Bit plane slicing technique to classify date varieties

Thomas Gabriel[1], Annamalai Manickavasagan[2*]
and Karuppannan Ganeshmoorthy[2]

(1. Department Electrical and Computer Engineering, Faculty of Engineering, University of Manitoba, Winnipeg, MB, Canada ;
2. Department of Soils, Water and Agricultural Engineering, College of Agricultural and Marine Sciences, Sultan Qaboos University, Al-Khoud, Sultanate of Oman.)

Abstract: Varietal purity is an important parameter in the quality standards of dates. In general, variety identification is done by visual inspection method in grading and handling facilities. Online variety assessment using computer vision methods with minimum features and fast image processing and classification algorithms would be highly beneficial for the date industry. Three date varieties (Khalas, Fard and Madina) were classified using a single type of feature, Euler number, used on the eight bit planes available from gray scale images. An overall classification accuracy of 91.48% was achieved using a two layer neural network classifier with hyperbolic tangent sigmoid transfer function. Additionally, image segmentation was performed using the two most significant bit planes. Therefore, a complete feature extraction module based on logic values and morphological image processing as proposed here can be easily implemented in hardware.

Keywords: date varieties; bit-plane slicing; bit-plane segmentation; Euler feature

Citation: Gabriel, T., A. Manickavasagan, and K. Ganeshmoorthy. 2015. Bit plane slicing technique to classify date varieties. AgricEngInt: CIGR Journal, 17(2):267-286.

1 Introduction

Although annual production of dates in Oman is 255,891 Mt, only 9000 Mt is exported which is 2.5% to 3.5% of total production (FAO, 2007). Quality assurance has always a problem for Omani dates to compete in the international market (Al-Marshudi, 2002). Varietal purity, color, uniformity of size and absence of defects are some of the important quality parameters for dates in domestic and international markets. Generally, manual grading of dates is followed in handling and processing facilities. This method has many constraints such as subjectivity, influence of mental stress, influence of environment, efficiency of individuals at various times of the shift and so on. Computer vision (CV) technology is a potential alternative method for visual inspection of quality assessment. It has been successfully used for the evaluation of different products in the automated inspection process. It has also proven to be a very good nondestructive method in the inspection of agricultural products. Automatic inspection improves productivity, reduces production costs and provides better quality and safe foods to consumers (Chen et al., 2002; Mendoza et al., 2006; Kang et al., 2008; Lunadei et al., 2012). Such CV systems require different signal processing steps and modules that may involve rigorous image enhancement, segmentation, feature extraction and classification protocols. For example, in a peach defect detection system, the image processing steps involved are: a. Correction of shading effects of images, b. Detection of edges for segmentation as well as region growing techniques and c. Use of morphological and spectral features such as mean and variance in a rule based decision tree and a Bayes classifiers (Miller and Delwiche, 1991).

Received date: 2014-03-08 **Accepted date:** 2015-03-28

***Corresponding author: Annamalai Manickavasagan,** Department of Soils, Water and Agricultural Engineering, College of Agricultural and Marine Sciences, Sultan Qaboos University, Al-Khoud, Sultanate of Oman. Phone: 968-24143646, Email: manick@squ.edu.om.

For the feature extraction part, statistical features are known to be excellent metrics in general texture analysis (Unser and Eden, 1989), thus they have been successfully used in the inspection of agricultural products (Chen et al., 2002; Miller and Delwiche, 1991; Pydipati et al., 2005). We propose in this paper a new method to extract features from a series of date images. To assess the quality of these features, a simple neural network classifier was used to differentiate between three different date varieties. Based on a single morphological feature, the Euler number, and using bit plane decomposition of gray level images, a very simple feature extraction signal processing module can be designed which requires no floating point operations. The simplicity can then allow the implementation of this CV system on an embedded system based on FPGA devices (Deschamps, 2012). Furthermore, this module can for example be implemented on the ARM based subsystem of the Texas Instruments DM3730 Digital Media Processor leaving the available TMS DSP subsystem for implementation of a classifier (Texas Instruments, 2011). Bit plane slicing has been proposed back in the sixties (Schwartz and Baker, 1966) and has been recently gathered attention for applications such as image retrieval (Bishnu and Bhattacharya, 2007), face recognition (Priyadarsini et al., 2012; Dai et al., 2009; Ting et al., 2008), medical image analysis (Gomathi and Thangaraj, 2010; Fraz et al., 2011) and image feature extraction (Sathik et al., 2010). To the best of our knowledge, bit planes have not been used for image analysis of agricultural products.

