Target recognition under nonuniform illumination conditions

Victor H. Diaz-Ramirez\textsuperscript{1,*} and Vitaly Kober\textsuperscript{2}

\textsuperscript{1}Centro de Investigacion y Desarrollo de Tecnologia Digital, Instituto Politecnico Nacional, Avenida del Parque No. 1310, Mesa de Otay, Tijuana, B.C., 22510, Mexico

\textsuperscript{2}Computer Science Department, Centro de Investigacion Cientifica y de Educacion Superior de Ensenada, Km 107 Carretera Tijuana-Ensenada, Ensenada B.C. 22860, Mexico

*Corresponding author: dira.vh@gmail.com

Received 9 July 2008; accepted 19 January 2009; posted 23 January 2009 (Doc. ID 98458); published 26 February 2009

A two-step algorithm for reliable recognition of a target imbedded into a two-dimensional nonuniformly illuminated and noisy scene is presented. The input scene is preprocessed with a space-domain pointwise procedure followed by an optimum correlation. The preprocessing is based on an estimate of the source illumination function, whereas the correlation filter is optimized with respect to the mean-squared-error criterion for detecting a target in the preprocessed scene. Computer simulations are provided and compared with those of various common techniques in terms of recognition performance and tolerance to nonuniform illumination as well as to additive noise. Experimental optodigital results are also provided and discussed. © 2009 Optical Society of America

\textit{OCIS codes:} 070.4550, 070.5010, 100.3008.

1. Introduction

Pattern recognition using the correlation operation has been vastly used in the last decades because it can be easily implemented in real-time optodigital processors \cite{1–3}. However, the performance of the processors degrades rapidly when input signals are distorted owing to imperfection of imaging sensors, quantization errors, and nonuniform illumination conditions. Various correlation filters were proposed for reliable detection of a target in the presence of additive and disjoint noise \cite{4–7}. On the other hand, a few techniques were proposed for pattern recognition under different illumination conditions \cite{8–11}, that is, input scenes are affected by multiplicative nonstationary interference signals. Arsenault and Lefebvre \cite{8} suggested homomorphic cameo filtering (HCF). It consists of a logarithmic preprocessing of an input scene followed by a synthetic discriminant function (SDF) filter \cite{12,13}. The filtering yields good results in the absence of additive sensor noise. Another fruitful approach is a weighted sliced orthogonal nonlinear generalized (WSONG) correlation \cite{10}. In this method the correlation output is a sum of weighted correlations between binary images obtained by threshold decomposition of the input scene. A drawback of the method is its high computational complexity. An optimum correlation filter for detecting a target embedded into a spatially uniform multiplicative and additive interference signals was proposed \cite{5}. However, for spatially inhomogeneous disturbances this filter may yield a poor performance. Recently, Valles et al. \cite{14} presented an illumination-invariant technique for 3D object recognition. The method takes into account reflectance properties of surfaces and physical relation between a distant light-source and the object surface. Actually, reflectance models describe how input scene signals are related to the light-source direction \cite{15}. If illuminant direction parameters are known, an estimation of the illumination function can be carried out \cite{16}.

In this paper, we propose a two-step algorithm for reliable recognition of a target under nonuniform
illuminations. First, a pointwise preprocessing of an input scene using an estimate of the illumination function is carried out. Next, a minimum mean squared-error filter for pattern recognition is designed [6,17]. The paper is organized as follows. In Section 2 we present a brief review of common correlation techniques for pattern recognition under variant illumination conditions. In Section 3 reflectance models are recalled. In Section 4 we describe the proposed method. In Section 5 computer simulations and experimental optodigital results are provided and discussed. Finally, Section 6 summarizes our conclusions.

2. Related Works
Here basic strategies for illumination-invariant pattern recognition are described. We consider the HCF [8] and the WSONG correlation [10]. Since any arbitrary illumination function can be modeled as a multiplicative noise function, an optimum filter design (OF) [5] is also reviewed. For simplicity, one-dimensional notation is used. Let \( t(x) \) and \( f(x) \) be a target signal and an input scene, respectively. Suppose that the scene is nonuniformly illuminated.

