Automatic Selection of Color Channels for Segmentation of Aerial Images with Photometric Variations

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Abstract

The choice of a color model is of great importance for aerial image segmentation algorithms. However, there are many color models available; the inherent difficulty is how to automatically select a single color model or, alternatively, a subset of features from several color models producing the best result for a particular task. To achieve proper colors components selection, in this paper, it was proposed the use of wrapper method, a data mining approach, to perform the segmentation process. The result yields good feature discrimination. The method was verified experimentally with 108 images from Amsterdam Library of Objects Images (ALOI) and 97 aerial images with different photometric conditions. Furthermore, it has shown that the color model selection scheme provides repeatability and distinctiveness for aerial segmentation.

1. Introduction

The choice of color systems is of great importance for the purpose of some computer vision algorithms. Stokman and Gevers [10] discussed that no color space can be considered as universal because color can be interpreted and modeled in different ways. To this end, it is possible that several color spaces are equally good candidates or that different color channels have similar properties. So, the color channels selection for image segmentation is an important task. Color systems have been developed for different purposes, such as, display process (RGB), color uncorrelation (I1I2I3), perceptual uniformity (L*a*b*), intuitive description (HSV) and others. And in fact, by [14] different adaptive methods, principal component analysis (PCA) and independent component analysis (ICA), have been also applied to generate basis functions that have correspondence to human visual perception and could be used as color system for segmentation.

For aerial image segmentation, especially for crop analysis, the inevitable question arise which color system to use. As those aerial images are recorded by different cameras, Gevers [1] proposed that the color system needed to be independent of the underlying imaging device. Another requirement presented is that the color system should exhibit perceptual uniformity as different image regions patterns should be visually similar. Also, Gevers [1] proposed that the color system should be composed of color models which are understandable and intuitive to the user and to achieve robust and that discriminative image patterns color invariance is an important criterion.

Further, Gevers [1] suggested that a proper computer vision application should be robust to imaging conditions discounting the disturbing influences caused by different viewpoints, object poses or illumination. The same object from different viewpoints will yield different shadowing, shading and highlighting color.

The selection and fusion of color models was proposed first by Stokman and Gevers [10], but using another approach where weights were selected to combine color components and models. Instead of fusion, in this paper, the aim was selecting a subset of color components using data mining approach. Feature selection has been used in computer vision where one or more visual features are chosen from a given initial set of candidates. In this paper, the features used were color channels commonly encountered in color image processing. In spite of that, there are others approaches that try to apply feature extraction from color images, as proposed by [15] but not using color channels.

Based on the notion of class separability, several methods have been proposed to select the feature subset [8]. Therefore, in this paper, to achieve proper color component selection, it was introduced the wrapper method described by [5], [6] e [7] using training samples. Some examples of wrapper application in segmentation and classification can be observed in [11] and [12].

The idea was selecting stable color components under varying viewing conditions, such as illumination, shading, highlights, and they should have high discriminative power. Stokman and Gevers [9], [10] have been shown that there exists a trade-off between color invariant models and their discriminative power. For this particular aerial segmentation task that assumes only the sun light, color models should be selected, which are invariant to this light source resulting in an augmentation of the discriminative power of the algorithm.

The paper is organized as follows: in Section 2, sample images sets are presented. In Section 3, it is described the wrapper method and Weka workbench. In Section 4, the experiments are described and the results and discussions are presented in Section 5. Finally, the conclusions are given in Section 6.

2. Sample Image Set

The obtained sample sets are referred to set I and set II:

Set I: 108 color images with 192x144 pixels of object 25 from Amsterdam Library of Objects Images (ALOI) [2]. The conditions of changing viewpoint, object pose and illumination were considered. Examples images can be observed in Figure 1.

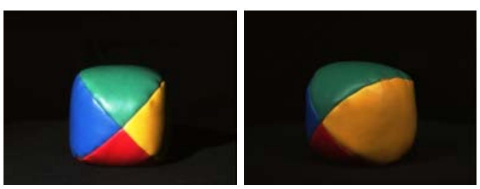

Figure 1: Object 25 from ALOI, changing viewpoint, object pose, and illumination

Set II: 97 color aerial images with 372x248 pixels acquired from different photometric conditions. Examples images taken from citrus and corn crops at 100 meters high and at different conditions of illumination and viewpoint are presented in Figure 2.

