Identification of Light Sources using Artificial Neural Networks

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The identification of light sources represents a task of utmost importance for the development of multiple photonic technologies. Over the last decades, the identification of light sources as diverse as sunlight, laser radiation and molecule fluorescence has relied on the collection of photon statistics. In general, this task requires an extensive number of measurements to unveil the characteristic statistical fluctuations and correlation properties of light, particularly in the low-photon flux regime. In this letter, we exploit the self-learning features of artificial neural networks and naive Bayes classifier to dramatically reduce the number of measurements required to discriminate thermal light from coherent light at the single-photon level. We demonstrate robust light identification with tens of measurements at mean photon numbers below one. Our protocols demonstrate an improvement in terms of the number of measurements of several orders of magnitude with respect to conventional schemes for characterization of light sources. Our work has important implications for multiple photonic technologies such as LIDAR and microscopy.

INTRODUCTION

The underlying statistical fluctuations of the electromagnetic field have been widely utilized to identify diverse sources of light [1, 2]. In this regard, the Mandel parameter constitutes an important metric to characterize the excitation mode of the electromagnetic field and consequently to classify light sources [3]. Similarly, the degree of optical coherence has also been extensively utilized to identify light sources [3–5]. Despite the fundamental importance of these quantities, they require large amounts of data which impose practical limitations [6–8]. This problem has been partially alleviated by incorporating statistical methods, such as bootstrapping, to predict unlikely events that are hard to measure experimentally [7, 8]. Unfortunately, the constraints of these methods severely affect photonic technologies for metrology, imaging, remote sensing and microscopy [9–13].

The potential of machine learning has motivated novel families of technologies that exploit self-learning and self-evolving features of artificial neural networks to solve a large variety of problems in different branches of science [14, 15]. Conversely, quantum mechanical systems have provided new mechanisms to achieve quantum speedup in machine learning [15, 16]. In the context of quantum optics, there has been an enormous interest in utilizing machine learning to optimize quantum resources in optical systems [17–19]. As a tool to characterize quantum systems, machine learning has been successfully employed to reduce the number of measurements required to perform quantum state discrimination, quantum separability and quantum state tomography [20–22].

In this letter, we demonstrate the potential of machine learning to perform discrimination of light sources at extremely low-light levels. This is achieved by training artificial neural networks with the statistical fluctuations that characterize coherent and thermal states of light. The self-learning features of neural networks enable the dramatic reduction in the number of measurements and the number of photons required to perform identification of light sources. Our experimental results demonstrate the possibility of using less than ten measurements to identify light sources with mean photon numbers below one. In addition, we demonstrate similar experimental results using the naive Bayes classifier, which are outperformed by our artificial neural network approach. Finally, we present a discussion on how artificial neural networks can dramatically reduce, by several orders of magnitude, the number of measurements required to discriminate signal photons from ambient photons. This possibility has strong implications for realistic implementation of LIDAR, remote sensing and microscopy.

EXPERIMENTAL SETUP AND MODEL

As shown in Fig. 1 (a), we utilize a continuous-wave (CW) laser beam that is divided by a 50:50 beam splitter. The transmitted beam is focused onto a rotating ground glass which is used to generate pseudo-thermal light with super-Poissonian statistics. The beam emerging from the ground glass is collimated using a lens and attenuated by neutral-density (ND) filters to mean photon numbers below one. The attenuated beam is then coupled into a single-mode fiber (SMF). The fiber directs photons to a superconducting nanowire single-photon detector (SNSPD). The beam reflected by the beam splitter is used as a source of coherent light. This beam, character-
The probability of finding \( n \) photons in coherent light is given by 
\[
P_{\text{coh}}(n) = e^{-\bar{n}}(\bar{n}^n/n!) ,
\]
where \( \bar{n} \) denotes the mean photon number of the beam. Furthermore, the photon statistics of thermal light is given by 
\[
P_{\text{th}}(n) = \frac{\bar{n}^n}{n!} e^{-\bar{n}} .
\]
It is worth noting that the photon statistics of thermal light is characterized by random intensity fluctuations with a variance greater than the mean number of photons in the mode. As described by their photon number probability distributions, coherent light and thermal light are different. For coherent light, the maximum of the photon-number probability sits around \( \bar{n} \). For thermal light, the maximum is always at vacuum. However, when the mean photon number is low, the photon number distribution for both kinds of light becomes similar. Consequently, it becomes extremely difficult to identify one source from the other. The conventional approach to discriminate light sources makes use of histograms generated through the collection of millions of measurements \([6, 8, 24, 25]\). Unfortunately, this method is not only time consuming, but also imposes practical limitations.

In order to dramatically reduce the number of measurements required to identify light sources, we make use of a custom-designed one-dimensional convolutional neural network (1D-CNN). In our case, the 1D-CNN is very effective since the shorter segments of the data likely contain characteristic features of coherent and thermal light throughout the data set. As shown in Fig. 1 (b), our network has the following structure: the input goes into two 1D-convolutional layers. Outcomes from these two layers are subsequently fed into a convolutional layer sandwiched between two max-pooling layers. Finally, a fully-connected and a flattening layer precede the output layer consisting of two softmax functions. In order to train the network, the input data was divided into smaller batches of data points. The network training was stopped after 50 epochs.

