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De-noising ghost imaging via principal components analysis and compandor

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A R T I C L E I N F O

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A B S T R A C T

Improving the ghost imaging quality and speed remains a challenging task. Here, we propose an optimization algorithm model to the ghost imaging by employing principal components analysis and companding technique. By choosing appropriate parameters of the principal components and the companding function, the ghost image quality is enhanced. A good agreement between the simulation and the experiment result is obtained. In addition, we demonstrate the method with a complicated sample compared with the other five existing algorithms, indicating its advantages for wide range of applications. At last, a criteria function is firstly proposed and built to optimize the parameters for better reconstruction result without the prior information of the object. This optimization model may offer a promising implementation of de-noising ghost imaging.

1. Introduction

Ghost imaging (GI) is a new type of imaging, which utilizes the high-order correlation of intensity fluctuation. Generally, a light beam is divided into signal and reference beams in a GI system. The signal beam after illuminating the object is collected by a bucket detector, meanwhile the reference beam which does not interact with the object is recorded by a spatial resolution detector, e.g. Charge Coupled Device-CCD. We cannot obtain the object image by either beam respectively. When the two signals are sent to the coincidence measurement module simultaneously, the object image can be reconstructed by applying the correlated imaging algorithm on acquired data. The first GI, a two-photon optical imaging type experiment utilized a photon-pair source, reported by Y H Shih et al. [1] in 1995. In this experiment, a pair of signal and idler photons generated in spontaneous parametric down conversion is contributed to get image owing to the entanglement of the source photons. Later, it was demonstrated that GI could be realized with pseudo-thermal sources [2–5] and thermal lights [6]. In addition, computational GI (CGI) is proposed by Shapiro [7], where the reference beam is instead by a computed field pattern and thus the setup is simplified.

By applying appropriate algorithm, the ghost imaging quality and speed can be improved effectively, which is crucial for remote sensing and other fields. Katz et al. proposed a compressive GI (CSGI) scheme based on compressive sensing technique, which reduced the required acquisition samples significantly [8]. In 2010, F Ferri et al. present a differential GI (DGI), which removes the background and dramatically enhances the SNR of ghost imaging [9]. In 2012, B Sun et al. present an experimental comparison between different iterative ghost imaging algorithms and this normalized weighting algorithm (NGI) can match the performance of DGI [10]. In 2014, Xu-Ri Yao et al. present a new technique to denoise ghost imaging called iterative denoising of ghost imaging (IDGI) [11]. Actually, algorithms mentioned above can be group into two types: one is a non-iterative algorithm (like GI, DGI, and NGI) and the other is an iterative algorithm (like CSGI and IDGI). Usually, in contrast to basic GI algorithm which is correlated imaging by directly using the acquired data, the improved non-iterative algorithms firstly preprocess the acquired data and then reconstruct the ghost image. Furthermore, the iterative algorithm can excavate more information from the data to get the higher SNR and lower noise, but, at a cost of its time consuming. Here, our work focuses on the former to get a better de-noising ghost imaging, where the preprocess method employs principal components analysis (PCA) with companding technique.

Principal component analysis, a common technique for finding patterns in data of high dimension, is a useful statistical technique that has found application in fields such as face recognition [12] and image compression [13]. It can project the data from a high dimension into a low dimension, taking the principal components of data easily to realize

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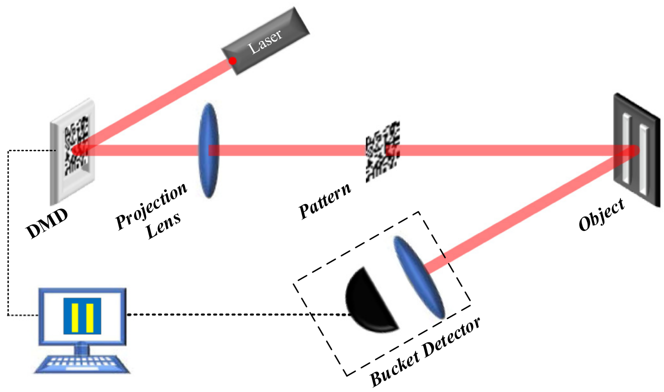

Fig. 1. The schematic diagram of CGI.

data reconstruction and de-noising on data feature. In 1901, PCA was firstly introduced in the study of physiological theory by Karl Pearson [14]. Later, in 1933, Ho Telling generalized it into random vector in the study of psychology [15]. And in 1947, Kar Hunen showed this theory with the form of probability theory [16]. And then, Loe Ve took it a further expansion and improvement, that the original indicators will be re-combined into a new set of several independent indicators to replace the original indicators, and according to the need to remove a few less comprehensive indicators as much as possible to reflect the original indicators of information [17].