2 Materials and methods

2.1 Image acquisition

Samples of three date varieties (Khalas, Fard and Madina) were obtained from at least three shops in Oman, and the varietal purity was confirmed by a “date variety expert” at Sultan Qaboos University. A conglomerate sample of 100 dates was taken for each variety (n=100 for each variety) and the sample was imaged (single date images) with a color camera (model: D3, Nikon, Japan, Resolution – 4256 × 2832 pixels). The date samples were illuminated with a halogen lamp (Visa tech, model SOLO 1600B) during imaging. Then all images were converted into gray scale images using Matlab software, and analyzed.

2.2 Bit plane slicing and segmentation

Gray scale images are usually eight bit images with values in the range of (0, 255). These integer values are represented in binary form with eight bits, and an image can be seen as a composition of eight binary planes. Figure 1 illustrates an example of this decomposition. From bottom to top: original image of a date, low resolution image, plane with the original integer pixel values of the low resolution image with range [0, 255], eight bit planes extracted from the binary representation of the integer values shown starting from the least significant bit plane to the most significant bit plane at the top. The corner pixel with a value of 206 is shown on the left. An important thing to mention is that this decomposition requires no numerical operations.

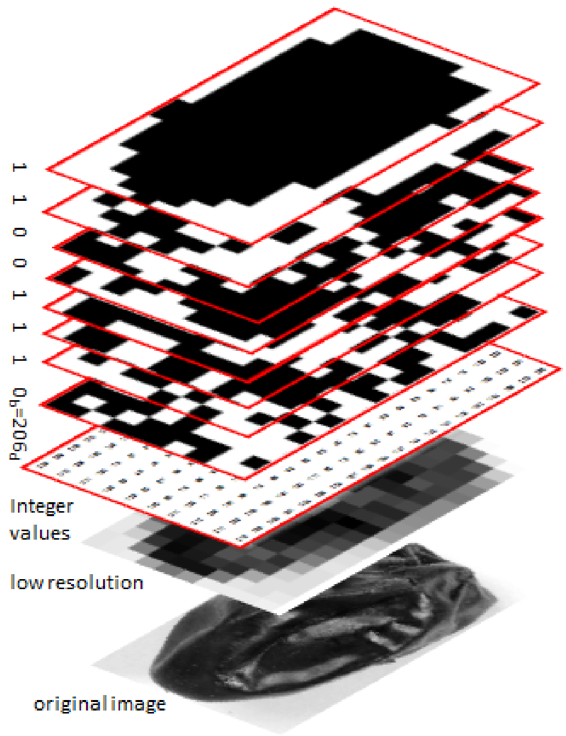


Figure 1 An example of bit plane slicing and segmentation

Mathematically, a bit plane image $f_{bp_i}(x,y)$ can be obtained by (Ting et al., 2008) :

$$f_{bp_i}(x,y) = \frac{R}{2} floor(\frac{1}{2^i} f(x,y)) \qquad (1)$$

for $i = 0,1,\ldots,7$, where R = remainder and $floor(x)$ rounds the elements to x nearest integers less than or equal to x. This information can be easily obtained from the camera hardware by forming the eight planes from the output of the imaging sensor. Figure 2 shows a 981×1526 pixels high resolution image and the eight bit planes. One can notice that the planes f_{bp_7} to f_{bp_4} capture the light reflections from the dates. Thus it can be said that they do vary depending on the date surface texture.

