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Date fruits classification using texture descriptors and shape-size features

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ABSTRACT

In this paper, we proposed a system of automatically classifying different types of dates from their images. Different dates have various distinguished features that can be useful to recognize a particular date. These features include color, texture, and shape. In the proposed system, a color image of a date is decomposed into its color components. Then, local texture descriptor in the form of local binary pattern (LBP) or Weber local descriptor (WLD) histogram is applied to each of the components to encode the texture pattern of the date. The texture patterns from all the components are fused to describe the image. Fisher discrimination ratio (FDR) based feature selection is utilized to reduce the dimensionality of the feature set. Size and shape features are appended to the texture descriptors to fully describe the date. As a classifier, we use support vector machines. The proposed system achieves more than 98% accuracy to classify the dates.

1. Introduction

According to the Food & Agricultural Organization (FAO), the Middle-East and the North African countries are currently the largest date producer countries in the world (Food and Agriculture commodities production, 2012). Fig. 1 shows the production amount in tons of dates for the top fifteen countries.

Dates of the Arab region are well known for their taste. Dates are delicious and rich in nutrition. Fresh date is a very good source of vitamin C, though it disappears once it is dried. It is also a good source of sugar, carbohydrate, fiber, calcium, iron, and potassium. However, it does not have significant amount of fat or cholesterol.

The scientific research on dates in an automated way is not very old. It started roughly around 15 years back; however, many things are still in questions. Most of the previous research focused on the grading of the date fruits. Al-Janobi proposed two methods, one with co-occurrence matrix and the other with color machine vision technique, to grade the date fruits in late 90s and early of this century (Al-Janobi, 1998; Al-Janobi, 2000). Defect dates were sorted out by image analysis in a method proposed by Wulfsohn et al. Wulfsohn et al., (1993); however it was a binary classifier that classified the dates as either defected or of good quality.

The maturity inspection of the dates by near infrared spectrometry was investigated by Schmilovitch et al. (1999). Shape and size based date grading system was introduced by Hobani et al. (2003) using neural network classifier. A similar approach but by using probabilistic neural networks was proposed in Fadel (2007).

One of the major researches on dates grading was conducted by Alohali by using computer vision techniques (Ohali, 2011). Size, shape, intensity features were extracted in RGB color space and back-propagation neural network was used to classify the dates according to the grades. In another research, the three color information, perimeter, length, width, and length-to-width ratio features together with multilayer neural network classifier were used to grade the dates (Alrajeh and Alzohairy, 2012). Some other recent automatic dates grading systems are proposed in Alavi (2013) and Abdellahhalimi et al. (2013). These systems either use fuzzy inference, computer vision techniques, or distinguished camera sensors. A list of recent date research can be found in the Date Palm Research Group, 2006.

Though some advances of date research have been made over the decades, much more are still needed. For example, there is no or little research in date recognition/classification (what kind of date). Almost all the previous works (except (Haidar et al., 2012)) are to classify the dates based on the grades. In Haidar et al. (2012), a total of fifteen features including mean, standard deviation, and entropy of each color component of RGB, shapes and size were used to classify dates; however, only 140 images were used in the experiments. We would like to mention that there are many works in the literature to classify other fruits, such as apples (Xiaobo et al., 2007; Mehl et al., 2004), berries (ElMasry et al., 2007), etc. Comparing to the amount of this research, date fruit research is less, though it is very important to this part of the world (Middle-East and North Africa). Alohali reported in 2010 that the date sorting is performed completely by humans (manually) and it is the main reason of delay in date production cycle

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(Ohali, 2011). Therefore, an automated computer vision based system can significantly reduce the delay in date industry.

In this paper, we propose a system to automatically classify the dates using shape, size features and texture descriptors. The major contribution of this system is the introduction of two well-known and powerful local texture descriptors in the form of local binary pattern (LBP) (Ahonen et al., 2006) and Weber local descriptor (WLD) (Chen et al., 2010). We also use multi-class support vector machine (SVM) as a classifier. The proposed system does not require any physical instruments to measure the size or the shape, and thereby can operate fast and is inexpensive.

The rest of the paper is organized as follows. Section 2 describes the proposed method; Section 3 gives experimental results with discussion, and Section 4 draws some conclusions.

2. Proposed method

Fig. 2 shows a block diagram of the proposed date fruits classification system. In the following, we describe the steps in detail.

The input of the system is a color image of a single date. The image can be taken with a uniform (non-texture) color background. There is no restriction on the size of the image. Once the image is input to the system, some pre-processing is applied. In the pre-processing step, first, a copy of the color image is converted into black and white image using the image histogram. The minimum and the maximum vertical and horizontal coordinates of the black image (corresponding to the date) are identified. Based on these coordinates, the original color image is cropped to produce the region of interest. Fig. 3 shows examples of four types of dates' images after cropping. The four types of the dates are Ajwah, Sagai, Sellaj, and Sukkary. These dates are available in plenty in the Arab region, especially in the Gulf countries.

