Machine Learning Assisted High-Precision Force Sensing

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Introduction

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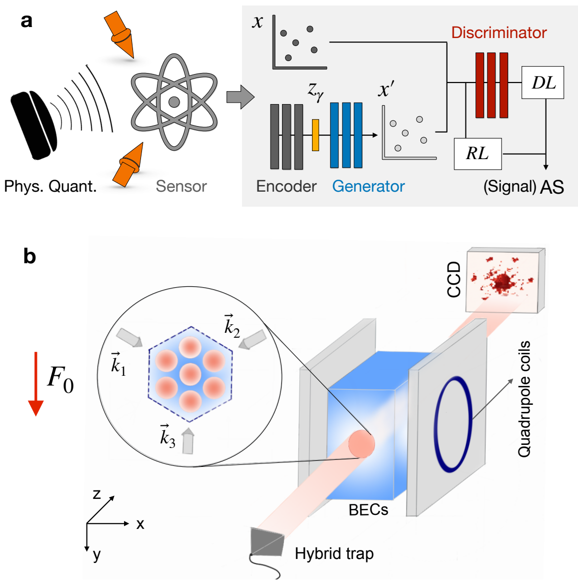
Sensitivity improvement plays a critical role in high-precision detection while facing the challenge of noise interference and hardware limitations. Despite advances in signal analysis and noise reduction, underlying techniques often either heavily integrate our understanding of signal behavior or require stringent conditions such as strong correlation and entanglements, limiting practical implementation. In this article, we propose a novel approach that harnesses the power of machine learning to significantly enhance the sensitivity of weak-signal detection only relying on a finite amount of signal-free measurement outcomes. Our approach leverages the anomaly detection configuration with generative adversarial networks to score the observable anomaly, providing a high-sensitivity quantity to identify the signal response without the need for extensive knowledge of signal behavior or strict assumptions. We validate our method with an atomic force-sensing experiment and show the sensitivity improvement over an order of magnitude.Our work employs machine learning-based signal processing while independent of the signal and noise properties, which can foster a variety of sensing applications.

Methods



First, we characterize the sensitivity as

$$\text{Sensitivity:}\mathcal{S} = \sqrt{T_0} \times \frac{\sigma_0}{|\partial_V q|},$$

where $\sigma_0$one-sigma deviation of the signal-free distribution $\mathbb{P}_0(\mu, \sigma_0^2)$, the signal response $\partial_V q = \delta q/\delta V$ and T_0 is the time cost for one experiment. We utilize the anomaly detection method to formalize the signal generation channel

$$\text{Signal (anomaly score)}: A = f_{AD}(x),$$

where $f_{AD}(\cdot)$ refers to a fixed generative neural network trained by a set of signal-free observable $\{x_i\}_{i=1}^{N}$. Hereby, an anomaly is interpreted as data from a signal-involved distribution $\tilde{x} \sim \mathcal{P}_\delta(\tilde{x})$ instead of the signal-free distribution $x \sim \mathcal{P}_0(x)$ (the training dataset), where $\{x, \tilde{x}\} \in \mathcal{X}$. This generative model is trained by an adversarial training by optimizing a standard min-max loss function

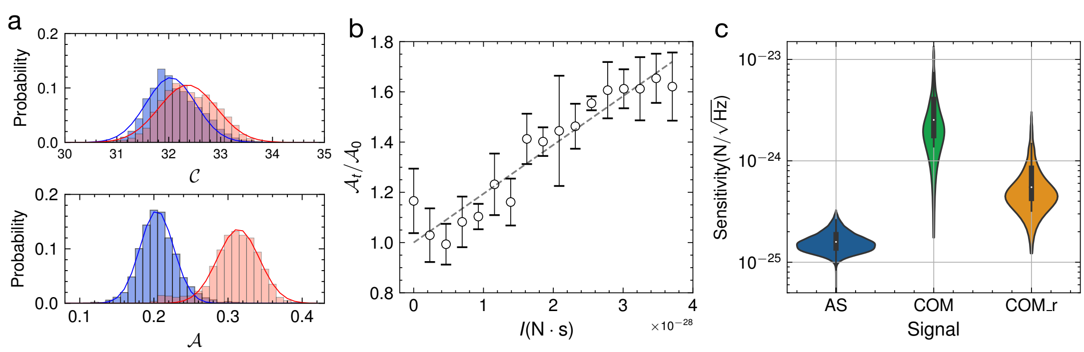
$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim \mathcal{P}_x}[\log D(x)] + \mathbb{E}_{z \sim \mathcal{P}_z}[\log(1 - D(G(z)))],$$

Where G: generator, D: discriminator.

Fig.1. The machine-learning assisted atomic force sensing. (a). The workflow of anomaly detection method. (b). The schematic diagram of experiment setup for an optical force sensor (Sci.Bulletin 67 2291-2297).

Results

Fig.2. (a). The probability distribution of the COM on the y-axis and anomaly score in the absence of force (blue) and in the presence of force (red), respectively. (b) The dimensionless anomaly score as a function of impulse $I = F_0 \cdot \Delta T$ for an identical optical force F_0, where the mean value $A_0 = \overline{A}(0)$ and the score $A_t(\Delta T)$ of signal-involved experiments for sensing time ΔT. The fitting line admits the slope $150(F_0^{-1})$. (c) We compare the sensitivity distribution of using the anomaly score (blue), COM with raw data (green) and with reduce datasets (yellow), respectively.



Improvement: $\mathcal{S}^{COM}/\mathcal{S}^{AS} \approx 40$, $\mathcal{S}_r^{COM}/\mathcal{S}^{AS} \approx 10$.

Discussion

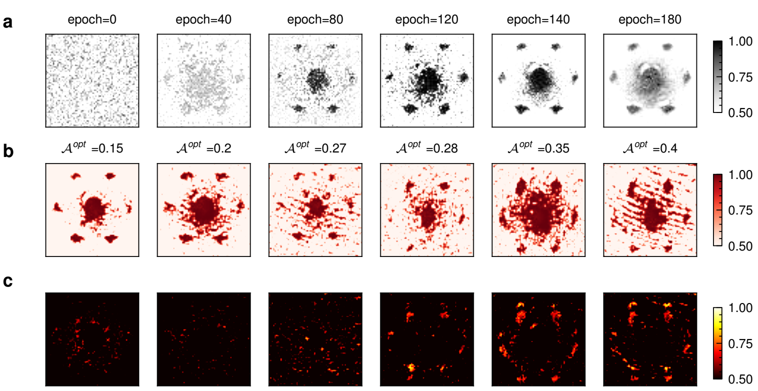


Fig.3.(a) The reconstructed atomic image produced by generator in different training epochs. (b). Six selected raw atomic images and corresponding anomaly localization $x_{res} = |x - G^*(E^*(x))|$ are illustrated in (c).

In a broader vision, our approach involves harnessing the power of machine learning to effectively explore and extract valuable information that may be obscured by noise, overlooked by traditional methodologies. By formulating a robust statistical quantity (anomaly score), we circumvent the reliance on a priori assumptions about the inherent properties of the signal and noise, thus facilitating a more rigorous and unbiased analysis of signal. This methodological framework enables a deeper understanding and interpretation of the underlying phenomena, contributing to advancements in the field and paving the way for novel insights and discoveries among high-precision sensing applications.