Figure 2: Aerial images samples

3. Wrapper Method

In supervised learning, feature selection is often viewed as a search problem in a space of feature subsets. To carry out this search it is necessary to specify a starting point, a strategy to cross the space of subsets, an evaluation function and a stopping criterion. Although this formulation allows a variety of solutions to be developed, usually two families of methods are considered. On one hand, filter methods use an evaluation function that relies solely on properties of the data, thus is independent on any particular learning algorithm. On the other hand, wrapper methods use the inductive algorithm to estimate the value of a given subset [6]. An induction algorithm is typically presented with a set of training instances, where each instance is described by a vector of features or attributes values and a class label. The task of the induction algorithm (inducer) is to induce from training data a classifier that will be useful in classifying future cases. The classifier is a mapping from the space of feature values to the set of class values. In the feature subset selection problems, a learning algorithm is faced with the problem of selecting some subset of features upon which to focus its attention, while ignoring the rest. The idea behind the wrapper approach [5], shown in Figure 3, is simple: the induction algorithm is used as a black box. For each selected feature subset during the search process, one classifier is created by the learning algorithm. Typically, the accuracy of this classifier is used evaluate the feature subset efficiency. Therefore, the selected subset is relevant to the learning task and the algorithm [6].

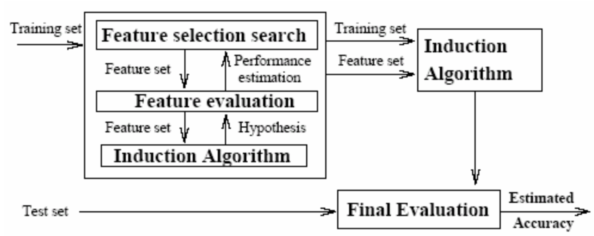

Figure 3: The wrapper approach to feature subset selection [6]

Practical machine learning algorithms i.e. decision tree algorithms such as C4.5 [5], [4] and instance based algorithms such as IBL [5] have shown lower classification performance when induced from sets with a lot of irrelevant features. Thus, the feature subset selection can improve the accuracy of classifiers induced by the same algorithm used in wrapper method.

In practical learning scenarios, however, it is faced with two problems. First, the learning algorithms are usually given a relatively small training set. Second, even quite similar algorithms may incorporate different heuristics to aid in quickly building models of the training data finding the smallest model consistent

Since C4.5 is an algorithm that performs well on a variety of real databases, it is might expected to be difficult to improve upon its performance using feature selection.

Wrapper methods are widely recognized as a superior alternative in supervised learning problems, since by employing the inductive algorithm to evaluate alternatives they have into account the particular biases of the algorithm. However, even for algorithms that exhibits a moderate complexity, the number of executions that the search process requires results in a high computational cost, especially as it is possible to shift to more exhaustive search strategies.

In this work, it was used wrapper with an exhaustive search by C4.5 algorithm.

4. Experiments

For all experiments described in this section, the RGB images were transformed into the following color channels: HSV, CIE L*a*b*, $I_1I_2I_3$ [1]. All 12 color components were used in the experiments.

These models were selected as they are commonly encountered in color image processing. Further, these color models contain both variant and invariant properties with regard to the imaging conditions. Stokman and Gevers [1] had shown that the components RGB, CIE L*, and SV are all sensitive to shadows, shading, illumination, and highlights. Further, CIE a*b* are invariant to shadows, shading, and illumination intensity.

As these color channels provide both repeatability (CIE a*b*), and distinctiveness (RGB, CIE L* and S, and V), it is allowed to test whether the proposed method will yield an optimal balance between repeatability and discriminative power just by the proper subset selection of the color channels.

From [13] it is derived that $I_1I_2I_3$ color invariant components followed by H are the most appropriate to be used for photometric color invariant segmentation.

A first experiment was conducted on a series of images taken from object number 25 of the Amsterdam Library of Images [2]. The image shows a ball with red, green, yellow and blue colors against a black background. Images are taken under various viewpoints and illuminations. The training patches were obtained from regions over each image. The defined pattern classes were red, green, yellow, and blue colors from the ball and a black background. For each pattern, five sample regions containing various kinds of colors: normal, very dark and highlights were selected. This methodology was carried out for all classes and all images.