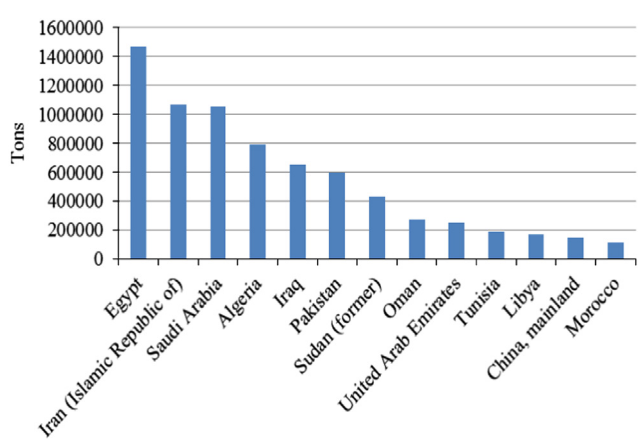

Fig. 1. Top fifteen date producer countries in 2012 published by FAO.

The cropped color image of a date fruit is converted into three separate color channels. We investigate the color spaces {red (R), green (G), and blue (B)}, {luminance (Y), chrominance (Cb and Cr)}, and {hue (H), saturation (S), and intensity (I)}. It can be noted that a color image is passed through three color filters (R, G, and B) inside the camera. YCbCr color space stores the color in terms of luminance and chrominance, where the human eyes are less sensitive to chrominance than luminance. Chrominance components can unveil some of the cues of differentiating the dates that can be impossible to detect by the naked human eyes. On the other hand, HSI attributes are the closest approximation to human interpretation of color. The logic behind using these color spaces is that the dates vary in colors and therefore contain important information in different color spaces. In this paper, we investigate the feasibility of using these color spaces in date fruits classification. Texture information in the form of LBP and WLD histograms is then extracted from these color components.

2.1. Shape and size features

The shape and the size of the dates are important features as they have high discriminative power between the types of the dates. The farmers usually consider shape and size features to recognize dates.

To define the shape and the size of a particular date, the cropped image is fit to an ellipse using the best least-square fitting ellipse method (Fitzgibbon et al., 1999). In this method, first, represent a general conic by an implicit polynomial of the set of N points (x, y) as Eq. (1). The N points are taken from the edges of the black and white image of the date.

$$F(\mathbf{a}, \mathbf{x}) = \mathbf{a} \bullet \mathbf{x} = ax^2 + bxy + cy^2 + dx + ey + f = 0, \tag{1}$$

where,

$\mathbf{a} = [a\ b\ c\ d\ e\ f]^T$ and $\mathbf{x} = [x^2\ xy\ y^2\ x\ y\ 1]^T$.

The minimization of the sum of squared distances between the points (x, y) and the conic F can be solved by a rank deficient eigenvalue system as Eq. (2).

$$\mathbf{D}^T\mathbf{D}\mathbf{a} = \lambda\mathbf{C}\mathbf{a}, \tag{2}$$

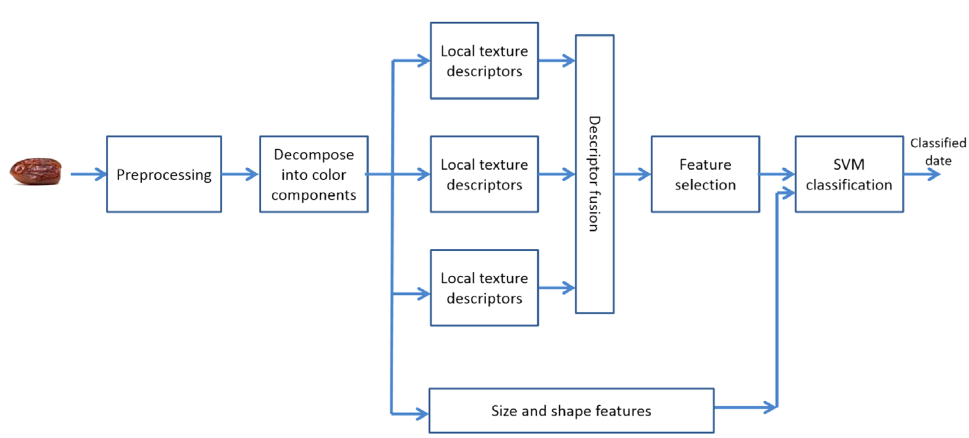

Fig. 2. Block diagram of the proposed dates classification system.

