

EMERGENCY LANDING SITE LOCATION USING AERIAL IMAGE SEGMENTATION

Tomáš Levora, Ondřej Bruna and Pavel Pačes
Czech Technical University in Prague

Keywords: *Emergency Landing, Region-Based Segmentation, Landing-Site Detection*

Abstract

This paper is focused on the aerial image segmentation for the emergency landing purposes. The goal of the described method is to segment the whole given image into homogeneous regions. This paper is split into two parts, the first one describes the algorithm for a determination of classes number and the second one describes the image segmentation method. The segmentation is based on the Expectation-Maximization algorithm for the Mixture of Gaussians with the feature vector containing pixel color and position and texture of pixel neighborhood.

1 Introduction

This work is a part of Emergency Landing Assistant, the computer-based electronic device designing at Czech Technical University in Prague [1]. The Emergency Landing Assistant is intended to support pilot of ultralight under emergency conditions.

The goal of this work is to segment aerial images to homogeneous regions. We focused on the region-based Expectation-Maximization method for the Gaussian Mixture Model. In this paper the feature vector is described and a method to determine a number of classes from the image histogram is introduced.

This work is broken down into six sections. Related works are mentioned in the section 2. Section 3 introduces a statistical model used for cluster description in the segmentation algorithm. The segmentation algorithm is summarized in section 5. Section 4 introduces initial segmen-

tation algorithm which is used for determination of number of classes. The feature vector and its variations are described in section 6. The demonstration result is illustrated in the section 7.

2 Related Works

An approach to an emergency landing site detection based on image processing is described in [2]. Authors based their research on the edge detection in the aerial images acquired by the on-board camera. A disadvantage of this method is a detection of landing sites represented by a texture containing sharp edges. This problem could be solved by a more sophisticated edge detector, e.g. a detector described in [3] is a learning edge detector in texture image data.

The emergency landing problem of Unmanned Aerial Vehicle (UAV) is described in [4]. This complex work is focused on the landing site detection using machine vision. Author compares several approaches to the aerial image segmentation and proposes a method based on the edge detection and pixel intensity measurement.

3 Model

The input image contains regions which are homogeneous with respect to its pixel color and position in the image. It means that the pixels with similar color usually belong to the same set and similarly the neighboring pixels tend to be in the same set. For all of the components in the feature vector x_m we assume normal distribution and therefore the probability distribution for the fea-

ture vector can be expressed by Gaussian (1)

$$N_k(x) = \frac{1}{|\Sigma_k|^{\frac{1}{2}} \sqrt{2\pi}} e^{-\frac{1}{2}(x-\mu_k)^T \Sigma_k^{-1} (x-\mu_k)}, \quad (1)$$

where μ_k is a mean vector and Σ_k is a covariance matrix of the normal distribution $N_k(x)$. For the all classes k we speak about the mixture of Gaussians. Gaussian mixture model (GMM) is the sum of Gaussians (2) for the all classes

$$G_{MM}(x_m) = \sum_{k=1}^n w_k N_k(x_m). \quad (2)$$

This model allows us to use Expectation-Maximization (EM) method to estimate unknown model parameters which are the mean vector μ_k , covariance matrix Σ_k and the weight w_k .

4 Initial Segmentation

The idea of the initial segmentation is to determine the number of classes in the image and the initial pixel classification for the future classification method based on a complex feature vector.

The initial segmentation algorithm is designed to be based only on the color of the image pixels. The texture and pixels position is not involved since the algorithm is tend to be as simple as possible and the quality of the segmentation is not a priority.



Fig. 1 Original Image (source: Google Maps).

As it was mentioned in the section 3, the color distribution of each class could be expressed by the Gaussian (1). A histogram of the image represents the sum of the color distributions of all the

classes, therefore the histogram is the Gaussian mixture (2) with the feature vector x_m containing the color of the image. The problem is to figure out the number of the gaussians in the histogram of a color part (figure 2). In the Algorithm 1 we propose to use peak detection in the histogram and sum the number of Gaussians for all the image color parts.