For each sample region *r*, of size (I,J) the image was decomposed in 12 images, one for each color components and the mean, variance and entropy of gray values *r(i,j), for i =1…I, j =1…J* ,as shown in equations (1), (2) and (3), were assessed to perform the wrapper feature subset selection. The entropy was determined by gray histogram *h(k)* where *v(h(k))* is gray values occurrences and *k* is the gray level.

$$Mean = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j-1}^{N} r(i,j) \tag{1}$$

$$Variance = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(r(i,j) - Mean_{ij})^2 \tag{2}$$

$$Entropy = \sum_{i=0}^{255} h(k) * v(h(k)) \tag{3}$$

The feature vector *FV* for all color components is:

FV = [meanR, meanG, meanB, meanH, meanS, meanV, meanI_1, meanI_2, meanI_3, meanL, meana, meanb, varianceR, varianceG, varianceB, varianceH, varianceS, varianceV, varianceI_1, varianceI_2, varianceI_3, varianceL, variancea, varianceb, entropyR, entropyG, entropyB, entropyH, entropyS, entropyV, entropyI_1, entropyI_2, entropyI_3, entropyL, entropya, entropyb]

After creating a database with all *FV*, the wrapper method was applied to select a feature subset using an exhaustive search with C4.5 algorithm.

To evaluate the performance of the selected subset, test images were segmented in regions corresponding to the pattern classes used. The segmentation process used a decision tree generated and the mean value, variance and entropy for each pixel were calculated using a kernel 3x3 over the image.

The second experiment was conducted on aerial images taken from citrus and corn crops areas in order to identify agricultural management quality. Image segmentation can be used to identify relative differences in crop vigor, plagues, diseases and plant development level. The goal is testing a color subset selection applied to image segmentation taken at real field conditions. This kind of application is especially interesting, because it is not possible to control the sun light, shadows and highlights. The photometric conditions are not controlled.

Like the first experiment, region samples pattern were taken, but using different size of regions selections. The proposed pattern classes were the main crop, the uncover soil and the weed infestation.

The training samples were repeated for all images. For each sample region *r*, the image was decomposed in 12 images, one for each color components and the mean, variance and entropy were assessed.

After *FV* determined, it was applied wrapper to select a feature subset using an exhaustive search.

To evaluate the performance of the selected subset, test images were segmented in regions corresponding to the pattern classes used. The segmentation process used a decision tree generated and the mean value, variance and entropy for each pixel were calculated using a kernel 3x3 over the image.

The last experiment was performed to compare wrapper with a classifier by decision tree with neural network segmentation. The same training samples from first and second experiments were applied to training a MLP neural network trained by Backpropagation algorithm, but using *FV* reduced to the mean values only.

After training the neural network, the segmentation was performed just presenting pixel by pixel to the MLP neural network. The mean value for each pixel was calculated from a kernel 3x3 over the image.

5. Results and Discussions

The proposed method has been tested on a wide variety of conditions. The proposed selection of color components using wrapper with exhaustive C4.5 algorithm was applied to the ball with different photometric conditions. The first two ball images have different color temperature; the third highlights from illumination and the last one, rotation from viewpoint, as shown in Figure 4. The exhaustive search has algorithm complexity $O(2^n)$, where n is the number of features corresponding to 12 means, 12 variances and 12 entropies. That is why only the means were pre-selected.

The experiment was divided in two steps. First, an exhaustive search only with the means was applied. In this case, the feature subset selection selected I_3, H, L and V. The second step adds the respective variance and entropy up i.e. those corresponding to I_3, H, L and V. The accuracy obtained with the best feature subset was 99.62% (10-fold cross-validation).

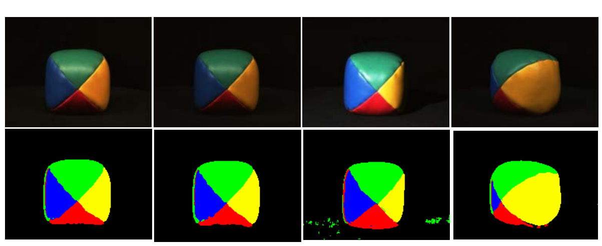

Figure 4: Original images of ALOI 25 and the results of image segmentation based wrapper at exhaustive search method

In spite of new features (variances and entropies) added up, it was obtained the same color subset of components I_3, H, L and V, and consequently the same decision tree. This indicated that, for this kind of images, variance and entropy don't contribute for classification very much. The segmentation results are shown in Figure 4 and decision tree in Figure 5.