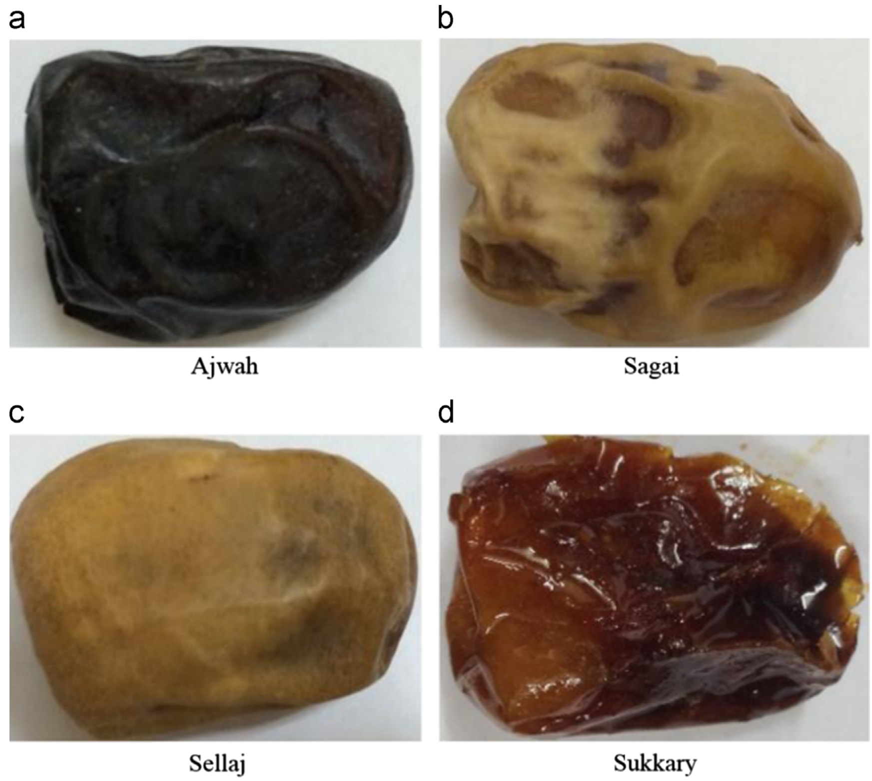

Fig. 3. Cropped images (region of interest) of four types of dates.

A = Fit_Ellipse(x, y)

Build design matrix, $D = [x^2\ xy\ y^2\ x\ y\ 1]$;

Build scatter matrix, $S = D^{\mathrm{T}}D$;

Build 6×6 constraint matrix, $C(6, 6) = 0$; $C(1, 3) = -2$; $C(2, 2) = 1$; $C(3, 1) = -2$;

Solve generalized eigen system, [*EigenVector EigenValue*] = EIGEN(S, C);

Find only the negative eigenvalue, [*NegativeRow NegativeColumn*] = FIND(*EigenValue* <0);

Get fitted parameters, **A** = GET_VECTOR(:, *NegativeColumn*)

Fig. 4. The pseudo code of the best least-square fitting ellipse.

where $\mathbf{D} = [x_1 x_2, \ldots, x_n]^T$ is called the design matrix and **C** is the constraint matrix. The matrix **C** is defined as

$$\mathbf{C} = \begin{bmatrix} 0 & 0 & -2 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ -2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}. \tag{3}$$

The pseudo code of the best least-square fitting ellipse method is given in Fig. 4 (Fitzgibbon et al., 1999).

After fitting the date image to an ellipse, the following four shape and size features are calculated in terms of pixels.

- Major axis length
- Minor axis length
- Ellipse eccentricity
- Area

Fig. 5 shows an example of a fitted ellipse to an Ajwah date fruit image. Major and minor axes lengths are also shown in the figure. The ellipse eccentricity is calculated as a ratio between p and m, where p is the distance from the center to a focus of the ellipse and m is the distance from a vertex to that focus.

The area feature is calculated by counting the number of black pixels in the black and white image (obtained before).

2.2. LBP

The LBP is a simple but powerful texture descriptor (Ahonen et al., 2006). The LBP labels the pixels of an image by decimal numbers called LBP codes. The local structure around the center pixel is encoded by thresholding the eight neighbors' pixels' grayscale values in a 3×3 neighborhood with the center value and considering the result as a binary number. The center pixel is subtracted from each of its eight neighbors. If the result of the subtraction is negative, it is encoded with 0, otherwise it is encoded with 1. The eight binary values are concatenated either clockwise or counter clockwise to form an 8-bit binary number. The corresponding decimal value of the generated binary number is then used as a label for the given center pixel. Fig. 6 shows an illustration of LBP calculation.

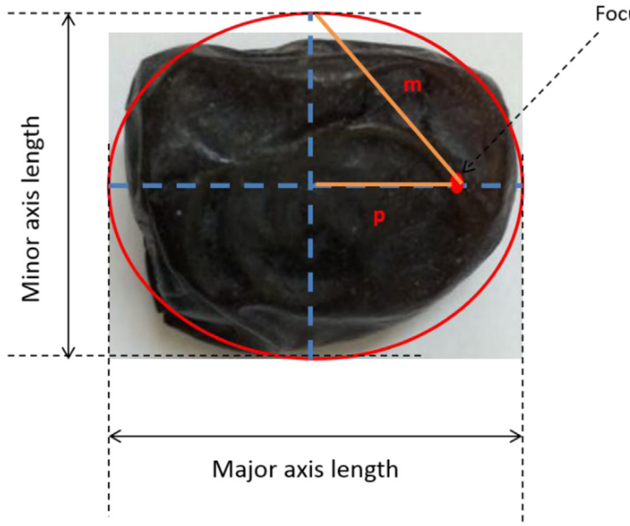

Fig. 5. Example of a fitted ellipse to a date fruit image.

