

# Self-optimizing ghost imaging with a genetic algorithm

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**Abstract:** To simplify the reconstruction algorithms in ghost imaging, we present a feedback-based approach to reduce reconstruction times. We introduce a genetic algorithm to optimize the illumination patterns in real-time to match with the object's shape. © 2020 The Author(s)

## 1. Introduction

Ghost imaging, also called single-pixel imaging, can form the images of objects with a one-pixel detector with no spatial resolution by applying a time-varying pattern [1]. Such a single-pixel detection configuration has the potential to enable low-cost imaging in the X-ray, infrared and terahertz wavebands, where detector arrays are often expensive [2]. It is a flexible imaging modality and can also be adapted for hyperspectral imaging, 3D imaging and time-resolved imaging.

Multiple measurements are needed to recover the object image in ghost imaging. The number should be fewer than the total number of pixels in an imaging area that covers the object. Usually more measurements lead to higher quality reconstruction but a lower imaging speed and longer reconstruction time. To improve this, multiple kinds of spatiotemporal illuminating patterns, for instance, the random basis, Hadamard basis, wavelet basis, Fourier basis, and discrete cosine basis have been proposed to either denoise the resulting image by sampling on its inherent sparsity or enable a computationally fast algorithm [3].

In this work we present a feedback-based ghost imaging method with optimized patterns generated in real-time. By highlighting the inherent reciprocity between the total light intensity signal from an unknown object and illumination patterns, we can create evolved patterns toward the image of an object as the iterated sampling loops. We adapt a genetic algorithm previously used in wavefront optimization to focus light through scattering medium [4] [5] to adaptively optimize the patterns in every generation.

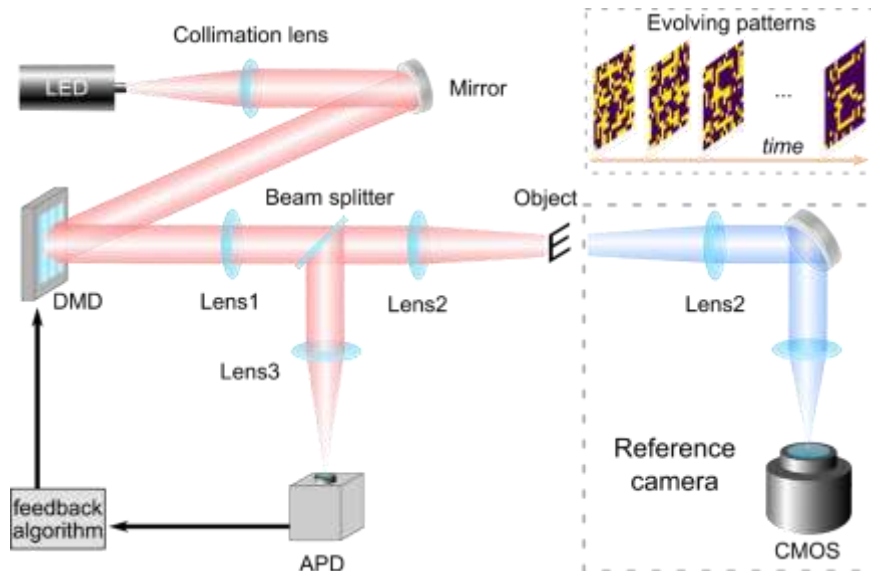


Fig. 1. Schematic of the self-optimizing ghost imaging with a single-pixel detector.

Our optical setup including a digital micromirror device (DMD) as binary spatial modulator, an avalanche photodiode (APD) as single-pixel detector and electrical control-feedback loop, as is depicted in Fig. 1. The detector monitors the fluctuations of the total light intensity in the object plane. A genetic algorithm, which uses principles inspired in nature to “evolve” toward a best solution, is used here to iteratively optimize the patterns through operations of breeding and mutation according to measured intensities and parent patterns.

## 2. Results

Typically, ghost imaging employs random illumination or other patterns without the prior knowledge of the object, thus the measured intensities would fluctuate around the average, as shown in Fig 2. (a). Here, we use a genetic algorithm to sequentially optimize the patterns with enhanced correlations with the target image. Initially, a pool of randomly generated binary patterns is used and then ranked according to the cost function. Here we define the ratio of measured intensity and sum of corresponding pattern's pixel values as the cost function, the pattern with a higher ratio gets a higher ranking. Then new offspring patterns are generated from parent patterns, which are selected according to the ranking, using a breed and mutation process. Thus, the ratios will be iteratively increased through this generational method. Fig 2. (b) shows the enhancement of the maximum cost function output in each generation, defining the average ratio of initial random patterns as 1.

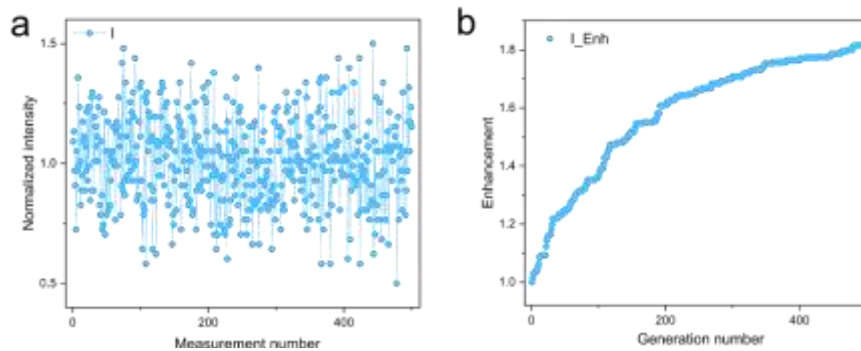


Fig. 2. Measurement results with (a) conventional ghost imaging and (b) self-optimizing ghost imaging.

We demonstrate this strategy by simulation results here in Fig. 3. A 64- by 64- pixel image of 'E' is served as the target image. Fig. 3 (b) is one of 30 initial randomly generated patterns used to illuminate the image. For each generation, we measure the total reflected intensities and the sum of each pattern's value to genetically optimize the offspring patterns. Fig. 3 (c) and (d) are the optimized patterns after 800 and 8000 generations, respectively.

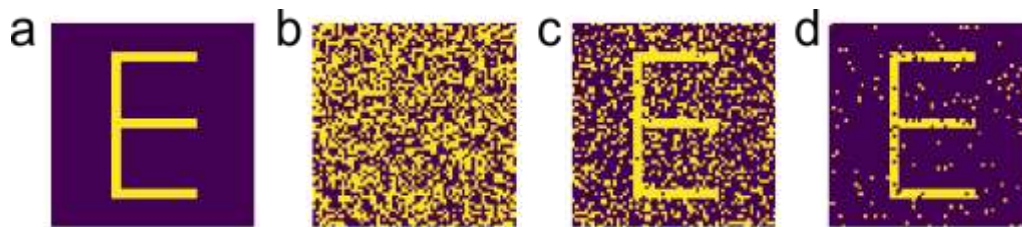


Fig. 3. Simulation results of self-optimizing ghost imaging with a genetic algorithm: (a) target image, (b) initial illumination patterns, (c) optimized pattern after 800 generations and (d) 8000 generations

### 3. Summary and conclusion

We report a ghost imaging method with genetically optimized illumination patterns. Since the patterns will evolve toward the object image, it could be designed to achieve the instant ghost imaging bypass the reconstruction process for time-saving. Furthermore, it has great potential to reduce generation number in dynamic imaging since structural continuity between the multiple frames can serve as a priori knowledge to guide image reconstruction.

### References

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