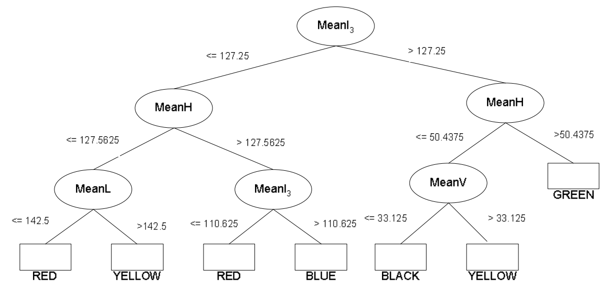

Figure 5: Decision tree for ALOI object 25

From [13] and [1], these color channels selected provide both repeatability (CIE a*b*, $I_1I_2I_3$, H), and distinctiveness (RGB, CIE L* and S, and V). So it is possible to have a good balance between repeatability and discriminative power in the segmentation process.

Using the same decision tree, it was tested others images from ALOI and football soccer databases that have the same colors but that had not used to generate the decision tree. The algorithm performance can be observed in Figure 6 and 7.

The second experiment was applied to aerial images. The proposed selection of color components using the wrapper approach with exhaustive C4.5 algorithm was used for all color components. In this case, the feature subset selection algorithm achieves accuracy of 99.52% and the selected features were mean G, mean a and entropy B. This decision tree was obtained using two step procedure, like before. Nevertheless, all entropies and variances were added to the means. The results of segmentation with the decision tree (Figure 8) are shown in Figures 9.

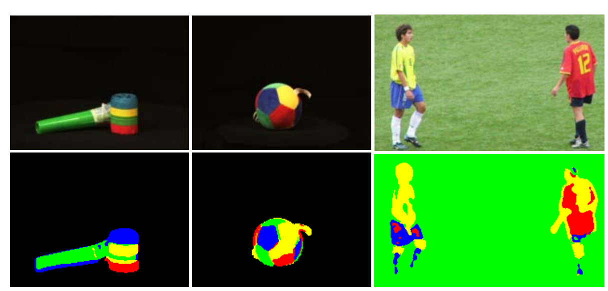

Figure 6: The same decision tree considered the best for this application and showed in Figure 5.

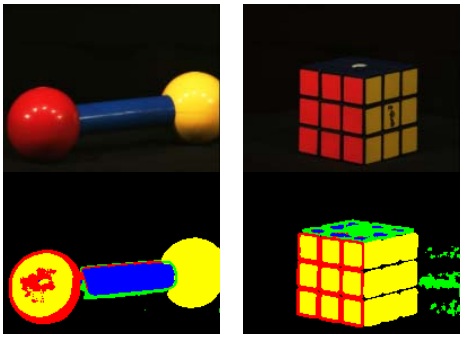

Figure 7: Results for the same decision tree considered in Figure 5

The wrapper has the potential to make an accurate selection but experiments suggest evidence that it is too prone to get trapped in local maxima, a well known problem for forward search strategies. The solution for this is the exhaustive search.

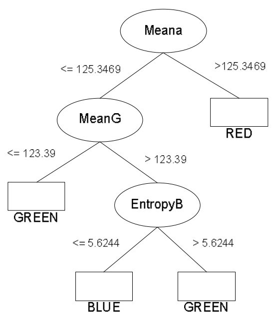

Figure 8: Decision tree for aerial citrus images

In figure 10 it is shown the results for corn segmentation with the same decision tree obtained from citrus as presented in Figure 8. It is possible to observe that the color of corn is more similar to weed infestation in citrus crop.

The results from those experiments were observed by visual inspection. For balls images, it was easy to identity if it was good or not instead of for aerial images.

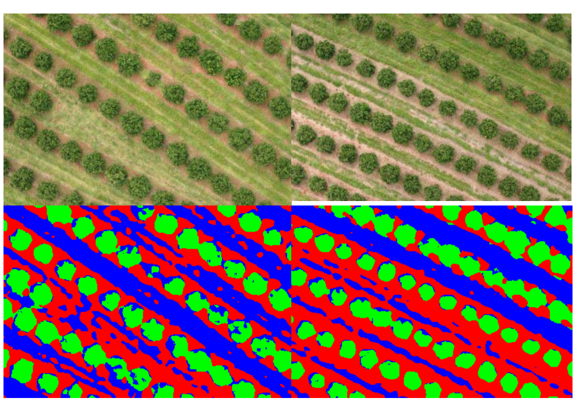

Figure 9: Aerial citrus images and the result using the decision tree from Figure 8.

