ROBUST POTATO COLOR IMAGE SEGMENTATION USING ADAPTIVE FUZZY INFERENCE SYSTEM

P. MOALLEM, N. RAZMJOOY AND B. S. MOUSAVI

Abstract. Potato image segmentation is an important part of image-based potato defect detection. This paper presents a robust potato color image segmentation through a combination of a fuzzy rule based system, an image thresholding based on Genetic Algorithm (GA) optimization and morphological operators. The proposed potato color image segmentation is robust against variation of background, distance and view of potato from digital camera. In the proposed algorithm, after selecting appropriate color space, distance between an image pixel and real potato pixels is computed. Furthermore, this distance feeds to a fuzzy rule-based classifier to extract potato candidate in the input image. A subtractive clustering algorithm is also used to decide on the number of rules and membership functions of the fuzzy system. To improve the performance of the fuzzy rule-based classifier, the membership functions shapes are also optimized by the GA. To segment potatoes in the input color image, an image thresholding is applied to the output of the fuzzy system, where the corresponding threshold is optimized by the GA. To improve the segmentation results, a sequence of some morphological operators are also applied to the output of thresholding stage. The proposed algorithm is applied to different databases with different backgrounds, including USDA, CFIA, and obtained potato images database from Ardabil (Iran's northwest), separately. The correct segmentation rate of the proposed algorithm is approximately 98% over totally more than 500 potato images. Finally, the results of the proposed segmentation algorithm are evaluated for some images taken from real environments of potato industries and farms.

1. Introduction

Potato, with a huge worldwide production, plays a major role in supplying human foods. Therefore, quality control of produced potatoes is an important factor in quality of potato-based produced foods. In potato industries, computer vision technology which can detect some external characteristics of potato has some advantages such as objectivity, low cost, and high precision. Moreover, for the fresh market, the main factor affecting consumer preference is physical appearance of potatoes which can be accurately evaluated by machine vision system [2].

Usually, computer vision algorithms used in potato industries include two main steps: potato segmentation and defect detection. In the first step, a proper segmentation algorithm should be applied to an input image to separate the potato

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regions from its background, while the second step detects the different defects in the segmented potato images [1][18]. The quality of the segmentation algorithm plays an important role in improving the output of the defect detection step. Generally, in all previous works, a controlled illumination and background are considered that simplifies the segmentation step. It means that in various backgrounds or shadow conditions, the performance of the defects detection effectively reduces since the performance of segmentation algorithm degrades. This paper presents a robust potato image segmentation algorithm which can be simply used in all image processing-based potato quality control algorithms. The proposed segmentation algorithm can improve the performance of corresponding machine vision system in practical applications where the background and imaging conditions are not fully controlled.

Currently, color, shape and texture image features are used in a vision-based automatic quality control of agricultural products [25]. Among these three image features, color is more robust than shape and texture which are not stable when the distance and view point of potato are varied respect to digital camera [29]. It means that color-based features are good candidate for potato image segmentation. Therefore, in this paper, a robust potato color image segmentation is proposed which is robust against variation of background, distance and view of potato respect to camera. Firstly, an automatically tuned fuzzy rule-based inference system with a color distance input is applied to the input image to highlight potato candidate. Then, a thresholding algorithm that is optimized by the Genetic Algorithm (GA) is used to extract potatoes from candidate image. Finally, the segmentation result is improved by a sequence of some morphological operators.

This paper is organized as follows: Section 2 presents a brief review on using color features in machine vision inspection of potatoes. Next section describes the proposed segmentation algorithm in details. Section 4 presents some implementation results on some different potato image databases, qualitatively and quantitatively, including totally about 500 potato images. Finally, the paper ends with conclusions and a short outlook for the future works in Section 5.

2. **Color Feature in Potato Inspection: A Review**

Formerly, color had not been employed in machine vision inspection of potatoes because of its high cost and high processing power required [11]. However, as imaging and processing costs were decreased and at the same time, processing power was increased, potato color information of potato images was used to further improve the results. Different color spaces and processing methods have been used in computer vision inspection of potato. Tao et al. [26] used an HSI color space for identifying green potatoes as well as yellow and green apples. This was achieved by the use of each HSI channel histograms which more bins in the histogram resulted in a higher performance. Chalana et al. [31] used an oval shape to characterize potatoes, then they applied thresholding to an HSV color space to distinguish green zones and unripe parts of potatoes.

Noordam et al. [19] used an RGB color space for potato pixels segmentation using a Linear Discriminant Analysis (LDA) in combination with a Mahalanobis

distance. Using a new clustering method called csiFCM, Noordam et al. [20] made an efficient system by applying the csiFCM to the RGB color space for potato image segmentation and detection; this system had a good performance for multivariate images. Pedreschi et al. [21] used an L*a*b* color space for acquiring potato chips images that color values in the L*a*b* color space were recorded at different sampling times during frying at the four oil temperatures; in such condition chips fried at higher temperatures were darker in all 3 dimensions of the color space.

Guannan et al. [9] detected potato sprouts using a comparison of the green channel (in the RGB color space) with the intensity. This value at each pixel was compared to the average value across the potato and if the difference was greater than a threshold, the pixel was determined to be part of a sprout. Hao et al. [10] used blue (B) of the RGB color space to a feasible and practical segment; this system was simple and real-time, but it could not response for other databases by different intensities. Dacal-Nieto et al. [5] used a special color space based on combination of the RGB and HSI color spaces in segmentation algorithm. Jin et al. [12] divided H and V channel of the HSV color space into several fixed intervals to segment potato skin-like parts.