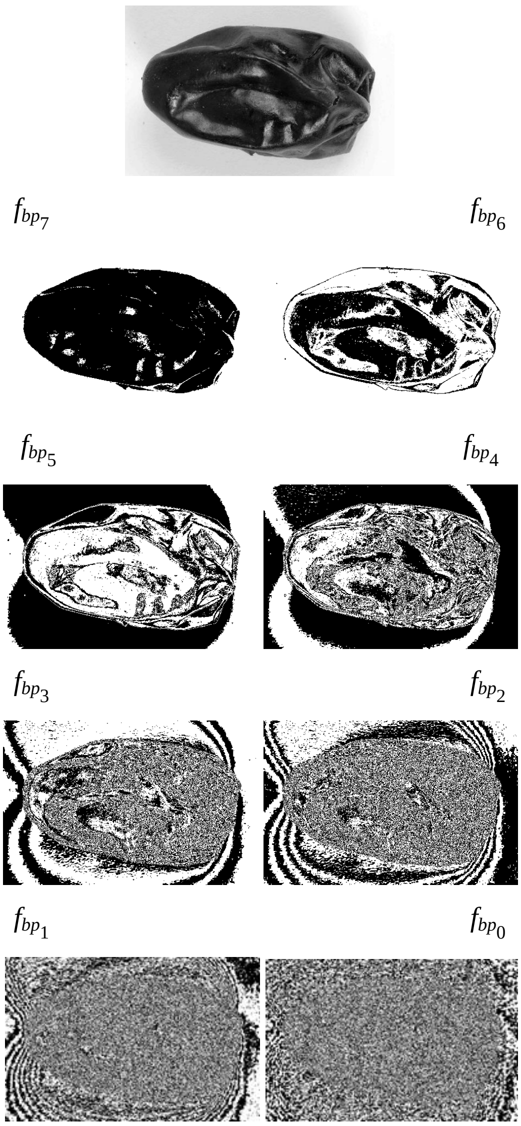


Figure 2 Original image and its eight bit planes

In order to eliminate the background, morphological image processing operations allowed us to implement segmentation of the date without using floating point operations. By logical ANDing the two planes corresponding to the two most significant bits f_{bp_7} and f_{bp_6}, most of the background area can be eliminated. Figure 3 shows this operation for the two planes shown in Figure 2.

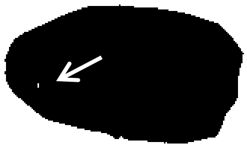


Figure 3 And operation of f_{bp_7} and f_{bp_6} shown in Figure 2

Notice how a hole appears on the left as highlighted by the arrow. For some images, some blobs appeared on the background as well. Thus, the final segmentation mask f_{sm} can be obtained by using the following algorithm:

1. Logical ANDing (Maragos, 1989):

$$f_1 = f_{bp_7} \cap f_{bp_6} \qquad (2)$$

2. Image filling by reconstruction (Vincent, 1993):

$$f_2 = \left(f_{bp_7} \oplus B\right) \wedge I \qquad (3)$$

Where $\oplus$ denotes morphological dilation, B is a structuring element, $\wedge$ denotes point wise minimum, and $f_1 \leq I$.

3. Eliminate spurious isolated backgrounds pixels/blobs by morphological opening (Vincent, 1993):

$$f_3 = f_2 \circ B \qquad (4)$$

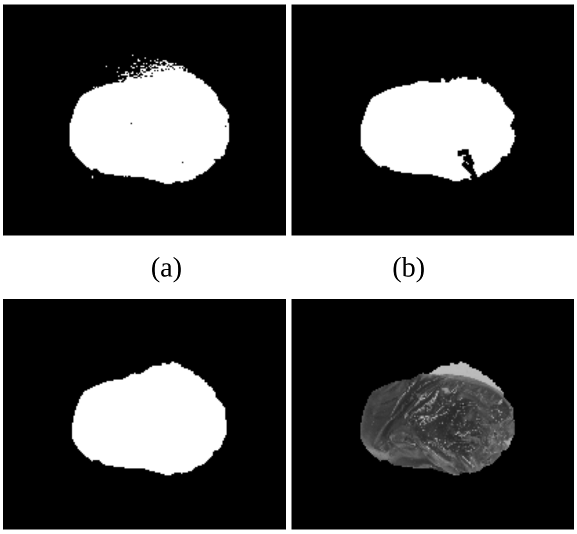
4. Reduce the size of the mask by morphological erosion (Vincent, 1993) to guarantee that only pixels within the date are used:

$$f_{sm} = f_3 \otimes B \qquad (5)$$

All the above steps were easily implemented in Matlab choosing a structuring element of size 21 in Equation (5), and 10% of the image size in Equation (4).

We would like to note that Step 2, image filling, must be the first step taken for enhancing the mask in Figure 3.

Otherwise small holes in Step 1 can breach to the background during erosion as shown in Figure 4 (b). Figure 4 shows a segmentation error, some background appears on top of the date (Figure 4(d)). Of the three classes of dates, Khalas did not show any errors, Madina had one (Figure 3), and Khalas had nine. Otherwise results such as the ones shown in Figure 4 were obtained for the rest. It is then up to the feature computed from these bit plane images to introduce or not a significant change from these errors and have an effect on the final classification. At this point, it can be mentioned that the background gray levels are quite constant.