In this paper, an alternative approach, that we call PCA-GI, is to pinpoint and then is used to remove the noise of GI. Firstly, with an appropriate parameters choice of the principal component associated with the companding function, the quality of image reconstruction is enhanced under this model. The simulation agrees well with the experiment results. Next, to indicating the advantages of PCA-GI method, we compare it with the other five existing algorithms with a complicated sample. At last, for better reconstruction result without the prior information of the object, a criteria function is firstly proposed and built to optimize the parameters of the GI system.

2. Theory

In current work, we take computational ghost imaging (CGI) process as a representative implement subject of PCA. Note that, such analytical method can be generalized easily to the other GI process.

2.1. Computational ghost imaging

Fig. 1 presents a schematic diagram of CGI. The signal beam, a random light pattern generated by a controllable spatial light modulator, illuminates a reflective target and then be collected by a bucket detector. The reference beam is considered as a unique feature of CGI. Knowing the deterministic modulation applied to the original laser beam allows us to use diffraction theory to calculate the intensity pattern of reference beam at the measuring position, instead of that be measured by an array detector in the usual lensless ghost imaging configuration.

Thus, each coincidence measurement consists of a signal measured by bucket detector and a correspondingly computed speckle pattern. After M measurements, one gets a signal column vector Y of length M, and the measurement matrix A of M rows with each row formed by the speckle pattern in the corresponding measurement. Denoting the object by a column vector X which has the length M of the speckle pattern, one has the expression of the mapping function of the imaging system

$$Y = AX. \tag{1}$$

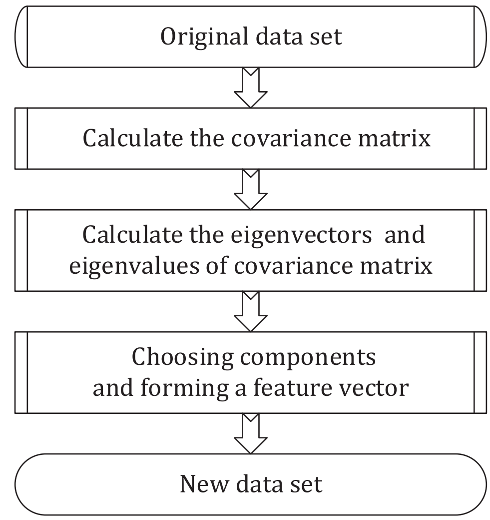

Fig. 2. Flow chart of the principal component analysis process.

The coincidence measurement related to the reconstructed image of CGI can be described as

$$G^{(2)} = \frac{1}{m}\sum_{i=1}^{m}(y_i - \bar{y})(A_i - \bar{A}),\ \bar{y} = \frac{1}{m}\sum_{i=1}^{m} y_i,\ \bar{A} = \frac{1}{m}\sum_{i=1}^{m} A_i, \tag{2}$$

where $G^{(2)}$ is a second-order spatial correlation, y_i is the ith bucket signal, A_i is the ith measurement matrix. So, one can obtain the image from $G^{(2)}$.

2.2. Principal component analysis

Principal component analysis (PCA) is an orthogonal basis transformation. Since one can find the description of PCA everywhere, we introduce the analytical process briefly. How does PCA work can be represented by a flow chart as shown in Fig. 2. The new basis is found by diagonalizing the centered covariance matrix of data set, defined by C. The coordinates in the eigenvector basis is called principal components. The size of an eigenvalue λ corresponding to an eigenvector $\boldsymbol{v}$ of C equals to the amount of variance in the direction of $\boldsymbol{v}$. Furthermore, the directions of the first n eigenvectors corresponding to the biggest n eigenvalues cover as much variance as possible by n orthogonal directions. In many applications they contain the most interesting information: for instance, in data compression, where we project onto the directions with biggest variance to retain as much information as possible, or in de-noising, where we deliberately drop directions with small variance.

2.3. Principal component analysis for computational ghost imaging

Fig. 3 is the flow chart of principal component analysis together with compandor for computational ghost imaging (PCA-CGI) algorithm of image prediction, which can be represented as five steps.

1) Data acquisition

In CGI system, after M measurements, one gets the signal column vector Y of length M and the measurement matrix A of M rows with each row formed by the speckle pattern in the corresponding measurement.

2) Data preprocessing (Compandor)

The equation $y_i = A_i X$ is equivalent to $Y_i = A_i^0 X$, with $Y_i = y_i/|A_i|$ and $A_i^0 = A_i/|A_i|$. we get the value Y_i that vector X projected onto the directions of A_i. In order to get better analysis results, we take normalization processing of Y that we process matrices by mapping row minimum and maximum values to $[\ -1 \quad 1\ ]$ and then put it into the companding function $(f(w,\ x) = 2/(1 - e^{-wx}) - 2)$ with variable parameter