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Single-pixel non-imaging object recognition by means of Fourier spectrum acquisition

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A B S T R A C T

Single-pixel imaging has emerged over recent years as a novel imaging technique, which has significant application prospects. In this paper, we propose and experimentally demonstrate a scheme that can achieve single-pixel non-imaging object recognition by acquiring the Fourier spectrum. In an experiment, a four-step phase-shifting sinusoid illumination light is used to irradiate the object image, the value of the light intensity is measured with a single-pixel detection unit, and the Fourier coefficients of the object image are obtained by a differential measurement. The Fourier coefficients are first cast into binary numbers to obtain the hash value. We propose a new method of perceptual hashing algorithm, which is combined with a discrete Fourier transform to calculate the hash value. The hash distance is obtained by calculating the difference of the hash value between the object image and the contrast images. By setting an appropriate threshold, the object image can be quickly and accurately recognized. The proposed scheme realizes single-pixel non-imaging perceptual hashing object recognition by using fewer measurements. Our result might open a new path for realizing object recognition with non-imaging.

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1. Introduction

Single-pixel imaging techniques are often referred to as ghost imaging (GI). As a new technology and an intriguing method, over the past 20 years, ghost imaging has attracted great attention and achieved significant development. In the 1980s, the former Soviet Union scholar Klyshko proposed a ghost imaging scheme according to the entanglement behavior of spontaneous parametric down-conversion photon pairs [1]. A research team at the University of Maryland realized ghost imaging based on an entanglement source in 1995 [2,3]. Later, scholars confirmed that pseudothermal light and thermal light can also be used in ghost imaging [4–12]. In 2009, Bromberg realized computational ghost imaging [13–15] through a spatial light modulator (SLM) preset light source. In recent years, some new ghost imaging schemes have been proposed. These include differential ghost imaging (DGI) [6], compressive sensing ghost imaging (CSGI) [5], correspondence ghost imaging (CGI) [16,17], sinusoidal ghost imaging (SGI) [18], and Fourier ghost imaging [19]. Ghost imaging can break through the diffraction limit to achieve high-resolution imaging [20,21]. In view of the above research, ghost imaging has potential applications in remote sensing [22,23], image encryption, weak light detection, and the imaging of penetrating scattering media.

In recent years, the focus of research on ghost imaging has increasingly turned from basic research to practical applications [24], especially with regard to interdisciplinary applications. Previous work realized object authentication in other ways through ghost imaging [25–28]. The proposed methods promoted the further application of ghost imaging in the direction of object recognition. It is necessary to reconstruct the object image in order to realize object recognition. The imaging process not only increases the complexity of the computation but also lengthens the time required for object authentication. However, to our knowledge, no single-pixel technique has successfully achieved non-imaging object recognition thus far.

The perceptual hashing algorithm (PHA) [29–33] is a hash algorithm that is mainly applied in the search for similar images. Perception hashing technology converts image data into thousands of binary sequences [29]. It is a promising and effective method to solve image content authentication. Specifically, PHA generates a "fingerprint" for each image. Traditionally, a metric must be defined to measure the distance between "fingerprints." The hash distance metric used in the

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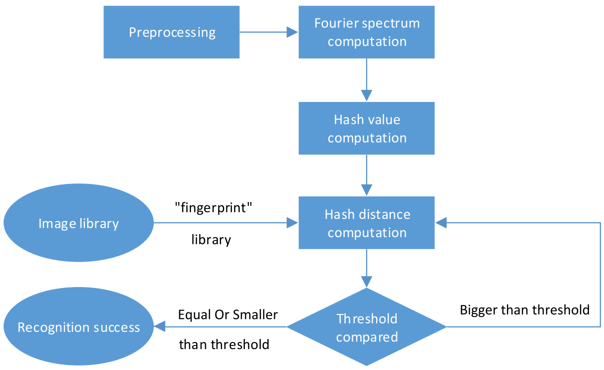

Fig. 1. Flowchart of non-imaging perceptual hashing object recognition.

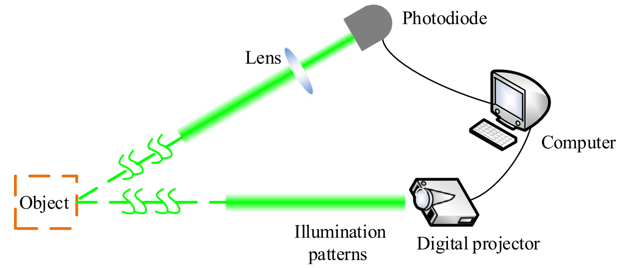

Fig. 2. Schematic of non-imaging perceptual hashing object recognition. Digital projector illuminates object image with four-step phase-shifting sinusoidal structured light patterns. Detection unit (a photodiode) collects scattered reflected light from object and feeds resulting signals to computer for a computational Fourier coefficient of images.

previous scheme is the bit error rate (BER) or the normalized Hamming distance [29,32]. The features of perceptual hashing are robust and secure. PHA can be applied to image content identification, retrieval, and authentication. Generally, PHA [31] calculates the hash value by computing the image of a discrete cosine transform (DCT) coefficient matrix. In Fourier ghost imaging [19] schemes, the Fourier coefficient matrix of the object image can be obtained directly by differential measurement using sinusoid structured illumination patterns instead of a random speckle pattern. We find that the PHA combined with Fourier ghost imaging has a more practical application.