(a) (b)

(c) (d)

Figure 4 Application of segmentation mask on a date image
(a) Results from Step 1 (b) Results from applying Equation (5) before Equation (3)
(c) Results from following the order estipulated above
(d) Final segmentation

2.3 Euler number as classification feature

The Euler number is a measure of the topology of an image. It is defined as the total number of objects P in the image minus the number of holes H in those objects; as such, this feature is robust to object rotation and deformation (Gonzalez and Woods, 2001). A run in a row (column) of an image is the maximum sequence of consecutive 1's in that particular row (column). Two runs in two adjacent rows (columns) are neighbors if one pixel of a run is in the eight neighborhood of a pixel from the other run. Let R (i) and O (i) be the number of runs and neighboring runs. The Euler number of image I can be calculated as (Bishnu and Bhattacharya, 2007; Gomathi and Thangaraj, 2010):

$$E(I) = P - H = \sum_{i=1}^{N} R(i) - \sum_{i=2}^{N} O(i) \quad (6)$$

The Euler numbers of the eight bit planes were calculated E_7, E_6, E_5, E_4, E_3, E_2, E_1, as well as combining bit planes by logical OR (Bishnu and Bhattacharya, 2007), using all the possible combination of two of the four most significant planes E_{ij},= $E(f_{bp_i}$OR $f_{bp_j})$ for i,j=7,6,5, and $i \neq j$ as well as all possible combinations using three planes E_{ijk} for a total of 18 features. Before continuing with the discussion on Euler numbers as features, let recall the results of segmentation for cases such as the one shown in Figure 4 (d). All the features were computed for an image segmented by the approach proposed here and a conventional technique based on Otsu's method (Otsu, 1979). Figure 5 shows the results for one of the images of class Khalas that had segmentation errors as shown in the images inserted within the figure. As can be seen, the results are very similar and a classifier should be able to take care of those small changes. Because our goal is to implement a feature extraction module without requiring floating point operations, Otsu's thresholding (Otsu, 1979) for segmentation was not tested any further since it requires mathematical operations not based on set theory as is the case with morphological operations.

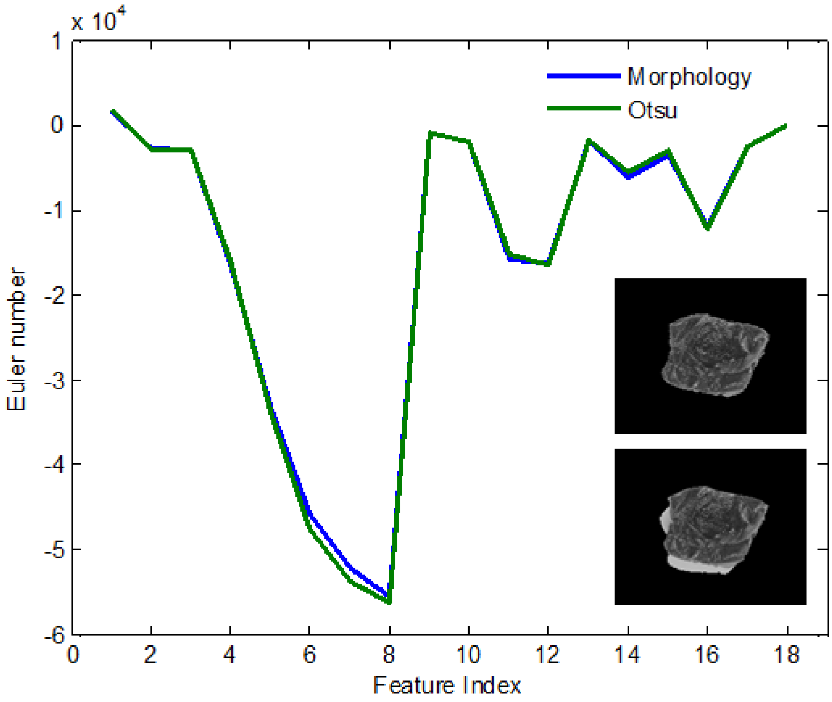


Figure 5 Effects on Euler number values when using morphology segmentation vs. Otsu's. Insert images show the two different segmentation results

Figure 6 shows the Euler features for 300 images (100 for each class) for E_6 and E_{56}. Because only 18 features are calculated, we decided to use most of them and use a neural network as the classifier.