Barnes et al. [2] used seven color channels: the RGB, normalized RGB and intensity channel. For each channel, color intensity, edgeness and texture information were used to segment the color potato images. Ebrahimi et al. [6] used a custom threshold on R, and B channels in the RGB image for potato segmentation, then the output was filtered by morphological operations for noise elimination. Wang et al. [30] applied a single threshold, which was computed by Otsu method, to H channel of the HSI image that was primary preprocessed for denoising with a mean filter. Moallem and Razjooy [17] tested various color channels, including RGB, CbCr (in YCbCr) and SV (in HSV) to select the best one for potato segmentation. They also used Invasive Weed Optimization (IWO) as one of powerful evolutionary algorithm for training of a Multi Layer Perceptron (MLP) neural network for potato segmentation. Moallem et al. [18] used the RGB color space for potato segmentation and co-occurrence texture features for potato defect detection. They also used MLP neural networks trained by a batch steepest gradient descent for both segmentation and defect detection steps.

3. **Proposed Algorithm**

The overall schematic diagram of the proposed segmentation algorithm is shown in Figure 1 which includes some different stages. The input of the proposed algorithm is a potato true color image (24 bits RGB), while in the output image, only the potato pixels remain and the background omits. Sometimes, it is necessary to use an additional preprocessing stage before segmentation. For example, a dynamic contrast manipulation when the input contrast is low and a denoising algorithm when the input noise level is high can be considered in the preprocessing stage [30]. The following sub-sections describe each stage of the proposed algorithm in details.

3.1. **Normalized Color Distance.**

There are several color spaces used in computer vision [14], but in the previous machine vision inspection of potato, RGB,

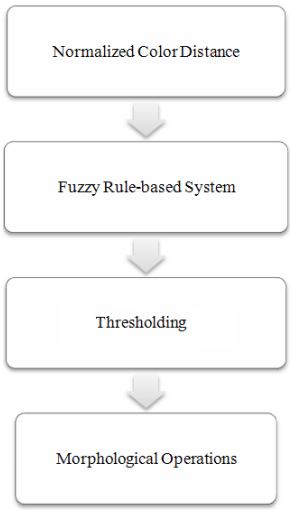


FIGURE 1. Overall Schematic Diagram of the Proposed Segmentation Algorithm

L*a*b*, HSV and HSI color space were more used. In a fixed uniform background, a simple potato segmentation algorithm can work well even in the RGB color space which is based on the human visual system [2][19][20][9][10][6]. In color image segmentation, the hue channel preserves pure color information which is not affected by intensity channel. Therefore, many researchers used the HSI [26][5][30] or HSV [31][12] color space in their machine vision inspection of potato.

In this research, we first focused on the HSI color format, but our experiments shows when a potato stands on its shadow, the intensity channel (I in HSI) of the potato is similar to the intensity of shadow which is wrongly segmented as the potato. On the other hand, V channel (value) of the HSV color space is more robust to shadow, since V channel is set to the maximum value of (R,G,B). In order to decrease the importance of V channel against H and S channels which are more important in potato segmentation, the color space (H, S, 0.75V) is chosen by trials and errors which is called hereinafter as HSV′. Our experiments also show that our proposed HSV′ color space is less sensitive towards light variations, for potato segmentation. Using following non-linear equations, the input RGB color space transforms to the proposed HSV′ color space:

$$\begin{aligned} H &= \arccos \frac{0.5[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \\ S &= 1-3\frac{\min(R,G,B)}{R+G+B} \\ V' &= 0.75\max(R,G,B) \end{aligned} \tag{1}$$

In the first stage of the proposed algorithm, after transforming the color space of the input image to the HSV′, it is necessary to provide a criterion for measuring the similarity of each pixel to potato one. The proposed segmentation algorithm uses

a Mahalanobis color distance which is a scale-invariant distance between a color point y and a predefined color distribution. Suppose a three dimensional random vector x for potato color distribution is defined as:

$$x = (x_H, x_S, x_{V'}) \tag{2}$$

where x_H, x_S, and $x_{V'}$ are the value of each H, S and V′ channel of the HSV′ color space. For N samples of random vector x, the sample mean vector $\hat{\mu}$ and the sample covariance matrix $\hat{\Sigma}$ of potato color distribution are defined as:

$$\begin{aligned} \hat{\mu} &= \frac{1}{N}\sum_{k=1}^{N} x_k \\ \hat{\Sigma} &= \frac{1}{(N-1)}\sum_{k=1}^{N}(x_k - \hat{\mu})(x_k - \hat{\mu})^T \end{aligned} \tag{3}$$

where x_k is k^{th} sample of random vector x. The Mahalanbis color distance of unknown vector y, $D_M(y)$, from the group of N samples is defined as [27]:

$$D_M(y) = \sqrt{(y - \hat{\mu})^T \hat{\Sigma}^{-1}(y - \hat{\mu})} \tag{4}$$

The normalized color distance $d_M(y)$ is defined as:

$$d_M(y) = \frac{D_M(y)}{\max(D_M(y))} \tag{5}$$

where $\max(D_M(y))$ is the maximum value of $D_M(y)$ over all y.

