Fuzzy decision system for threshold selection to cluster cauliflower plant blobs from field visual images

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ABSTRACT

Current work deals with the design of a fuzzy reasoning system capable of selecting the most appropriate threshold to binarize a sequence of cauliflower crop images. Binary images speed up the processing time to detect the crops and calculate their position. The proposed threshold algorithm is based on a performance criterion, the emergence of a binary image wherein cauliflowers are easily distinguished from the background and no relevant parts of the plants are lost. Once the best threshold is applied and the binary image is obtained, a fuzzy clustering algorithm has been designed to rejoin the fragmented blobs of the plants and recover the cauliflower image. Finally, plant positions are calculated based upon the area and location of the blobs belonging to a plant. This technique is extremely valuable for real time precision agriculture tasks, as are those of selective spraying.

Keywords: fuzzy decision system, image analysis, fuzzy clustering, crop treatment, precision agriculture.

1. INTRODUCTION

One of the major tasks of autonomous agricultural vehicles deals with the unsupervised chemical treatment of crop plants. To this final aim, one of the necessary steps concerns the knowledge on the plant positions in the field. To obtain precise plant location images are usually thresholded to quickly separate foreground or relevant structures from background. During last years, Artificial Intelligent techniques have been carried out in the Agriculture domain, related to plant classification through the use of neural networks [1], or linguistic expressions [2].

Most of the effort has been focused on improving image segmentation [3]: 1) Classical techniques mainly use gray-level histogram [4], but the performance is reduced when regions in the image are ill defined. This case is particularly important in outdoor scenes due to highly variable lighting conditions, 2) Fuzzy techniques have been employed for improving thresholding, being some of them related with fuzzy indexes, entropy and compactness [5]. Fuzzy clustering methods are also employed to perform image segmentation [6].

Present work is involved with the dynamic selection of the threshold for sequences of images of cauliflower crops. The crops are transplanted in rows, keeping between them a constant distance both between rows and columns. Rows and columns generate a grid pattern, wherein cauliflowers are fixed to the nodes. The images are recorded with a camera installed on the top-front of a vehicle, which is guided using algorithms that detect the cauliflower rows [7], [8]. These algorithms give rise to a new predicted grid position for the plants appearing at each new image in a sequence, based on Kalman Filter [9]. The predicted positions are used for clustering the features that make up individual plants from parts.

2. VISION SYSTEM AND IMAGE BINARIZATION

The images are recorded during the run of a vehicle equipped with a CCD monochrome camera adapted with an infrared filter. Real time performance imposes requirements on image processing, such are: short processing time and low memory consumption. This points to a quick conversion of gray-level images through a thresholding process. For an effective thresholding, it is extremely important to select the most adequate intensity level to separate the background from the foreground. In this case, this is of paramount relevance as after the segmentation process the cauliflower fragments into several parts that must be rejoined around the plant center. As the position of the cauliflower in the field is to be determined, it is fundamental not to lose some parts of the plants using an incorrect threshold. All the image processing can be divided in two stages:

- Dynamic threshold selection for segmenting the image, to obtain a binary image with the background (soil) in black and the foreground (cauliflower, weed and stones) in white.

- Estimation of the position of the cauliflower. Due to shadows, dark zones and to the fact that cauliflower is a three-dimensional object, individual plants in the binary image can fragment. These fragments must be rejoined in order to rebuild the original plant and to be able to calculate its position.

In present work the threshold selection is based on a performance criterion pursuing a binary image wherein cauliflower are enhanced from the background without loosing any relevant parts of the plant.

3. FUZZY DECISION SYSTEM

Fuzzy logic has successfully applied in classification and control processes that are described through a set of linguistic expressions due to the difficulty to derive an analytical model. Fuzzy sets conveniently model the uncertainty inherent to human experts approximate reasoning processes and to the imprecision of real sensors [10], [11], [12], [13].

