# Demodulation of an LPFG sensor cascaded by an FBG sensor array using machine learning


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***Abstract*— In this work, we show the use of a fiber Bragg grating sensor array to demodulate a cascaded long-period fiber grating sensor using a machine learning model. We show the use of transfer learning from synthetic data training as a promising tool for calibrating machine learning models in optical sensing.**



***Keywords*— optical sensors, Bragg gratings, interrogation, neural networks, self-attention**


## I. Introduction

Interrogating long-period fiber grating (LPFG) is a significant challenge and a limiting factor for its in-field application as sensors [1]. One could attribute this to the need of wideband spectrum measurement to express the measurand. Moreover, for such measurement, bulky and/or expensive equipment is often needed to demodulate a single optical sensor. Fiber Bragg gratings (FBGs), on the other hand, can be easily multiplexed in the wavelength domain, contributing for the cost-effectiveness of such sensing system. Consequently, commercial FBG interrogators have become widely available, leading to a broad adoption of FBGs by the industry.

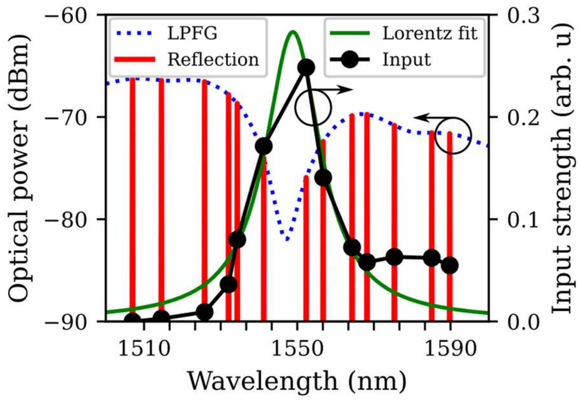


**Fig. 1.** At the left axis, the spectra of the LPFG sensor and FBG array. At the right axis, the ML model input strength and its Lorentzian fit.


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To improve the applicability of LPFGs, we have been studying means to interrogate an LPFG sensor using a static FBG filter bank by means of machine learning (ML) [2]. Such approach is interesting due to its low-cost and wide adaptation to different LPFGs. However, until now, we only tested static FBGs. Hence, the main advantage of this approach has not been studied yet. Note that FBG sensor array is commonly used under wavelength division multiplexing. So, an FBG sensor array could be used in such LPFG interrogator. In this work, we extend the previous proposal by letting the FBG filter array fluctuate around its designed Bragg wavelength, acting as both sensor and filter bank.

## II. Methods

We considered an LPFG sensor with an FBG sensor array cascaded, and the reflection spectrum obtained by a commercial FBG interrogator. We used a self-attention fully connected neural network to demodulate the LPFG, based on features obtained by the reflection spectrum. The spectrum was preprocessed to extract: each FBG peak intensity and its position. In the context of LPFG demodulation, the FBGs' peak amplitude were processed as in [3]. The Bragg wavelengths were scaled accordingly to their design values ( $\lambda_{Bragg,0}$ ). Fig. 1 shows an example of the system's reflection spectrum with the LPFG spectrum for reference. We also show the ML model input: input strength by FBG's

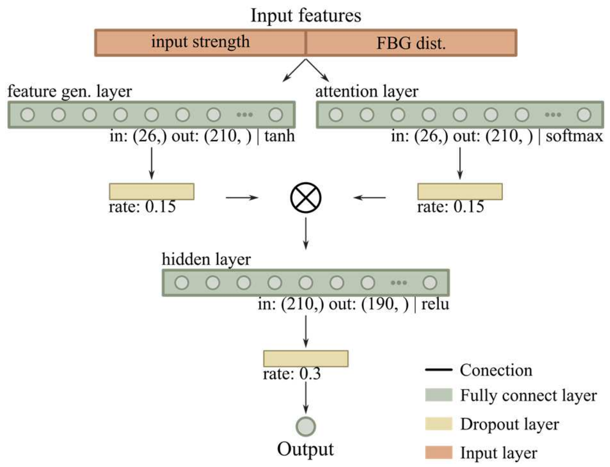


**Fig. 2.** Machine learning model: attention-based fully connected neural network.

relative deviation from $\lambda_{Bragg,0}$.

