinearity

The block diagram of nonlinearity modeling in TLMI based on the neural networks is shown in Figure 1. Using artificial neural networks, it is possible to approximate the full complexity computational problems in a high dimensional space. As shown in Figure 2, ANNs will consist of at most a few hundred neurons and very limited connections between them. Generally, artificial neural networks are basic input and output devices with the neurons organized into layers [19]. In this paper, input layers are output voltage of base and measurement arms ($V_{ob}$ and $V_{om}$) and output layer is nonlinearity error ($\psi_{nl-total}$). The learning process consists of finding the correct values for the weights between the input and output layer. In the metrology industry, it is increasingly led to small (nano) dimensions and of course we need more precise measurement system with higher resolution. The main goal of using neural network is its fast feasibility.

![Figure 1](image1.png)

**Figure 1.** The block diagram of nonlinearity modeling in TLMI.

![Figure 2](image2.png)

**Figure 2.** The schematic of MLPN for nonlinearity modeling in the TLMI.

The Multilayer perceptron is an artificial neural network that is used extensively for the solution of a number of different problems, including pattern recognition and interpolation [20]. The network consist of a layer of input neurons, coupled with a layer of output neurons, and one or more layers
between them, as shown in Figure 2. The back propagation algorithm is most famous to layered feed forward networks, or multilayer perceptron is used generally to train neural networks. In this paper, we used MLP network with input and output layers and one hidden layer.

4. Simulation Results

In this section, the performance of the MLP network is studied in terms of modeling nonlinearity accuracy and training time. The results obtained are compared with actual nonlinearity. Input data for networks are output voltage of electronic circuit from base and measurement arms. The input vector and output vector are respectively as [19]:

\[ \mathbf{P} = [V_{in}, V_{ob}] \]
\[ \mathbf{T} = [\psi_{nl-total}] \]

The full data are about 6000 data, which 4000 is for training phase and the rest is for test phase. The training input vector is obtained by inserting constant nonlinearity parameters in Eqs. (1) and (2) and the target vector is generated from Eq. (3). Table 1 represents properties of MLP network for nonlinearity modeling and time consuming for some deviation parameters.

According to Table 1, multi-layer perceptron with one hidden layer is used for all deviation parameters. There are 6 neurons with 60 epochs and learning rate about 0.01 for the best mean square error. The time consuming for this result is 3.09s. The result of nonlinearity modeled with MLP network according to wavelength is plotted in Figure 3 for parameters of Table 1.

Comparison of mean square error as the number of training samples for nonlinearity modeling for deviation parameters \(\delta = 0.2\), \(\delta = 0.28\) (ellipticity), \(\tau = 0.90\), \(\tau = 0.95\) (transmission coefficients of the polarizing-beam splitter), and \(\alpha = 2\) (rotation angle) is summarized in Table 2. According to the Figure 4, by increasing number of training data, the neural network can model nonlinearity better. In conclusion, the number of training samples affect on the results. Table 3 represents the performance of nonlinearity modeling as number of epochs for same deviation parameters by MLP network. Results are plotted in Figure 5. It is concluded that the optimum mean square error is with 60 epochs and by increasing the number of epochs from 60, the performance is not modified, although the time consuming is increased.

### Table 1. Properties of multi-layer perceptrons (MLP) network for nonlinearity modeling for some deviation parameters.

| Curve | Condition | Properties of nonlinearity modeling by MLPs network | Results |
|-------|-----------|-----------------------------------------------------|---------|
|       | \(\delta\) | \(\delta\) | \(\tau\) | \(\tau\) | Number of neurons in the hidden layer | Number of epochs | Learning rate | Consuming time for neural network (seconds) | Mean square error (dB) |
| a     | 0.2       | 0.28      | 0.90     | 0.95     | 2        | 5              | 50            | 0.01          | 3.935                  | -66.07                 |
| b     | 0.2       | 0.28      | 1        | 1        | 2        | 5              | 50            | 0.01          | 3.15                   | -76.61                 |
| c     | 0.2       | 0.2       | 1        | 1        | 2        | 5              | 50            | 0.01          | 3.072                  | -100.90                |
| d     | 0.2       | 0.2       | 0.9      | 0.95     | 0        | 6              | 60            | 0.01          | 3.09                   | -105.83                |
| e     | 0.2       | 0.28      | 1        | 1        | 0        | 6              | 50            | 0.01          | 3.243                  | -83.15                 |
Figure 3. The difference between expected nonlinearity and modeled nonlinearity with MLP network for deviation parameters listed in Table 1.

Figure 4. Mean square error as increasing the number of training samples of MLP network for nonlinearity modeling in the TLMI.
Figure 5. Mean square error as increasing the number of epochs of MLPN for nonlinearity modeling in the TLMI.

Table 2. Results of mean square error as the number of training samples for nonlinearity modeling with MLP network.

| Parameter | Number of training samples |
|-----------|---------------------------|
| MSE (dB)  |                            |
|           | 1  | 50  | 100 | 200 | 400 | 800 | 1000 | 2000 | 3000 | 4000 |
|           | -11.91 | -16.18 | -17.05 | -14.55 | -13.97 | -66.09 | -66.49 | -65.65 | -66.53 | -65.06 |
| Time (seconds) | 1.18 | 1.62 | 1.995 | 2.1715 | 1.995 | 2.126 | 2.066 | 2.282 | 2.562 | 2.574 |

Table 3. Results of mean square error as the number of epochs for nonlinearity modeling with MLP network.

| Parameter | Number of epochs |
|-----------|-----------------|
| MSE (dB)  |                 |
|           | 1  | 5  | 10 | 15 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|           | -14.79 | -17.64 | -19.97 | -22.34 | -23.05 | -33.96 | -47.72 | -67.07 | -67.07 | -66.80 | -66.61 | -66.15 |
| Time (seconds) | 2.52 | 1.99 | 2.06 | 2.48 | 2.30 | 2.72 | 2.93 | 3.33 | 3.05 | 4.04 | 4.25 | 5.07 | 5.45 |
5. Conclusion
In this paper, an approach based on neural network for modeling nonlinearity in a three-longitudinal-mode laser heterodyne interferometer (TLMI) has been introduced. We modeled nonlinearity errors that arise from elliptically and non-orthogonally polarized laser beams, rotational error in the alignment of laser and beam splitter, rotational error in the alignment of the mixing polarizer, and unequal transmission coefficients in the polarizing beam splitter. The MLP neural network algorithm was used. The simulation results have shown that this network has successfully modeled nonlinearity errors with simplest and fast structure, including 5 neurons in the hidden layer. It was also confirmed that the system with the neural network modeling part could respond at a speed about that exceeds only to 3 seconds. We note that the method presented here is applicable to all of nano-metrology systems like conventional and extended two- or three-frequency heterodyne interferometers to extend the integrated measurable system of the heterodyne frequency.

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