The threshold selection criterion can be easily described through a set of linguistic expressions of the type: *IF there* ***are too many blobs*** *in the image THEN* ***increase*** *the previous threshold* value. For these reasons the performance criterion has been implemented through a fuzzy feedback decision system, that is described by means of a set of linguistic expressions, Figure 1 The fuzzy decision system provides the variation to be performed on the current threshold value to improve the image segmentation.

Input variables

The analysis of a large set of images, has conducted to the determination of the relevant variable in the process, that are the input variables of the fuzzy system:

BLOBS_NUMBER: Correspond to the number of blobs in the image. Very low or very high values indicate too high or too low thresholds intensity values, respectively. However in the best performance region, appropriate threshold values for each image show a great variation, in strong dependence weeds amount on the image. If the threshold is too low, BLOBS_NUMBER

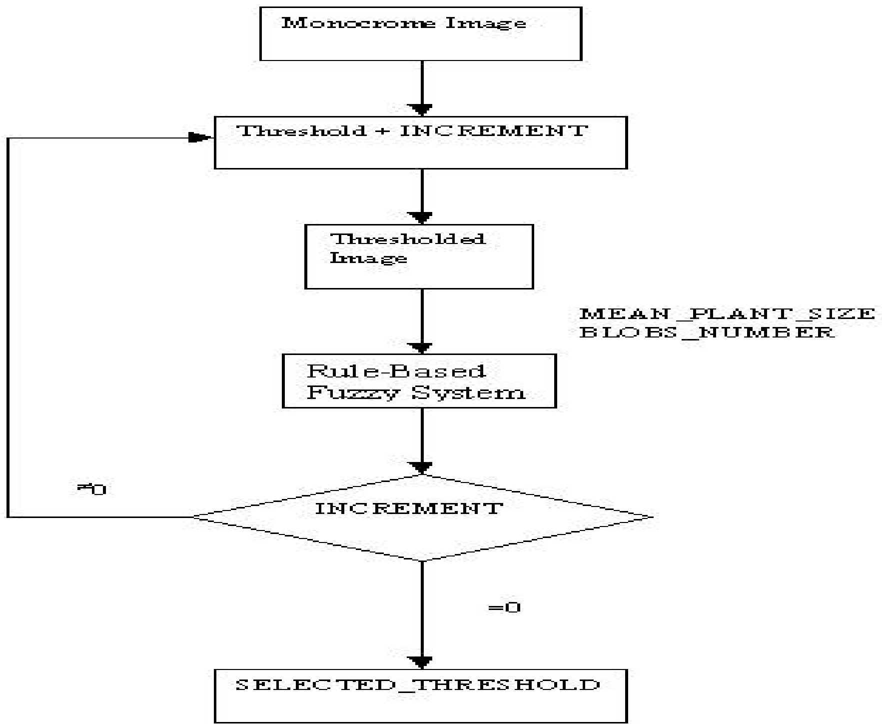

Figure 1: Fuzzy feedback decision system

will be large, as many background areas will be considered as foreground. Conversely, if the threshold is too high, BLOBS_NUMBER will be small compared with the desired value, as some parts of the plant will fall below the threshold value and so would be misclassified as background.

As the image conditions are unknown, it is an extreme simplification to consider " a priori" an optimal number of blobs. Thus this variable has been modeled as a fuzzy variable with three linguistic labels: {Few, OK, A lot}, where each of them is represented by a trapezoidal membership function, Figure 2. The membership defining parameters, as are the slopes, the location and the width are fixed following a fine tuning heuristic.

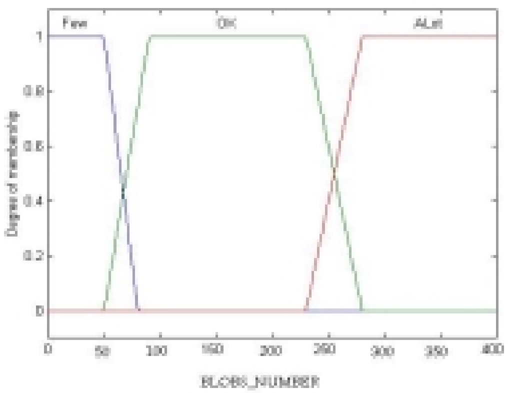

Figure 2: BLOBS_NUMBER.