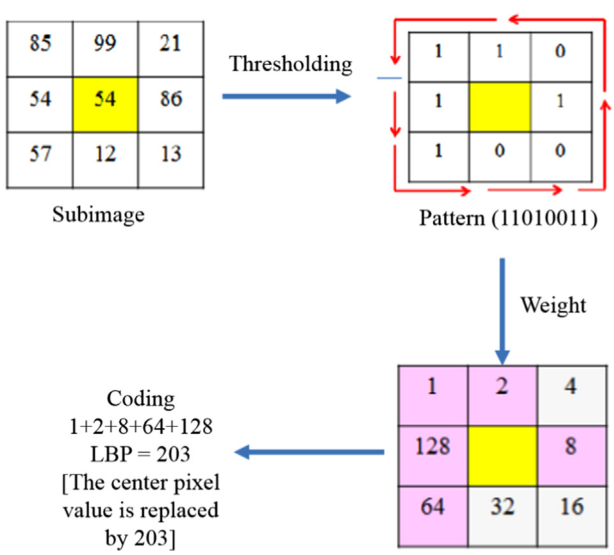

Fig. 6. Illustration of the LBP calculation.

It has been realized that certain patterns contain more information than others, so it is possible to use a small subset of the total number of patterns to describe any texture. This subset is called ‘uniform' and it includes at most two bitwise transitions from 0 to 1 or vice versa. In the proposed method, a uniform version of LBP ($LBP^{u2}_{(P,R)}$) is used. The neighboring 8 pixels ($P=8$) are located on a circular position with radius 1 ($R=1$).

Fig. 7 shows examples of LBP histograms of green channel of the four types of dates, Ajwah, Sagai, Sellaj, and Sukkary. From the figure, it can be seen that the histograms are different from each other, which implies the discrimination capabilities of the LBP between different types of dates.

2.3. WLD

The WLD was based on psychological law called “Weber's Law” that states the fact that human perception of a pattern depends not only on the change of a stimulus like sound, lighting, but also on the original intensity of the stimulus. WLD includes two components, which are differential excitation (DE) and gradient orientation (GO) (Chen et al., 2010). The DE is a function of the ratio between two terms: one is the relative intensity differences of a current pixel against its neighbors and the other is the intensity of the current pixel. The orientation component is the GO of the current pixel.

If x_c is the center pixel of a 3×3 window, and x_i, $i=1,2,\ldots,8$ are the neighbors of the center pixel, DE is calculated as Eq. (4).

$$DE=\tan^{-1}\left[\sum_{i=1}^{N}\frac{I_i-I_c}{I_c}\right], \tag{4}$$

where I is the gray level intensity of the corresponding pixel. The positive value of DE indicates that the current pixel is darker than the neighboring pixel, while the negative value represents the opposite.

The GE of the center pixel x_c is calculated as Eq. (5).

$$GO=\tan^{-1}\left[\frac{I_7-I_3}{I_5-I_1}\right], \tag{5}$$

where the numerator is the intensity difference between the left and the right of x_c, while the denominator is the intensity difference between the below and the above of x_c. The GO is then quantized into T dominant orientations. For each dominant orientation, histogram, H_t ($t=1, 2,\ldots, T$), is calculated using the DE. Each histogram is then divided into M sub-histograms each with S bins. Sub-histograms are concatenated to represent the feature of the image. For details, the readers can go through (Chen et al., 2010).

There are three parameters (T, M, and S) associated with the WLD. In the experiments, we investigated different combinations of the values of T, M, and S. We found ($T=6$, $M=4$, $S=5$) combination to be the optimum. Fig. 8 shows examples of WLD histograms of green channel of the four types of dates. From the histograms, we see that they are different for various types of dates, though similarity exists to some extent between the histograms of Sellaj and Sagai.

2.4. Fisher discrimination ratio (FDR)

The feature dimension of the proposed system using either LBP or WLD is relatively high. Not all the features (histogram bins) are equally important to a particular task. In the proposed method, the FDR is applied to select the important features from LBP or WLD.

FDR takes both the mean and the variance of the features. For a two-class problem, the ith feature FDR (Fi) is expressed by Eq. (6).

$$F_i(1,2)=\frac{(\mu_{1i}-\mu_{2i})^2}{\sigma_{1i}{}^2-\sigma_{2i}{}^2}, \tag{6}$$

where μ_{1i}, μ_{2i}, σ^2_{1i}, and σ^2_{2i} are the mean values and the variances of the ith feature of class 1 and class 2, respectively. For A number of classes and B dimensional features, Eq. (6) will produce $[A\times(A-1)/2]\times B$ entries (column × row). The overall FDR for the ith feature can be calculated by Eq. (7).

$$FDR_i=\frac{\mu_i{}^2}{\sigma_i{}^2}, \tag{7}$$

where, μ_i and σ_i are mean and variance of Fi across columns. The higher the value of FDR, the better the feature for a given classification problem. After sorting the FDR values in the descending order, we select the highest 10 features from the LBP histogram or the WLD histograms. It can be mentioned that the total number of features in LBP histograms is $3\times59=177$ (3 channels, each channel has 59 bins), and in WLD histogram is $3\times120=360$. The 10 features are then combined with the shape and size features to feed into the classifier.

