Object Extraction in Spatially Transformed Images

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Abstract

This work is addressed to the problem of object extraction in the images distorted by spatial transformations. The solution of this problem has been obtained using the method based on the Johnson distribution parameters estimation. The simplified real-time algorithm for an object extraction was developed.

Keywords: *object extraction, spatial transform, Johnson distribution.*

1. INTRODUCTION

Object extraction is defined as a partitioning of the image into object points and background points. The quality of object extraction determines the performance of solving of high-level image analysis problems [1]. One of the most popular approaches to object extraction is an estimation of a background image and comparison of this estimation and the observed image [2], [3].

In this work the main attention is given to the problem of object extraction under the effect of the random spatial transformations of images. The main reasons of them are the error of spatial transformation parameters estimation and the athmospheric ununiformity.

The particularity of the presented approach is the using of the asymmetric thresholding.

2. PROBLEM DEFINITION AND SOLUTION

Let $g(x,y)$ be a known background image. Fix the point of the current image with coordinates (x_0, y_0) and make some definitions for this point: r – the binary parameter corresponding to the existence of the object at this point, h – the luminance of the object, l – the observable luminance, $z_x \sim N(0,\sigma_z^2)$, $z_y \sim N(0,\sigma_z^2)$ – the independent gaussian random values with the given variance defining random transformations of the image, ξ – the gaussian white noise of the image sensor: $\xi \sim N(0,\sigma_\xi^2)$.

Then the luminance of the observable image at the point (x_0, y_0) can be represented as:

$$l = g(x_0 - z_x, y_0 - z_y)(1-r) + hr + \xi . \quad (1)$$

The object luminance is assumed to be a random value with uniform distribution with boundaries $c_{\min}, c_{\max}$, $\sigma_\xi(x,y) << c_{\max} - c_{\min}$.

Thus, $g(x,y)$, l, σ_z^2, σ_ξ^2 are known. The problem is to find $\hat{r}$ to be the estimation for r.

The requirements for the estimation are defined with the Neumann-Pirson criteria:

$$P(\hat{r} = 1/r = 0) \le p_- , \ P(\hat{r} = 1/r = 1) = p_+ \to \max , \quad (2)$$

where p_- is the preliminary defined false extraction probability, p_+ is the true extraction probability.

The optimal decision rule for the problem is determined as:

$$\hat{r} = u^*(l) = \begin{cases} 1, \text{ if } \dfrac{p(l/r=1)}{p(l/r=0)} > \Lambda_0, \\ 0, \text{ otherwise,} \end{cases} \quad (3)$$

where Λ_0 is the threshold likelihood ratio, $p(l/r=1)$, $p(l/r=0)$ the probability distributions of the observable object luminance in the presence or absence of the object, respectively.

When $r=1$ the observed luminance is a composition of the variables h and ξ. Neglecting the noise ξ, $p(l/r=1)$ may be concerned as regular between $c_{\min}$ and $c_{\max}$.

Then the rule of the decision making is:

$$\hat{r} = u^*(l) = \begin{cases} 1, \text{ if } p(l/r=0) < (\Lambda_0 (c_{\max} - c_{\min}))^{-1}; \\ 0, \text{ otherwise.} \end{cases} \quad (4)$$

In order to find the conditional distribution $p(l/r=0)$ it is possible to apply the Taylor decomposition of $g(x,y)$ at the point (x_0, y_0) restricting to 2-nd order members. Then

$$l = g(x_0, y_0) + f + \xi , \quad (5)$$

where

$$f = -\frac{\partial g}{\partial x} z_x - \frac{\partial g}{\partial y} z_y + \frac{1}{2}\frac{\partial^2 g}{\partial x^2} z_x^2 + \frac{1}{2}\frac{\partial^2 g}{\partial y^2} z_y^2 + \frac{\partial^2 g}{\partial x \partial y} z_x z_y . \quad (6)$$

The analytical derivation of the distribution of (5) is impossible. In order to find the approximation of this distribution we can represent (6) as quadratic form, diagonalize it, apply known expressions for the moments of normal distribution, calculate four moments for random value l and use them for the numeric calculation of the Johnson distribution parameters [4].

