Single-pixel imaging using reweighted amplitude flow optimization

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ABSTRACT

When random patterns are applied, correlation-based reconstruction is widely used in single-pixel imaging (SPI). The performance of the correlation algorithm still needs to improve in achieving high-quality object reconstruction, although some methods have been developed (e.g., Gerchberg-Saxton-like). Here, we present an approach to enhancing SPI performance by integrating the reweighted amplitude flow (RAF). The method optimizes the reconstruction process by weighting the measurement data adaptively to improve robustness and reconstruction accuracy. An efficient estimation of the object is first obtained through the weighted maximal correlation initialization. Subsequently, iterative updates refine the estimate using the reweighted gradient descent. This approach improves SPI performance, providing high-quality object reconstruction. The results demonstrate effectiveness of the RAF-enhanced SPI, showing its potential for the applications.

Keywords: Single-pixel imaging, Correlation, Reweighted amplitude flow.

1. INTRODUCTION

Single-pixel imaging (SPI) is an advanced computational imaging technique that captures object information using a single sensor instead of a camera with many sensors [1–5]. The SPI is particularly beneficial for imaging in scenarios where conventional imaging faces challenges, e.g., scattering environments, low-light conditions, infrared and terahertz [6–15]. The SPI is based on the principle of structured illumination and computational reconstruction. The object is illuminated with a series of known patterns (e.g., random patterns), and these patterns modulate the light that interacts with the object. A single-pixel detector collects light intensity transmitted or reflected by the object. Correlation algorithm and some developed algorithms (e.g., Gerchberg-Saxton-like) in the SPI are usually used to reconstruct the object from the set of single-pixel measurements [16–20]. However, these algorithms often require a large number of pattern illuminations and have a time-consuming process. In addition, quality of the reconstruction still needs to be improved.

In this paper, we introduce an approach to enhancing the performance of SPI by integrating the reweighted amplitude flow (RAF) strategy [21]. This method optimizes object reconstruction process by adaptively weighting the measurement data, which improves robustness and reconstruction accuracy. The first step involves obtaining an efficient initial estimation of the object. The initialization is achieved by a weighted maximal correlation, where some weights are strategically assigned to the measurements based on their reliability. By emphasizing more accurate data and diminishing the influence of noise-affected measurements, the initialization establishes a robust foundation for subsequent iterations. Following the initial estimation, object reconstruction is refined using iterative updates, which is similar to a gradient descent approach. In each iteration, the algorithm adapts the weights of data points, focusing on high-confidence measurements. This adaptive weighting enhances the convergence speed and accuracy of the reconstruction, addressing the challenges. The RAF-enhanced SPI demonstrates substantial improvements in image quality and reconstruction accuracy. The algorithm enhances the reconstruction performance by leveraging an adaptive weighting mechanism.

2. METHODOLOGY

In SPI, a series of random patterns $P(x,y)$ are applied to illuminate an object $O(x,y)$, and the total intensity transmitted or reflected by the object for each illumination pattern is collected by a single-pixel detector. When each illumination pattern is considered as a row vector a_i of a random Gaussian matrix A and the object is considered as a column vector x, the process of single-pixel measurements can be described by

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$$y = \left| Ax \right|^2, \tag{1}$$

where y denotes a measurement vector containing a series of measured values y_i. Here, i ranges from 1 to m where m denotes the total number of measurements.

In terms of reconstruction, correlation algorithm is widely used to reconstruct object information when random patterns are applied in SPI. However, performance of the correlation algorithm suffers from low quality in reconstruction even when a large number of measurements are used. Some methods, e.g., Gerchberg-Saxton-like, are developed to improve the performance of correlation algorithm. A number of iterations are necessary for Gerchberg-Saxton-like ghost imaging to enable high-quality reconstruction.

Here, RAF is utilized to simultaneously speed up reconstruction and improve the reconstruction quality. In the strategy of RAF, there are two essential components, i.e., initialization and iteration. For initialization, it is necessary to select a subset of measurements from the whole set of measurements. In this case, the selected measurements can be used to obtain a better initialization and can correlate the reconstruction. Hence, based on the measurement in Eq. (1), a series of measured values that are larger than a threshold $y_{\text{threshold}}$ are chosen.

$$y' = \left\{ y_i \middle| y_i > y_{\text{threshold}} \right\}, \tag{2}$$

where y' denotes the chosen values according to the threshold. The row vectors in the matrix A corresponding to the chosen values are also selected to form a matrix A'. Then, an initialization z^0 can be described by

$$z^0 = \tilde{z}^0 \sqrt{\sum\nolimits_{i=1}^{m} y_i \big/ m}, \tag{3}$$

where $\tilde{z}^0$ denotes unit-norm principal eigenvector of $A'^T diag\{(y')^{1/4}\} A'$, T denotes matrix transpose, and $diag$ represents a diagonal matrix.