2.5. SVM

The SVM classifier is a binary classifier that is widely used for data classification in many applications. It follows a procedure to find the optimal boundary that separates two classes with the

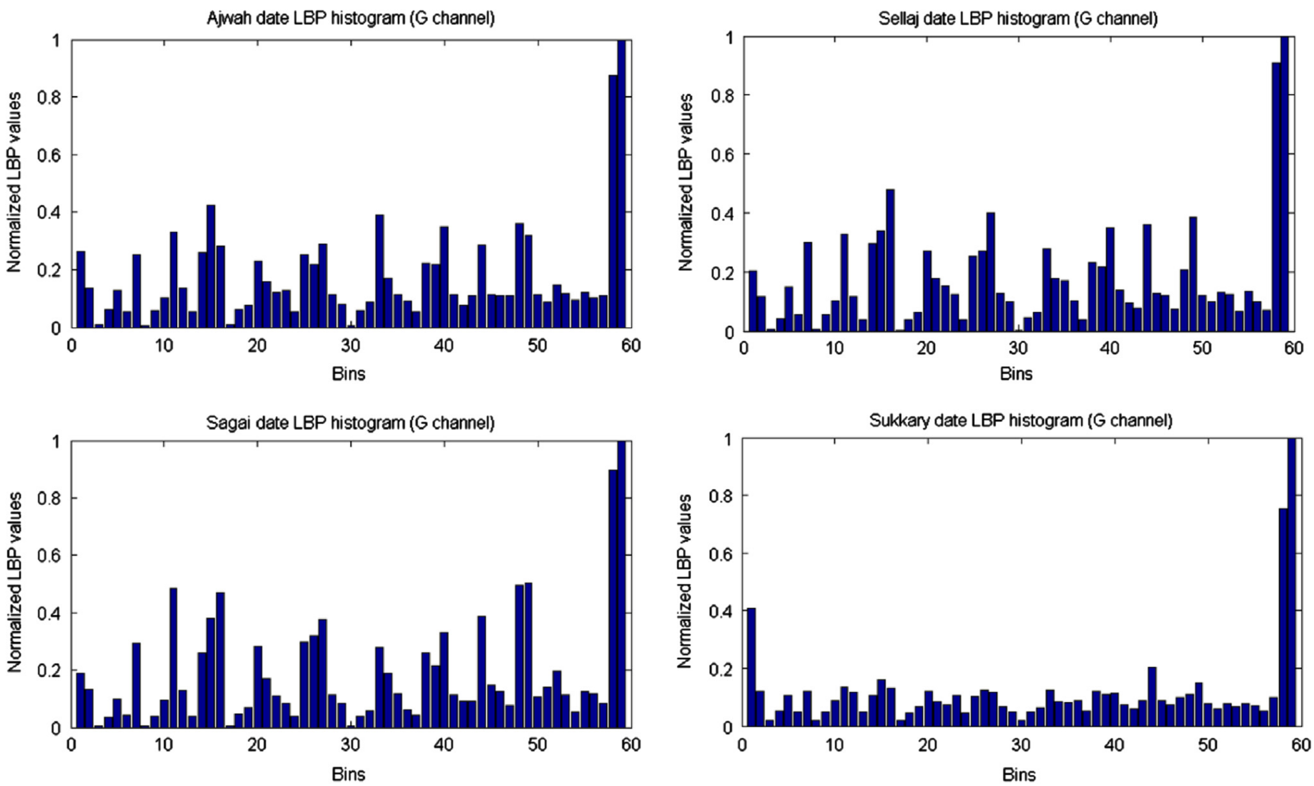

Fig. 7. LBP histograms of green channel of four types of dates.

