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# USING NEURAL NETWORK AND K-MEANS CLUSTER FOR IMAGE SEGMENTATION IN OUTDOOR SCENES

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***Abstract.*** *The present paper discusses the image processing algorithms that treat the problem of image segmentation. The idea is evaluate segmentation algorithms performance applied to captured images in outdoor scenes under natural illumination. This light source type can cause low image quality. Both, K-means cluster and neural network based on pixel RGB space colour are described like segmentation algorithms. The neural network and K-means performance evaluation will be measured by a method based on discrepancy. In order to handle digital images, a computational environment is then implemented. Besides the image capture and the pre-processing algorithms, this environment is composed by the K-means, neural network and discrepancy method applied on performance evaluation, which is the main theme of this paper. The digital images describe plants species and land captured by a video camera (CCD - Charged Coupled Device). These images will then be segmented with the purpose of separating the plant species from the land regions. With the K-means algorithm, one may get some faulty segmented pixels while the use of neural network techniques may increase the performance but some errors might remain. The paper introduces the combination of both these methods and shows that a much better performance can be achieved.*

***Keywords:*** *Segmentation, K-means, Neural net, Backpropagation.*

## 1. INTRODUCTION

Currently, there is an increasing concern in applications performance based on digital image in outdoor scenes based on natural illumination. This happens because natural illumination can cause low quality image (Sage, 1999 and Bulanon et al., 2004). A common example is when light variations occur, as consequence of the different day-time of image capture. Thus, the image low quality can commit the image processing computational algorithms performance.

Alternative solutions to the question of light variation in outdoor scenes have become an important research theme (Vitabile et al., 2001 and Battle et al., 2000). However, there is no simple solution to this problem. Some researchers, for instance, try to control the light illumination conditions, but in this case a natural illumination approach can not be considered. On the other hand, there are researchers who try to increase the algorithms performance. This situation happens due to the light condition to be a rather difficult aspect to regulate and control (Vitabile et al., 2001 and Battle et al., 2000).

There are many applications that use image processing algorithms in outdoor scenes. Amongst them one could mention: robotic systems, such as mobile robot navigation system (Batlle et al., 2000), robotic manipulators (Bulanon et al., 2004), satellite images detention (Keramitsoglou, et al., 2005), plants species images recognition (Kavdir, 2004), intruders detection systems (Sage, 1999) and transit signals recognition (Vitabile et al., 2001).

Here K-means cluster and artificial neural network (ANN) were studied with the purpose of obtaining a set of algorithms that can be combined in order to achieve a better performance in image segmentation. A comparative study has been carried out to find out which algorithms perform best for the plant species images case.

## 2. SEGMENTATION

The main idea of the image segmentation is to group pixels in homogeneous regions and the usual approach to do this is by 'common feature'. Features can be represented by the space of colour, texture and gray levels, each exploring similarities between pixels of a region (Kurugollu et al., 2001, Navon et al., 2004, Kim et al., 2002). In Mery (2005) the segmentation is treated as an image division of regions which are not coincident.

Among the algorithms normally used to segment a digital image, the K-means algorithm and the ANN are possible alternatives.

There are many options to evaluate the performance of image segmentation algorithms. As an example of that is the disparity on the segmented objects features based methods (Yu, 2001). It consists in the use of figures, such as the area, the colour, the texture to evaluate objects in the segmented image and compare it to the one obtained using a reference image. So, an image that was conveniently segmented has the value of its objects features near of the respective ones in the reference image. This technique is usually called as AUMA (Absolute Ultimate Measure) and it represents a discrepancy measure (Yu, 2001).

### 2.1 K-means cluster

Algorithms based on cluster methods are normally used to obtain data, which are based on the features space, where these groups are represented by clusters (Venkatesh, 2003).

Consider a given $n$ input data, each having dimension $d$. The main goal of the cluster algorithm is to satisfactorily separate this input data in $T$ groups of patterns, in such way that every partition minimizes the dispersion of the components of each of these groups. Krishna's method (Krishna, 1999) is called "Total Within Cluster Variance" (TWCV).