We also establish the baseline performance for our 1D-CNN by using naive Bayes classifier. This is a simple classifier based on Bayes’ theorem \([20]\). Throughout this letter, we assume that each measurement is independent. Moreover, we represent the measurement of the photon number sequence as a vector \( x = (x_1, ..., x_k) \). Then, the probability of this sequence generated from coherent or thermal light is given by 
\[
p(C_j|x_1, ..., x_k) = p(C_j)p(x|C_j)/p(x) .
\]
By using the chain rule for conditional probability, we have 
\[
p(C_j|x_1, ..., x_k) = p(C_j)\prod_{i=1}^{k} p(x_i|C_j) .
\]
Since our light source is either coherent or thermal, we assume \( p(C_j) = 0.5 \). Thus, it is easy to construct a naive Bayes classifier, where one picks the hypothesis with the highest conditional probability \( p(x_i|C_j) \). We used theoretically generated photon-number probability distributions as the prior probability \( p(x_i|C_j) \), and used the experimental data as the test data.
FIG. 2. A set of histograms displaying theoretical and experimental photon number probability distributions for coherent and thermal light beams with different mean photon numbers. Our experimental results are in excellent agreement with theory. The photon number distributions illustrate the difficulty in discriminating light sources at low-light levels even when large sets of data are available.

RESULTS

In Fig. 2, we compare the histograms for the theoretical and experimental photon number distributions for different mean photon numbers $\bar{n} = 0.40, 0.53, 0.67$ and 0.77. The bar plots are generated by experimental data with one million measurements for each source; the curves in each of the panels represent the expected theoretical photon number distributions for the corresponding mean photon numbers. Fig. 2 shows excellent agreement between theory and experiment which demonstrates the accuracy of our surjective photon counting method. Furthermore, from Fig. 2 (a)-(d), we can also observe the effect of the mean photon number on the photon number probability distributions. As shown in Fig. 2 (a), it is evident that millions of measurement enables one to discriminate two light sources. On the other hand, Fig. 2 (d) shows a situation in which the source mean-photon number is low. In this case, the discrimination of light sources becomes cumbersome, even with millions of measurements. In order to illustrate the difficulty of using limited sets of data to discriminate light sources at low mean photon numbers, we restrict the size of our dataset to 10, 20, 50, 100 and 100000. As shown in Fig. 3, the photon number distributions obtained with limited number of measurements do not resemble those in the histograms shown in Fig. 2 (a), for both coherent and thermal light beams.

In Fig. 4, we show the overall accuracy for light discrimination using naive Bayes classifier. The accuracy increases with the number of data points. For example, when $\bar{n} = 0.40$, the accuracy of discrimination increases from approximately 72% to 88% as we increase the number of data points from 10 to 160. It is worth noting that even with small increase in number of measurements, the naive Bayes classifier starts to capture the characteristic feature of different light sources, given by distinct sequences of photon number events. This is obvious since larger sets of data contain more information pertaining to the probability distribution. Furthermore, mean photon number of the light field significantly changes the discrimination accuracy profile. As the mean photon number increases, the overall accuracy converges faster towards 100% as expected. This is due to the fact that the photon number probability distributions become more distinct at higher mean photon number.

The overall accuracy of light source discrimination with respect to the number of data points is shown in Fig. 5. Using only 10 data points, the 1D-CNN leads to an average accuracy between 65%-75% for $\bar{n} = 0.40$, whereas when using 160 points of data, the accuracy is greater than 95%. The comparison of Fig. 4 and Fig. 5 reveals that the 1D-CNN outperforms naive Bayes classifier in general. Similar to naive Bayes classifier, 1D-CNN classifier accuracy increases with the number of data points and mean photon numbers. However, there

FIG. 3. Probability distributions of coherent and thermal light, for varying dataset sizes (10, 20, 50, 100, 10k). Data used here is randomly selected from of the measurement presented in Fig. 2 (a).
FIG. 4. Overall accuracy of light discrimination versus the number of data points used in naive Bayes classifier. The curves represent the accuracy of light discrimination for $\bar{n} = 0.40$ (red line), $\bar{n} = 0.53$ (blue line), $\bar{n} = 0.67$ (green line) and $\bar{n} = 0.77$ (red line). The error bars are generated by dividing the data into ten subsets.

FIG. 5. Overall accuracy of light discrimination versus the number of data points used in 1D-CNN. The curves represent the accuracy of light discrimination for $\bar{n} = 0.40$ (red line), $\bar{n} = 0.53$ (blue line), $\bar{n} = 0.67$ (green line) and $\bar{n} = 0.77$ (red line). The error bars represent the standard deviation of the training epochs.

are some clear distinctions between the 1D-CNN and naive Bayes classifier. The rate of convergence for 1D-CNN classifier is significantly higher than that of naive Bayes classifier. For low mean photon numbers such as $\bar{n} = 0.40$, the improvement in accuracy scales linearly for naive Bayes classifier, as opposed to almost logistic growth that shows our 1D-CNN. Surprisingly, the accuracy for $\bar{n} = 0.67$ and $\bar{n} = 0.77$ overlaps; this shows that for a low mean photon number regime, the peak performance for 1D-CNN saturates much faster than naive Bayes classifier. Despite the vital differences between the performances of these two techniques at low mean photon number, they demonstrate similar overall accuracy at $\bar{n} = 0.77$. These results suggest that for light discrimination at relatively high mean photon numbers, one could resort to naive Bayes classifier, which requires less computational resources. However, when the light has substantially low mean photon numbers, 1D-CNNs outperform naive Bayes classifier.

CONCLUSION

In this letter, we have demonstrated smart discrimination of light sources at mean photon numbers below one. Our protocols show an improvement, in terms of the number of measurements, of several orders of magnitude with respect to conventional schemes for light identification. Our results indicate that 1D-CNN outperforms naive Bayes classifier at low-light levels. We believe that our work has important implications for multiple photonic technologies, such as LIDAR and microscopy of biological materials.

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