Acta Universitatis Palackianae Olomucensis. Facultas Rerum Naturalium. Mathematica

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Acta Universitatis Palackianae Olomucensis. Facultas Rerum Naturalium. Mathematica, Vol. 55 (2016), No. 1, 73–86

Persistent URL: `http://dml.cz/dmlcz/145819`

Acta Univ. Palacki. Olomuc., Fac. rer. nat.,
Mathematica **55**, 1 (2016) 73–86

Classification of Images Background Subtraction in Image Segmentation

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(Received August 21, 2015)

Abstract

Many image segmentation algorithms have been proposed to partition an image into foreground regions of interest and background regions to be ignored. These algorithms use pixel intensities to partition the image, so it should be good practice to choose an appropriate background color as different as possible from the foreground one. In the case of a unique digitizing operation the user can make the choice of background color by himself in order to obtain a good result in the segmentation process, but in the case of several digitizing operations it would be useful to automate the whole process by removing any decision of the user about the choice of background color. Furthermore modern instruments allow capturing images with a high resolution characterized by a huge number of pixels, and pose speed problems to the image segmentation algorithms based on an idea of local thresholding. In this work an approach that adapts a widely used method for detecting moving objects from a video, called background subtraction (foreground detection), to the image segmentation framework is introduced. This approach combines local and global thresholding techniques to take advantage of the computational efficiency of the former and the accuracy of the latter. It provides good results in segmentation, and allows automating the process when foreground color of images is not constant, as well as speeding it up significantly. An application to the real data concerning botanical seeds is presented in order to compare, from a statistical perspective, the results derived from the proposed approach with those provided by standard image segmentation methods.

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Key words: Image segmentation, background subtraction, foreground detection, thresholding, computational efficiency, classification trees, classification accuracy.

2010 Mathematics Subject Classification: 62H35, 62H30, 62P10

1 Introduction

During the last years, one of the most important goals for botanists is to raise the alarm about the loss of plant diversity, and to try to remedy in some way to this disaster. In order to achieve the latter goal, they can apply two strategies: *In situ* and *ex situ* plant conservation. Applying an *in situ* conservation means to protect threatened plant species in their natural habitat, that is going to natural habitat of plants and performing several operations for saving them such as to plant new plants and to build protections for avoiding damages by wild animals. On the other hand, *ex situ* conservation is about all protections that can be applied outside plant species natural habitat, for instance to plant threatened species in botanical gardens. Despite the *in situ* conservation strategy is considered the best one, it is difficult to follow it because its cost, inasmuch its measures are much more expensive than *ex situ* ones. That is the main reason because the latter conservation strategies is nowadays the most applied. Among all *ex situ* methods, the most effective is to preserve the genetical material of endangered plants in germplasm banks. The simplest way to do that is to store their seeds in seed banks. This strategy allows to save large amounts of genetic material in a small space and with minimum risk of genetic damage. A consequence of the adoption of this strategy is that the number of seeds gathered is rapidly raising day by day. As a result more attention has been focused on classification of accessions in entry. Despite manual classification is labor-intensive, subjective, and suffers from inconsistencies and errors, it is still a common practice. For those reasons, the need of defining statistical classification rules for seeds classification is day by day more valued. This work is a part of a larger project, which aim is to provide an automated, consistent, and efficient method of morphological classification of seeds through extracting information directly from their digital images.

The concept of image is quite clear to everybody, because we deal with it everyday. In mathematics, it can be modeled by a continuous function of two variables $f(x, y)$ where (x, y) are coordinates in a plane (see, among others, Shapiro and Stockman, 2001). If image is greyscale then $f(x, y) \to [0, 1]$ is a scalar function, whereas if image is expressed in color mode its dimension is three or four. The Red-Green-Blue (RGB) is a very common image color mode, in which the value of a particular color is expressed as a vector of three elements, i.e. $f(x, y) \to (R_i, G_i, B_i)$ where $(R_i, G_i, B_i) \in [0, 1]^3$ and represent intensity of the red, green and blue color channel, whereas $i \equiv (x, y)$ indicates pixel (Hunt, 2004).