A. Homomorphic Cameo Filtering
Assume that the target size is sufficiently small, so the target is approximately uniformly illuminated at a position \( x_0 \):

\[
\tilde{t}(x - x_0) = bt(x - x_0),
\]

where \( b \) is an unknown illumination constant. The HCF performs a logarithmic transformation of the input scene to convert the multiplicative model to the additive one:

\[
\log[f(x)] = \log[t(x - x_0)] + \log[b].
\]

Next, a cameo correlation filter for the target detection is designed. The impulse response of the cameo filter \( h_{cm}(x) \) can be expressed as

\[
h_{cm}(x) = a_1 \log[t(x)] + a_2 \log[w_t(x)],
\]

where \( a_1 \) and \( a_2 \) are coefficients to be determined, and \( w_t(x) \) is a binary function defined as unity inside the target area and zero elsewhere. Note that \( h_{cm}(x) \) corresponds to the impulse response of a conventional SDF filter [12]. The impulse response of the filter is synthesized in such a way to yield prespecified central correlation outputs in the response to \( \log[w_t(x)] \) and \( \log[t(x)] \), respectively.

B. Weighted Sliced Orthogonal Nonlinear Generalized Correlation
According to the threshold decomposition concept [18], a quantized signal can be expressed as a sum of binary slices:

\[
a(x) = \sum_{i=0}^{N-1} i \text{BIN}_i[a(x)],
\]

where \( N \) is the number of gray levels of the signal, and “BIN” is defined as

\[
\text{BIN}_i[a(x)] = \begin{cases} 1 & a(x) = i \\ 0 & a(x) \neq i \end{cases}.
\]

The correlation “\( \otimes \)” between images \( f(x) \) and \( g(x) \) can be computed as

\[
f(x) \otimes g(x) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} i j \text{BIN}_i[f(x)] \otimes \text{BIN}_j[g(x)].
\]

The WSONG correlation is defined as follows [10]:

\[
\Omega_{f,g}(x) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} W_{ij} \text{BIN}_i[f(x)] \otimes \text{BIN}_j[g(x)],
\]

where \( W_{ij}(x) \) is a matrix of weighting coefficients, which are able to take into account nonuniform illumination conditions [10].

C. Optimum Filtering
Assume that the target is imbedded into a nonoverlapping background at unknown coordinate \( x_0 \). The input scene is corrupted by a stationary multiplicative function \( u(x) \) and a zero-mean additive noise \( n(x) \):

\[
f(x) = u(x)[t(x - x_0) + \tilde{w}_t(x - x_0)b(x)] + n(x),
\]

where \( \tilde{w}_t(x) \) is an inverse support function defined as zero within the target area and unity elsewhere. It is assumed that the random variable \( x_0 \) is uniformly distributed over the scene area, white additive noise \( n(x) \) and multiplicative interference \( u(x) \) are statistically independent of each other. The OF is optimized with respect to the peak-to-output-energy [19]:

\[
H_{of}(\omega) = \frac{\mu_m[T(\omega) + \mu_b \tilde{W}_t(\omega)]^*}{\frac{1}{2\pi} N_m(\omega) \otimes \left| T(\omega) + \mu_b \tilde{W}_t(\omega) \right|^2 + \frac{1}{2\pi} N_b(\omega) \otimes \left| \tilde{W}_t(\omega) \right|^2 + N(\omega)},
\]

1 March 2009 / Vol. 48, No. 7 / APPLIED OPTICS 1409
where \( \hat{W}(\omega) \) is the Fourier transform of \( \hat{u}(x) \), \( \mu_m = E\{u(x)\} \), and \( \mu_b = E\{b(x)\} \); \( N_m(\omega) \), \( N(\omega) \), and \( N_b(\omega) \) are power spectral densities of \( u(x) \), \( n(x) \), and \( b(x) = b(x) - \mu_b \), respectively.