In this paper, we present a single-pixel non-imaging perceptual hashing object recognition scheme, which exploits the sparsity and concentration characteristics of a natural object in the low-frequency region of the Fourier domain and the framework of computational ghost imaging. A hash "fingerprint" of the object is used for recognition by comparing it with the "fingerprint" in the image library. To obtain the hash "fingerprint," we record the Fourier spectrum of the object by using grayscale, analytic, harmonic four-step phase-shifting sinusoid patterns for illumination [34–36], and a single-pixel detector that has no spatial resolution, to collect the reflecting light. We obtain the hash value directly in the Fourier domain and calculate the hash distance. Thus, the imaging procedure is eliminated, and non-imaging object recognition is realized. Our scheme is a compressive-sampling-like method that can realize non-imaging object recognition with fewer measurements.

2. Theory

Fig. 1 presents a flowchart of the algorithm.

The process of preprocessing simplifies the object image color and reduces the size to $M * N$ of the object image in the simulation. The process of preprocessing obtains data in experiments. The PHA calculates the hash value of the image in the Fourier domain. The real part or the imaginary part of the Fourier coefficient of the image both contain characteristic information about this image. In our experiment, the real part or the imaginary part of the Fourier coefficient of the image can be obtained directly by measurement; hence, we only need to calculate the mean value of the real part or the imaginary part of the Fourier coefficients. This not only obtains the characteristic information of the image but also reduces the number of samplings and calculations. Then, we can transform the Fourier coefficients into binary numbers by using the mean value. Specifically, we assign a coefficient of 1 if it is larger than the mean value; otherwise, we assign a coefficient of 0. The 0 or 1 sequence is the hash value of this image, which is referred as a "fingerprint." We compare the difference of the "fingerprint" between the object image and the "fingerprint" library. Then, we can obtain the hash distance. To set a unified standard, we define the hash distance (HD) to represent a hash value difference between the object image and contrast images in the image library. It is given by

$$D_{objcon} = \frac{1}{M * N} \sum_{i=1}^{M*N} \left| obj_i - con_i \right|, \tag{1}$$

where D_{objcon} is the hash distance between the object image and the contrast image. obj_i represents the hash value of the object image. con_i represents the hash value of the contrast images. We conduct normalization processing in Eq. (1), regardless of whether M, N, or D_{objcon} ranges from 0 to 1. obj_i, con_i is a binary sequence of 0 or 1. In general, the hash distance of the same images is 0. In most cases, the experimental results are not perfect, or the object image is slightly different. Thus, we need to find a suitable threshold through the experimental results. If the hash distance between the object image and a contrast image is less than or equal to this threshold, recognition is successful. Otherwise, we continue to compare the "fingerprint" of an object image with the "fingerprint" library until recognition succeeds.

An experimental diagram of the scheme is presented in Fig. 2. A four-step phase-shifting sinusoidal light irradiates on the target object, which is collected by a lens and detected by a single-pixel detection unit.

The four-step phase-shifting sinusoidal patterns of different spatial frequencies with $M * N$ pixels are generated by P_0, P_π, $P_{\pi/2}$, $P_{3\pi/2}$, which are given by

$$P_0 = \cos\left(\frac{2\pi * k * n}{N} + \frac{2\pi * l * m}{M}\right) + 1, \tag{2}$$

$$P_{\pi/2} = \cos\left(\frac{2\pi * k * n}{N} + \frac{2\pi * l * m}{M} + \frac{\pi}{2}\right) + 1, \tag{3}$$

$$P_\pi = \cos\left(\frac{2\pi * k * n}{N} + \frac{2\pi * l * m}{M} + \pi\right) + 1, \tag{4}$$

$$P_{3\pi/2} = \cos\left(\frac{2\pi * k * n}{N} + \frac{2\pi * l * m}{M} + \frac{3\pi}{2}\right) + 1, \tag{5}$$

where $l, m \in \{1, 2, 3, \ldots, M\}$ and $k, n \in \{1, 2, 3, \ldots, N\}$. In Eqs. (2)–(5) [19], P_0, P_π, $P_{\pi/2}$, $P_{3\pi/2}$ has a constant phase shift $\pi/2$ between two adjacent patterns. Since the actual light intensity value is always positive, 1 is added to Eqs. (2)–(5) [19] to ensure that the light intensity is a positive value in theory. Therefore, the simulation process can also be used in the experiment.

A 2D sinusoid pattern is specified with the spatial frequency (f_x, f_y) and initial phase θ. Thus, Eqs. (2)–(5) can be written as [19]

$$P_\theta(x, y; f_x, f_y) = \cos(2\pi * f_x * x + 2\pi * f_y * y + \theta) + 1, \tag{6}$$

where (x, y) represents the 2D coordinates. When illuminating a scene with a pattern, the total intensity of the reflected light arising from the structured light source can be expressed as [19]

$$D_\theta(f_x, f_y) = \iint_\Omega O(x, y) P_\theta(x, y; f_x, f_y) dx dy, \tag{7}$$

where Ω represents the illuminated area, and $O(x, y)$ is the distribution of the surface reflectivity of the imaged objects. Each Fourier coefficient

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