Detection theory approach to multichannel pattern location

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We propose and assess new algorithms for detecting and locating an object in multichannel images. These algorithms are optimal for additive Gaussian noise and maximize the likelihood of the observed images. We consider two cases, in which the illumination of the target and the variance of the noise in each channel are either known or unknown. We show that in the latter case the algorithm provides accurate estimates of variance and luminance. These algorithms can be viewed as postprocessed versions of the correlation of a reference with the scene image in each channel.

Multichannel information can be obtained with color images. It can also result from the fusion of visible and infrared images. In these situations one can improve the location of the object by taking into account the different data contained in each channel. Recently, multichannel recognition based on correlation techniques was developed[1−3] for color images. For example, several authors[2,4,5] have proposed using a different matched filter for each color image target. Phase-only filters[6] have also been proposed to improve optical efficiency and discrimination capabilities. Different strategies have been developed to combine this multichannel information[7,8] to detect or locate a target. The maximum-likelihood (ML) approach has already proved its efficiency for difficult optical pattern recognition problems in various situations with unknown parameters.[9,10] In Ref. 11 the optical localization of an object in a multichannel image was found for ML estimation for an object luminance the same in each channel and a known variance of the noise. Here we develop the ML optimal algorithm for the location of a target with multichannel images that have different luminance in each channel. This model is particularly interesting for multichannel images that result from the fusion of images acquired by different sensing systems. We analyze performance when the luminance and the variance of the noise in each channel are either known or unknown. In the following mathematical developments, one-dimensional notation is used for simplicity and boldface symbols denote N-dimensional vectors. Let $\mathbf{r}^l$ be the vector representation of the reference in the channel l when the object to be detected is located at pixel 0. Thus r_i^l is the value of the reference in channel l and at pixel i. In each channel l ($l = 1, \ldots P$) the luminance of the object is denoted α^l. Furthermore, the object is assumed to appear in each channel corrupted with white additive Gaussian noise b_i^l at pixel i with zero mean and variance denoted $(\sigma^l)^2$. If the object is located at pixel j we obtain the following model for the observed image $\mathbf{s}^l$ in channel l:

$$s_i^l = \alpha^l r_{i-j}^l + b_i^l \,. \tag{1}$$

Let $L(j, \bar{\alpha}, \bar{\sigma})$ denote the logarithm of the likelihood of the hypothesis that the target is located at pixel j with luminance vector $\bar{\alpha} = (\alpha^1 \ldots \alpha^P)$ and noise variance vector $\bar{\sigma} = (\sigma^1 \ldots \sigma^P)$. On the assumption that the noise is white, additive, and Gaussian, the log likelihood can be written as

$$L(j, \bar{\alpha}, \bar{\sigma}) = -\sum_{l=1}^{P}\left[\frac{1}{2(\sigma^l)^2}\sum_{i=1}^{N}(s_i^l - \alpha^l r_{i-j}^l)^2 + N \ln\left(\sqrt{2\pi}\sigma^l\right)\right]. \tag{2}$$

When the luminance factor $\bar{\alpha}$ of the object and the variance $\bar{\sigma}$ of the noise are known, it is easy to show that the ML estimate of the location j is

$$j_{\mathrm{ML}} = \arg\max_j L(j, \bar{\alpha}, \bar{\sigma}) = \arg\max_j\left[\sum_{l=1}^{P}\frac{\alpha^l C_{rs}^l(j)}{(\sigma^l)^2}\right], \tag{3}$$

where $C_{rs}^l(j) = \sum_{i=1}^{N} r_{i-j}^l s_i^l$ is the correlation function between $\mathbf{r}^l$ and $\mathbf{s}^l$ and $\arg\max_j$ stands for the value of j that maximizes the expression. The optimal detector is thus a weighted sum of the intercorrelation functions between the object and the input image in each channel with linear combination coefficients $\alpha^l/(\sigma^l)^2$. Note that, if the noise variances and the luminance terms are approximately the same in the various channels, the simple addition of the amplitude of the correlation functions is a good approximation of the ML processor.

In many situations the parameters α^l and σ^l are unknown, and it is impossible to apply the processor of Eq. (3). However, it is possible to estimate these parameters from the multichannel image itself. Indeed, a classical approach in statistics[12] considers the value of these parameters that maximizes the likelihood for each hypothesis of location j. If $\alpha_{\mathrm{ML}}^l(j)$ and $\sigma_{\mathrm{ML}}^l(j)$ are the ML estimates of these parameters in each channel, their values can be obtained by solution of the equations

$$\frac{\partial L(j, \bar{\alpha}, \bar{\sigma})}{\partial \alpha^l} = 0, \qquad \frac{\partial L(j, \bar{\alpha}, \bar{\sigma})}{\partial \sigma^l} = 0, \qquad \forall l = 1, \ldots P. \quad (4)$$