### 3. Illumination Models

Reflectance models describe relations between the illuminant direction and the surface shape. Surfaces can be Lambertian, specular, or hybrid (combination of both) [15]. Figure 1 shows a geometrical model of a surface being illuminated by a light source. The \( z \) axis is an observation point. In the Lambertian model, surfaces reflect the light in all directions with equal amplitudes [20]: \( I_L(\theta) = \cos(\theta) \). where \( \theta \) is the incident angle, i.e., the angle between the surface-normal vector \( \mathbf{N} \) and the illuminant direction vector \( \mathbf{S} \) (see Fig. 1). Specular surfaces reflect the light as a mirror. They can be described as follows [20]: \( I_S = \delta(\theta_s - \theta) \), where \( \delta(x) \) is the Dirac delta function.

\[
\beta = \arctan \left[ \frac{S_x}{\sqrt{(S_x - x_0)^2 + (S_y - y_0)^2}^{1/2}} \right] = \arctan \left[ \frac{r}{\cos(\tau) \left[ (r \times \tan \tau \times \cos \alpha - x_0)^2 + (r \times \tan \tau \times \sin \alpha - y_0)^2 \right]^{1/2}} \right].
\]

Substituting Eq. (11) into Eq. (10), the reflected light is given by

\[
I(x_0, y_0) = \cos \left( \frac{\pi}{2} - \arctan \left[ \frac{r}{\cos(\tau) \left[ (r \times \tan \tau \times \cos \alpha - x_0)^2 + (r \times \tan \tau \times \sin \alpha - y_0)^2 \right]^{1/2}} \right] \right). (12)
\]

\[
\theta_s = \theta_N - \theta_v, \theta_N \text{ is the angle between } \mathbf{N} \text{ and the } z \text{ axis, and } \theta_v \text{ is the angle between } \mathbf{N} \text{ and the viewer's direction. Hybrid surfaces are combinations of Lambertian and specular reflection components: } I_H = k_1I_L + k_2I_S, \text{ where } k_1 + k_2 = 1. \text{ Different hybrid reflectance models were proposed [21–23]. An extended review of illumination reflectance models can be found in [20,24,25]. We use the Lambertian reflectance model. It can be seen from Fig. 1 that the illuminant direction is determined by the following parameters: } \tau \text{ (slant angle), } \alpha \text{ (tilt angle), and } r \text{ (magnitude of vector } \mathbf{S}). \text{ These parameters define the position of the light source with respect to the surface origin. For a Lambertian surface, the reflected light from a point } (x_0, y_0) \text{ is given by}
\]

\[
I(x_0, y_0) = \cos(\theta) = \cos \left( \frac{\pi}{2} - \beta \right). (10)
\]

Note that \( I(x_0, y_0) \) depends on the illuminant direction parameters \( \tau, \alpha, \text{ and } r \). In real applications these parameters are either known or can be estimated. Zheng and Chellappa [16] proposed a technique for estimating \( \tau, \alpha, \text{ and the surface albedo } \rho \) from an observed image as follows:

\[
\alpha = \arctan \left( \frac{E \left( \tilde{x}_L/\sqrt{\tilde{x}_L^2 + \tilde{y}_L^2} \right)}{E \left( \tilde{y}_L/\sqrt{\tilde{x}_L^2 + \tilde{y}_L^2} \right)} \right);
\]

\[
\begin{bmatrix} \delta I_1 \\ \delta I_2 \\ \vdots \\ \delta I_N \end{bmatrix} = (\mathbf{B}'\mathbf{B})^{-1}\mathbf{B}' (\tilde{x}_L \tilde{y}_L), (13)
\]

where \( (\tilde{x}_L, \tilde{y}_L) \) are the \( (x, y) \) components of the tilt’s local estimate, \( \delta I_i \) is the derivative of the image intensity in the \( (\delta x_i, \delta y_i) \) direction, and \( \mathbf{B} \) is the \( N \times 2 \) direction matrix. Slant \( \tau \) is evaluated by solving the nonlinear equation:

