Identification of Oxtongue Flowers using Image Processing Technique

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ABSTRACT

The Oxtongue plant has abundant nutritional properties, and it is consumed worldwide. Identification of flowers from other parts of the plant using image processing is the main step in manufacturing automatic Oxtongue harvesting machine. Our objective is to find suitable color spaces for flower identification by color features. In this study, images were captured in three different conditions, under direct sunshine, in the shadow and under black background. The distance between crop and camera for these three states was 25 cm. Light intensity for under direct sunshine, in the shadow and under black background states were 1800, 407 and 407 lux respectively. After imaging, four color spaces (RGB, HSV, YCbCr and NTSC) were used to determine the suitable color space to identify flowers. For condition under direct sunshine, in the shadow and under black background, HSV, YCbCr and YCbCr were recognized suitable color spaces, respectively. Threshold and run time algorithm for these spaces were $H<0.5$, $S<0.3$, $V<0.45$ and 8.999s, $Cb<150$ and 7.284s and $Cb>150$ and 7.204s, respectively. The identification accuracy rate for imaging under direct sunshine, in the shadow and under black background were calculated 100%, 94% and 97.37%, respectively.

Keywords: Oxtongue, Image processing, Identification, Machine vision.

INTRODUCTION

The Oxtongue is a yearlong medicinal plant that grows to 60cm. Their leaves are simple and are covered by tough strings. The Oxtongue has three varieties with blue, white and purple flowers. Now, In Iran the Oxtongue is harvested manually by human laborers, that it is time-consuming and costly. On the other, on time harvesting of these flowers raise their quality. So, it is needed for making a device to detect the ripeness flowers. One of the methods for detection of ripeness time of flower is image processing. Nowadays, image processing method uses widely in all fields. In agriculture, image processing is used for sorting, diagnosis of disease in plants and etc. With the advent of artificial intelligence and image-processing techniques, many successful plant identification techniques have been reported.

Chowdhury et al. (2015) presented a new texture feature based on stable expert system to identify roadside vegetation. The database included 110 images in natural light conditions. From this database 60 images were corresponding to dense grass and the remaining 50 images were corresponding to sparse grass. Proposed system included 5 steps of image pre-processing, feature extraction, training with classification, classification and validation and finally statistical analysis to classify these

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two weed types. Using Co-occurrence of Binary Pattern method extracted texture features corresponding to the images of vegetation. In the step of training and classification three classifiers were used to combine the multiple decisions. These classifiers were support victor machine, feed forward back-propagation neural network and Nearest Neighbor respectively. Overall classification accuracy after applying these three classification was 92.72. Mursalin et al. (2013) classified five weed types including *Capsicum*, *Burcucumber*, *Cogongrass*, *Marsh herb* and *Pigweed* using three classifier including Naïve Bayes, SVM and C4.5. The images were captured using a digital camera. The digital camera was fixed at 40 cm of ground and perpendicular to it. In this study were used 400 images (80 images for every weed type). After pre-processing, 9 features including Area, Perimeter, Ponvex Perimeter, Convex Area, Thickness, Solidity, Convexity, Form Factor and Elongatedness were extracted from weeds. The results showed that Naïve Bayes classifier had the highest accuracy- 99.3%- among these classifiers.

Ahmed et al., (2012) classified chili and five weeds (Pigweed, Marsh herb, Lamb's quarters, Cogon grass, and Bur cucumber) using a support vector machine approach. In this study fourteen features from chili crop and weeds were extracted. The results revealed that support vector machine approach obtained above 97% accuracy over a set 224 images. Arribas et al., (2011) distinguished leaf of sunflower crops and non-sunflower using computer vision and neural networks. The proposed system had four main stages. First, a segmentation based on RGB color space. Second, several features were extracted from the segmented image. Third, the important features were selected. Finally, the neural network was used for classifying between sunflower crops and non-sunflower. The results showed an average correct classification rate of 85%. Burgos-Artizzu et al., (2011) identified maize crops from weeds using real-time image processing. The main system consists of two subsystems, a fast image processing (FIP) and robust crop row detection, RCRD). The results showed that this method had a recognition rate of 96.5% of weeds and 80% of crops under different soil humidity, illumination and weed/crop growth conditions. Rumpf et al. (2012) focused on discrimination of small-grain weed species with special regard to Cirsium arvense and Galium aparine and crops using sequential support vector machine classification. In this study the first group of plants with similar shapes was identified. Then, the classification by different features and second and third support vector machine completed. The accuracy of classification for first classification was 98.15% and for final classification was 80%. Swain et al. (2011) identified weed and crop using an automated active shape matching (AASM) technique. They extracted several morphological features from weed and crop and, these features used for classification. Using the AASM algorithm, the leaf model was aligned on main plant and, they compared together. 90% of the nightshade plant were identified correctly using AASM algorithm. The processing time was 0.053s. Peng and Jun (2011) applied image blur information for identifying wild buckwheat, foxtail and pigweed. In this study the low quality color weed images with these image blurs were used to recognize weeds. The proposed method consists of three stages. First, the soil and plant were distinguished in images. Second, the image-moment-based blur invariant features were calculated. Third, the weed was identified using the computed Euclidean distance based on the moment invariants.