In our implementation, we consider more than $100,000$ samples of potato pixels from different color images to compute the sample mean vector and the sample covariance matrix of potato color distribution in the HSV′ color space. In fact, the Mahalanbis color distance of unknown vector y measures its similarity to the potato color. A small (large) value of $d_M(y)$ means that corresponding pixel of the vector y is (is not) similar to potato.

3.2. **Designing a Fuzzy Rule-based Inference System.** The second stage of the proposed segmentation algorithm provides a likelihood image, which pixels value is potato likelihood based on color information. Then by applying a proper threshold on the likelihood image, which is implemented in the third stage of the proposed segmentation algorithm, the potato pixels detects. In a real environment, the potato pixel detection problem involves two main challenges, including variable illumination conditions, and uncertainty of potato color. In such conditions, fuzzy color segmentation can be effectively used [4]. So, in this paper, a Mamdani-type fuzzy rule-based inference system is developed for computing the likelihood image.

The proposed fuzzy rule-based inference system is one-input/one-output system that the input is the normalized Mahalanbis color distance, and the output is the potato likelihood. In order to optimize and decide on the number of membership functions (MF's) and rules, a subtractive clustering algorithm is applied to more than $150,000$ potato and non-potato sample pixels in the HSV′ color space. The subtractive clustering is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data [22]. This algorithm utilizes data points as the candidates for cluster centers, which means that the algorithm computation is proportional to the problem size instead of the problem dimension. However, the

actual cluster centers do not need to place at one of the data points, but it is a good approximation in most cases, especially with the reduced computation that this clustering algorithm presents. Since each data point can be considered as a candidate for cluster center, a density measure at data point x_i, D_i, is defined as:

$$D_i = \sum_{j=1}^{N} \exp(1 - \frac{\|x_i - x_j\|}{r_a/2}) \tag{6}$$

where N is the number of data and r_a is a positive constant indicating a neighborhood radius. It means that when a data point has many neighboring data points, it will have a high density value.

The point with the largest density value, D_{c1}, is selected as the first cluster center x_{c1}. Then the corresponding density measure of each data point x_i is updated as follows:

$$D_i = D_i - D_{c1} \exp(1 - \frac{\|x_i - x_{c1}\|^2}{r_b/2}) \tag{7}$$

where r_b is a constant neighborhood that provides measurable reductions in the density measure.

Therefore, the data points near the first cluster center x_{c1} will have significantly reduced density measure. After updating the density function, the next cluster center is chosen as the point having the next greatest density value. This process carries on till a sufficient number of clusters is achieved.

Figure 2 shows distribution of plenty of potato pixels and four cluster centers in the HSV′ color space. Since there are four clusters, four MF's should be considered, one MF for potato, one for non-potato and two others are between potato and non-potato, which can be fuzzified simply. The general form of an achieved rule in the fuzzy rule-based inference system for potato segmentation is [16]:

IF *input is Z* THEN *output is Z*

where $Z \in$ {Potato, Rather Potato, Low Probability Potato, Non-Potato}.

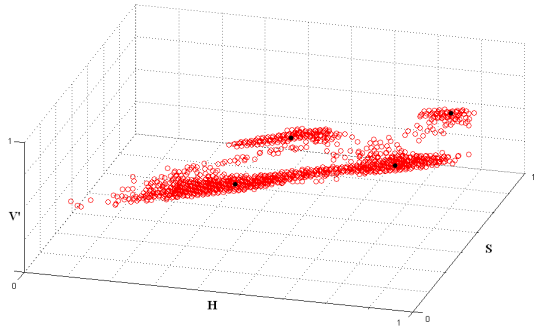


FIGURE 2. More than 150,000 Potato and Non-potato Sample Pixels (Red Circles) in HSV′ Color Space and Four Cluster Center (Black Circles) which are the Output of Subtractive Clustering Algorithm

Four input and output membership functions, which are primary selected by trial and errors, are shown in Figures 3 and 4, respectively. As it can be seen, the Potato and Non-Potato shapes are bell shape, and Rather-Potato and Low-Probability-Potato are triangle shape, for both input and output MF's. These shapes are designed experimentally in this stage, and then they are tuned by GA-algorithm.

The input membership functions are the fuzzified Mahalonobis distance of an input unknown pixel from potato color distribution, d_M, in equation (5) and, the output membership functions are the fuzzified likelihood to potato. In order to defuzzify the fuzzy output, the *Center of Area* (COA) is then chosen which is the most widely used among all defuzzification approaches. For the fuzzy set B, the COA minimizes the following expression [23]:

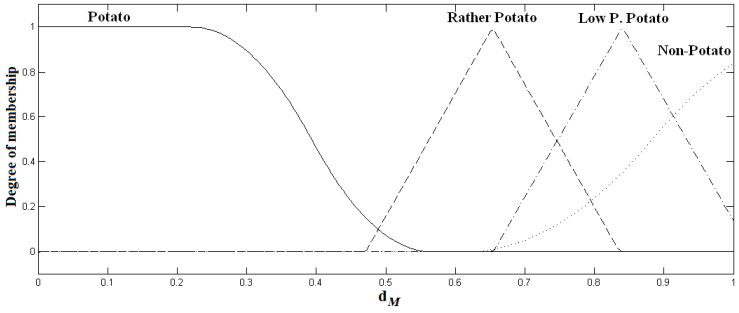


FIGURE 3. Four Input Membership Functions for Input Fuzzy Variables Including "Potato", "Rather Potato", "Low P. (Probability) Potato" and "Non-Potato", which are Primary Selected by Trial and Error