\[
\beta = \arctan \left[ \frac{S_x}{\sqrt{(S_x - x_0)^2 + (S_y - y_0)^2}^{1/2}} \right].
\]
where $\Lambda(x) = P_n(x)/P_i(x)$ is the noise-to-signal ratio at the coordinate $x$. $P_i(x)$ and $P_n(x)$ are estimates of the power spectra in the spatial domain of $T(\omega)$ and $N(\omega)$, respectively. Since the signals $\tilde{t}(x, x_0)$ and $\tilde{n}(x, x_0)$ are nonstationary, we assume that $x_0$ is random and uniformly distributed over the scene area. So, $P_i(x)$ and $P_n(x)$ are evaluated as averages over the random variable $x_0$. It is interesting to note that the signals $\tilde{t}(x, x_0)$ and $\tilde{n}(x, x_0)$ are converted to stationary signals by applying a statistical averaging with respect to $x_0$. Since we use the Lambertian surface model, the illumination function $u(x)$ can be estimated with the help of Eq. (12) for any $\tau$, $\gamma$, and $r$. The restored image [see Eq. (20)] is still degraded with additive nonstationary noise. Next, an optimum correlation filter for detection of a new target is designed. We are looking for a filter that yields a desired delta-function output at the position of the target, i.e., $y_d = \delta(x - x_0)$. This filter can be obtained by minimizing the mean-squared-error (MSE) [6] as follows:

$$\text{MSE} = \int_{-\infty}^{\infty} E\{(y_d(x) - y_o(x))^2\} dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h_c(\mu)h_r(\nu)C_{\tilde{t}}(\nu - \mu) d\nu d\mu$$

$$- 2 \int_{-\infty}^{\infty} h_c(\mu)\tilde{t}(\mu) d\mu$$

$$+ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h_r(\nu)N_{\tilde{n}}(\nu - \mu) C_{\tilde{n}}(\nu - \mu) d\nu d\mu$$

$$+ \int_{-\infty}^{\infty} \delta^2(x - x_0) dx,$$  \hspace{1cm} (22)

where $y_o = \tilde{t}(x) \otimes h_r(x)$ is the filter output, $h_r(x)$ is the impulse response of the optimum correlation filter, and $C_{\tilde{t}}(x)$, $C_{\tilde{n}}(x)$, and $C_{\tilde{n}}(x)$ are autocorrelation functions of $\tilde{t}(x)$, $h_r(x)$, and $\tilde{n}(x)$, respectively. The latter equation can be written in the Fourier domain as

$$\text{MSE} = \frac{1}{2\pi} \int_{-\infty}^{\infty} |H_c(\omega)|^2 S_{\tilde{t}}(\omega) d\omega$$

$$+ \frac{1}{2\pi} \int_{-\infty}^{\infty} |H_c(\omega)|^2 S_n(\omega) d\omega$$

$$- \frac{1}{\pi} \int_{-\infty}^{\infty} H_c(\omega) T(\omega) d\omega + c,$$  \hspace{1cm} (23)

where $S_{\tilde{t}}(\omega)$ and $S_n(\omega)$ are the power spectral densities of $\tilde{t}(x)$ and $\tilde{n}(x)$, respectively, and $c$ is a constant. Finally, after some manipulations the frequency response of the optimum filter is given by

$$h_r(x) = \frac{u^*(x)P_i(x)}{P_i(x)[u(x)]^2 + P_n(x)} = \frac{1}{u(x)} \frac{|u(x)|^2}{|u(x)|^2 + \Lambda(x)},$$  \hspace{1cm} (21)
where \( B_0(\omega) \) and \( N(\omega) \) are the power spectral densities of \( b_0(x) \) and \( n(x) \), respectively. The obtained filter takes into account information about nonuniform illumination by \( H_r(\omega) \). A block diagram of the proposed method is shown in Fig. 2.

5. Results

A. Computer Simulations

Here we analyze the performance of the proposed method in terms of discrimination capability (DC) and tolerance to both nonuniform illumination and input additive noise. The DC is formally defined as the ability of a filter to distinguish a target from other objects. If a target is embedded into a background that contains false objects, then the DC can be expressed as follows:

\[
DC = 1 - \frac{|C^B(0)|^2}{|C^T(0)|^2},
\]

(25)

where \( |C^B(0)|^2 \) is the intensity maximum in the correlation plane over the background area to be rejected, and \( |C^T(0)|^2 \) is the intensity maximum in the correlation plane over the target area. The target area is determined in the close vicinity of the actual target location. The background area is complementary to the target area. Negative values of the DC indicate that a tested filter fails to recognize the target.