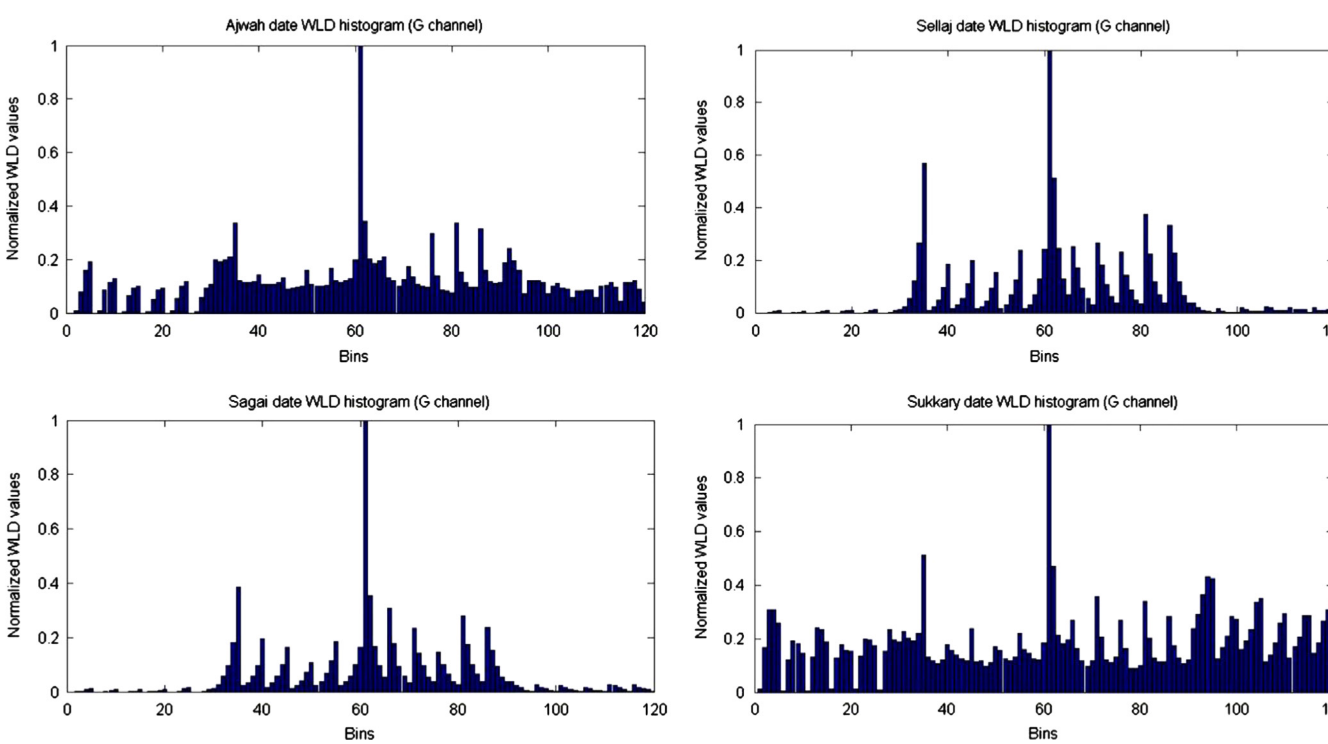

Fig. 8. WLD histograms of green channel of four types of dates.

largest margin between separating boundary and support vectors. SVM nonlinearly maps the original input space into a higher-dimensional feature space. This mapping maximizes the generalization capabilities of the classifier. Because SVM is a two-class classifier, the output given by this classifier for each image sample can be interpreted as the likelihood that the sample belongs to a specific class (Vapnik, 1998). Support vectors are created during training phase, and these vectors are used to classify the samples during testing phase. Given the training samples$\{(x_i, lab_i) : i = 1, 2, \ldots, n\}$, where x_i is the feature vector and $lab_i \in [-1, +1]$ is the class label, respectively, of the ith training samples, the optimum boundary is defined as

$$f(x) = \mathbf{w} \bullet \mathbf{x} + b \tag{8}$$

where $\boldsymbol{w}$ and b can be found by solving the following optimization problem, where C is the penalty parameter ($C > 0$), and ε is the error:

$$\text{Minimize } \frac{1}{2}||\mathbf{w}||^2 + C\sum_i \varepsilon_i$$

Subject to the constraints $lab_i(\mathbf{w} \bullet x_i + b) \geq 1 - \varepsilon_i, i = 1, 2, ..., n.$

The solution of this optimization problem maximizes the margin of the boundary. SVM is basically a linear classifier; however, in most of the cases, the features are not linearly separable. Therefore, a kernel function is used to map the original input space to a higher dimensional space, where the features are linearly separable. Radial basis function (RBF) kernel gives the best results in many applications, and hence we use it in the proposed solution. With RBF kernel, f(x) in Eq. (8) becomes

$$f(x) = \sum_{i \in \Omega} \alpha_i \left(lab_i \left(\exp(\gamma||x - x_i||^2)\right)\right) \tag{9}$$

where α_i is the Lagrange coefficient, Ω is the set of nonzero indices of α_is, γ is a free parameter, x is a testing sample, and $||.||^2$ is the Euclidean distance.

As the proposed method deals with four types of dates, we apply a multi-class SVM for classification. In the multiclass SVM, we adopted one versus the rest approach. For implementation, the well-known LIBSVM is used (Chang and Lin, 2011).

3. Experiments

To evaluate the proposed system, an image database is created. The database contains 200 different images of each of the four types of the dates (Ajwah, Sagai, Sellaj, and Sukkary). Therefore, the total number of images is 800 (all are distinct dates). The images are taken by iPhone 5 mobile. Each image contains only one date picture with uniform background.

In the experiments, a 10-fold cross validation approach is utilized. In the 10-fold cross validation approach, the whole database is divided into 10 folds (with equal number of each of the four types). In one iteration, 9 folds are used for training, while the remaining is used for testing. Therefore, after ten iterations, all the folds are tested. The feature selection step is carried out with the training data. The optimal values for the RBF kernel parameter γ and the penalty parameter C of SVM are automatically set by an intensive grid search process using the training set. The performance of the proposed system is given in terms of accuracy averaged over the 10 iterations.

The proposed system is evaluated with five different combinations, which are (i) selected LBP (10 features), (ii) selected WLD (10 features), (iii) shape, size features (4 features), (iv) selected LBP + shape, size features (14 features), and (v) selected WLD + shape, size features (14 features).