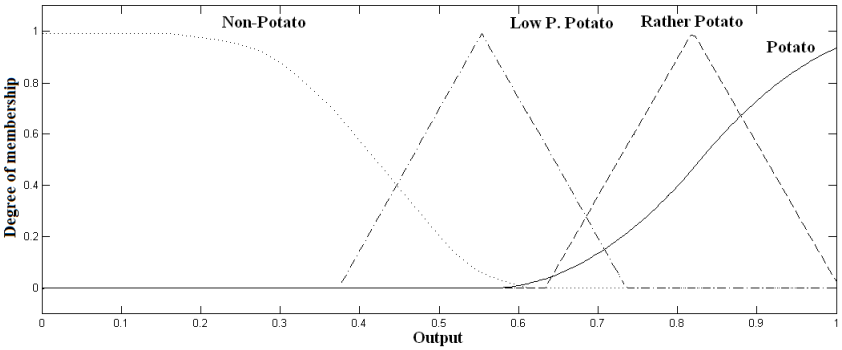


FIGURE 4. Four Output Membership Functions for Output Fuzzy Variables Including "Potato", "Rather Potato", "Low P. (Probability) Potato" and "Non-Potato", which are Primary Selected by Trial and Error

$$|\sum_{\inf y}^{COA(B)} B(y) - \sum_{COA(B)}^{\sup y} B(y)| \tag{8}$$

where inf is the greatest lower bound, and sup is the least upper bound of the support of the fuzzy set B, respectively.

The expression (8) gives numerical value $y_0 = y_{COA}(B)$, which divides an area under the membership function in two (approximately) equal parts. After applying COA defuzzification to the fuzzy output, the output is between 0 and 1. It means that if the proposed fuzzy rule-based inference system applies to all pixels of the input image, the output image is likelihood image that pixels value shows probability of being potato.

Figure 5(a) shows a sample potato input image in a variable lighting, and Figure 5(b) shows the output of applying the proposed fuzzy rule-based inference system to the input image. The brighter pixels are more similar to potato, because they are closer to 1 towards the other pixels that are closer to 0.

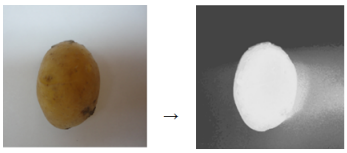


FIGURE 5. (a) Input Potato Image in a Variable Lighting, (b) Likelihood Image by the Proposed Fuzzy Rule-based Inference System

After computing the likelihood image, which the sample is shown in Figure 5(b), it is necessary to make a binary image that separates the potato(es) and background. The likelihood image can be considered as a gray level image and since the potato candidates are brighter than others, a simple thresholding can be used. Figure 6(b) shows the binarization of the Figure 6(a) by applying the global threshold value 0.8 that is selected manually. It is clear that some shadow region is incorrectly segmented as potato.

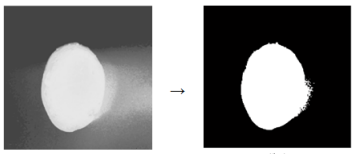


FIGURE 6. (a) Likelihood Image by Applying the Proposed Fuzzy Rule-based Inference System on Figure 5 (a), (b) Applying Thresholding which Threshold is Set Manually on 0.8

3.3. **GA-based Parameter Tuning.** In fact, the key parameters of the proposed algorithm are the threshold value of thresholding step, and the shape of fuzzy MF's. In this paper, in order to compute an optimized threshold and MFs, we propose to use the GA, which is known as "global optimizer", to optimize proposed fitness functions. At first, the primary shapes of MFs are achieved by trial and error which are shown in Figures 3 and 4. Experiential knowledge (described in subsection 3.2) is also employed to diminish the searching space and to enhance the

process. MF's parameters are considered as the GA inputs, and the defined fitness function attempts to maximize the likelihood of being potato for potato pixels, over 50 randomly selected images. In this system, GA parameters are: crossover= 0.85, migration= 0.14 and mutation (non-uniform type)= 0.05. The Figures 7 and 8 are shown the obtained MFs after applying GA optimization.

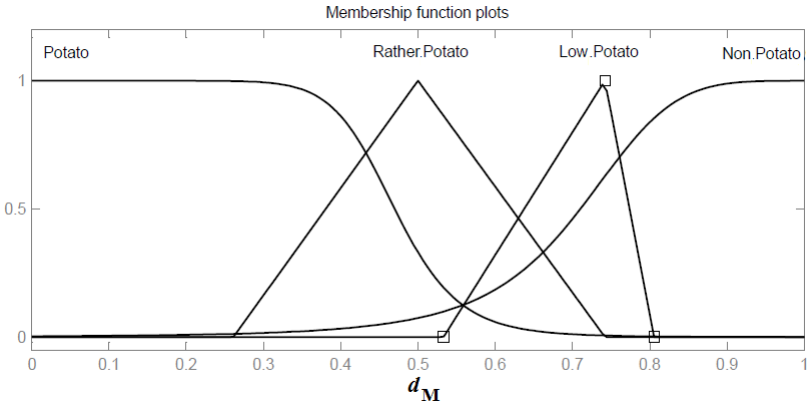


FIGURE 7. Four Input Membership Functions for Input Fuzzy Variables Including "Potato", "Rather Potato", "Low P. (Probability) Potato" and "Non-Potato", which are Optimized by GA