The results obtained with the proposed method are compared with those obtained with the HCF [8], the WSONG correlation [10], the OF [5], and the homomorphic MSE filtering (HMSE). The latter method consists of a logarithmic preprocessing of an input scene followed by a linear correlation optimized with respect to the MSE criterion. If a target is embedded into a background, the input signal can be written as

\[
f(x) = [t(x-x_0) + \tilde{w}_t(x-x_0)b(x)]u(x).
\]

(26)

The model ignores additive noise. The logarithmic preprocessed scene \( f_{\log}(x) \) is written as

\[
f_{\log}(x) = \log[t(x-x_0) + b(x) \tilde{w}_t(x-x_0)] + \log u(x).
\]

(27)

Since target and background signals are mutually exclusive, then Eq. (27) can be rewritten as

\[
f_{\log}(x) = \log[t(x-x_0)] + \log[b(x) \tilde{w}_t(x-x_0)u(x)]
\]

\[= t_{\log}(x;x_0) + n_{\log}(x),
\]

(28)

where \( t_{\log}(x;x_0) = \log[t(x-x_0)] \) and \( n_{\log}(x) = \log[b(x) \tilde{w}_t(x-x_0)u(x)] \) are new target and noise functions, respectively. Finally, following the procedure described in Section 4, the frequency response of the optimum correlation filter is given by

\[
H_{\text{hmse}}(\omega) = \frac{T_{\log}(\omega)}{|T_{\log}(\omega)|^2 + S_{N_{\log}}(\omega)},
\]

(29)

where \( T_{\log}(\omega) \) and \( S_{N_{\log}}(\omega) \) are the Fourier transform of \( t_{\log}(x;x_0) \) and the power spectral density of \( n_{\log}(n) \), respectively.
respectively. The size of all gray-scale images used in our experiments is 256 × 256 pixels. The signal range is [0–255]. Figure 3(a) shows a test scene. The mean value and standard deviation of the background are 75 and 52, respectively. The target is a fish placed at unknown coordinates. The target area is about 76 × 34 pixels. The mean value and standard deviation of the target are 63 and 49, respectively. Nonuniform illumination is modeled by means of the Lambertian function given in Eq. (12) with \( \tau = 80^0 \), \( \gamma = 45^0 \), and \( r = 0.2 \). This illumination function is shown in Fig. 3(b). The observed scene is obtained from the test scene by applying the nonuniform illumination and adding a zero-mean noise with a standard deviation \( \sigma_n = 16 \). Figure 3(c) shows a nonuniformly

![Correlation intensity planes obtained with: (a) HCF, (b) WSONG, (c) HMSE, (d) OF.](image1)

---

Fig. 4. (Color online) Correlation intensity planes obtained with: (a) HCF, (b) WSONG, (c) HMSE, (d) OF.

![Preprocessed scene obtained with the proposed method.](image2)

---

Fig. 5. Preprocessed scene obtained with the proposed method.

![DC = 0.85](image3)

---

Fig. 6. (Color online) Correlation intensity plane obtained with the proposed method.
Fig. 7. Observed scenes with different levels of nonuniform illumination degradation: (a) low severity, (b) medium severity, (c) hard severity. Illumination functions used in observed scenes with: (d) low severity, (e) medium severity, (f) hard severity.

Fig. 8. Recognition performance of tested filters: (a) HMSE, (b) OF, (c) proposed method. Corresponding standard deviations obtained with: (d) HMSE, (e) OF, (f) proposed method.
are r:

\[ \alpha = \frac{C6}{C6} = \frac{8}{\alpha} \]

shows the scene degraded with a medium:

\[ \sigma = \frac{C6}{C6} = \gamma \]

show results obtained:

\[ \alpha \]

shows a

\[ \alpha \]

nonuniform illumination.