To extract information contained in images for further statistical analyses, it is necessary to transform them into inputs for statistical methods to be used. This operation, called image processing, is very important because all results can be strongly influenced by the data input accuracy. Image segmentation is one of the most important phases concerning that operation. Its main goal is to divide an image into parts that are strongly associated to real objects or areas contained in the image. Binary image segmentation is a specific case of image segmentation field. It is applied when image consists of contrasted objects located on a uniform background and the aim is to separate foreground from background. Although object recognition is trivial (almost always) to human vision, it is still one of the most challenging problems in image processing, image understanding and artificial intelligence (Chan & Shen, 2005).

It is useful to introduce a distinction between images where the background is unchangeable, such as a landscape taken by a camera, and those where it is changeable, such as a scanning. From the point of view of image processing, the main difference is that in the first case it is not possible to change any information conveyed by the image, whereas in the second one it can be modified to accomplish some specific goals. In fact, it would be useful to choose a background with a color that allows us to create a more substantial contrast between background and foreground to simplify segmentation process. In spite of that, a problem for automating the whole process can appear if foreground color "switches" between images.

In this paper we present a process that takes advantages of background changeability enabling automating and improving the quality of image segmentation. It is based on an approach that adapts a widely used method for detecting moving objects from a video, called background subtraction (foreground detection), to the image segmentation framework. Background subtraction combines local and global thresholding techniques to take advantage of the computational efficiency of the former and of the accuracy of the latter. It is shown that it provides good results in segmentation, and allows to automate the image segmentation process when foreground color of images is not constant, as well as to speed it up significantly.

An application on real data concerning botanical seeds is presented to compare, from a statistical perspective, the results derived from the proposed approach with those provided by standard image segmentation methods. More precisely, we assume that the separation of background pixels from foreground ones operated by a segmentation method needs to be further validated since, particularly for pixels located on the borders of a seed, it is very difficult to distinguish between the two categories even by a human eye or by powerful zooming. In this respect, the idea is to use a classification method, or classifier, in order to assess the degree of reliability of the separation between background and foreground pixels obtained from a standard segmentation image method.

To this end, we considered seeds of *Ferula communis* with the specific goal of increasing the complexity of the image segmentation process, since they present non-homogeneous pixel intensity. The comparison is made by evaluating, through the use of classification trees, the accuracy of an image segmentation processes. The statistical analysis involves six different settings in which the black background, the white background and the background subtraction are, in turn, considered as the reference pre-processing method in the image segmentation process and the approaches proposed by Otsu and by Savuola are used for image segmentation for each pre-processing method. In each setting the response variable is binary and corresponds, for each individual pixel, to the background/foreground assignment deriving from a specific segmentation method. The classification task is to ask a classifier to predict in the most accurate way the pixel category on the basis of the RGB intensities deriving form a specific pre-processing method. If a classifier is able to correctly predict all the available pixels, the relative segmentation method is 100% reliable. Thus, the more accurate is a classifier the more reliable is the pre-processing method at hand. The classification experiment was made with respect to a complex predictive setting, since a random sample of size 0.05 was used as training set and the rest of the data (0.95) was used as test set. An index expressing? the coherence of the classification outcomes evaluated as the degree of equivalence between the pre-processing method used before performing image segmentation (input image) and the method defining the origin of the RGB intensities is also proposed. The results of the classification experiment show that when the input of the image segmentation process is an image processed with background subtraction then the classier shows the highest level of accuracy. In this respect, background subtraction can be seen as the most reliable pre-processing method in image segmentation.

The rest of the paper is organized as follows. Section 2 introduces the background subtraction method and Section 3 discusses the basics of standard thresholding techniques. The problem of segmenting images of botanical seeds is presented in Section 4 and, based on this data set, a classification experiment is carried on to validate, from a statistical perspective, the results of the image segmentation process for each method. Section 5 reports the results of the classification experiment. Finally, Section 6 contains concluding remarks.

2 Background subtraction

All information available for the image segmentation process is usually held in a single image, but this information is often not sufficient to provide good segmentation output. In fact, it is possible that objects convey in them different information, which makes segmentation difficult even if background can be chosen freely. An example how an object can convey non-homogeneous information is shown in Figure 1. It refers to a seed whose color on the left part is bright, whereas that in the right part is much darker. This means that on the left part the pixel intensity values are higher than those on the right. This increases the complexity of the image segmentation process, since it separates foreground from background as a function of a thresholding value of pixel intensities. Consequently, if foreground objects present in them both low and high intensity values, and background middle ones, it is difficult to find a threshold value capable to separate background from the foreground.

