Measurement of molecular alignment with deep learning-based M-XFROG technique

Wanchen Tao (陶皖辰) 1, Siqi Sun (孙思琦) 1, Lixin He (何立新) 1, Yanqing He (何炎清) 1, Jianchang Hu (胡建昌) 1, Yu Deng (邓宇) 1, Chengqing Xu (徐诚清) 1, Pengfei Lan (兰鹏飞) 1, and Peixiang Lu (陆培祥) 2
1 Wuhan National Laboratory for Optoelectronics and School of Physics, Huazhong University of Science and Technology, Wuhan 430074, China
2 Hubei Key Laboratory of Optical Information and Pattern Recognition, Wuhan Institute of Technology, Wuhan 430205, China

*Corresponding author: helx_hust@hust.edu.cn
**Corresponding author: pengfeilan@hust.edu.cn
Received June 16, 2023 | Accepted August 16, 2023 | Posted Online October 3, 2023

We demonstrate a deep-learning neural network (DNN) method for the measurement of molecular alignment by using the molecular-alignment-based cross-correlation polarization-gating frequency resolved optical gating (M-XFROG) technique. Our network has the capacity for direct measurement of molecular alignment from the FROG traces. In a proof-of-principle experiment, we have demonstrated our method in O2 molecules. With our method, the molecular alignment factor $I(t) = \cos^2(\theta)$ of O2, impulsively excited by a pump pulse, was directly reconstructed. The accuracy and validity of the reconstruction have been verified by comparison with the simulations based on experimental parameters.

Keywords: molecular alignment; deep-learning neural network; M-XFROG.

DOI: 10.3788/COL202321.120021

1. Introduction

Molecular alignment using the interaction of molecules with femtosecond laser pulses plays a crucial role in the exploration of molecular reactions and dynamics. In the past two decades, significant progress has been made in achieving molecular alignment in various molecules [1–6]. This advancement has paved the way for widespread applications of molecular alignment in numerous scientific fields, such as multiphoton ionization [7,8], ultrashort pulse compression [9,10], molecular structure imaging [11–14], and high-order harmonic generation (HHG) [15–26]. Despite these achievements, attaining perfect molecular alignment in experimental settings remains a formidable challenge. In most cases, partial molecular alignment is obtained, resulting in measured results that represent an average over the distribution of molecular alignment. Consequently, an accurate measurement of the molecular alignment in the experiment is essential for probing the molecular dynamics and structure within the molecular frame.

Previously, it has been reported that molecular alignment can be indirectly determined using a comprehensive measurement of the molecular rotational temperature as well as the pump laser parameters including pulse duration, laser frequency, and pump intensity [27,28]. Since the molecular alignment is impulsively excited by a pump laser, the molecular rotational temperature determines the initial thermal distribution of the molecular rotational states, while the pump laser determines the redistribution of the rotational states after the laser-molecule interaction. With these parameters determined, molecular alignment then can be evaluated by numerical simulation of the time-dependent Schrödinger equation (TDSE) of the molecular rotational wave-packet [29]. To date, several methods have been reported to measure molecular rotational temperature in experiment, for instance, using the coherent anti-Stokes Raman scattering (CARS) [28–30] and degenerate four-wave mixing (DFWM) [31] processes and also using the Fourier spectrum of time-dependent HHG signals [32]. A simultaneous measurement of molecular rotational temperature and pump laser intensity is also demonstrated from the HHG signal [33–35] and the molecular alignment echo measurement [36]. However, these methods are still limited by their inherent restrictions. A direct and widely applicable method to measure the molecular alignment is still desired.

Analogous to the conventional frequency-resolved optical gating (FROG) technique, recently, a molecular-alignment-based cross-correlation polarization-gating frequency resolved optical gating (M-XFROG) technique was introduced to measure the ultrashort femtosecond lasers [37,38]. In M-XFROG, laser-induced impulsive molecular alignment serves as a transient gate function. The resulting FROG trace is given by [39,40]

$$I(\omega, \tau) = \left. \int_{-\infty}^{+\infty} E(t)G(t-\tau) \exp(-i\omega t) dt \right|_{t=\tau},$$

(1)
where $E(t)$ is the electric field of the probe pulse, and $G(t) \propto |\langle \cos^2 \theta \rangle(t) - 1/3|$ is the gate function, with $\langle \cos^2 \theta \rangle(t)$ being the molecular alignment factor in experiment. A recovery algorithm, such as the principal component generalized projects algorithm (PCGPA), has routinely been used to retrieve the electric field of the probe pulse from the FROG trace\(^{[41]}\). In addition to the electric field of the probe pulse, the M-XFROG trace also encodes the information of molecular alignment, which therefore provides a potential way for measuring molecular alignment.

In this paper, we extend the M-XFROG technique to measure the molecular alignment by using a deep-learning neural network (DNN) method. Our network is trained to learn the relationship between the M-XFROG trace and the molecular alignment factor $\langle \cos^2 \theta \rangle(t)$, which enables a direct measurement of the molecular alignment in experiment. We have demonstrated our scheme on a prototype O$_2$ molecule, both theoretically and experimentally. The accuracy and validity of our method have been examined by comparing the reconstructed molecular alignment factor $\langle \cos^2 \theta \rangle(t)$ to the indirect measurement with the experimental parameters (including the molecular rotational temperature and the pump laser intensity) and also the retrieved electric field of the probe pulse to the PCGPA result.

