Denoising the Reflection Spectrum of an LSPR-Based Optical Fiber Sensor Using Fast Fourier Transform in Python

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Abstract—This study explores the use of Fast Fourier Transform (FFT) for denoising signals from a Localized Surface Plasmon Resonance-based Optical Fiber (LSPR-OF) sensor. By applying FFT, high-frequency noise was effectively suppressed, enhancing measurement precision. An optimal cut-off frequency of 0.01 was identified for balancing noise reduction and signal preservation. Results demonstrated shifts in resonance wavelengths, with varying sensitivity across metals. The findings highlight the potential of FFT filtering to improve the clarity of LSPR spectrum.

LSPR sensors are highly sensitive and widely used for detecting minute changes in refractive index, representing a significant advancement in the field of sensing [1]. However, their accuracy is often compromised by noise, which can affect measurement precision [2–4]. To ensure reliable detection and accurate results, advanced signal processing techniques are essential for filtering out unwanted noise while preserving the key signal components. Previous work utilizing FFT for denoising has demonstrated various effective techniques. One such approach, applied to denoise an Electrocardiogram (ECG) bio-signal, involves subtracting a reference sine wave from the output signal, applying FFT to both the ECG and the noise replica, generating an ideal Wiener filter transfer function based on the noise replica, and then using inverse FFT to produce a noise-reduced ECG signal [5].

By transforming the LSPR intensity-wavelength spectrum into the frequency domain, the FFT enables the identification and suppression of high-frequency noise components that could otherwise distort sensor readings. The mathematical expression for the Discrete Fourier Transform (DFT) is given by:

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-\frac{i2\pi kn}{N}}, k = 0,1,2,\ldots,N-1. \tag{1}$$

The inverse DFT, used to reconstruct the filtered signal in the LSPR wavelength domain, is expressed as:

$$\hat{x}[n] = \frac{1}{N}\sum_{n=0}^{N-1} \hat{X}[k] e^{\frac{i2\pi kn}{N}}. \tag{2}$$

The aim of this study is to investigate the use of FFT for filtering noisy signals from an optical fiber sensor based on LSPR. Using Python's computational tools, we develop and evaluate a method to mitigate noise, with a particular focus on disturbances caused by environmental and instrumental factors. This preliminary analysis seeks to lay the groundwork for advanced signal processing techniques that could significantly enhance the accuracy and reliability of LSPR sensors in practical applications.

In this study, an LSPR-OF sensor was fabricated using a sensor probe, as illustrated in Fig. 1, featuring gold nanoparticles (Au-NPs) coated onto the optical fiber. The fabrication process began by immersing the fiber in a piranha solution, consisting of a 4:1 volume ratio of H_2SO_4 and H_2O_2, for 20 minutes. After this, the fiber was rinsed with deionized (DI) water and dried using N_2 gas. The optical fiber was then soaked in a 5% (3-Aminopropyl) triethoxysilane (APTES) solution, with ethanol as the solvent, for 90 minutes. Afterward, it was rinsed with ethanol and dried again with N_2 gas. Next, the Au-NPs were coated onto the surface of the optical fiber core by soaking the fiber in a gold nanoparticle solution overnight. Finally, the fiber was washed with DI water and dried with N_2 gas to remove any unattached Au-NPs.

Heavy metals in the environment were detected using the LSPR-OF sensor with Au-NPs deposition. The sensing probe, which measured 3 cm in length, was immersed in the analyte solutions, as depicted in Fig. 1. A DH-mini-

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UV-Vis-NIR Deuterium-Halogen Light Source, with a wavelength range of 200 to 1100 nm, was employed to observe the optical signal. As the laser propagated through the probe, a resonance phenomenon occurred. Changes in the refractive index of the analytes led to shifts in the observed resonance wavelength. These spectral shifts were monitored using an Ocean Optics Maya 2000 series spectrometer.

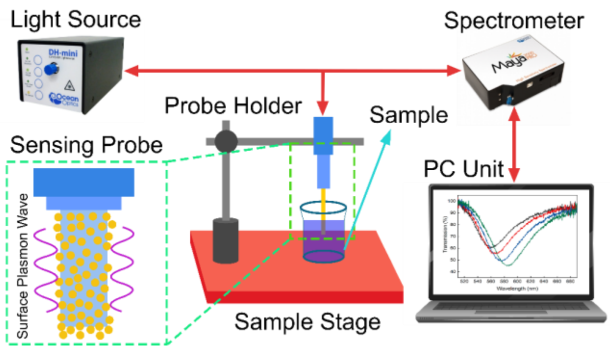

Fig. 1. Experimental setup for the LSPR-FO sensing system.