(b)

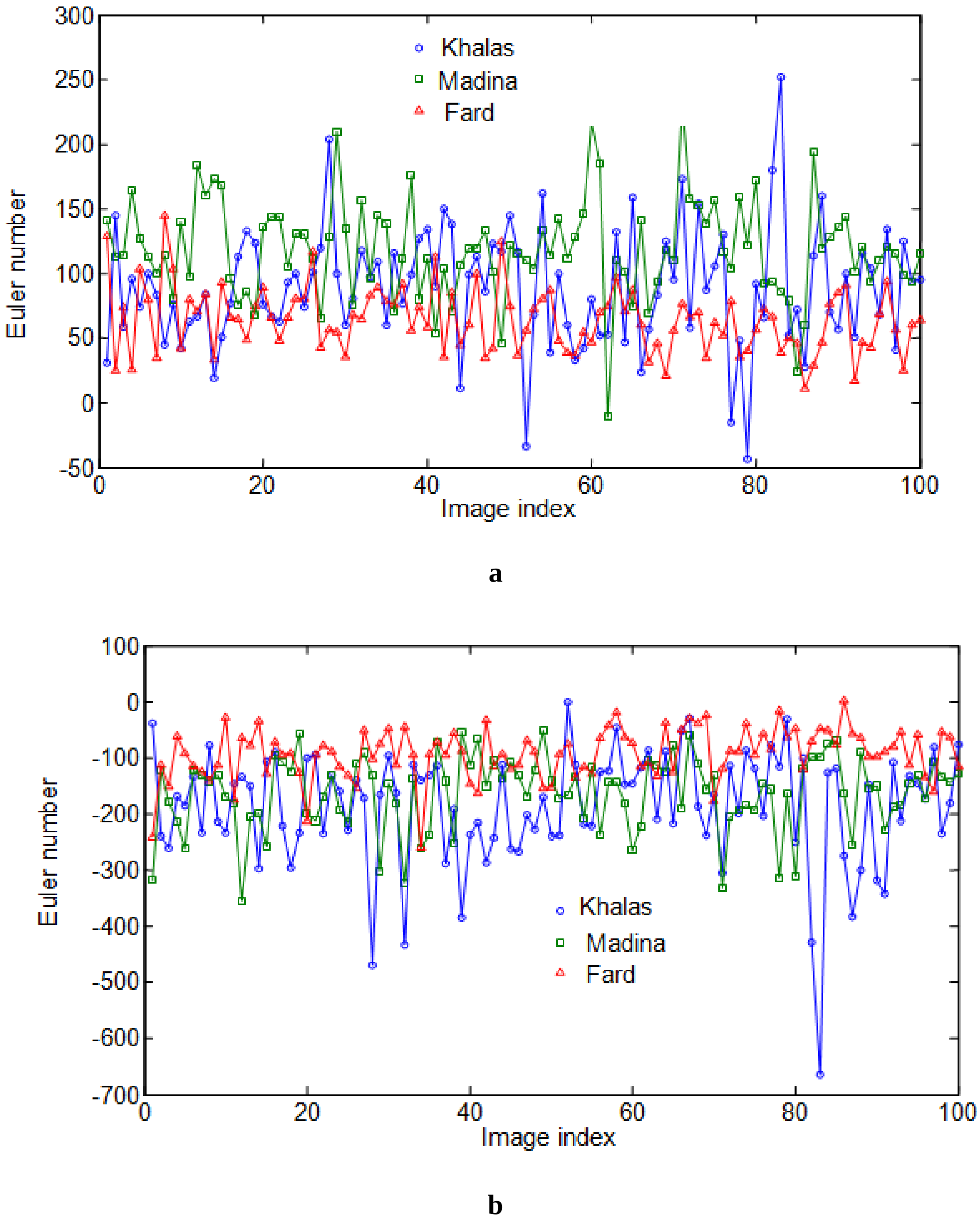


Figure 6 Euler features for 100 images of each class

(a) Using bit plane f_{bp_6} (b) ORing bit planes f_{bp_5} and f_{bp_6}

3 Results and discussion

Having established the method to obtain features from the images, classification with a neural network is performed. Before attempting to use all the features, we selected the best features and thus the following subsection 3.1 explains the method used for this task in order to improve the performance of the classification step with the neural network as described in section 3.2.