Algorithm 1 Initial Segmentation

```

1: procedure INITIALISECLASSES( $X$ )
2:    $n \leftarrow 0$ 
3:    $c \leftarrow \emptyset$ 
4:   for  $k \in \{\text{red, green, blue}\}$  do
5:      $X_C \leftarrow \text{GetImageColorPart}(X, k)$ 
6:      $h \leftarrow \text{Histogram}(X_C)$ 
7:      $h_f \leftarrow \text{ExponentialFilter}(h)$ 
8:      $\Delta h \leftarrow \text{CalculateDerivation}(h_f)$ 
9:      $z_c \leftarrow \text{CalculateZeroCrossings}(\Delta h)$ 
10:     $c \leftarrow c \cup \text{Classify}(h, z_c)$ 
11:     $n \leftarrow n + \text{CountFallingEdge}(z_c)$ 
12:   end for
13:   return  $n, c$ 
14: end procedure
    
```

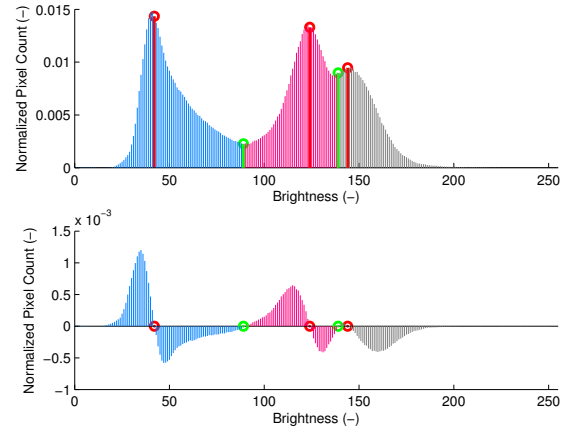


Fig. 2 Normalized Histogram Example of a Image Red Color Part with the Detected Gaussians (top), Derivation of the Histogram Example with Highlighted Zero-Crossings (bottom).

The input to the algorithm is a RGB color image X . For each color part of the image the histogram h is calculated. The second step is a

histogram filtration. In the filtered histogram h_f the derivation in each point is calculated and in this signal Δh all falling edge zero crossings are counted and stored into n . The n is a number of peaks in the histogram and as well the number of classes for the current image color part. The initial classification is done in the last step. A result of the classification is shown in the figure 2. The Histogram is split into three colored parts, each of them stands for one class. The red marks highlight local maximums and the green ones local minimums of the histogram.

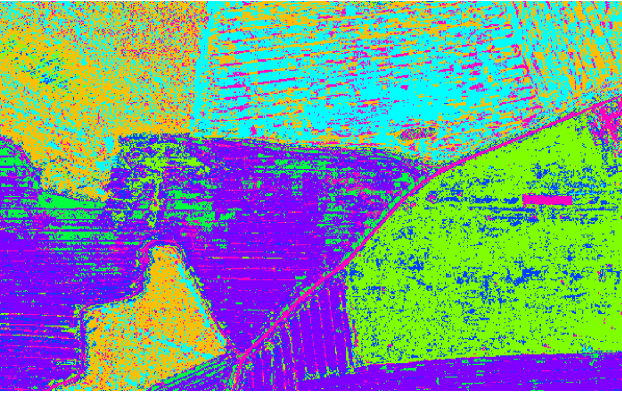


Fig. 3 Initially Segmented Image.

The result of the initial segmentation is shown in the figure 3. Each color stands for an unique class. This result is used as an initial segmentation for the segmentation method described in the section 5. The original image for all the examples in this paper is shown in the figure 1.

5 Method

In this section the method for the image segmentation is described. The method clusters given pre-processed image into the given number of classes. The number of classes and the initial segmentation could be determined by the algorithm proposed in the section 4.

5.1 Expectation-Maximization

The Expectation-Maximization (EM) algorithm was introduced in [5] and is used for an estimation of a statistical model parameters. The model

is usually expressed in a form of a probability distribution. The EM is an iterative algorithm with two steps – an Expectation (E) and a Maximization (M). E-step calculates a log-likelihood (3) using current state of estimated parameters μ_k , Σ_k and w_k . In this section the EM for the GMM is described. In the M-step algorithm estimates the parameters of the model. These parameters are estimated with a respect to maximizing the log-likelihood

$$l(X) = \sum_{x \in X} \log G_{MM}(x). \quad (3)$$

The E-step calculates conditional probability (4) of affiliation to class C_k for each random variable x_m

$$P(C_k|x_m) = \frac{w_k N_k(x_m)}{\sum_{i=1}^n w_i N_i(x_m)}. \quad (4)$$

After the E-step is done each random variable can be assigned to one class. The variable is usually assigned to the class with the highest conditional probability. The M-step then estimates new Gaussian parameters $\hat{\mu}_k$ (5), $\hat{\Sigma}_k$ (6) and \hat{w}_k (7) so that

$$\hat{\mu}_k = \frac{\sum_{m=1}^M P(C_k|x_m)x_m}{\sum_{m=1}^M P(C_k|x_m)}, \quad (5)$$

$$\hat{\Sigma}_k = \frac{\sum_{m=1}^M P(C_k|x_m)(x_m - \hat{\mu}_k)(x_m - \hat{\mu}_k)^T}{\sum_{m=1}^M P(C_k|x_m)}, \quad (6)$$

$$\hat{w}_k = \frac{1}{M} \sum_{m=1}^M P(C_k|x_m). \quad (7)$$

The algorithm is formally described in Algorithm 2.