One can thus show that

$$\alpha^l_{\mathrm{ML}}(j) = \frac{C^l_{rs}(j)}{C^l_{rr}(0)}, \qquad [\sigma^l_{\mathrm{ML}}(j)]^2 = C^l_{ss}(0) - \frac{[C^l_{rs}(j)]^2}{C^l_{rr}(0)}. \quad (5)$$

With these estimates of the parameters, the log likelihood can be written as

$$L(j, \bar{\alpha}_{\mathrm{ML}}, \bar{\sigma}_{\mathrm{ML}}) = -\frac{1}{2}\sum_{l=1}^{P}\left(\ln C^l_{ss}(0) + \ln\left\{C^l_{ss}(0) - \frac{[C^l_{rs}(j)]^2}{C^l_{rr}(0)}\right\} + 1\right). \quad (6)$$

The ML estimation of the location j of the object is given by

$$j_{\mathrm{ML}} = \arg\min_j \left(\sum_{l=1}^{P} \ln\left\{[\sigma^l_{\mathrm{ML}}(j)]^2\right\}\right). \quad (7)$$

In other words, the optimal location j_{ML} is the one for which the product of the estimated variances of the noise in each channel is minimum.

Let us define the correlation coefficient $[\rho^l(j)]^2 = [C^l_{rs}(j)]^2/C^l_{rr}(0)C^l_{ss}(0)$. One can obtain the optimal location j_{ML} of the target relative to the normalized correlation plane as

$$j_{\mathrm{ML}} = \arg\min_j \left(\sum_{l=1}^{P} \ln\left\{1 - [\rho^l(j)]^2\right\}\right). \quad (8)$$

The most intensive calculation involves the determination of $\rho^l(j)$. Indeed, the calculations in Eq. (8) have linear complexity (i.e., they can be performed for each pixel independently of the others) and are less time consuming than the determination of $\rho^l(j)$. Thus the total complexity is roughly the same as for classical intercorrelation, and it may be interesting to implement this algorithm with optical correlators.

To evaluate the performance of the proposed optimal multichannel matching algorithms we describe some numerical simulation tests. We consider images with three color channels (red, green, and blue). Multichannel images are generated from a source image **r** [butterfly, Fig. 1(a)]. We generate 500 images to estimate the probability of good detection with classical processing methods (addition of amplitudes or intensity of the correlation plane) and the proposed optimal processing methods. We consider two cases: (1) $\bar{\alpha}$ and $\bar{\sigma}$ are known and the optimal location is estimated according to Eq. (3), and (2) $\bar{\alpha}$ and $\bar{\sigma}$ are unknown and the estimation is made according to Eq. (8). The results are presented as a function of the parameter $R(\mathrm{Mean}) = M(\sigma)/M(\alpha)$, where $M(\sigma)$ and $M(\alpha)$ are the mean values of σ^l and α^l, respectively. For the experiments the values of α^l are kept constant and the value of $M(\sigma)$ varies. According to Eq. (3), if the coefficients $\alpha^l/(\sigma^l)^2$ take the same values in each channel, the addition of amplitudes and the optimal algorithms yield the same results. Thus using the optimal algorithm instead of the addition of amplitudes does not provide any significant improvement. If the luminance values α^l are far apart in each channel and if the variances σ^l and the energies $C^l_{rr}(0)$ are constant or have only small variations in each channel, then the addition of intensities is better than the addition of amplitudes, as can be seen from Eqs. (3) and (5) and as illustrated in Fig. 2(a) ($\alpha^l = 1, 1, 10$; $\sigma^l = 1, 1, 1$). In Fig. 2(b) we analyze the case for which the three luminances are equal ($\alpha^l = 1$) but the noise is proportional to $\sigma^l = 10, 10, 1$, respectively. A similar result is obtained in Fig. 2(c) ($\alpha^l = 10, 10, 1$; $\sigma^l = 20, 20, 0.5$). In this case two of the three channels have higher luminance but are also noisier. In the last two examples one channel is less noisy than the two others. This disparity is taken into account automatically by the optimal algorithms [Eqs. (3) and (8)] because the least noisy channel is enhanced compared with the noisiest channels. By contrast, in the classical algorithms the three channels are equally important, and if two of them are noisy the correct location is not obtained. For instance, in the example shown in Fig. 2(b) with parameter $R(\mathrm{Mean}) = 18$, the two classical algorithms give a probability of good detection that is equal to 0.1, whereas a probability near 1 is obtained with the optimal proposed algorithms of Eqs. (3) and (8). The three channels of the noisy input scene are shown in Fig. 1(b). Thus the optimal algorithms provide better results than classical algorithms. Note that for all experiments there is no difference between the results obtained with the optimal algorithm when $\bar{\alpha}$ and $\bar{\sigma}$ are known and when $\bar{\alpha}$ and $\bar{\sigma}$ are unknown, which means that the second algorithm has estimated these parameters accurately.