In order to explore more details about Wrapper and compare with other methods, it was implemented a MLP neural network as a segmentation algorithm. The results for balls and aerial images could be observed in Figures 11, 12 e 13. The neural network was trained with the same mean RGB vector and presented a training error less than 0.1%. After an exhaustive training phase, it was selected the best result of segmentation. It is possible to observe that the results show more problems to uncover soil and weeds. For balls, photometric conditions could not be a problem.

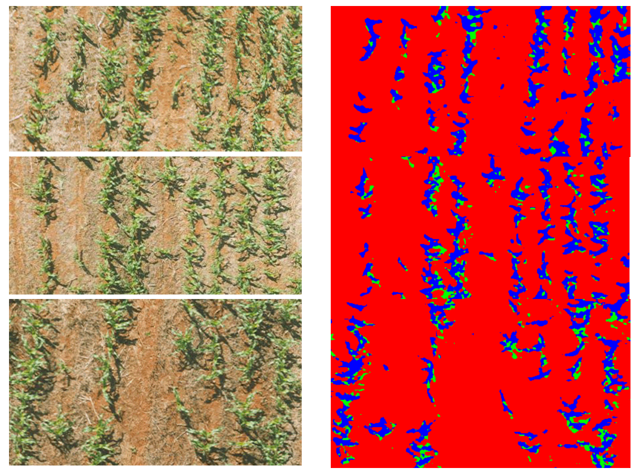

Figure 10: Aerial corn images and the result using the decision tree from Figure 8.

The main goal here went to evaluate a segmentation system with the RGB components once the other color systems are derived from this and they present some redundancy. An appropriate acting was observed in the segmentation of the ALOI 25 object, showing that even under different illumination conditions, color temperature and point of view, it is possible to segment them with little color components. However, in more complex images, as the aerial images, zeroth order statistics can be an important and necessary factor, besides the invariant components. Furthermore, the selection of the colors components provided by the Wrapper approach stands out, presenting better acting even with simple algorithms of classification (C4.5) compared to the traditional models of neural nets.

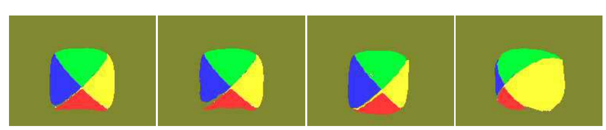

Figure11: Segmentation of balls images using the MLP Neural Network with mean values of RGB.

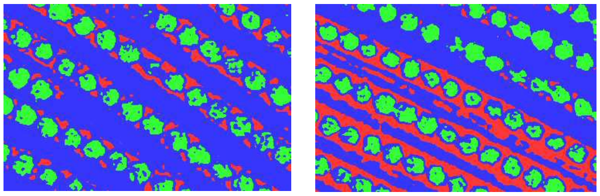

Figure12: Segmentation of aerial citrus images using the MLP Neural Network with mean values of RGB.

There exists redundancy among some color components of the different color models involved in this work, although the combination of these can improve the precision of the algorithms of machine learning. However, this work shows that the appropriate selection of a subset of color components contributes to the balance between the repeatability and distinctiveness, what is desirable in the segmentation of aerial images.

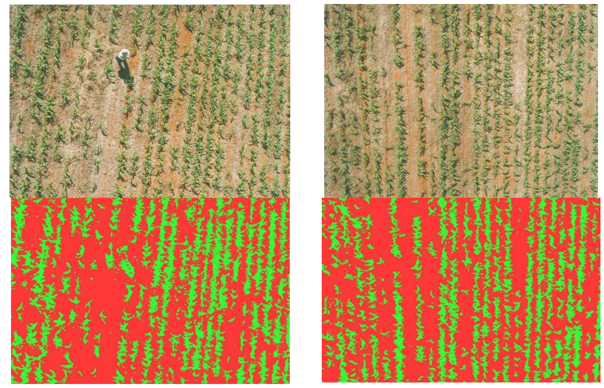

Figure13: Segmentation of aerial corn images using the MLP Neural Network with mean values of RGB.

The correlation between the different color channels reveal that taking combinations of color channels performs better than taking only a single color space.