Algorithm 2 Expectation Maximization

- 1: **procedure** EM(C_k)
 - 2: $k, w_k, x_m, \mu_k, \Sigma_k \leftarrow \text{InitSegmentation}(X)$
 - 3: **for** $t \in \{1, 2, \dots, N\}$ **do**
 - 4: $P(C_k|x_m) \leftarrow \text{GetProb}(w_k, x_m, \mu_k, \Sigma_k)$
 - 5: $\mu_k, \Sigma_k, w_k \leftarrow \text{Update}(P(C_k|x_m))$
 - 6: **end for**
 - 7: **return** $w_k, x_m, \mu_k, \Sigma_k, C_k$
 - 8: **end procedure**
-

6 Feature Vector

This section is broken down into two parts. The first one describes a motivation for the feature vector consisting of a pixel color and position. In the second part of this section the feature vector is extended by the texture description. The results are discussed in the section 7.

6.1 Color & Position

The feature vector is designed to consist of a color information in HSV color space. This color representation was selected because of its color and luminance parts which represents color in more natural way then e.g. RGB. This color representation (figure 5) gives better results than the RGB one (figure 4).

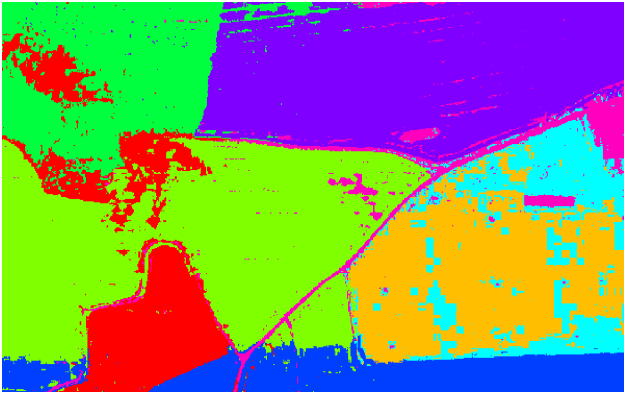


Fig. 4 Segmented Image with the RGB Color-Position Feature Vector.

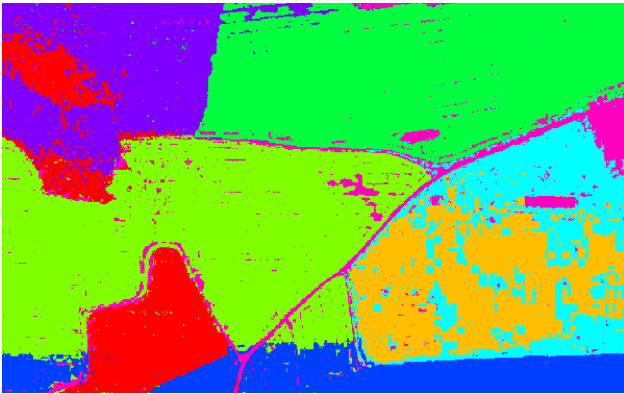


Fig. 5 Segmented Image with the HSV Color-Position Feature Vector.

In the testing data there exist a good Gaussian mixture fitting to the Saturation and Value parts of the aerial images. The pixels in each class are not homogeneous only by their color values. The feature vector contains pixel positions to improve the homogeneity of the regions. Since there is no known relationship between region shapes and their classification, we assume to append the feature vector by the pixel positions directly. This approach causes the preference of elliptic regions.

6.2 Texture

The color-position feature vector gives good segmentation for input images with color-related homogeneous areas only. As we can see in the figure 5 the regions with a texture surface like plowed up fields contain a number of small gaps. In this section the texture representation is introduced. The goal of the texture feature vector is to eliminate the number of gaps.

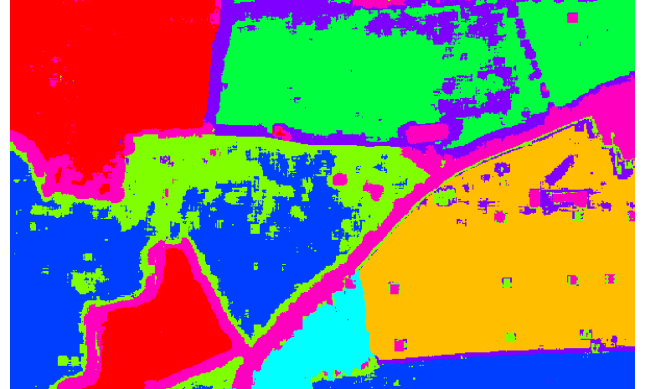


Fig. 6 Segmented Image with the HSV Color-Position-Texture Feature Vector.