MEAN_PLANT_SIZE: To represent this parameter the mean value of the ten biggest blobs in the image has been used. This avoids problems caused by small stones and highlights, as the cauliflower is the largest object in the image. If this area is small, the

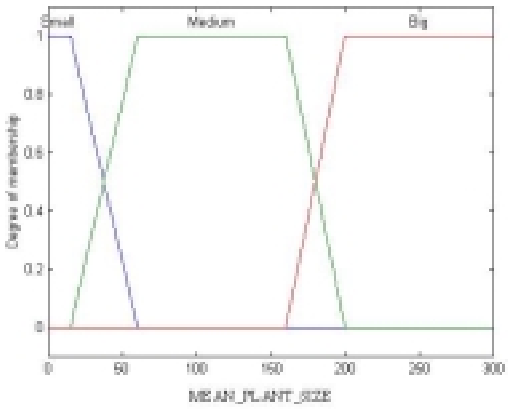

Figure 3: Mean Plant Size

threshold would probably be too high, and parts of the plants will be misclassified as background. The main disadvantage of this criterion concerns the crop variation, as the size changes with their growing stage. The three linguistic labels for this variable are: {Small, Medium, High}, Figure 3. The slope and width of membership functions are carefully selected after a fine-tuning process.

Output variable
The output variable is the increment or decrement that must be applied to the previous threshold, Figure 4, in order to improve the segmented image, following the designed fuzzy decision system. The threshold is the intensity level, which defines the border between black and white structures. Pixels having a grey level below the threshold are classified as black, and correspond to background, and pixels whose grey-level is greater than the threshold are classified as white and define the foreground objects.

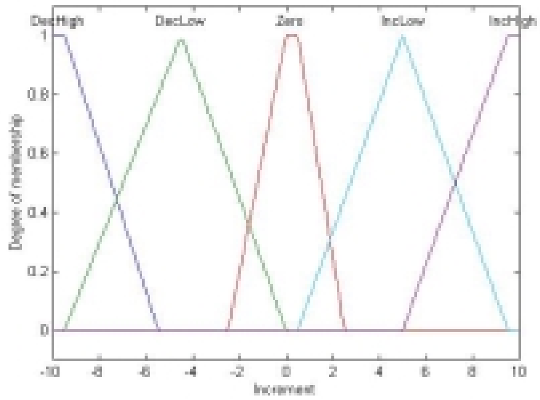

Figure 4: INCREMENT RULES

The required threshold is a number between *0.0* and *1.0* (Matlab restrictions) but for simplicity we have used directly the grey-level, an integer *n* between *0* and *256*, that needs the scaling-step. The INCREMENT value is directly applied to this integer.

$$threshold = n \cdot \frac{1}{256} \quad \textbf{[1]}$$

Rules
The fuzzy rule base has been built to mimic the human approximate reasoning process, that means to follow "common sense" rules. If the criterion for selecting the most appropriate threshold were the "goodness" of the segmented image, this would be achieved when the image reflects the real world. That means here that we can not see more object that the current one and that the size of this object corresponds to its real size. The rules embrace the expectations on the structures that usually

appear on the image, based upon previous images. In average in each image there will be about ten big objects and the rest are smaller structures.

Current implementation uses the classical choices for the conjunction and disjunction operations with logic expressions, the maximum and minimum respectively. Knowledge base is displayed in Table 1. The fuzzy rules set embodies our perception of the problem and of its solution. The BLOBS_NUMBER variable is the main descriptor, as it decides whether or not the threshold is correct and then it must remains unchanged or it must be decreased or increased. It is slightly modulated by the MEAN_PLANT SIZE variable that specifies the increment / decrement amount, low or high.

The first three rules contemplate all cases in which the image does not reflect as many blobs as they really are. This situation can be explained by the fact that if the threshold is too high there would be many pixels defining plants that remains below it. So, the threshold must be decreased. The modulating variable, MEAN_PLANT_SIZE decides between a high increment if the perceived size is small or a low increment in the rest of the cases. The rule number four fires when the segmented image reflects the appropriate conditions. If this rule fires, the threshold is labelled as correct and therefore INCREMENT is ZERO.

