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Cat-eye effect target recognition with single-pixel detectors

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ABSTRACT

A prototype of cat-eye effect target recognition with single-pixel detectors is proposed. Based on the framework of compressive sensing, it is possible to recognize cat-eye effect targets by projecting a series of known random patterns and measuring the backscattered light with three single-pixel detectors in different locations. The prototype only requires simpler, less expensive detectors and extends well beyond the visible spectrum. The simulations are accomplished to evaluate the feasibility of the proposed prototype. We compared our results to that obtained from conventional cat-eye effect target recognition methods using area array sensor. The experimental results show that this method is feasible and superior to the conventional method in dynamic and complicated backgrounds.

1. Introduction

Imaging systems such as cameras and optical sights, when illuminated by a laser, can often reflect back the incident light along the original light path. This characteristics is known as the cat-eye effect [1–3]. The experiments have proved that the echo intensity of the cat-eye effect target is 2–3 orders of magnitude more than that of the diffuse target [4]. Cat-eye effect target detection plays an important role in military reconnaissance and free-space communication. Various detection methods have been presented in the past decades. For instance, Ren and Li [5] proposed the shape-frequency dual criterions (SFDC) method, based on target shape and modulation frequency. This method requires a large number of image sequences so it cannot meet the requirement of real-time applications. Another cat-eye effect target recognition method named Multi-channel Saliency Processing before Fusion (MSPF) [6]. This method combines traditional cat-eye target recognition with the selective characters of visual attention. By parallel processing, the runtime of MSPF is shorten. However, the recognition rate of MSPF may greatly decrease when the targets exist in dynamic backgrounds. Compressive sensing (CS) [7–9], which combines sampling and compression into a single non-adaptive linear measurement process, provides novel ideas to target recognition. Motivated by this, Li, and Li [10] proposed a cat-eye effect target recognition method with compressive sensing. In this method, the linear projections of original image sequences are applied to remove dynamic background. The measurement vectors of images sequences are directly processed before reconstruction. The cat-eye effect target information, regarded as sparse signal, can be reconstructed with CS theory. This method shortens the acquisition times and reduces data storage.

All the target detection methods mentioned above are based on the subtraction between active and passive images, that is to say between images acquired by the detector with laser and images acquired by the detector without laser [11]. Limited by the system structure, the conventional methods may work ineffectively in dynamic and complicated backgrounds. What's more, when applied to military reconnaissance, the detection system requires the laser at a wavelength above 900 nm which is invisible to human eye. However the area array sensor that can detect such kind of laser is very expensive.

Ghost imaging is an alternative technique to conventional imaging and removes the need for a spatially resolving detector [12]. The object can be recovered by correlating the known spatial information of a changing incident light field with the reflected (or transmitted) intensity which can be measured by a single-pixel detector. Ghost imaging have been improved dramatically in the past several years, advancing to the fields that include 3D imaging [12], optical security [13,14] and objects recognition [15,16]. Optical nonlinear correlation algorithm is used for optical authentication. Computational ghost imaging is similar to standard computational imaging systems, which projected light patterns to the objects. Ghost imaging can be extended for imaging applications at nearly any desired wavelength where light sources and single-pixel detectors exist, but the recovered image quality is low and the measurement process may take a very long time.

Duarte et al. [17] presented a “single-pixel” CS camera which can operate efficiently across a much broader spectrum with

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cheaper sensor. In both single-pixel cameras and ghost imaging systems, the main computational problem is reconstructing an image from the projected known patterns and the measured intensities. In this paper, an approach based on the CS theory and single-pixel imaging to recognize cat-eye effect targets is presented. The new recognition method uses a digital light projector (DLP) to illuminate the scene with binary patterns and three spatially separated single-pixel detectors to measure the intensity of reflected light. Based on the cat-eye effect, both static and dynamic backgrounds can be suppressed by the subtraction of observation vectors. Then targets can be extracted by recovering low-rank and sparse matrices from difference vectors. It is simpler, smaller, and less-expensive in comparison with the conventional cat-eye effect target recognition systems, but more feasible in dynamic backgrounds.

The following will describe the prototype of target recognition with single-pixel detectors and the detailed recognition process based on sparse and low-rank decomposition. Furthermore, we will give the simulation to prove the feasibility of this method. We will also analyze the robustness and the complexity of our method. Finally, predictions of the future improvements and conclusions are given.