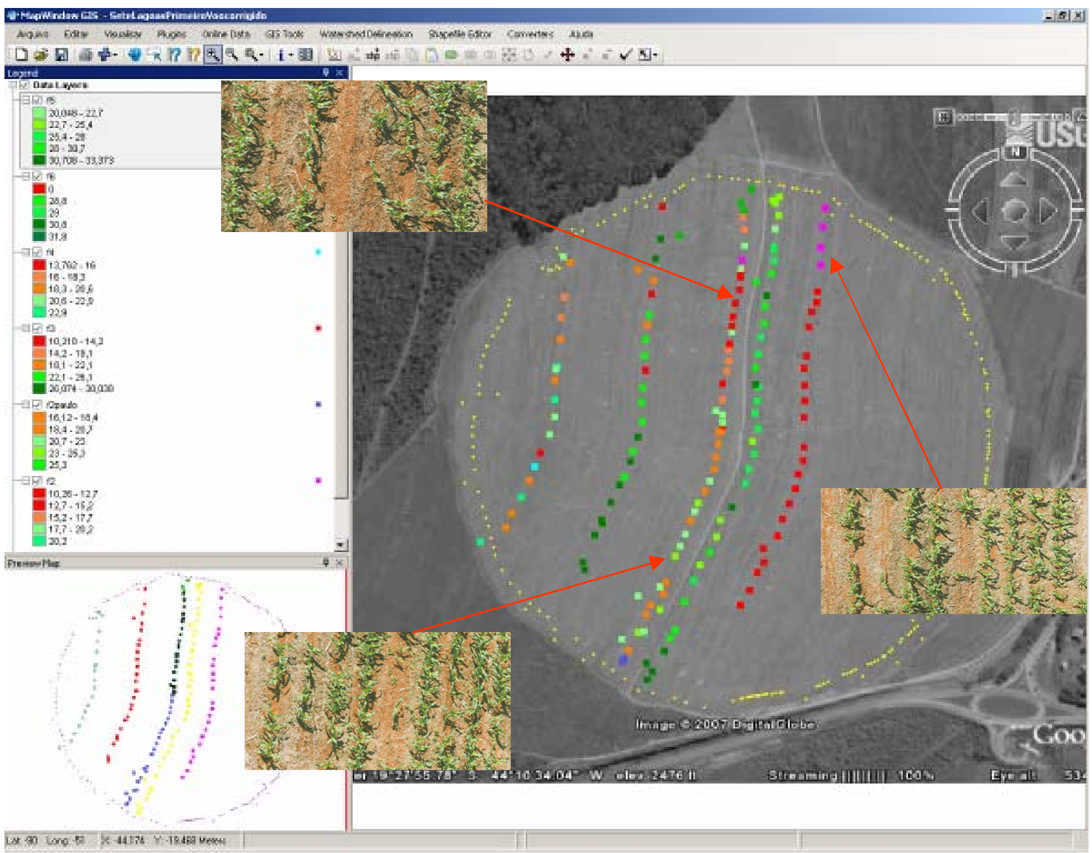

Figure14: Application of color segmentation for corn aerial images.

6. Conclusions

In this paper, a wrapper method was proposed to select a subset color components for image segmentation. Further, the method was experimentally verified and showed that the selection algorithm can be applied successfully.

The selection and fusion of color models was proposed first by Stokman and Gevers [1], but using another approach where weights were selected to combine color components and models. Instead of fusion here was used a subset selection algorithm to identify color components.

The subset selection algorithm obtained CIE a*, G and B components, for those aerial images. From [13], it is derived that G and B are sensitive to shadows, shading, illumination and highlights. Further, CIE a* are invariant to shadows, shading and illumination intensity. So, the method will yield a good balance between repeatability and discriminative power just by the proper subset selection of the color channels.

Recently there has been a growing interest in feature selection for clustering, but a number of questions still remain open. Wrappers for feature selection have been recently proposed with some success. Many examples of these approaches are focused on numerical clustering, and there is no theoretical or experimental evidence related to their behavior on color images data, but in segmentation and classification [11], [12].

The extensive experiments conducted on a wide variety of images show that proposed method is widely applicable. In Figure 14, it is possible to observe a complete application. A corn crop area under irrigation was studied by aerial images and each image was processed with Wrapper approach. The percentage value of crop yield calculated by segmented areas was indicated in the map by color scale, where red is bad yield and green a good one.

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