Rules number five to number seven, make decisions on those cases having very low threshold values, where the binary image displays more blobs that are in real world, as some part of the soil is misclassified as foreground. To improve the segmentation the threshold must be increased. The increment amount is now again tuned by the MEAN_PLANT_SIZE.

Defuzzification is performed through the gravity centre algorithm, Eq(2):

$$y = \frac{\int_Y \mu_0(y)ydy}{\int_Y dy} \quad \textbf{[2]}$$

Computing time is slightly over the second, as the algorithm is implemented using Matlab. Because of the number of rules (7) and variables (2 input and 1 output) we expect that computing time will be heavily reduced, when the algorithm is implemented in real time. Previous works with a similar number of rules and variables have shown that process time is around the millisecond. [14].

4. FUZZY CLUSTERING ALGORITHM.

Segmentation gives rise to a fragmentation of the cauliflower plants and further on each blob must be identified with the plant it belongs to. In this process all the fragments must be rejoined around the new plant centre.

In recent years the synthesis between clustering algorithms and fuzzy set theory has led to the development of several fuzzy clustering algorithms [15], [16].

This fuzzy clustering algorithm recognises each blob as belonging to one of the plants located in a specific grid position. It performs this task based on the membership functions associated with each of the predicted grid positions [6]. The "a-priori" image information that is handled correspond to:

1. The estimated grid points, wherein there should be a plant.

2. The image's perspective. This means that the mapping between pixels on the image and distance on the ground

1. IF BLOBS_NUMBER is Few & MEAN_PLANT_SIZE is Small THEN INCREMENT is DecrementHigh
2. IF BLOBS_NUMBER is Few & MEAN_PLANT_SIZE is Medium THEN INCREMENT is DecrementLow
3. IF BLOBS_NUMBER is Few & MEAN_PLANT_SIZE is High THEN INCREMENT is DecrementLow
4. IF BLOBS_NUMBER is OK THEN INCREMENT is Zero
5. IF BLOBS_NUMBER is ALot & MEAN_PLANT_SIZE is Small THEN INCREMENT is IncrementHigh
6. IF BLOBS_NUMBER is ALot & MEAN_PLANT_SIZE is Medium THEN INCREMENT is IncrementHigh
7. IF BLOBS_NUMBER is ALot & MEAN_PLANT_SIZE is High THEN INCREMENT is IncrementLow

Table 1: Rules Set

is not constant throughout the image [9].

Based on these two points, we build one membership function for each grid position, that integrates the knowledge about the scale. Two-dimensional beta functions have been used [6], [17] as membership functions, Eq.(3) and Figure 5. These functions depend on two parameters: γ, the point around which the bell shapes are centred (i.e. the grid positions) and β, the width of the bells (i.e. the scale):

$$\mu_i(x, y) = \frac{1}{1 + \left(\frac{x - \gamma_{ix}}{\beta_{ix}}\right)^2 + \left(\frac{y - \gamma_{iy}}{\beta_{iy}}\right)^2} \quad \textbf{[3]}$$

Where

γ_x is the predicted position of the *x* co-ordinate for the point *i*

γ_y is the predicted position of the *y* co-ordinate for the point *i*

β_x is *nx*scalex* (*scalex* is the predicted scale for the *x* axis in pixels/metre for the grid point *i* γ_x and *nx* is a

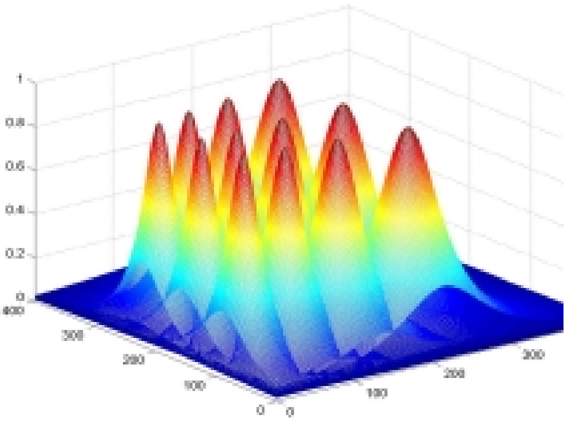

Figure 5: Membership clustering functions.