3.1 Feature selection

Because the main goal of this work was to design a simple feature extraction technique for the type of date images taken by the group, the following considerations were made: ① reduce the resolution of the original images to work with less pixels by scaling the images by a factor $s < 1$, Matlab uses an antialising filter for this image size reduction. ②see the effects of only using the four most significant bits as other methods have successfully used fewer than eight bit planes before for other applications (Bishnu and Bhattacharya, 2007;

Gomathi and Thangaraj, 2010; Fraz et al., 2011). ③ asses the importance of the segmentation of the dates and background, if a successful classification is still achievable with the background, then this step can be omitted.

In order to quantitatively choose between the different sets of feature vectors obtained from the above considerations, we calculated the similarities $S(x,v)$between the sample x to be classified and an ideal vector $\mathbf{v}_i = (v_1(f_1), \ldots, v_i(f_t))$ that represents the class i as good as possible by calculating the mean values of available vectors in each class $v_i(f_i)$ for i=1,2,…,t features where (Luukka, 2011):

$$S\langle \mathbf{x},\mathbf{v}\rangle = \frac{1}{t}\sum_{r=1}^{t}(1-|x(f_r)-v(f_r)|) \qquad (7)$$

In order to calculate the relevance of the features, fuzzy entropy values are calculated with similarity values $\mu_A(x_j)$ as suggested by Luca and Termini (DeLuca and Termini, 1971):

$$H_1(A) = -\sum_{j=1}^{n}\begin{pmatrix}\mu_A(x_j)log\mu_A(x_j)+\\ \left(1-\mu_A(x_j)\right)\ log\left(1-\mu_A(x_j)\right)\end{pmatrix} \qquad (8)$$

where low entropy indicates high similarity values and high entropy values are obtained otherwise. Figure 7 shows the results obtained when evaluating Equation (8) versus scaling for four different cases: ① using 18 features described in the previous section on images that contain the background; ② same as in① but with the background eliminated; ③ and④ same as in① and② but using only the four most significant bit planes. The averaged entropy of the ten best features was calculated knowing that the neural network would then assigns high value weights to the neurons associated with those inputs. From Figure 7, we can deduct that background removal can be discarded and that scaling factors of 0.8 would work well for all cases.

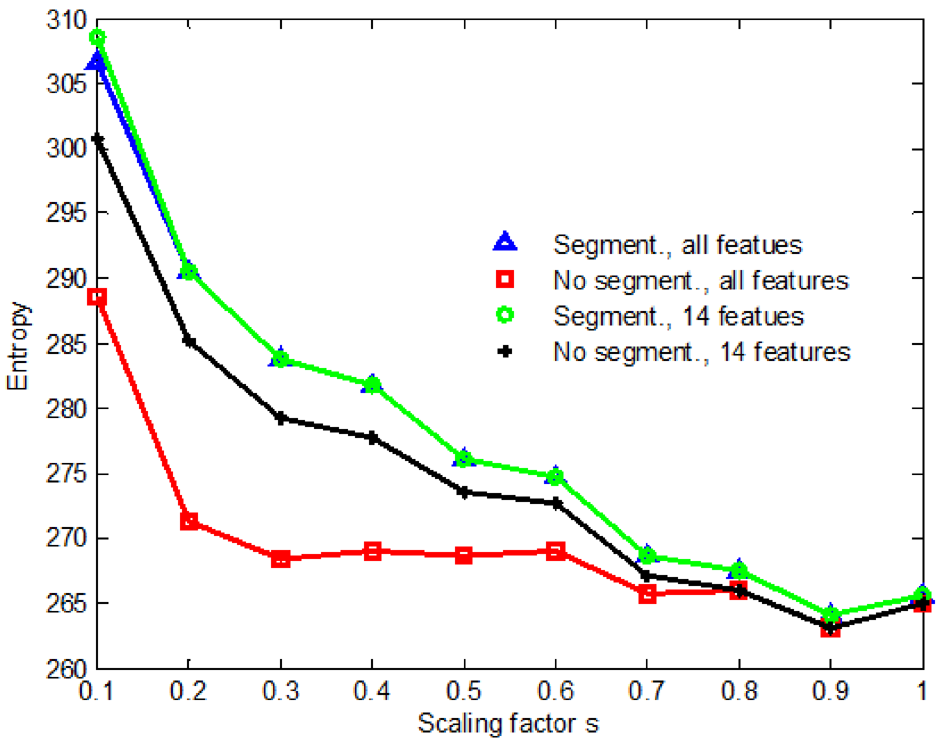


Figure 7 Average entropy vs scaling considering images with the background (no segmentation) and without it (segmentation) and omitting the four least significant planes using only 14 features