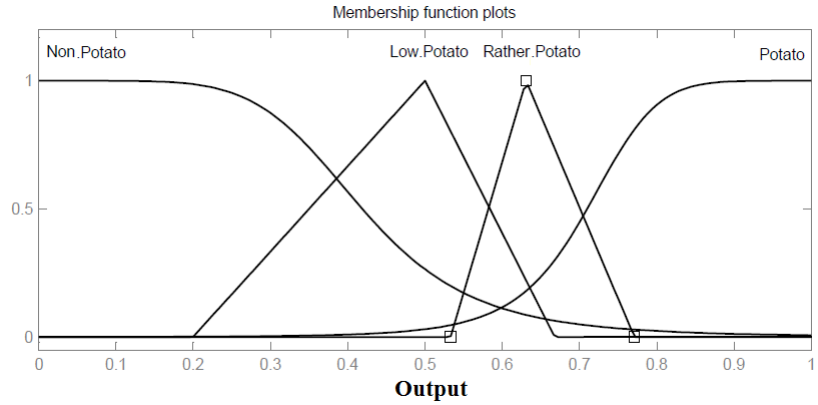


FIGURE 8. Four Output Membership Functions for Output Fuzzy Variables Including "Potato", "Rather Potato", "Low P. (Probability) Potato" and "Non-Potato", which are Optimized by GA

Computing the threshold value is not always straightforward in potato image segmentation [7]. An automatic global thresholding method tries to compute a single threshold value automatically for the whole image based on some image information [8]. There are several methods in computing the global threshold value [24] which the evolutionary-based methods show the best results [13] [15].

In the proposed thresholding algorithm, in order to use the GA for optimization of the threshold value, the objective function which should be minimized is presented here. Suppose that there are N_P and N_{NP} potato and non-potato pixels which are selected randomly as the training sample set. In order to improve the result achieved during optimization, it is necessary to select the ambiguous regions which are affected by shadow and variable lighting, from the sample likelihood images. Figure 9 shows a sample ambiguous region which is inside the black border. After applying a threshold value to the training sample set, the C_P and C_{NP} are the correctly segmented pixels as potato and non-potato pixels, respectively. The fitness function, which should be maximized, is considered as follow:

$$\text{Fitness Function} = \frac{C_P + C_{NP}}{N_P + N_{NP}} \tag{9}$$

The computed threshold, which is the chromosome of GA, should be limited in the range $[0 - 1]$. As the initial population, a set of 100 random thresholds in the range $[0.6 - 1.0]$ is selected, since the threshold value 0.8, which is already selected manually, shows an acceptable result (Figure 6). In our implementation, the crossover, migration and mutation (non-uniform type) coefficients set to 0.8, 0.2, and 0.04, respectively. The final achieved threshold value is 0.863. It means that the pixels with potato-likelihood more than 0.863 are segmented to the potato pixels. Figure 10(b) shows the binarization of the Figure 6(a) by applying the global threshold 0.863 which is computed by the GA. It is clear that the result is better than Figure 6(b) which threshold was selected manually.

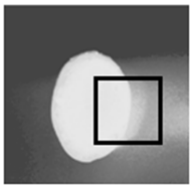


FIGURE 9. A Sample Ambiguous Region which is Inside of the Black Border

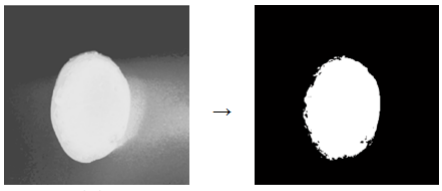


FIGURE 10. (a) Likelihood Image by Applying the Proposed Fuzzy Rule-based Inference System on Figure 5(a), (b) Applying Thresholding which Threshold is Optimized by GA

3.4. **Morphological Operations.** The output of applying the proposed fuzzy rule-based inference system and GA-based thresholding is a binary image which separates potato and background (non-potato) pixels. As shown in Figure 10 (b), the results on the border region of the segmented potato may be noisy. In the proposed segmentation algorithm, three morphological operations with a 5×5 square structuring element, including region filling, closing, and area opening are used in order to improve the final segmentation results [15]. The algorithm for region filling that is based on set dilation, complementation, and intersections is expressed as:

$$X_k = (X_{k-1} \oplus B) \cap A^c \quad k = 1, 2, 3, ... \tag{10}$$

where $\oplus$ is dilation operator, A is a set of boundary and B is structuring element. The algorithms terminate at iteration step k if $X_k = X_{k-1}$.

The closing operator typically makes counters smooth, fuses narrow breaks and long thin gulfs, eliminates small holes, and fills gaps in the contour. The closing of set A by structuring element B, denoted $A \bullet B$, is defined as:

$$A \bullet B = (A \oplus B) \ominus B \tag{11}$$

where $\ominus$ is erosion operator. The closing might result in amalgamation of disconnected components, consequently, generating new holes.

The opening of A by B is obtained by the erosion of A by B, followed by dilation of the resulting image by B, which is shown as follows:

$$A \circ B = (A \ominus B) \oplus B \tag{12}$$

The opening operator tries to eliminate small area blemishes that can be ignored by the potato processing industries [31]. Figure 11 shows the result of applying the proposed morphological operators to the sample potato thresholded image which is shown in Figure 10(b) . In fact, the morphological operators help to improve the image contours and eliminate or reduce noise and undesired speckles outside the contour of the potato.