Fig. 9. Nonuniformly illuminated scene containing: (a) small target, (c) enlarged target. (b) Correlation plane profile obtained from (a). (d) Correlation plane profile obtained from (c).

| Table 1. DC Obtained with Different Illuminant Parameters Versus Real Parameters “u_{uni}”a |
|-----------------|--------|--------|--------|--------|
| Illuminant parameters | \( \sigma_n = 2 \) | \( \sigma_n = 4 \) | \( \sigma_n = 8 \) | \( \sigma_n = 16 \) |
| \( u_{uni}; \tau = 70^\circ, \alpha = 35^\circ, \gamma = 0.4 \) | 0.89 ± 0.004 | 0.87 ± 0.004 | 0.85 ± 0.004 | 0.84 ± 0.006 |
| \( \tau = 67^\circ, \alpha = 35^\circ, \gamma = 0.4 \) | 0.87 ± 0.004 | 0.85 ± 0.004 | 0.84 ± 0.005 | 0.81 ± 0.007 |
| \( \tau = 73^\circ, \alpha = 35^\circ, \gamma = 0.4 \) | 0.89 ± 0.004 | 0.86 ± 0.007 | 0.85 ± 0.006 | 0.84 ± 0.006 |
| \( \tau = 70^\circ, \alpha = 32^\circ, \gamma = 0.4 \) | 0.89 ± 0.003 | 0.86 ± 0.005 | 0.84 ± 0.006 | 0.83 ± 0.007 |
| \( \tau = 70^\circ, \alpha = 38^\circ, \gamma = 0.4 \) | 0.89 ± 0.004 | 0.88 ± 0.003 | 0.86 ± 0.005 | 0.85 ± 0.006 |
| \( \tau = 70^\circ, \alpha = 35^\circ, \gamma = 0.6 \) | 0.85 ± 0.010 | 0.84 ± 0.011 | 0.81 ± 0.014 | 0.80 ± 0.012 |
| \( \tau = 70^\circ, \alpha = 35^\circ, \gamma = 0.2 \) | 0.80 ± 0.025 | 0.75 ± 0.033 | 0.76 ± 0.029 | 0.75 ± 0.025 |
| \( \tau = 73^\circ, \alpha = 32^\circ, \gamma = 0.4 \) | 0.89 ± 0.004 | 0.86 ± 0.006 | 0.85 ± 0.007 | 0.83 ± 0.009 |
| \( \tau = 67^\circ, \alpha = 38^\circ, \gamma = 0.4 \) | 0.88 ± 0.005 | 0.86 ± 0.005 | 0.85 ± 0.006 | 0.83 ± 0.007 |
| \( \tau = 73^\circ, \alpha = 38^\circ, \gamma = 0.6 \) | 0.82 ± 0.015 | 0.80 ± 0.017 | 0.80 ± 0.019 | 0.77 ± 0.026 |

aWith 95% confidence.

be known. A preprocessed scene obtained from the observed scene by applying the pointwise restoration filtering given in Eq. (21) is shown in Fig. 5. The intensity correlation output of the optimum MSE filter in Eq. (24) is presented in Fig. 6. One may observe that the target can be easily detected. Note that recognition of a target placed in an input scene at unknown coordinates under nonuniform illumination conditions is equivalent to detection of a set of targets with different mean values and standard deviations. In other words, the signal parameters depend on the target position. Therefore, the DC of a correlation filter is a function of target coordinates. Next, we analyze the recognition performance of the HMSE, the OF, and the suggested method in the test scene when the parameters of nonuniform illumination and the standard deviation of additive noise \( \sigma_n \) are varied. The HCF and the WSONG are not considered because they yield a poor performance in noisy input scenes. Figure 7(a) shows an input scene degraded with a low severity of distortion; that is, illuminant parameters: \( \tau = \alpha = 0 \), \( r = 1.1 \) and \( \sigma_n = 1.0 \). Figure 7(b) shows the scene degraded with a medium severity, i.e., \( r = 0.4 \) and \( \sigma_n = 9.0 \). Figure 7(c) shows a hardly degraded scene with parameters of distortion: \( r = 0.1 \) and \( \sigma_n = 18.0 \). Figures 7(d)–7(f) show nonuniform illumination functions used in Figs. 7(a)–7(c). We vary \( r \) and \( \sigma_n \) while \( \tau \) and \( \alpha \) are fixed. 30 statistical trials for each varying parameter (4320 trials in total) were carried out. Figure 8 show results obtained with the tested methods. The DC values vary from black color (DC ≤ 0) to white color (DC = 1). From