Also from Figure 7, one can identify that working without segmentation and a scaling factor of s = 0.3 using all the 18 features is as good an option as working with 14 features with a scaling factor of 0.8. Considering that the bit planes are available, it took Matlab 0.37 s to obtain the 18 features in low resolution images versus 1.65 s when higher resolution and 14 features were used. These times were obtained based on using an Asus Ee Slate tablet computer with an Intel i5 1.33 GHz processor and 4 GB of RAM memory. Thus, as expected, is faster to compute the Euler numbers by having to identify less objects and holes in them by going with less resolution. The image sizes vary from 1833×2257 for s = 1.0 to 184 ×226 for s = 0.1. This time difference will vary depending on the hardware implementation of the feature extraction method.

3.2 Classification using a neural network

Without being the classification part the main objective of this research, a two layer neural network was used with hyperbolic tangent sigmoid transfer functions using Matlab as the software platform for development. Figure 8 shows a diagram of the architecture used in this section. Good classification using this neural network would help on validating the quality of the feature extraction approach. Using 30 hidden neurons, we could obtain a correct classification of 91.48% when using the feature set for s = 0.3 and no segmentation. The training algorithm used for training was the scaled conjugate gradient backpropagation (Møller, 1993).

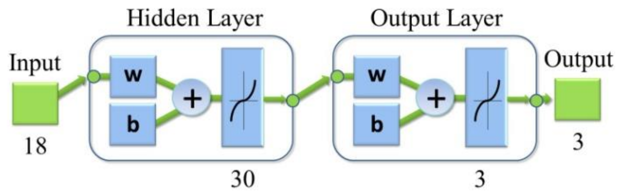


Figure 8 Diagram of the neural network used for classification

Figure 9 shows the classification MSE during training for the test and train sets where 70% of all the feature vectors available were used for training and the rest for testing.

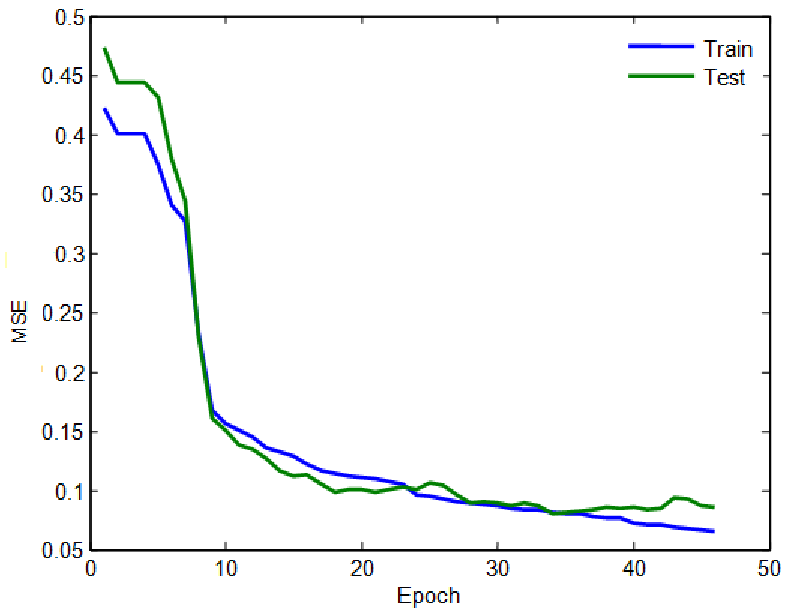


Figure 9 Mean squared error of training and test data set while using s=0.3 (no segmentation) in a neural network

Figure 10 shows the Hinton diagram of the weights for the hidden layer of the neural network. Each square's area represents a weight's magnitude. Each square's projection (color) represents a weight's sign: inset (red) for negative weights, projecting (green) for positive. As the final magnitude of a weight indicates how useful it is in reducing the error (Hinton, 1989), we can see from this Figure that averaging ten entropy values was a good metric since not all the similarity vectors would have contributed equally to the successful neural network classifier.