Figure 1: Example of different information (i.e. pixel intensities) conveyed by objects

To be able to solve this problem, more information is needed. New information can be obtained by adding to the segmentation process an additional image having the same foreground but different background compared to the original one. In the literature it is not common to carry out this process using two images that differentiate themselves just for background because, due to time and memory storage issues, the image to analyze is just one. Despite that, nowadays memory storage capacity is increasing day by day, whereas the problem of time analysis is relative because it depends on the situation at hand.

Our approach to the image segmentation is based on the following idea. Since we want to take advantages of difference between the two backgrounds, it is in our opinion useful to enlarge that difference by choosing white and black as background colors of the two, otherwise identical, images. In order to use information added by the second image, it is possible to apply an approach resembling to background subtraction, being an approach widely used for detecting moving objects from a video. It consists of subtracting each image that arranges the video to its background image, i.e., an image with no moving objects (Piccardi, 2004). In image subtraction the absolute difference between pixel intensities of the first image to those of the second one is performed. As a result, non-zero differences represents a moving objects. Whereas in background subtraction what changes in images is foreground (i.e. objects), here it is the contrary: what changes is background. Therefore, if subtraction is applied before segmentation process to the two images which differ just in the background, non-zero differences will represent background instead of foreground, and vice versa for the zero ones. If an image is taken twice, usually it is very hard to have the pixel intensity values of the first image identical to the correspondent ones of the second image, because some little changes in lighting often occur. As a result, it is very likely that the absolute difference between foreground pixels of the two images will assume tiny non-zero values. However, it is anyway possible to distinguish between background and foreground. In fact we know that background changes from white to black, i.e. from high (close to 1) to low (close to 0) intensity values, so that their absolute difference will provide values with high intensity. Instead, foreground absolute difference will provide values close to zero. This situation is a perfect starting point of the image segmentation process, because the difference between background and foreground pixel intensities are now more pronounced then that considering one image only.

3 Thresholding techniques

In the literature there were suggested several image segmentation techniques. Despite that, there does not exists a single method that can be recommended as the preferable one for all types of images (Munoz et al., 2003, and Padmavathi et al., 2010). Therefore, let us recall several approaches that might be suitable for our problem.

Grey level thresholding is one of the most commonly used techniques for image segmentation. Thresholding can be interpreted as the transformation of a grey level image f into a binary image $o(\cdot,\cdot)$, i.e.

$$o(x,y) = \begin{cases} 0 & \text{for } f(x,y) < T \\ 1 & \text{for } f(x,y) \geq T \end{cases} \tag{1}$$

where T is the threshold value; $o(x,y) = 1$ stands for foreground pixels and $o(x,y) = 0$ stands for background pixels (Šonka et al., 2014). The main critical task of this method is to select a correct threshold, which is essential for a successful segmentation. In this technique it is possible to use global or local information, and as a consequence to distinguish between global and local thresholding. Global thresholding consists in finding a single threshold value for the whole image. Concerning the local thresholding, it is characterized by calculating a threshold value $t(x,y)$ for each pixel using the information about neighboring pixels.

Badekas & Papamarkos (2005) studied seven binarization algorithms, and found the Otsu's approach (Otsu, 1979) and the Sauvola's approach (Sauvola & Pietikäinen, 2000) as the two best performing ones.

3.1 Otsu's approach

Otsu suggested to calculate global threshold value T after analyzing the grey level distribution between the two classes, indicated in following text by letters F (foreground) and B (background). Let us assume that the image is represented using L grey levels $\{0,1,\ldots,L-1\}$, denote by n_k number of pixels with grey level k and put $N = \sum_k n_k$. Then we can describe the probability distribution of grey levels as $\{k, p_k\}_{k=0}^{L-1}$ with $p_k = n_k/N$, and to calculate for a fixed value T, $0 < T < L$, probability that a pixel belongs to foreground (F) or background (B) class as

$$\pi_F = \sum_{k=0}^{T} p_k \quad \text{and} \quad \pi_B = \sum_{k=T+1}^{L-1} p_k. \tag{2}$$