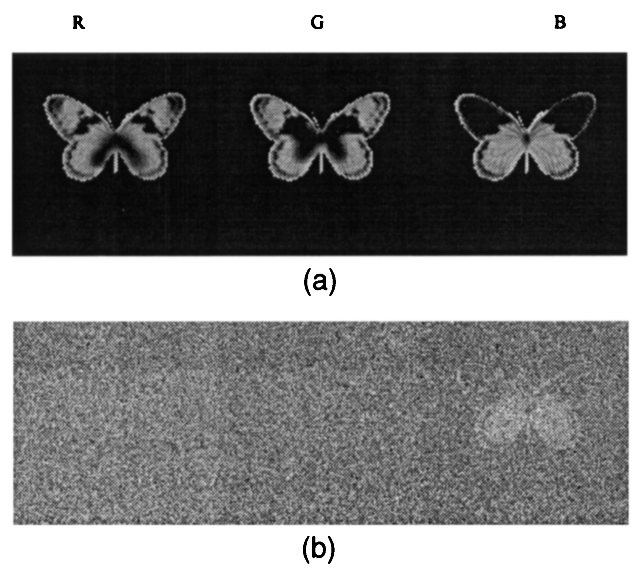

Fig. 1. Image of a butterfly used for the numerical simulations: (a) Red, green, and blue channels of the image of the butterfly used in the simulations. (b) Butterfly image corrupted by noise. $\alpha^l = (1, 1, 1)$, $\sigma^l \propto (10, 10, 1)$, $R(\mathrm{Mean}) = 5$.

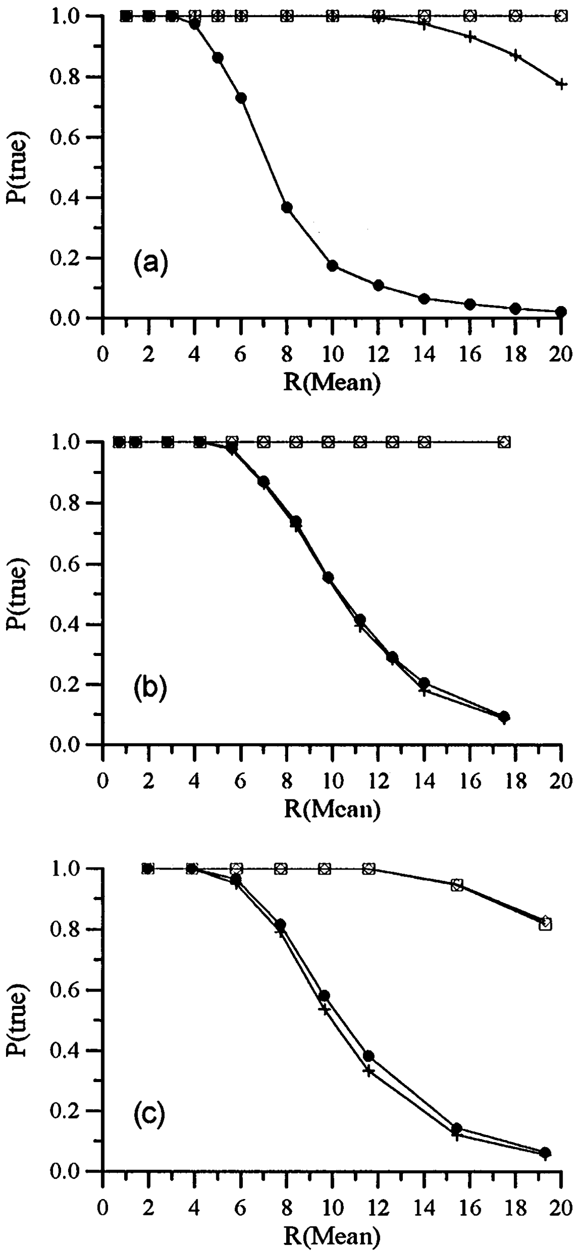

Fig. 2. Probabilities of good detection as function of $R(\text{Mean}) = M(\sigma)/M(\alpha)$ (see text). Open squares, optimal algorithm for α^l and σ^l known [Eq. (3)]; open diamonds, optimal algorithm for α^l and σ^l unknown [Eq. (8)]; filled circles, the detection made by addition of amplitudes of correlation terms in each channel; crosses, the detection made by addition of intensities of correlation terms in each channel. (a) $\alpha^l = (1, 1, 10)$, $\sigma^l \propto (1, 1, 1)$; (b) $\alpha^l = (1, 1, 1)$, $\sigma^l \propto (10, 10, 1)$; (c) $\alpha^l = (10, 10, 1)$, $\sigma^l \propto (20, 20, 0.5)$.

In this Letter we have developed a new maximum-likelihood processor for multichannel images. We have analyzed the cases in which the illumination and the power noise in each channel are known or unknown. We have shown with numerical simulations that the proposed algorithms improve performance in comparison with previous techniques. We have also demonstrated with these numerical experiments that the ML estimation of the unknown parameters is efficient for multichannel images.

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