Accordingly to Krishna (1999), TWCV technique initially assumes a set of n input data $\{\psi_\upsilon\}$, where $\upsilon$= 1, 2, …, $n$, $\psi_{\upsilon\varsigma}$ represents the $\varsigma^{th}$ feature of $\psi_\upsilon$, each one associated to a specific cluster $\tau$ = 1 ,2, …, $T$. The assignment of each pattern $\psi_{\upsilon\varsigma}$ to a cluster $\tau$ is represented by a $\chi$ matrix (Fig. 1) where $\varphi_{\upsilon\tau} \in \{0,1\}$ is the $\upsilon^{th}$ row and the $\tau^{th}$ column of the $\chi$ matrix and $\varphi_{\upsilon\tau}$ = 1 means that the input data $\{\psi_\upsilon\}$ belongs to the $\tau^{th}$ cluster.

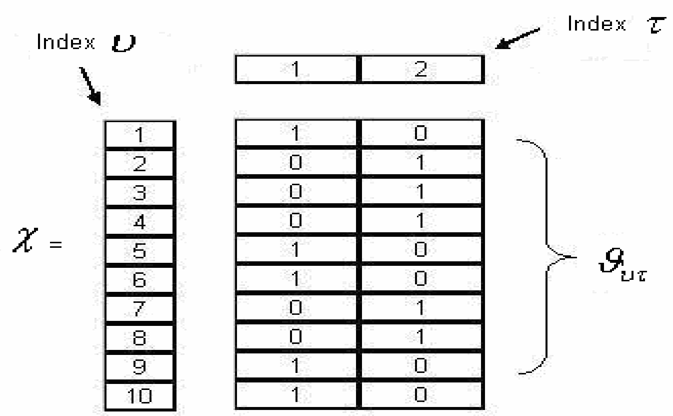


Figure 1 - Matrix representing the features attribution for a cluster.

The algorithm runs in loop and for each data input analysis, this data is associated to a pattern and increases the array $\varphi_{\upsilon\tau}$ of the corresponding cluster. Thus, a new centroid for the pattern is computed as:

$$c_{\tau\zeta} = \frac{\sum_{\upsilon=1}^{n} \vartheta_{\upsilon\tau} \psi_{\upsilon\zeta}}{\sum_{\upsilon=1}^{n} \vartheta_{\upsilon\tau}} \tag{1}$$

Since the new centroid is computed, one can also compute the deviation of each component of this group. One of the most common criteria is based on the Euclidian distance, which can be computed as*:*

$$S^{(\tau)}(\vartheta) = \sum_{\upsilon=1}^{n} \vartheta_{\upsilon\tau} \sum_{\zeta=1}^{d} \left(\psi_{\upsilon\zeta} - c_{\tau\zeta}\right)^2 \tag{2}$$

If all clusters are considered, the total variation (TWCV) is defined as:

$$S(\vartheta) = \sum_{\tau=1}^{T} S^{(\tau)} = \sum_{\tau=1}^{T} \left( \sum_{\upsilon=1}^{n} \vartheta_{\upsilon\tau} \sum_{\zeta=1}^{d} \left(\psi_{\upsilon\zeta} - c_{k\zeta}\right)^2 \right) \tag{3}$$

## 2.2 Artificial neural network (ANN)

One of the significant advantages to use ANN is the fact that it can take decisions based on complex and noisy data (Demir et al., 2005).

ANN can be trained in order to develop the ability to map the relation between the feature vectors through a nonlinear model, and becomes capable to manipulate complex data. Moreover, the ANN can generalize patterns which were not manipulated in its learning stage. Hence, the new patterns can be correctly classified.

In some pattern recognition application cases, the ANN feed-forward multi layer perceptron topology are used, reaching a satisfactory performance.

A basic point in a neural network is its learning rule. The Levenberg-Marquardt algorithm (Hagan, 1996) usually presents an adequate performance for a wide range of applications including pattern recognition applications. It consists in weight updating (4) based on Hessian matrix (6) and on the error gradient direction (5).

$$w_{k+1} = w_k - [H + \mu I]^{-1} gr \tag{4}$$

$$gr = J^T E \tag{5}$$

$$H = J^T J \tag{6}$$

where,

$\mu$ = Constant

$I$ = Identity matrix

$J$ = Jacobian matrix

$J^T$ =Transpose Jacobian matrix

$E$ = Error signal

## 3. CASE STUDY FOR APPLICATION

A computational environment is here built in order to acquire images and then to evaluate the influence of the luminosity variation in the performance of the image processing algorithms.