Now it is possible to calculate means and variances of the grey level of each class and of the whole image as

$$m_F = \sum_{k=0}^{T} kp_k, \quad m_B = \sum_{k=T+1}^{L-1} kp_k \quad \text{and} \quad m = \pi_F m_F + \pi_B v m_B, \tag{3}$$

$$\sigma_F^2 = \sum_{k=0}^{T} \left(k - m_F\right)^2 p_k \quad \text{and} \quad \sigma_B^2 = \sum_{k=T+1}^{L-1} \left(k - m_B\right)^2 p_k. \tag{4}$$

From here we get for a fixed value of T the between and within variances as

$$\sigma_{between}^2(T) = \pi_F(m_F - m)^2 + \pi_B(m_B - m)^2 \text{ and } \sigma_{within}^2(T) = \pi_F\sigma_F^2 + \pi_B\sigma_B^2. \tag{5}$$

Finally, searched threshold value of T is obtained by maximizing

$$\eta(T) = \frac{\sigma_{between}^2(T)}{\sigma_{within}^2(T)}, \quad \text{i.e.} \quad T = \underset{0<T<L}{\arg\max}\ \eta(T). \tag{6}$$

3.2 Sauvola's approach

The Sauvola's method, instead, calculates $t(x, y)$ using the mean $m(x, y)$ and standard deviation $s(x, y)$ of intensity values included in a $(2W + 1) \times (2W + 1)$ window centered in the pixel (x, y), i.e.

$$t(x, y) = m(x, y) \left[1 + \alpha \left(\frac{s(x, y)}{Q} - 1\right)\right], \tag{7}$$

where $Q = \max_{x,y}\ s(x, y)$ and α is a parameter which takes positive values and controls the value of the threshold in the local window. Badekas & Papamarkos (2005) suggested to use α in the range $[0.2, 0.5]$, $\alpha = 0.34$ gave the best results in their study.

Main shortcoming of Sauvola's algorithm is its high computational complexity. In fact, naive computing of $m(x, y)$ and $s(x, y)$ produces a computational complexity of $O(W^2N^2)$ for an $N \times N$ image and a $W \times W$ window. A solution has been proposed by Shafait et al. (2008), who suggested to compute $m(x, y)$ and $s(x, y)$ using so called integral images introduced already by Crow (1984). An integral image of an input image f is defined as the image in which the intensity at a pixel position is equal to the sum of the intensities of all the pixels above and to the left of that position in the original image, inclusive of the pixel itself. Thus, the integral intensity at position (x, y) can be written as

$$I(x,y) = \sum_{i=1}^{x} \sum_{j=1}^{y} f(i,j). \tag{8}$$

From (8) it is possible to compute efficiently both $m(x, y)$ and $s(x, y)$ using the fact that

$$\begin{aligned} m(x,y) = \Big(& I\left(x+w, y+w\right) + I\left(x-w, y-w\right) \\ & - I\left(x+w, y-w\right) - I\left(x-w, y+w\right)\Big)/w^2, \end{aligned} \tag{9}$$

and

$$s^2(x,y) = \frac{1}{(2w+1)^2} \sum_{i=x-w}^{x+w} \sum_{j=y-w}^{y+w} f^2(i,j) - m^2(x,y). \tag{10}$$

An important hint from implementation point of view is that the values of the squared integral image get very large, so overflow problems might occur if 32-bit integers are used. Once computed the integral image of the pixel intensities and the square of the pixel intensities, local means and variances can be computed very efficiently, independent of the local window size. Notice that the computational complexity decreases from $O(W^2N^2)$ to $O(N^2)$.

4 Segmentation of images of botanical seeds

In this section a comparison between the background subtraction approach and the standard methods is presented. Let us start defining the input of the segmentation process. The first task is the definition of the objects, i.e. the foreground. To increase complexity of the image segmentation process, we consider six seeds characterized by different inner pixel intensities. They have been scanned twice using a black and a white background, as shown in the top-left and the top-middle images in Table 1. Next, the absolute difference between the pixel intensities of these two images is calculated. The result of this procedure is a new "artificial" image, where foreground pixels have values close to zero and background ones close to 1 (image in the top-right corner of Table 1). To evaluate the background subtraction approach, we decided to compare its output to those obtained from a standard image segmentation approach, i.e. using a single image as input. In other words, the segmentation process has been repeated three times:

1. Using as input the image obtained from the background subtraction procedure.
2. Using the black background of the image.
3. Using the white background of the image.