constant)

β_y *ny*scaley* (*scaley* is the predicted scale for the *y* axis in pixels/metre for the grid point *i* γ_y and *ny* is a constant)

Each object in the image is described by a feature vector, with two components corresponding to the spatial co-ordinates of its centroid. For every object, represented by its feature vector, we evaluate each of the membership functions corresponding to each of the grid points, to obtain a matrix *mxn* (*m* objects in the image, *n* grid positions) containing the membership grade with which the object *i* belongs to the crop *j*, Eq.(4).

$$\begin{vmatrix} \mu_{11}(x_1, y_1) & \mu_{12}(x_2, y_2) & \mu_{1m}(x_m, y_m) \\ \mu_{21}(x_1, y_1) & \mu_{22}(x_2, y_2) & \mu_{2m}(x_m, y_m) \\ \mu_{31}(x_1, y_1) & \mu_{32}(x_2, y_2) & \mu_{3m}(x_m, y_m) \\ \mu_{n1}(x_1, y_1) & \mu_{n2}(x_2, y_2) & \mu_{nm}(x_m, y_m) \end{vmatrix} \quad \textbf{[4]}$$

The object *i* is classified as belonging to the grid position *j* whose value is the row-maximum. If this maximum does not exceed a fixed value, the object is taken as weed i.e. not belonging to any plant, Eq. (5) [6].

$$\mu_{ij}(x_j, y_j) = \max_m\left(\mu_{mj}(x_j, y_j)\right) \qquad Object_j \in Grid_i \quad \textbf{[5]}$$

We also take into account S_{M}. If it is below a threshold, the object is discarded in the sense that is not considered as a crop.

At this point, all the segments considered as part of the same plant are rejoined. The last step is now to calculate the new cauliflower's centroid. This task is accomplished by taking into account the area weighted mean of centroids of every object corresponding to the same plant, Eq.(6) and Figure 6.

$$\bar{x}_k = \frac{\sum_i x_i \cdot a_i}{\sum_i a_i} \qquad \bar{y}_k = \frac{\sum_i y_i \cdot a_i}{\sum_i a_i} \quad \textbf{[6]}$$

No weed is misclassified as crop in Figure 6, and every cauliflower segment is correctly rejoined to the plant it belongs to. The results for this image can be generalized. We have worked with two series of real-time recorded images, each containing 200 different images. We have compared the results of the clustering algorithm to the human perception: errors in classification, i.e. weeds considered as crop or crop as weed, are below 5.2%. Our error rate is similar to the rates provided by other clustering algorithms [18].

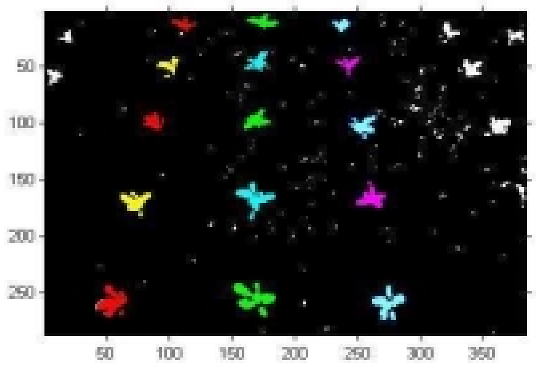

Figure 6: Clustering results: blobs of the same crop are plotted with the same color.

5. CONCLUSIONS

Present work shows a fuzzy dynamic thresholding algorithm that can be implemented for real time outdoor scenarios, due to its adaptation to varying weather conditions, as strong changes in lighting.

A fuzzy clustering algorithm is also presented that performs well in a 94.8% of the situations

All image processing has been performed on gray level images, however in natural scenes color is a major information source, that still remains unexplored [19] Future work will be conducted with the same algorithms on color images

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