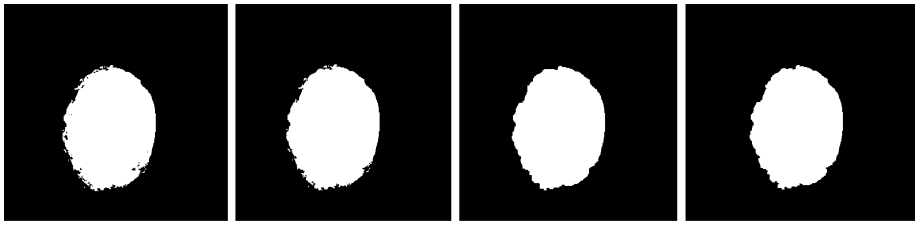


FIGURE 11. (a) The Sample Thresholded Image, and the Results After Consecutively Applying the Filling Operator (b), Closing Operator (c) and Finally Opening Operator (d)

4. **Experimental Results**

In order to evaluate the performance of the proposed algorithm in different conditions, totally more than 500 potato images are provided as image database. Firstly, two standard images set, including United States Department of Agriculture (USDA) [28], and Canadian Food Industries (CFIA) [3] with totally about

100 potato images are considered. Then about 400 potato images are added to the image database. These images have been taken by an intelligent auto Sony cyber-shot DSC-W350 digital camera (14.1 mega pixel) from a set of 50 bags of potatoes were randomly selected from the Ardabil (Iran's northwest) farms on 2011 harvest. The light, color and contrast variations of the last set are more than two first ones. Since the images are in different resolutions and formats, all images are converted to 448×336 pixels and RGB color format.

To compare the performance of the proposed algorithm with other methods, three performance metrics are described. The first metric is the correct detection rate (CDR). The false acceptance rate (FAR) is the percentage of identification moments in which false acceptance occurs. The false rejection rate (FRR) is the percentage of identification moments in which false rejection occurs. These performance metrics are expressed in equation (13).

$$\begin{aligned} \text{CDR} &= \frac{\text{Number of samples correctly classified in dataset}}{\text{Total number of samples in dataset}} \\ \text{FAR} &= \frac{\text{Number of non-potato samples classified as potato samples}}{\text{Total number of samples in dataset}} \\ \text{FRR} &= \frac{\text{Number of potato samples classified as non-potato samples}}{\text{Total number of samples in dataset}} \end{aligned} \tag{13}$$

As mentioned in the introduction section, some researchers such as us, suggested using the HSV or HSI color space for potato color segmentation. Again, the morphological operators are also used to improve the segmentation results. We believe that the novelty of our proposed method is a combination of fuzzy rule-based inference system and GA-based thresholding for potato image binarization. Therefore, we replace our proposed fuzzy rule-based inference system and GA-based thresholding with the Fuzzy-C means and K-means algorithms which inputs are the proposed HSV$'$ color value. The number of clusters in both algorithms is set to four which is already confirmed by the subtractive clustering algorithm. Moreover, in order to achieve the best results, our experiments show that one of the output clusters should be labeled for potato pixels, while the others are labeled for non-potato pixels.

We also compare the results of our proposed segmentation algorithm with two other color-based potato image segmentation algorithms which tested various color channels to select the best one for segmentation. These two algorithms which are based on MLP neural network, used Back Propagation (BP) as well as Invasive Weed Optimization (IWO) as one of powerful evolutionary algorithm, for MLP training [17].

Table 1 represents the CDR, FRR and FAR performance metrics for all compared algorithms, for different image set, separately. For USDA and CFIA image set which background and imaging conditions are nearly constant, all compared methods work well. For Ardabil's image set which background is more complex and imaging conditions are different, the proposed method shows the best results. In fact, the proposed algorithm shows the highest CDR and the lowest FRR and FAR against the other compared algorithm. All algorithms are implemented under Matlab environment [8].

In order to demonstrate the importance of GA-based thresholding in the performance of the proposed algorithm, Figure 12 indicates CDR variations in term

Performance metric	dataset	K-means	Fuzzy-C means	MLP trained by BP	MLP trained by IWO	Proposed method
CDR	USDA+CFIA image set	90.00	90.00	94.00	98.00	100.0
	Ardabil's image set	77.50	83.75	89.00	93.50	97.50
	Total image set	80.00	85.00	90.00	96.00	98.00
FRR	USDA+CFIA image set	10.00	6.00	2.00	1.00	0.00
	Ardabil's image set	17.80	11.60	2.50	3.75	1.75
	Total image set	16.25	10.50	2.40	3.20	1.40
FAR	USDA+CFIA image set	2.00	4.00	3.00	0.00	0.00
	Ardabil's image set	4.20	4.60	8.75	1.00	0.75
	Total image set	3.75	4.50	7.60	0.80	0.60

TABLE 1. Comparison of the Performance Metrics of the Proposed Method toward the Other Algorithms, in Fuzzy-C mean and K-Mean Clustering Algorithm, the number of Clusters is Set to Four which is Already Confirmed by Subtractive Clustering, MLP-based Segmentation Algorithm is a Neural Network which Receives the Color Information on Input Pixels and Decides whether this Pixel is Potato or Non-potato, based on the MLP Output Value [17], in all Compared Algorithms, the same Post-processing Morphological Operations are Used to Present a Fair Comparison

of different manually selected threshold value, considering total image data set. As shown in this Figure, without applying GA-based optimization the threshold value around 0.86 reaches to the highest CDR value. On the other hand, GA-based thresholding, which results in automatically selecting the global threshold value equal to 0.863, shows the highest CDR value.