### 2. Experiments and Methods

The network architecture used in this paper refers to a convolutional neural network named GoogLeNet\(^{[42]}\), as shown in Fig. 1. Our network contains four convolutional layers, four Inception blocks, and three pooling layers. The convolutional layers enable the network to obtain enough information with fewer connection weight parameters. The output of the convolutional layer is calculated by multiplying the input by weight matrices called kernels and summing the product\(^{[43]}\). The kernels in each convolutional layer reduce the number of weights stored, which can optimize the accuracy and training time of the neural network. The Inception block is the key component of our network. Each block has four channels with kernels of different sizes (see inset in Fig. 1), which allows it to extract image information from multi-scale features. The pooling layers are used to reduce the size of the image, increase the computational speed, and improve the robustness of the extracted features.

Our network is trained on the simulated dataset. The input of the network is the M-XFROG trace which is simulated in terms of Eq. (1). In our simulations, the gate function $G(t)$ is obtained by solving the TDSE of the molecular rotational wavepacket with different molecular rotational temperatures and pump intensities (the wavelength and pulse duration can be measured from experiment)\(^{[44]}\). In our TDSE simulations, we adopt

![Fig. 1. Architecture of the neural network used for reconstructing the molecular alignment from the FROG trace. The inset shows the architecture of the Inception block.](image-url)
oxygen (O_2) as the target molecule, as in our experiment (see below). For the electric field \( E(t) \) of the probe pulse, we have measured its spectral intensity \( A(\omega) \) in experiment. By generating a random spectral phase \( \phi(\omega) \), we can get the electric field of the probe pulse in the frequency domain by \( E(\omega) = \sqrt{A(\omega)} e^{i\phi(\omega)} \). Then, the time-domain \( E(t) \) is obtained by the inverse Fourier transform of \( E(\omega) \). In our training, we have created 80,000 data samples with different electric fields of the probe pulse and gate functions to construct the training set and test set. The network is trained using the GPU P100 on Kaggle to increase the training speed. In the process of training, the loss function is defined as the root mean squared error (RMSE) between the output and expectation. The training is stopped when the value of the loss function reaches the target set of 0.001.

We first demonstrate the validity and performance of our network by using the test dataset. Figure 2(a) shows a randomly selected M-XFROG trace as the input for the network. With the network, we can predict the outputs of the electric field of the probe pulse as well as the alignment factor \( \langle \cos^2 \theta \rangle(t) \) of the molecule. The predictions of our network are shown as the solid lines in Figs. 2(c) and 2(d). One can see that, the predicted electric field of the probe pulse, including both the laser intensity and phase, and also the alignment factor \( \langle \cos^2 \theta \rangle(t) \), agree well with the ground truth. With the predicted electric field and \( \langle \cos^2 \theta \rangle(t) \), we have recalculated the M-XFROG trace [see Fig. 2(b)], which is also in excellent agreement with the input in Fig. 2(a). These results prove the accuracy and validity of our network.

In the following, we demonstrate the application of our network to the experimental data. Figure 3 displays the schematic of the experimental setup. The experiment is carried out by using a commercial Ti:sapphire laser system (Astrella-USP-1K, Coherent), which delivers 35-fs, 800-nm laser pulses at a repetition rate of 1 kHz. The output laser is split into two beams. One is used as a pump pulse to create molecular alignment. The other one is frequency doubled via a barium borate (BBO) crystal, serving as the probe pulse. The remaining 800-nm laser in the probe beam is filtered by a polarizer (P1), of which the transmission direction is perpendicular to the polarization of the 800-nm laser. A motorized delay line (DL) is installed in the arm of the probe pulse to adjust the time delay between these two pulses. The polarization of the pump pulse is rotated by 45° by using a half-wave plate (HWP) with respect to the probe pulse to ensure an optimal contrast ratio. These two pulses are focused into a gas cell filled with O_2 gas using a concave mirror \( f = 250 \text{ mm} \) in the non-collinear geometry. The change in the polarization state of the probe pulse by the impulsive alignment of molecules was analyzed with another polarizer (P2) placed after the gas cell. The M-XFROG trace is then obtained by measuring the transmission spectra with a spectrometer at different time delays between the pump and probe pulses.

3. Results

Figure 4(a) shows the M-XFROG trace measured around the half rotational revival of O_2. By using the measured M-XFROG
In summary, we have demonstrated a direct measurement of molecular alignment from the M-XFROG traces by using the deep-learning neural network (DNN). The network is trained on simulated data to learn the mapping relationship between the M-XFROG trace and the molecular alignment. With the trained network, the molecular alignment factor \( \langle \cos^2 \theta \rangle(t) \), and the laser field of the probe pulse, are accurately reconstructed. The reconstructed alignment factor shows good agreement with the result indirectly obtained by measuring the molecular rotational temperature and pump laser intensity, proving the validity of our method. We have demonstrated our method using the \( \text{O}_2 \) molecule in experiment. In the future, the method proposed here can be extended to more complex molecules, e.g., asymmetric-top molecules and even to liquids.

Finally, it is worth mentioning that our method is based on the unique relationship between the M-XFROG trace and the molecular alignment factor \( \langle \cos^2 \theta \rangle(t) \). In principle, it can also be applied to measure other kinds of molecular alignment dynamics, such as adiabatic and permanent alignments, of which the degree is also described by \( \langle \cos^2 \theta \rangle(t) \) [45,46,47]. However, in these cases, we may not employ the method in Fig. 5 to extract the experimental parameters, including the rotational temperature and the pump laser intensity from the curve of \( \langle \cos^2 \theta \rangle(t) \), since the dependence of \( \langle \cos^2 \theta \rangle(t) \) on these parameters may be different. Moreover, we observe that our method is not suitable for measuring the molecular orientation in experiment since the degree of molecular orientation is usually described by the factor \( \langle \cos \theta \rangle(t) \) [48].

**4. Discussion**

This work was supported by the National Key Research and Development Program of China (No. 2019YFA0308300), the
References