Some images of outdoor scenes of sunflower production have been captured in different days as well as in different hours of the days.

The first group of images was acquired in the 15th day after being seeded, between 13:08 and 13:19 and also between 11:30 and 11:40. A second group of images was captured in the 21$^{st}$ day after the sowing, between 9:40 and 10:10 with the aim of assuring different illumination conditions, provided by luminosity variation in the environment.

Electronic devices have been used for image acquisition. These devices are essentially: a 'CCD video camera'; a 'transmitting and receiving video equipment' in order to provide the camera mobility; a '12 volts battery' to serve as a transmitter and 'the video camera power source'. A computer, equipped with a frame grabber video capture, is also used to receive and store the images which have been transmitted.

The algorithms used in the computational environment created were based on the algorithms of the next section (Section 4).

## 4. ALGORITHMS' PERFORMANCES AND PROPOSED SOLUTION

Image segmentation was applied using the K-means cluster. A second image segmentation using an ANN has also been applied. Finally, the discrepancy measure based on area feature of segmented objects (AUMA) was used to evaluate the performance of image segmentation algorithms.

A K-means cluster was designed with T=2. It means two clusters that represent the background and foreground regions in image. N is equal to 76000 pixels presents in the image.

A new feed-forward back-propagation ANN was designed with three layers. The neurons in the second and third layers are in the 8-1 format, which means eight neurons in the second layer and one neuron in last layer. The second layer has a hyperbolic tangent activation function whereas the last layer has a purely linear activation function. The input data of ANN is the RGB colour space and therefore the first layer has three inputs.The learning rule was defined by the Levenberg-Marquardt algorithm (1).

Discrepancy measures obtained to K-means and ANN algorithms can be seen in Table 1.

Table 1. The K-means and ANN discrepancy values for segmented and captured images in 15th day, from 13:08 to 13:19.

| *Image Number* | *K-means* | *ANN* |
|---|---|---|
| 1 | 121.44 | 37.78 |
| 2 | 624.51 | 17.35 |
| 3 | 148.19 | 26.76 |
| 4 | 252.63 | 212.73 |
| 5 | 685.96 | 379.76 |

The discrepancy measures AUMA represent the value of its objects features near of the respective ones in the reference image when the values approximates to zero. So,the obtained results, when each of these standard algorithms was used, show that there are a lot of erroneous or undesirable classifications, which means that many pixels were not adequately grouped. This suggests that the overall performance can be increased. A combination of both K-means and ANN algorithms is then proposed.

A K-means/ANN algorithm consist in use of K-means algorithm to image segmentation and a feed-forward back-propagation ANN to segment pixels that were not adequately grouped by K-means algorithm.

Discrepancy measures obtained to K-means/ANN algorithm can be seen in Table 2.

Table 2. The K-means/ANN discrepancy values for segmented and captured images in 15th day, from 13:08 to 13:19.

| *Image Number* | K-means/ANN |
|---|---|
| 1 | 36.232 |
| 2 | 31.45 |
| 3 | 28.99 |
| 4 | 43.69 |
| 5 | 106.22 |

Consider the discrepancy mean results, K-means/ANN obtained 49,3, while k-means and ANN obtained 366,5 and 134,8 respectively. So, the lower mean represents the best result. Based on the results shown in both table1 and table2, the K-means/ANN proved to be better when the performance between the ANN and the K-means algorithms for plant images were compared.

## 5. CONCLUSIONS

The use of K-means algorithm alone presents some difficulties in the image segmentation, either in single day data collection as well as in data collection done in distinct days.

However when it is used simultaneously with an ANN, it eliminates pixels which are faulty segmented and satisfactory results can be obtained.

Despite the fact that illumination of the captured scenes varies, it is possible to associate a class of algorithms with the purpose of being robust for such variations. So, with this framework, that class of algorithms can be created by using the K-means/ANN algorithm in the segmentation stage.

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