Finally, to compare the differences in using both local and global thresholding approach, the three segmentation processes have been run applying both Sauvola's method and Otsu's method.

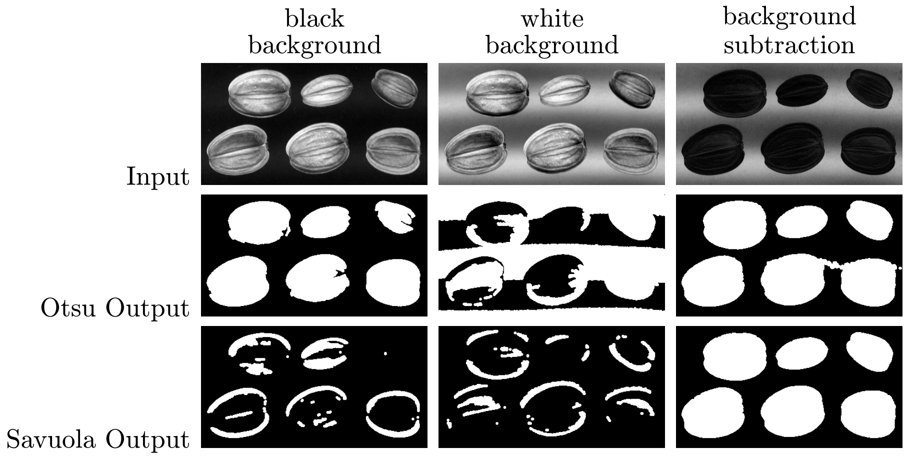

Table 1: Nine figures, arranged in a matrix 3×3, show different combinations achieved by applying two different segmentation approaches to three different input images. In the first row, the input images are placed, whereas in the last two rows the outputs achieved by applying, respectively, the methods of Otsu and Sauvola are shown. Looking at the table column by column allows to compare results for different input image, i.e. the black background one (first column), the white background one (second column) and the background subtraction (third column).

The results of the segmentation processes are illustrated in the second and third row of Table 1, where binary images show the foreground objects identified by each method. It appears out that application of the background subtraction operation provides the best results for both Otsu's and Sauvola's method, but it is simple to note that the best one is achieved by the local method.

Since the output obtained using the Sauvola's method on background subtraction image (image in the bottom-right part of Table 1) can be clearly considered as the best one, it would be interesting to measure how much the other outputs are similar to it. To do that, we calculated how many pixels have been classified in the same way. The worst results are achieved when using the white background as input image. Only the 44.65 % and 59.38 % of image pixels have been classified, respectively for Otsu's and Sauvola's methods, as the best output. Inefficiency is due to the similarity between intensity of seed color and background, and to the presence of shadows that obstructs a correct definition of the thresholds. A better result is achieved by using the black background as input image. Here, the percentages of pixels classified as the best output go up to 95.58 % and 68.44 %, respectively for Otsu's and Sauvola's method. The main reason is the stronger contrast between seed color and background. In this case we notice that a global threshold method works better than the local one, in contrast with what has been observed in the white background situation. The reason is that global approaches suffer a lot from the presence of shadows, inasmuch just one threshold value is calculated for all pixels.

5 Validation of the output produced by the image segmentation procedures

In this section we describe a classification experiment allowing to assess whether a classifier is able to validate the results provided by a segmentation method. The basic idea motivating this experiment is the following, i.e., the classification of single pixels into a background or foreground category obtained from described segmentation method is used as (binary) response variable by a classifier and observations (pixels) are classified into one of the two categories on the basis of the RGB intensities. A good performance of the classifier is an indication of reliability of the image segmentation procedure used.

To accomplish this goal, *decision trees* implementing the FAST algorithm suggested by Mola and Siciliano (1992) are used as classifiers. Decision trees are generally considered as powerful tools enabling to extract meaning patterns from a data with records characterized by a dependent variable and a set of explanatory variables. Decision tree algorithms are simple. Typically they split recursively the feature space, i.e., the space defined by the predictors, into non overlaping regions. Corresponding splits usually correspond to one of the predictors at each time. For a detailed description of decision trees see, e.g., Hastie et al. (2009).