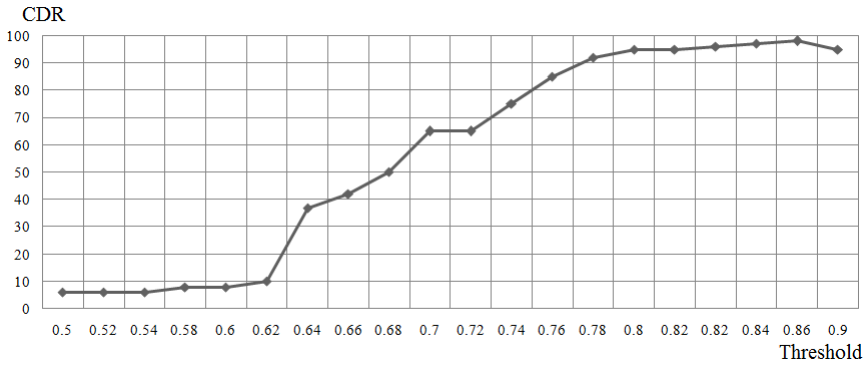


FIGURE 12. Variation of CDR in Term of the Thresholded Value which is Selected Manually between 0.5 to 0.9, the Threshold Value of 0.86 Shows the Highest CDR about 98.0%

To demonstrate the performance of the proposed segmentation algorithm in some hard situations, the input images and outputs of different stages are shown in Figure 13. Six particular potatoes are especially chosen to show the inherent difficulties due to the high variability encountered in potato segmentation. In this Figure, the potato images in 1^{st} to 4^{th} row are selected from Ardabil's databases, 5^{th} row is

from CFIA, and the last row is from USDA, respectively. The backgrounds of all input images in Figure 13 are different. The first and third row is in non-uniform lighting, while in the second row, the shadow is clear. In the last two rows, the over exposure is obvious which could results in some mistakes in segmentation.

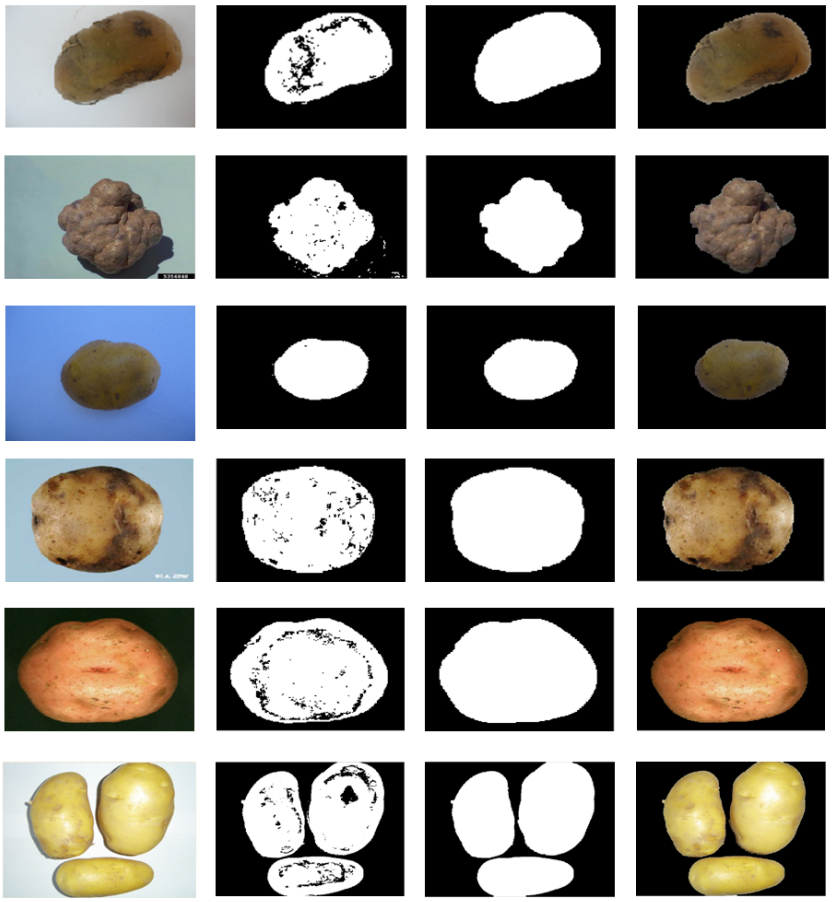


FIGURE 13. Six Different Potato Color Images and the Outputs of the Proposed Segmentation Algorithm, a) Input Images, b) Images after Fuzzification and GA Thresholding, c) Images after Morphological Operations, d) Output Segmented Images

To visually compare the results of all compared segmentation algorithms, Table 4 shows four image samples of defected potatoes in which the proposed method shows acceptable outputs in all test, while the other compared methods fail in two first cases. So, the proposed segmentation algorithm shows acceptable segmentation results even when the potatoes are severely defected, which are quite common in the defect detection algorithms.