Fig. 10. Optical setup used for generation of observed scene with nonuniform illumination.

illuminated and noisy input scene. Intensity correlation planes obtained with the HCM, the WSONG, the HMSE, and the OF are shown in Fig. 4. Note that the OF is able to recognize the target, whereas the other methods fail to detect the target. Next, we evaluate the recognition performance of the proposed method. The illuminant direction parameters are assumed to
Fig. 8(a) it can be seen that the black area (correlation filter fails to recognize the target) is about 39% of the total area. We see that the nonuniform illumination performs mapping of the statistical parameters from the recognition area to a failure one. Figures 8(d)–8(f) shows the standard deviations of the corresponding DC values in Figs. 8(a)–8(c), respectively. The HMSE method yields a high variation of the DC owing to a logarithmic preprocessing of a noisy input scene. The OF yields a failure area of about 7.6%. However, Fig. 8(e) shows that this method also possesses a high variability of its performance in terms of the DC. The proposed method yields the best and most robust performance with respect to the DC. In other words, the proposed method is tolerant to nonuniform illumination as well as to input additive noise.

One can also observe that after applying nonuniform illumination to an input scene, the signal inside the target area remains approximately homogeneous. Strictly speaking, this assumption is only valid when the target area is small and the illumination function is smooth. Actually, the performance of a filter under nonuniform illumination conditions deteriorates quickly when the target size enlarges. Figures 9(a) and 9(c) show input scenes containing two nonuniformly illuminated versions of the target. We see that the point light source distorts the larger target more. So, it is expected that the recognition performance of a spatially invariant operation (correlation) decreases when the size of a target increases. Figures 9(b) and 9(d) show the profile of maximum column values in the correlation plane of the OF for recognition of two versions of the target under nonuniform illumination conditions. Finally, robustness of the proposed method to variation of estimated illuminant parameters is investigated. We carried out 30 statistical trials (1200 in total) for different positions of a target and additive noise realizations with $\sigma_n = 8$, while varying the illuminant parameters: $\tau$, $\alpha$, and $r$. The results are presented in Table 1. It can be seen that the method is robust to a variation of the illumination parameters.

B. Optodigital Results

For the test scene shown in Fig. 3(a) under nonuniform illumination conditions experimental optodigital results were obtained. The observed scene was generated with the help of the optical setup shown in Fig. 10. The test scene was printed in the 2D Lambertian surface (mate paper sheet) by means of a laser printer. The point light source was located according to the parameters: $\tau = 84^0$, $\alpha = 55^0$, $r = 20$ cm with respect to the surface origin. The obtained observed scene is shown in Fig. 11(a). We estimated [2] that the standard deviation of additive white noise is $\sigma_n = 7$. The estimated illumination function is shown in Fig. 11(b). The preprocessed image is
shown in Fig. 11(c). Next, for the target detection we used the joint transform correlator (JTC) [2]. The optical setup is shown in Fig. 12. Since the frequency response of the MSE correlation filter given in Eq. (24) is a fully complex-valued function, the reference image in the spatial domain is a real-valued bipolar image. This means that the reference image cannot be directly displayed in conventional amplitude-only spatial light modulators (SLM). To overcome this problem we used the bipolar decomposition method [28]. The method requires two optical correlations and a simple postprocessing. The resultant joint input images are shown in Fig. 13. Finally, the intensity correlation plane obtained with the proposed method is shown in Fig. 14. We see that the target can be easily detected with a value of DC = 0.71.

6. Conclusions
A new method for reliable pattern recognition under nonuniform illumination conditions was presented. The method performs an optimum pointwise preprocessing in the spatial domain followed by an
optimum correlation filtering in the Fourier domain. Computer simulation results showed that the proposed method yields good results for pattern recognition under nonuniform illumination conditions, and it is robust to additive sensor’s noise. A good accordance between computer simulation and experimental results was obtained.

References