Thus the rule of the decision making is:

$$\hat{r} = u^*(l) = \begin{cases} 0, \text{ if } l_{\min} < l < l_{\max}, \\ 1, \text{ otherwise,} \end{cases} \quad (7)$$

where $l_{\min}$, $l_{\max}$ are the boundaries of $(1-p_-)100\%$ confidence interval for the Johnson distribution. In general this interval is asymmetrical relatively to the background luminance value; therefore the procedure defined by (7) is named here as the asymmetric thresholding. If the luminance in the neighborhood of

(x_0, y_0) variates linearly, then the algorithm comes to the proposed algorithm [1].

If the background image and the additive noise variance are unknown, they can be estimated with use of the procedures, explained in [1]. At the same time, the estimation of the variance of geometrical distortion σ_z^2 is a problem. In practice, a good result can be achieved with $\sigma_z = 0{,}1 \div 0{,}5$.

3. THE SIMPLIFIED OBJECT EXTRACTION ALGORITHM

The algorithm given with the expression (7) has sufficiently luck in computational complexity, especially in real-time applications.

The simplified object extraction algorithm concludes in the following operations for each pixel:

1. The calculation of the difference between the luminance of the current pixel and the luminance of its neighborhood. For the point (i, j) there must be calculated:

$$d_1 = \hat{g}(i,j) - \hat{g}(i-1,j),\ d_2 = \hat{g}(i,j) - \hat{g}(i+1,j),$$
$$d_3 = \hat{g}(i,j) - \hat{g}(i,j-1),\ d_4 = \hat{g}(i,j) - \hat{g}(i,j+1), \quad (8)$$

where $\hat{g}(i,j)$ – the estimation of the background image.

2. The finding of the estimations of low and high boundaries of the confidence interval of the centered asymmetric distribution:

$$L = \sigma_z \min\{d_1, d_2, d_3, d_4, 0\},\ R = \sigma_z \max\{d_1, d_2, d_3, d_4, 0\}. \quad (9)$$

3. The finding the estimations of low and high boundaries of the confidence interval

$$\hat{l}_{\min}(i,j) = g(i,j) + \left(L - \hat{\sigma}_\xi(i,j)\right)T,$$
$$\hat{l}_{\max}(i,j) = g(i,j) + \left(R + \hat{\sigma}_\xi(i,j)\right)T, \quad (10)$$

where T – half-width of $(1 - p_-)100\%$ confidence interval for the normalized Gaussian random variable, $\hat{\sigma}_\xi(i,j)$ – the estimation of the standard deviation of the additive noise.

4. Making of the decision about the presence of the object

$$\hat{r} = u * (l(i,j)) = \begin{cases} 0, \text{ if } \hat{l}_{\min}(i,j) < l(i,j) < \hat{l}_{\max}(i,j), \\ 1, \text{ otherwise.} \end{cases} \quad (11)$$

The described algorithm has a low computational complexity and can be effectively used in real-time image processing systems.

4. EXPERIMENTAL RESEARCH

During the experimental research three algorithms was compared:

I. The algorithm without using of background uniformity ($\sigma_z = 0$ in (9)).

II. The simplified algorithm.

III. The algorithm based on the Johnson distribution.

Two video sequences (50 frames long) were selected to conduct the quantitative experimental research. The image sequences contain the moving object observed in the cross-country background. The signal-to-noise ratio is about of 10. The size of the images is 300x300. The difference between the image sequences is in the spectral band of the observation (IR and TV).

The figure 1 illustrate operating curves for the IR sequence. The result for TV sequence is similar to the result for IR sequence.

An analysis shows that the algorithm (II) allows to improve the quality of object extraction. At the same time the algorithm (III) has no disadvantages in comparison with the algorithm (II).

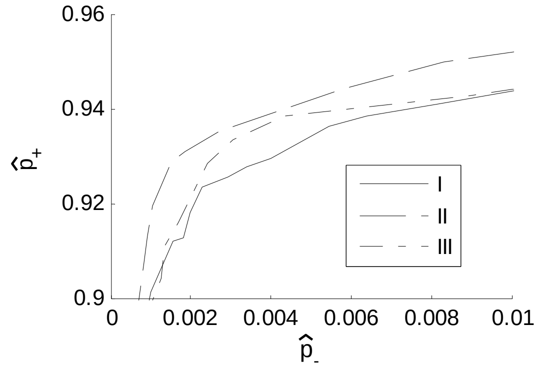

Figure 1: The operating curves for IR sequence

5. CONCLUSION

An improvement of the effectiveness of object extraction requires taking into the account the influence of spatial transforms. The research can be used to develop and enhance of real-time image processing and analysis systems. The research has been supported by the grant for the leading scientific school НШ-10.2008.10.

6. REFERENCES

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