2. Compressive sensing and single-pixel imaging

Many natural signals have the feature of sparsity, that is to say, signals can be represented or approximated well using a small number of nonzero parameters [18]. This feature has been widely exploited for signal estimation and compression. Particularly natural images can be compressed in the discrete cosine transform (DCT) [17]. Consider a 2D image X, which can be viewed as an $N \times 1$ column vector with elements $X[n], n = 1, 2, \ldots N$. Suppose that the basis $\Psi = [\psi_1, \psi_2, \ldots, \psi_N]$ provides a linear representation of X:

$$X = \Psi\theta = \sum_{i=1}^{N} \theta_i \psi_i \tag{1}$$

where $\theta \in R^N$ is a column vector with K-nonzero elements. $\Psi \in R^{N\times N}$is called a sparse basis of signal X. Based on compressive sensing theory, suppose we have a measurement matrix $\Phi = [\phi_1|\phi_2|\ldots|\phi_M]^T \in R^{M\times N}(M < N)$ which does not depend in any way on the signal X, linear projections of the signal X onto Φ can be measured:

$$Y = \Phi X \tag{2}$$

K-sparse and compressible signals X can be reconstructed from only $M \approx K$ or slightly more measurements by solving the optimization problem:

$$X = \arg\min \|X\|_p s.\ t.\ \Phi X = Y \tag{3}$$

where $\|\bullet\|_P$ for $P = 0$ or $P = 1$ is the l_0-norm or l_1-norm, respectively.

The single-pixel camera developed at Rice University is an example of how compressive sensing allows us to move from a "Digital Signal Processing" (DSP) paradigm to a "Computational Signal Processing" (CSP) paradigm [19]. The main device to achieve CS is a digital micromirror device (DMD) which consists of an array of N tiny mirrors. Each mirror can be positioned rapidly in one of two states ($+12°$and $-12°$ from horizontal). The incident light corresponding to the image X is selectively reflected off a DMD, and then is collected by a lens and focused onto an avalanche photodiode (APD). In each measurement, the random number generator (RNG) sets the mirror orientations to a 0/1 pattern corresponding to the measurement vector ϕ_m. The process is repeated M times to obtain all of the entries in Y.

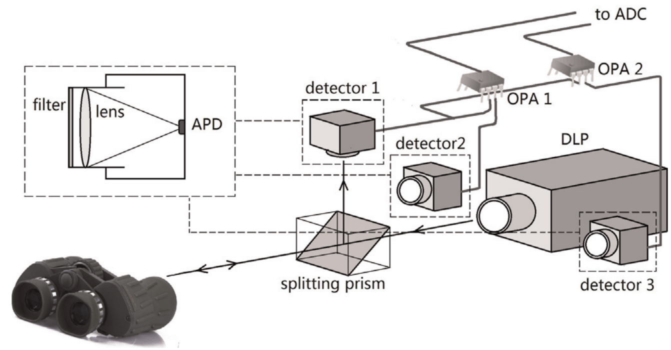

Fig. 1. Schematic of cat-eye effect target recognition system with single-pixel detectors.

3. System description

Compared to the single-pixel CS camera, our prototype is an active imaging system. The prototype is shown in Fig. 1. The system uses a DLP to display a sequence of random binary patterns. The DLP contains a DMD, which redirects parts of the light beam selectively. Considering that the DMD has an array switching rate up to 40 kHz [20], the patterns change very quickly so the measurement time is shortened greatly.

The light from DLP goes through a beam splitting prism and reaches the scene. Then the backscattered light is recorded by three single-pixel detectors with condenser lenses and optical filters which blocks any light except the light at a wavelength of the DLP lamp source. The detectors are placed in different locations while only detector 1 shares the common optic axis with the DLP by the splitting prism. According to the principle of cat-eye effect, the light which reaches the target will be reflected back in the original optical path, so detector 1 detects the light reflected from the targets but detector 2 and detector 3 do not. However, the light intensities from the background received by each detector are almost the same. It is easy to extract cat-eye effect targets from background by using this feature.

In order to reduce the total capture time, compressive sensing technique is applied. In our prototype, every structured-light pattern projected to the objects corresponds to ϕ_i in the measurement matrix $\Phi = [\phi_1|\phi_M|\ldots|\phi_M]^T$. To be more exact, Walsh Hadamard matrix chosen as the measurement matrix is generated by the DMD. In fact, to correctly implement DMD, the matrix entries -1 and 1 are shifted to 0 and 1, which are respectively corresponding to the black block and the white block in the patterns. Backscattered light is focused onto each detector, which makes an observation $Y_i[m]$ in $Y_i, i \in \{1, 2, 3\}$. Y_i is the observation vector obtained by detector i. Considering that the background is dynamic, this process can be expressed as:

$$Y_i[m] = \ < X_i + w_i(m), \phi_m> \tag{4}$$

where $w_i(m)$, $i \in \{1, 2, 3\}$ are vector functions corresponding to the dynamic part of the scene and X_i, $i \in \{1, 2, 3\}$ are length-N vectors corresponding to the static part of the scene. After Mmeasurements, three entire observation vectors Y_i, $i \in \{1, 2, 3\}$ are obtained. To each detector, the measurement process is the same. The signal output ends of the detectors are connected to two operational amplifiers (OPA) which calculate the differences of the detector signals:

$$Y'_1 = Y_1 - Y_2 \tag{5}$$