The texture of each pixel is considered to be a part of an image in the pixel neighborhood. The texture describes a structure of the image color part. We propose to represent the texture in the spectral domain by the Discrete Cosine Transform (DCT) coefficients (9). The DCT for the pixel neighborhood is described in (8)

$$X_{k_1 k_2} = \sum_{i=0}^{R-1} \sum_{j=0}^{R-1} x_{ij} c_{k_1 k_2}, \quad (8)$$

where

$$c_{k_1 k_2} = \cos \left[\frac{k_1 \pi}{N} \left(i + \frac{1}{2} \right) \right] \cdot \cos \left[\frac{k_2 \pi}{M} \left(j + \frac{1}{2} \right) \right]. \quad (9)$$

The number of the DCT coefficients increases with the square of a pixel neighborhood radius. The texture size and the neighborhood radius correlation influence the segmentation results. For good segmentation results the neighborhood radius should be adjusted to the camera zoom level, camera position and the texture size.

7 Results

The algorithm was tested on satellite images of Czech Republic. The initial segmentation method gives the initial pixel class affiliation. This segmentation is usable for further region-based segmentation methods. Better results could be achieved by processing Hue part of the HSV color representation. In this paper we did not focus on the Hue processing since the RGB histograms processing is more robust and gives satisfactory results. The robustness consists in the distances between each two peaks in the histogram.

The segmentation using the feature vector without the texture description is not sufficient since the most of regions are homogeneous by its texture or contain colors with the various shades e.g. forest, plowed fields and so on. In the figure 1 we can see the texture of forest, plough field and slightly changing color of airfield. As we can see in the figure 5 the regions with a textural characteristic contain a number of of small gaps. Similar behavior will cause a noise. In this paper we compared the RGB (figure 4) and the HSV (figure 5) color models. Better results are obtained for the HSV one, however this model is not optimal for the earth surface modeling since the distance between e.g. brown and green colors is large in the model and in the real images the green color converts into brown and vice versa.

In the figure 6 we can see that the number of classes is larger than the number of expected ones. This is the main disadvantage of our approach to the problem. Knowledge of the num-

ber of classes is an important characteristic of the method. Another problem of a texture segmentation is the poor edge location, which depends on the texture neighborhood radius. For the texture-oriented segmentation should be considered a camera pitch angle. The pitch angle deviation from the top-view influences a texture distortion.

8 Summary

The image segmentation method for aerial images was described. At the first part we introduced the initial segmentation which estimates the number of classes in the image. This method is based on the RGB histograms processing. For the future we will consider the Hue (from HSV model) spectrum. The second part of this paper describes EM method application. Image segmentation using this method supports region with textures. This method brings a disadvantage which lie in the sensitivity on the given number of classes. For the future we propose to improve the algorithm in the edge detection.

References

- [1] Tomas Levora. Emergency Landing Assistent for Small Airplanes. *16th International Student Conference on Electrical Engineering*. Czech Technical University in Prague. pp 1–4. 2012.
- [2] Yu-Fei Shen, Zia-Ur Rahman, Dean Krusien-ski. A Vision-Based Automatic Safe Landing-Site Detection System. *IEEE Transactions on Aerospace and Electronic Systems*. Vol. 49, No. 1, January 2013.
- [3] Piotr Dollár, C. Lawrence Zitnick. Structured Forests for Fast Edge Detection. *International Conference on Computer Vision*. 2013.
- [4] Daniel Liam Fitzgerald. *Landing Site Selection for UAV Forced Landings Using Machine Vision*. PhD. Thesis. Brisbane Australia. 2007.
- [5] A. P. Dempster, N. M. Laird, D. B. Rubin. Maximum Likelihood from Incomplete Data via the EM Algorithm. *Journal of the Royal Statistical Society*. Vol. 39, No. 1, pp 1–38, 1977.

Contact Author Email Address

Tomáš Levora

mailto: tomas.levora@fel.cvut.cz

Ondřej Bruna

mailto: ondrej.bruna@fel.cvut.cz

Pavel Pačes

mailto: pavel.paces@fel.cvut.cz

Copyright Statement

The authors confirm that they, and/or their company or organization, hold copyright on all of the original material included in this paper. The authors also confirm that they have obtained permission, from the copyright holder of any third party material included in this paper, to publish it as part of their paper. The authors confirm that they give permission, or have obtained permission from the copyright holder of this paper, for the publication and distribution of this paper as part of the ICAS 2014 proceedings or as individual off-prints from the proceedings.