After the initialization is completed, the second step (i.e., iteration) is applied to improve quality of the initialization and finally realize high-quality object reconstruction. In terms of iteration, the following formula can be used.

$$z^{t+1} = z^t - \left\{ \frac{\mu^t}{m} \sum_{i=1}^{m} \omega_i^t \left[a_i z^t - \text{sign}(a_i z^t) \sqrt{y_i} \right] a_i \right\}^T, \tag{4}$$

where z^t denotes the updated reconstruction in the iterations, μ denotes a learning rate, $\text{sign}(\bullet)$ denotes a mathematical signum function, and

$$\omega_i^t = \frac{\left| a_i z^t \right|}{\left| a_i z^t \right| + \beta \sqrt{y_i}}, \tag{5}$$

where β denotes a weighting parameter set as 10.

As a result, the combination of initialization and iteration, i.e., Eqs. (3) and (4), can lead to a robust reconstruction with high quality.

3. RESULTS AND DISCUSSION

Simulation results based on the model are shown in Fig. 1. Figures 1(a) and 1(c) show the groundtruth used to test the model. The resolution of the ground truth is 64×64 pixels, and the number of measurements is 8192. The threshold in Eq. (2) is chosen with the 6302nd measured value. Using the theoretical model in Section 2, two reconstruction results corresponding to the ground truths are respectively shown in Figs. 1(b) and 1(d). To quantitatively show quality of the reconstruction, peak signal-to-noise ratio (PSNR) is used [17]. PSNR values for Figs. 1(b) and 1(d) are respectively 58.23 dB and 55.70 dB. It is indicated by PSNR values that the reconstruction is of high quality.

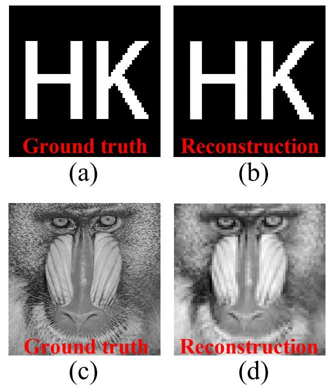

Figure 1. (a) and (c) The groundtruth, and (b) and (d) the reconstructed images respectively corresponding to (a) and (c).

The number of iterations is 300. Figures 2(a) and 2(b) show the MSE decreasing with the number of iterations. As can be seen in Fig. 2, the MSE decreases quickly as the number of iterations increases, meaning that the method is efficient.

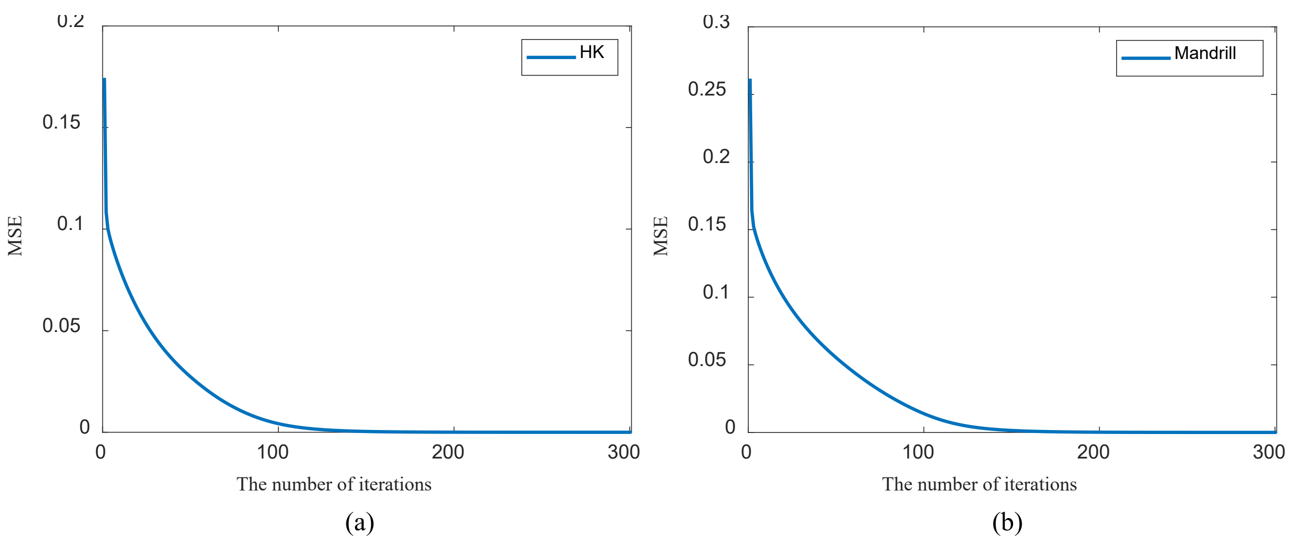

Figure 2. (a) MSE versus the number of iterations corresponding to that in Fig. 1(a), and (b) MSE versus the number of iterations corresponding to that in Fig. 1(c).

4. CONCLUSION

We have presented a SPI system by incorporating RAF. This method enhances the object reconstruction process by adaptively weighting measurement data, leading to the enhanced accuracy. Firstly, we estimate the object using weighted maximal correlation initialization. Then, we use iterative updates to refine the estimate through a reweighted gradient descent. This approach enhances SPI performance, resulting in high-quality reconstruction. The results demonstrate effectiveness of the RAF-enhanced SPI, showing a potential for a wide range of applications.

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