Fig. 9 shows dates classification accuracy using LBP with different number of bins in three color spaces. In the figure, 'All' represents all the LBP histogram bins without feature selection. From the figure, we see that though the highest accuracy is obtained using all the bins, there is no significant drop of accuracy until 10 selected features. Therefore, we choose 10 selected features keeping in mind that a high number of features causes delay in execution. Among the three color spaces, YCbCr performs the best. Using 10 selected features in YCbCr color space, the accuracy is 94.7%. It can be noted that the chrominance channels (Cb and Cr) are less sensitive to human eyes; however, the results suggest that they are useful for automatic classification of date fruits.

A similar trend in accuracy is observed using WLD. Fig. 10 shows the accuracy using WLD. The best performance is obtained with the YCbCr color space, and using 10 selected WLD features, the accuracy is 95%. This accuracy is slightly better than that of using LBP. WLD takes into account the ratio information, while LBP considers only subtractive information; this is the reason why WLD performs better than LBP.

Using the shape-size features, the system achieves 87% accuracy with 3.12 average standard deviation. It can be mentioned that these features are independent of the color space.

The last two experiments involve fusion of texture descriptors and shape-size features. The results are given in Fig. 11. 10 selected LBP and 4 shape-size features achieve 97.5% accuracy in YCbCr color space, while 10 selected WLD and 4 shape-size features obtain 98.1% accuracy in the same color space. The confusion matrix in the case of YCbCr color space and WLD + shape-size features is given in Table 1. From the confusion matrix, we see that the dates Ajwah and Sukkary are almost correctly classified; however, Sagai and Sellaj confuse between each other. This confusion is also evident visually from Fig. 3.

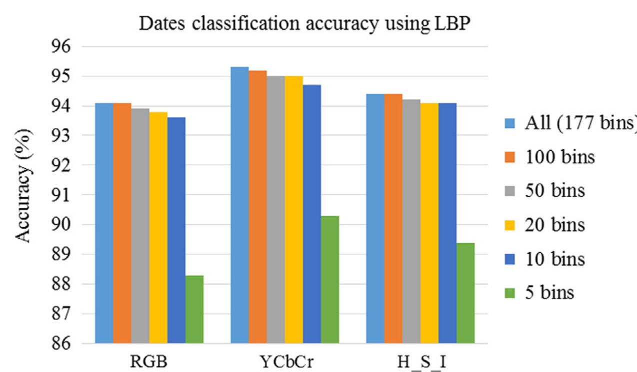

Fig. 9. Dates classification accuracy using LBP in three different color spaces.

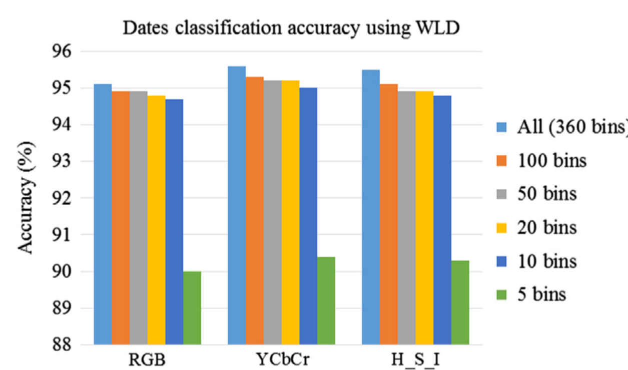

Fig. 10. Dates classification accuracy using WLD in three different color representations.

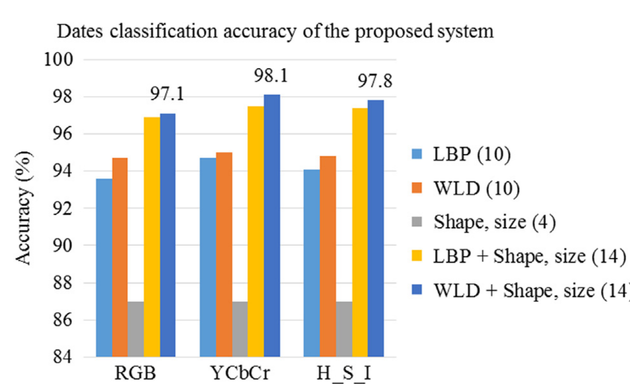

Fig. 11. Dates classification accuracy of the proposed system. The number inside the parenthesis in the legend corresponds to the feature dimension.

Table 1
Confusion matrix of the proposed system in YCbCr color space and using WLD+shape-size features. The numbers inside the cells correspond to the accuracy (%).

		Output			
		Ajwah	Sagai	Sellaj	Sukkary
Input	Ajwah	100	0	0	0
	Sagai	0	96.2	3.4	0.4
	Sellaj	0	3.2	96.6	0.2
	Sukkary	0.1	0	0.3	99.6

Table 2
Accuracy (%) comparison between the systems.