To run the validation experiment, we split the original data (91,052 pixels) into a training set and a test set. The training set is composed of 5 % randomly selected pixels from the original image. Such a low value was chosen to increase the complexity of the classification experiment and, in this way, to further validate the effectiveness of the segmentation method.

The validation experiment involves six alternative settings described in the following text. For each of them we consider the pixels as background or foreground, taking into account individually the output of the segmentation methods presented in Section 4 and reported in the first column of Table 2, where the borders of foreground objects are projected in green into the respective original RGB images. Schematically, the features of the different experimental settings are described from the second to the fourth column of Table 3. For example, in the first experimental setting the input image is the one presenting a black background, cf. Table 2, 1st row and 1st column, which is segmented by applying the Savuola's method. The output of this segmentation process, i.e., the classification into background or foreground categories obtained for each pixel, allows to define the response variable of the classification experiment which is run by using, in turn, the RGB intensities deriving by the black background, the white background and the background subtraction method applied on the same image.

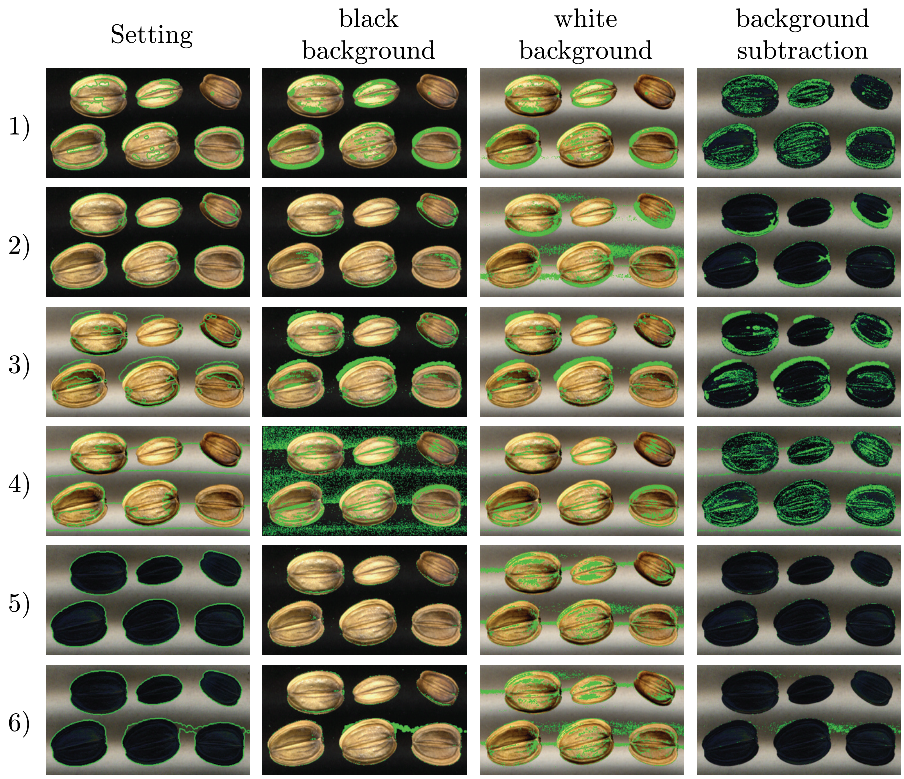

Table 2: 24 figures, arranged in a matrix 6×4, show the different predictions achieved by applying classification trees algorithm to the three different input images. In the first column six possible settings are shown.They correspond to the six possible ways considering pixels as background or foreground, originated from the results of the segmentation processes run in Section 4, where the borders of foreground objects are projected in green into the original RGB images. In Setting 1 are shown result of the segmentation process using as input black background image and Sauvola's approach. In Setting 2 the black background image and Otsu's method are considered, while in Setting 3 white background image and Sauvola's method are depicted. Setting 4 covers white background of the image and Otsu's method. Finally, Setting 5 contains background subtraction of the image and Sauvola's method, respectively Setting 6 background subtraction of the image and Otsu's method. Other columns show the graphical output of the predictions, where the green points represent the misclassified pixels.