In the data analyzer, the original dataset, stored in CSV format, contains a normalized intensity spectrum. Data processing begins by loading the CSV file and extracting the wavelength and intensity columns using Python's Pandas library. The intensity data is transformed using the FFT to identify its frequency components, after which a filter is applied to eliminate high-frequency noise by setting frequencies above a defined cutoff to zero. The cleaned signal is then retrieved by performing an inverse FFT, which reconstructs the signal in the wavelength domain. The process involves loading the data, separating the wavelength and intensity columns, applying FFT to convert the intensity values to the frequency domain, filtering out noise, and using inverse FFT to obtain the filtered signal back in the wavelength domain.

As shown in Fig. 2, the graphical user interface (GUI) is implemented using the Tkinter library, with the main window created via `Tk()`, defining a fixed size and title for the application. A label displaying the text "Denoising LSPR Spectrum with FFT" guides users in navigating the interface. The GUI features two main buttons: the "Upload" button, which allows users to select and load CSV data for processing, and the "Save" button, enabling the export of filtered data as CSV files. Additionally, a Matplotlib canvas is embedded within the GUI to display plots of both the original and filtered spectra after processing. Event handling is managed by two core functions: one for loading data, applying FFT-based filtering, and displaying the results, and the other for saving the processed data into CSV files for further analysis.

To determine the appropriate cut-off frequency, we examined one of the generated spectra, specifically from the Fe 1% environment. The denoised spectrum, as illustrated in Fig. 3, shows a significant improvement in signal clarity using FFT filtering at various cut-off frequencies. A cut-off of 0.01 was identified as the most effective choice, as it offered a balance between noise reduction and signal preservation, aligning well with the Lorentzian curve. This cut-off allowed for a substantial reduction of high-frequency noise while maintaining critical signal features, which is essential for accurately detecting low concentrations of heavy metals. Although higher cut-off frequencies can suppress noise more aggressively, care must be taken to preserve key signal characteristics to ensure accurate measurements. Furthermore, as shown in Fig. 4, we analyzed all spectra, demonstrating the effectiveness of the FFT-based filtering technique in reducing noise across all LSPR-OF sensor signals. The normalized reflected intensity spectra for the sensor exposed to various concentrations of Hg, Pb, Co, and Fe revealed that the original spectra were significantly impacted by noise.

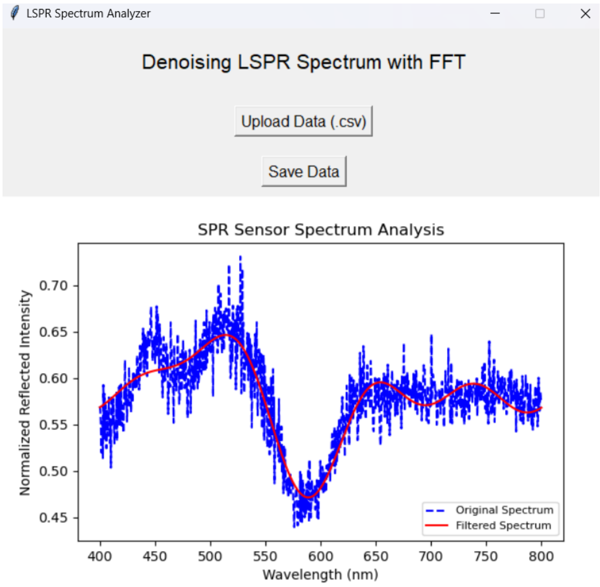

Fig. 2. Graphical user interface of the LSPR-FO Spectrum Analyzer.

Furthermore, after applying FFT denoising, the fitting curve exhibits a minimum normalized reflected intensity $R_{normalized}^{after}$ that is consistently higher than the original curve $R_{normalized}^{before}$. Similarly, the resonance wavelengths shift after denoising, resulting in either a redshift or a blueshift. This wavelength shift should be carefully considered, as it impacts detection accuracy. Although most shifts are redshifts, two datasets, specifically Co 10% and Fe 10%, demonstrate blueshift, as shown in Table 1. Additionally, the sensor sensitivity can be quantified using the following equation:

$$S = \frac{\lambda_{min}^{*} - \lambda_{min}^{0}}{c^{*} - c^{0}}, \tag{3}$$

where λ_{min}^{*} represents the resonance wavelength at a higher concentration (c^{*}) and λ_{min}^{0} is the resonance wavelength at a lower concentration (c^{0}).