Concerning the ML model, its topology can be seen in Fig. 2. The model was optimized by Bayesian search to determine the layer sizes and activation functions. The idea of this topology is to split the input values into a feature generation layer and an attention layer. The features derived from the feature generation layer are multiplied by the attention map, to preserve the most important features for the given input, this approach is quite promising for sequence problems [4]. After that attention filtering, another layer processes the result before outputting the estimated LPFG resonant wavelength. The feature generation and attention layer connections were set with a 15% rate dropout and the hidden layer with 30% dropout. After training, dropout was used to estimate the LPFG resonant wavelength and the prediction's uncertainty [5].

The proposed model was optimized and trained using synthetic LPFG spectra and FBG array simulation. The model selection dataset comprised of 100.000 datapoints and the training dataset of 500.000 datapoints. In both cases, a third of these points was used for validation and early stopping. The test set, on the other hand, was comprised by real LPFG spectra.

We evaluated the results by the $R^2$, root mean squared error (RMSE), and mean absolute percentual error (MAPE). No further optimization or fine-tuning was performed using measured data, to evaluate the effectiveness of transfer learning. We compared the proposed model against a Lorentzian fit of input strength data, as base model (green line in Fig. 1).

## III. Results

Based on the validation results, using synthetic data, we calculated $R^2$ of 0.999, RMSE of 0.50 nm, and MAPE of 0.01%. The validation data, however, only gives us the information that the model was properly trained and works well on the synthetic LPFG spectra. The results for real LPFG spectra can be seen in Fig. 3. One can also see the comparison between the proposed model and the Lorentzian fit model.

Regarding the base model, we noted that the fitting approach performs well for relatively simple spectra. However, for sensors that exhibit an additional resonant dip – one that falls outside the range of the FBG array but is still close enough to be detected by some FBGs – the estimation is poor. This was evident for the outliers near the 1555 nm. Considering the high variability of actual LPFGs and their deviation from a Lorentzian function, the parameter uncertainty is also high.

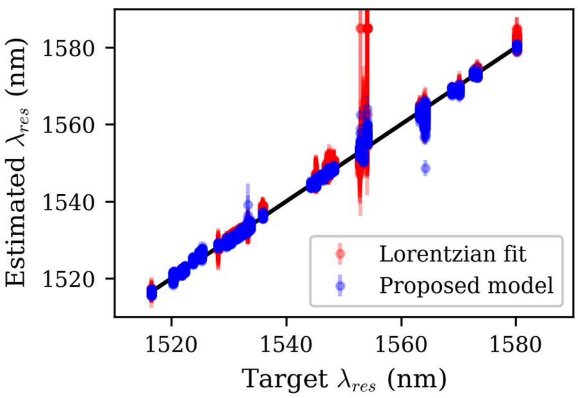


**Fig. 3.** Comparison between target LPFG position and estimated LPFG position.

The proposed model, though, overcomes such problems. We attribute this improvement to the attention mechanism. Note that attention layer selects only the most important features. Therefore, features regarding resonant dips outside the scope of the FBG array were suppressed.

All metrics calculated using the measured LPFG spectra for our proposal can be seen in Table I. We compared the models with the whole dataset and excluding poorly fitted. We noted that the proposed model performed better than the base model in all aspects, for both the complete test set and the test set excluding the spectra were the Lorentzian fit failed to properly demodulate the LPFG. Our findings were equivalent to previous findings for neural networks trained with actual LPFG data and static FBGs, showing the effectiveness of both the FBG sensor interrogating LPFG sensor and the synthetic training transfer learning.

TABLE I. Performance metrics

| | | $R^2$ | RMSE (nm) | MAPE |
|---|---|---|---|---|
| Proposed model | *All data* | 0. 996 | 0. 93 | 0. 038 % |
| | *Without outliers* | 0.997 | 0.89 | 0.038 % |
| Loretzian fitted model | *All data* | 0. 983 | 1.94 | 0.050 % |
| | *Without outliers* | 0.995 | 1.07 | 0.045 % |

## IV. Conclusions

In this paper we proposed a method to demodulate an LPFG sensor cascaded by an FBG sensor array. This method used a self-attention neural network to estimate the LPFG resonant wavelength based on the FBG array reflection. The model was trained on synthetic data and tested on real LPFG spectra, showing high accuracy and robustness against noise and spectral variations. This work showed the feasibility of FBG sensors as both sensor and filter bank for LPFG interrogation, and the potential of transfer learning.

## References


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