Setting	Input image	Method	Origin of RGB intensities	Error rate (%)	Coherence
1	black background	Savuola	black background	9.69	(−)
			white background	9.40	
			background subtraction	11.38	
2	black background	Otsu	black background	3.14	(+)
			white background	9.81	
			background subtraction	4.32	
3	white background	Savuola	black background	8.58	(+)
			white background	7.42	
			background subtraction	10.15	
4	white background	Otsu	black background	20.52	(+)
			white background	6.74	
			background subtraction	14.62	
5	background subtraction	Savuola	black background	11.40	(++)
			white background	8.70	
			background subtraction	**0.53**	
6	background subtraction	Otsu	black background	2.16	(++)
			white background	9.05	
			background subtraction	**0.98**	

Table 3: Settings and results of the validation experiments

Thus, for each setting we have three classification experiments, so that the total number of experiments is 18. A classification tree is grown for each experiment on the training data and a final tree is selected through pruning with 10-fold cross-validation. Next, the pruned tree is used to predict the response class (background or foreground) for test set observations. The fifth column of Table 3 reports the error rates on test set observations produced by each pruned classification tree in each experiment. The same results are shown graphically in Table 2, from the second to the third column. Here, the green points in each image represent the misclassified pixels.

The results of the classification experiments should be analyzed from a twofold perspective. First, it is natural to assume that in each setting the best classification is the one obtained when the origin of the RGB intensities and the input image are the same. This means, for example, that in the first setting we expect that the minimum error rate is the one obtained when using the RGB intensities derived from the black background image since the latter is the image processed, in this setting, with the Savuola's segmentation method. The second perspective involves the investigation of the best performing classification tree, to understand in which experiment the classification tree is able to classify better the two categories of the response variable on the basis of the RGB intensities and, consequently, to validate the outcome of a segmentation method. In this respect Table 3 clearly shows that the lowest values of the error rate are those obtained when the input image is the one pre-processed with the background subtraction and the RGB intensities are those obtained from the same method.

When simultaneously considering both the above mentioned perspectives, a coherence index is used in the last column of Table 3. This index is equivalent to a rating indicator with three possible categories. The first category is (−) which refers to a situation in which there is no equivalence between the pre-processing method used before performing image segmentation (input image) and the method defining the origin of the RGB intensities. This is the case of the first setting, where it was expected that the origin of the RGB intensities deriving from the black background method leads to the best performing classification tree but the best result is achieved in the case of white background. The second category of the coherence index, denoted (+), indicates equivalence between the pre-processing method and the origin of the RGB intensities. This is the case of Settings 2–4, where such an equivalence exists. The third category of coherence, denoted (++), refers to a situation in which the pre-processing method corresponds to the origin of the RGB intensities (similar to the (+) case) but, at the same time, the lowest error rate (best performing classification tree) is less than half with respect to the error rate produced by the second best classification tree: this is the case of Settings 5 and 6 where background subtraction method provides an error rate which is less than half if compared to the one deriving from the white background method (Setting 5) and the black background one (Setting 6).

6 Conclusions

The background subtraction approach provided the best results in terms of the quality of segmentation both for Otsu's method and Sauvola's method. In the segmentation of images involving botanical seeds, the main problem occurred with a single images having on input shadows and non-homogeneous intensity values of foreground pixels. Both problems have been overcome by the background subtraction approach.

Another important result achievable by the background subtraction is the possibility of automatization of the whole segmentation process. Indeed, the absolute difference between the pixel intensities of images with the same foreground allows to obtain a new "artificial" images characterized by tiny non-zero values in correspondence of foreground pixels, independently from original values of foreground pixels. If we use background subtraction approach choosing as background colors of the two images white and black, we can expect to obtain a good result similarly as in the examples presented above and independently from the foreground pixel intensity values and their inner homogeneity.

Acknowledgements The work was supported by the Regione Autonoma della Sardegna under the Grant "Pacchetti Integrati di Agevolazione Industria, Artigianato e Servizi", PIA – 2013 No. 282/13. The work of Jaromír Antoch was also partially supported by the Czech Science Foundation under

Grant No. P403/15/09663S. Support from the BELSPO IAP P7/06 StUDyS network is also prominently acknowledged.

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