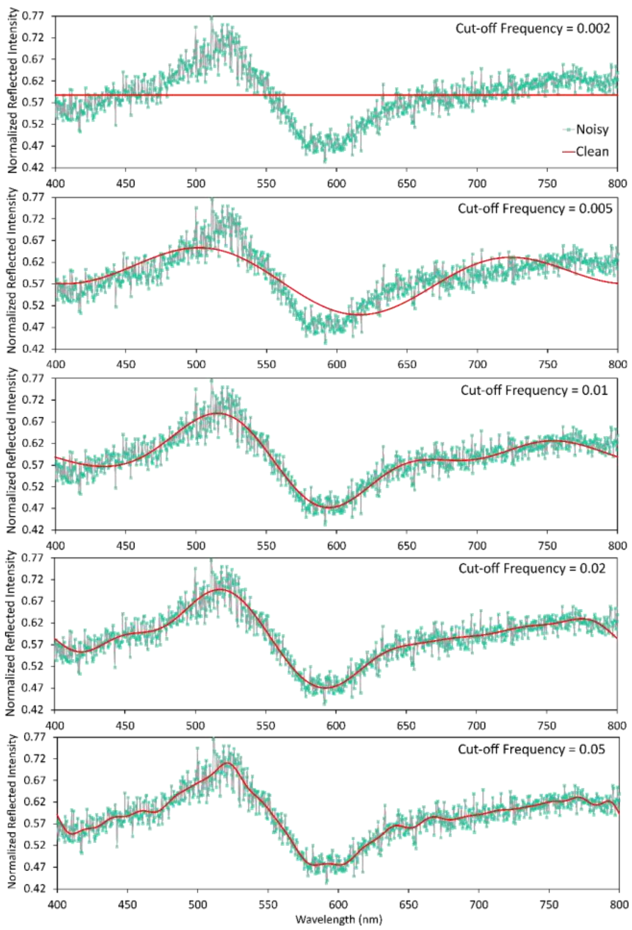

Fig. 3. Comparison of the original noisy spectrum and the denoised spectrum of Fe 1% at different cut-off frequencies.

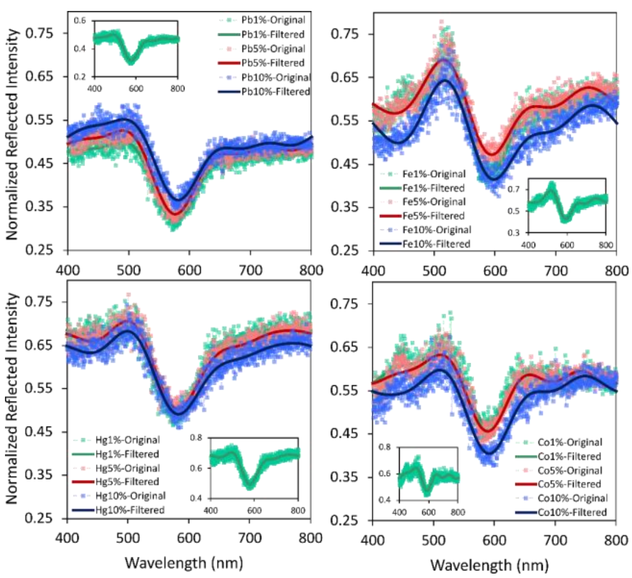

Fig. 4. Comparison of the original noisy spectrum and the denoised spectrum of Fe, Co, Hg, and Pb at varying concentrations.

Table 1. Resonance wavelength (λ_{min}) and normalized reflected intensity ($R_{normalized}$) before and after denoising.

	C%	Co	Pb	Fe	Hg
$R^{before}_{normalized}$	1	0.3780	0.3445	0.3755	0.4604
	5	0.4235	0.3151	0.4332	0.4779
	10	0.4393	0.2969	0.4029	0.4657
$R^{after}_{normalized}$	1	0.4047	0.3660	0.4145	0.4914
	5	0.4558	0.3332	0.4715	0.5032
	10	0.4714	0.3181	0.4277	0.4933
λ^{before}_{min}(nm)	1	576.02	571.11	585.84	574.24
	5	579.15	571.11	591.63	571.11
	10	597.86	572.9	605.42	582.27
λ^{after}_{min}(nm)	1	588.96	576.02	592.07	579.15
	5	588.51	576.02	594.3	582.27
	10	591.18	580.93	597.86	583.61

The measurements reveal fluctuations in resonance wavelength shifts. As shown in Table 1, the original data displays redshift with increasing concentrations of heavy metals, which aligns with theoretical expectations. However, after denoising, the resonance wavelength exhibits blueshift, indicating that the fitting may not be sufficiently accurate. Conversely, for Hg 1% to Hg 5%, the original data shows blueshift, while the denoised data results in redshift. Thus, the sensitivity observed from the original noisy data ranges from 1% to 10%. Among the metals tested, Co demonstrates the highest sensitivity at 2.4267 nm/%, followed by Fe at 2.1756 nm/%, Hg at 0.8922 nm/%, and Pb at 0.1989 nm/%. After denoising the data, however, the sensitivity values change, with Co at 0.6433 nm/%, Pb at 0.5455 nm/%, Fe at 0.6433 nm/%, and Hg at 0.4955 nm/%. This variation highlights the need for additional data collection and analysis to ensure that the sensitivity accurately reflects actual measurements. In conclusion, the LSPR-OF sensor, combined with FFT filtering, demonstrates considerable potential as a valuable tool for environmental monitoring. The sensor's sensitivity to heavy metals, along with the noise reduction capabilities of FFT filtering, enables accurate detection and quantification of these pollutants, highlighting its promise for advancing environmental protection efforts.

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