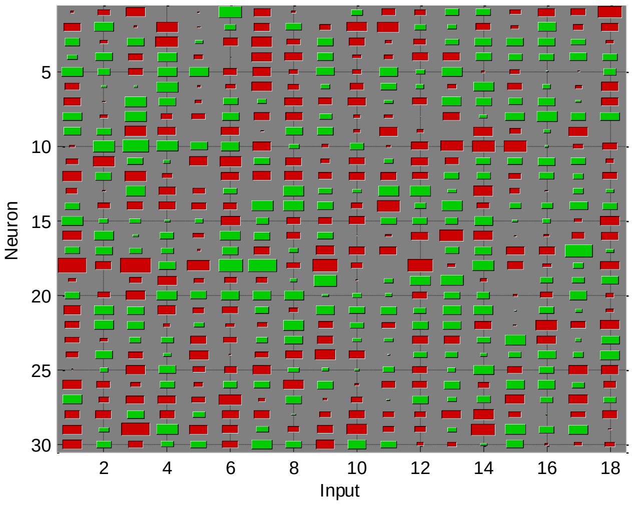


Figure 10 Hinton diagram of the neural network weights trained in the example shown in Figure 8

Figure 11 shows another example of a neural network that yielded a correct classification of 90.56% with the same architecture as before, two layers and 30 hidden neurons, but with s = 0.8, thus using images of size 1465 ×1806. Classifications with more than 90% accuracy were obtained for feature sets obtained from Figures that contain no background as well as other image resolutions validating the quality of the features and opening the door for the use of other classifiers, which once again is a topic left for future research.

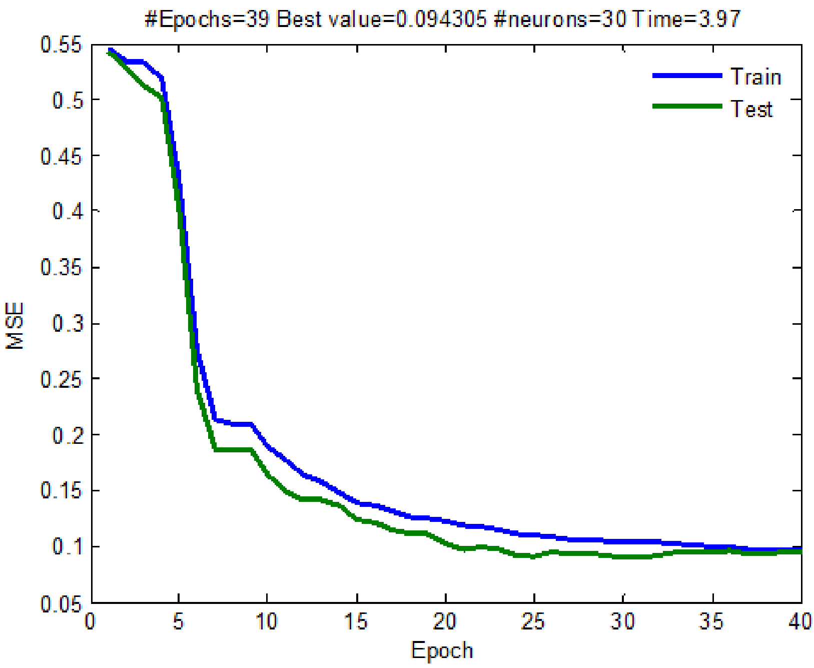


Figure 11 Mean squared error of training and test data set while using s=0.8 (no segmentation) in a neural network

4 Conclusions

The use of bit plane slicing and the Euler number defined a methodology for image feature extraction that was used for the classification of three varieties of dates. The mathematical simplicity of the proposed approach can allow the implementation of such a signal processing module in hardware that only supports integer value operations. Furthermore, bit plane slicing was used for segmentation purposes as well. In order to validate the quality of the features, neural networks were used, and that obtained correct classification rates of more than 90%.

Acknowledgement

We thank The Research Council (TRC) of Sultanate of Oman for funding this study (Project No. RC/AGR/SWAE/11/01-Development of Computer Vision Technology for Quality Assessment of Dates in Oman).

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