Sample	Input image	K-means	Fuzzy-C means	MLP trained by BP	MLP trained by IWO	Proposed method
1		N	N	N	N	A
2		N	N	N	N	A
3		A	A	A	A	A
4		A	A	A	A	A

TABLE 2. Some Defected Potato Samples which are Hard Situations for Correct Potato Segmentation and the Output of the Compared Segmentation Algorithms in Term of Acceptable Segmentation (A: Acceptable Segmentation, N: Non-acceptable Segmentation)

Figure 14 shows two input images taken from a sorting section of potato industries with different backgrounds, and the output of the proposed segmentation algorithm. The output of the proposed algorithm for the first row test image including different size of potatoes is perfect where the background hue is nearly constant and the background brightness and edges are different. The second row test image is a difficult situation where the background color, brightness and edges are very different, and the potato sizes are also different. The output of the proposed algorithm is also acceptable, but there are some false segmented regions in upper side of the output image which are highlighted by the white circles. Please note that the color information of the false positive regions is very similar to potato ones. These false accepted outputs can be simply removed considering the fixed position of the potato conveyer.

Figure 15 shows two input images taken from a potato farm on background of soil and leaves. The output of the first row test image including soil background

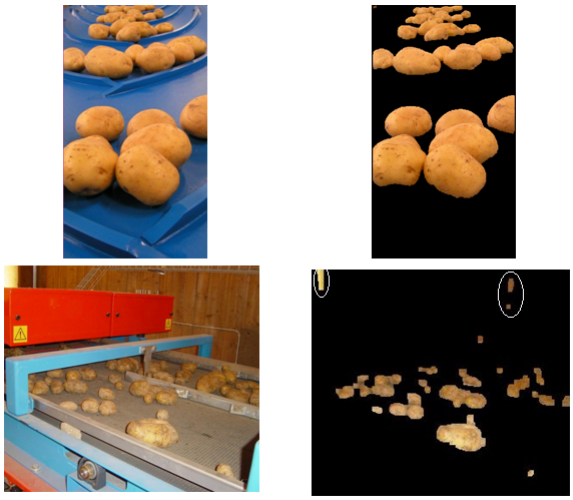


FIGURE 14. a) Two Different Potato Color Images Taken in Real Potato Industries, and b) The Outputs of the Proposed Segmentation Algorithm, the False Accepted Regions in upper Side of the Output Image are Highlighted by the White Circles

is perfect that the entire soil regions are eliminated. The second row test image where the background is green leaves is a hard situation for color segmentation since the white green color is similar to the potato color. Therefore, there is a false segmented region in the output of the proposed algorithm which is shown by a white circle. We should inform that we did not consider white green color in rule tuning of the proposed fuzzy rule-based system, therefore these types of false outputs can be removed considering more proper colors in the rules tuning step.



FIGURE 15. a) Two Different Potato Color Images Taken in Real Potato Farm, and b) the Outputs of the Proposed Segmentation Algorithm, the False Accepted Region in the Output of the Proposed Algorithm is Shown by the White Circle

5. **Conclusions**

Typically, the segmentation of potato or any other vegetables or fruits is a primary step in all defect detection and grading algorithms. In most of previous

works, the segmentation step is simplified considering simple background and uniform lighting. Since the errors in segmentation step result in decreasing the overall performance, the segmentation step in real conditions play, a major role in improving performance of defect detection and grading algorithms.

In real conditions, the lighting is not uniform, the background may be changed and a potato shadow may be existed. In this paper, a robust segmentation algorithm for potato color image is presented to separate the potato and background. In the first step, the input color space is converted to the HSV′ color space (V′=0.75V) and the Mahalanobis distance from the color distribution of potato is computed. Then a Mamdani-type fuzzy rule-based inference system is used to produce a potato likelihood image and a thresholding algorithm is then used to segment potato pixels. The performance of the both fuzzy rule-based inference system and thresholding algorithm is optimized by the GA. In fact, the proposed algorithm comprises soft computing methods to improve the accuracy. The number of clusters for the proposed fuzzy rule-based inference system is also determined by applying the subtractive clustering to a training sample set. After that, the sequence of morphological operations is used to improve the segmentation results. Implementation results of applying the proposed segmentation algorithm to more than 500 potato images indicate that the correct segmentation rate achieves to 98%.

The results of the proposed segmentation algorithm in hard situations imply that there may be some mistakes in the output which can be reduced considering these types of hard situations in the rules tuning step of the proposed fuzzy rule-based inference system, the threshold tuning of the thresholding step and, selecting more suitable morphological operators. On the other hand, after determination of system operating conditions and fixing the imaging system, some proper pruning technique (for example based on the texture features) can be used to improve the system performance in such hard situations. Therefore, we believe the proposed potato segmentation algorithm can be used in different defect detection and grading algorithms to improve the overall results in practical applications.

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P. Moallem*, Electrical Engineering Department, University of Isfahan, Isfahan, Iran
E-mail address: p_moallem@eng.ui.ac.ir

N. Razmjooy, Young Researchers and Elite Club, Majlesi branch, Islamic Azad University, Isfahan, Iran
E-mail address: navid.razmjooy@hotmail.com

B. S. Mousavi, Electrical Engineering Department, Hatef Higher Education Institute, Zahedan, Iran
E-mail address: bbmoosavi@gmail.com

*Corresponding author