Proposed system (WLD+Shape, size)			System in Haidar et al. (2012)
RGB	YCbCr	H_S_I	
97.1	98.1	97.8	96.2

To compare the performance of the proposed system with that of other system, we chose the system described in (Haidar et al., 2012), because it is the only one existing date classification system that was evaluated using many classifiers. There are 15 features in (Haidar et al., 2012) and we chose the artificial neural network classifier to implement (Haidar et al., 2012). Both the systems were evaluated on the same database that we created. Table 2 shows the average accuracy obtained by the proposed system with selected WLD and shape-size features in three color spaces, and the system in (Haidar et al., 2012). From the result, we find that the proposed system outperformed the system in (Haidar et al., 2012).

4. Conclusion

An automatic date fruit classification system based on local texture descriptors and shape, size features has been proposed. SVM with RBF kernel is used for the classification. Four types of dates are used in the experiments. The findings of the date fruit classification can be summarized as follows.

- Texture descriptors, either LBP or WLD, are better than shape, size features.
- WLD performs better than LBP.
- Texture descriptors fused with shape, size features give the highest accuracy.
- YCbCr and HSI color spaces provide more discriminative information than RGB color space.

The highest accuracy of 98.1% is obtained by the combination of selected WLD descriptors together with shape and size features in YCbCr color space. One area to investigate in future is the confusion between Sellaj and Sagai dates.

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References

Abdellahhalimi, A. Roukhe, Abdenabi, B., El Barbri, N., 2013. Sorting dates fruit bunches based on their maturity using camera sensor system. J. Theor. Appl. Inf. Technol. 56 (2), 325–337.
Ahonen, T., Hadid, A., Pietikainen, M., 2006. Face description with local binary patterns: application to face recognition. IEEE Trans. Pattern Anal. Mach. Intell. 28 (12).
Al-Janobi, A., 2000. Date inspection by color machine vision. Journal of King Saud University 12 (no. 1), 69–97.
A.A. Al-Janobi, 1998. Application of co-occurrence matrix method in grading date fruits, in ASAE Paper, no. 98-3024.
Alavi, N., 2013. Qualilty determination of Mozafati dates using Mamdani fuzzy inference system. J. Saudi Soc. Agric. Sci. 12 (2), 137–142.
Alrajeh, K.M., Alzohairy, T.A., 2012. Date fruits classification using MLP and RBF neural networks. Int. J. Comput. Appl. 41 (10), 36–41.
Chang, C.C., Lin, C.J., 2011. LIBSVM: a library for support vector machines. ACM Trans. Intell. Syst. Tech. 2/27, 1–27.
Chen, J., Shan, S., He, C., Zhao, G., Pietikainen, M., Chen, X., Gao, W., 2010. WLD: A robust local image descriptor. IEEE Trans. Pattern Anal. Mach. Intell. 32 (9), 1705–1720.
Date Palm Research Group, 2006. King Saud University, Riyadh. Available at: ⟨http://cfas.ksu.edu.sa/en/content/date-palm-research-group⟩.
ElMasry, G., Wang, N., ElSayed, A., Ngadi, M., 2007. Hyperspectral imaging for nondestructive determination of some quality attributes for strawberry. J. Food Eng. 81, 98–107.
Fadel, M., 2007. Date fruits classification using probabilistic neural networks. Agric. Eng. Int.: CIGR Ej. 9, 1–11.
Fitzgibbon, A., Pilu, M., Fisher, R.B., 1999. Direct least-squares fitting of ellipses. IEEE Trans. Pattern Anal. Mach. Intell. 21 (5), 476–480.
Food and Agriculture commodities production, FAOSTAT 2012. Available at: ⟨http://faostat.fao.org/site/567/default.aspx⟩ (Retrieved on 22.02.14).
A. Haidar, D. Haiwei, N. Mavridis, 2012. Image-based date fruit classification. In: 4th International Congress on Ultra-Modern Telecommunications and Control Systems and Workshops (ICUMT), pp. 357–363.
Hobani, A.I., Thottam, A.M., Ahmed, K.A., 2003. Development of a neural network classifier for date fruit varieties using some physical attributes. King Saud Univ.-Agric. Res. Center 126, 5–18.
Mehl, P.M., Chen, Y., Kim, M.S., Chan, D.E., 2004. Development of hyperspectral imaging technique for the detection of apple surface defects and contaminations. J. Food Eng. 61, 67–81.
Ohali, Y.A.L., 2011. Computer vision based date fruit grading system: Design and implementation. J. King Saud Univ. – Comput. Inf. Sci. 23 (1), 29–36.
Schmilovitch, Z., Hoffman, A., Egozi, H., Ben-Zvi, R., Bernstein, Z., Alchanatis, V., 1999. Maturity determination of fresh dates by near infrared spectrometry. J. Sci. Food Agric. 79, 86–90.
Vapnik, V., 1998. Statistical Learning Theory. Wiley, New York.
Wulfsohn, D., Sarig, Y., Algazi, R.V., 1993. Defect sorting of dry dates by image analysis. Can. Agric. Eng. 35 (2), 133–139.
Xiaobo, Z., Jiewen, Z., Yanxiao, L., 2007. Apple color grading based on organization feature parameters. Pattern Recognit. Lett. 28, 2046–2053.