Objective

The goal of this work was to develop an algorithm to identify flowers of Oxtongue using image processing to develop the automatic Oxtongue harvesting machine.

This work is organized as follows; in Section 3, data acquisition, Work algorithm, Color space (RGB color space, HSV color space, YCbCr color space NTSC color space) are presented. Results and discussion, namely, imaging under direct sunshine, imaging in shadow and imaging under black background introduces in section 4 and finally Section 5 discusses about Conclusions.

Materials and methods

Nomenclature	
R	The Red channel of a color image
G	The Green channel of a color image
B	The Blue channel of a color image
H	The Hue in HSV color space
S	The Saturation in HSV color space
V	The Value in HSV color space
Y	The Luminance in NTSC color space
I	The Hue in NTSC color space
Q	The saturation in NTSC color space
CCD	Charge-coupled devices
MP	Megapixel

Data acquisition

In this study -345 images captured from Oxtongue plant grows in Kermanshah (longitude: 7.03 °E; latitude: 4.22 °N), Iran, and under three different conditions, namely under direct sunshine, in shadow and under black background (115 images for each condition) (Figure1). Selecting samples were healthy and free of any injuries. Images captured by SAMSUNG WB151F (CCD, 14.2 MP, auto focus) camera. Table 1 shows imaging conditions.

Work algorithm

Work algorithm is shown in Figure 2.

Color spaces

- RGB color space

An RGB image consists of three components of Red, Green and Blue. In fact, RGB image is stacked from three images in grayscale. The images can have different data classes such as, double, uint8 and uint16. RGB color spaced is played graphically with the RGB color cube (Figure3) (Gonzalez et al, 2004).

- HSV color space

HSV color space (Hue, Saturation, and Value) is closer to human perception related to colors than RGB color space. HSV color space introduces according to the gray axis of RGB color cubic (Gonzalez et al, 2004). Color hexagonal related to this color system is shown in Figure 4 (a, b). Figure 4 (c) and Figure 4 (d) shows RGB and HSV image related to Oxtongue plant respectively.

- YCbCr color space

YCbCr color space is used in digital video images. In this format luminance information saved in Y and color information in Cr and Cb. Cb represents the difference between blue component and reference value and Cr represents difference between red component and a reference value. Equation (1) shows the relationship between RGB and YcbCr (Gonzalez et al, 2004).

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.00 \\ 112.00 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

- NTSC color space

NTSC color system is used in TV systems in United States. One benefit of this system is separation gray scale information from color information. In NTSC format, image information is formed from three component: luminance(Y), hue (I) and saturation (Q). Luminance component consist of gray scale and other components consist of color information. YIQ components have relation with RGB by equation (2) (Gonzalez et al, 2004).

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (2)$$

System Performance Analysis

In this study two criterions of sensitivity and precision were used to identification performance analysis of color spaces. Sensitivity is a fraction of the samples that were correctly classified. Precision is the total classification rate of classifier. The equations 3 and 4 calculate these two criterions (Liu et al., 2015).

$$\boldsymbol{Sensitivity} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \qquad (3)$$

$$\boldsymbol{precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \qquad (4)$$

where TP is the number of classified samples correctly. FN is the number of misclassified samples in other classes. FP is the number of samples that classified correctly in interest class (Wisaeng, 2013).

Results and discussion

In this study, images captured in three difference conditions of under direct sunshine, in shadow and under black background. After imaging, images were moved into different color spaces to find the best color space to extract flowers from other parts of plant.

Imaging under direct sunshine

Figure5 shows four different color spaces namely RGB, HSV, NTSC and YCbCr related to Oxtongue. Histograms were plotted for all spaces. According to Figure 5, it can be understood that RGB and YCbCr histograms are continues, so they can't be usedto accurate identification flowers from other parts but, the histograms of H component of HSV and Y component of YCbCr provide identification possibility. Peaks from left to right are related to the maximum frequency of color pixels of flower and other parts, respectively. According to distance between pixel values of flowers and other parts, the hue image related to HSV was selected. So, Figure6 achieved by choosing the threshold for components of image namely, H, S and Ve-H<0.5, S<0.3, V<0.45-. Table2 shows the sensitivity and precision rate for four color spaces. In among four color spaces HSV with three thresholds (H<0.5, S<0.3,V<0.45) has the highest sensitivity and precision, namely 100%. This means that HSV color space identify flowers completely. The results corresponding to other color spaces shown in table2.Since in HSV and YCbCr color spaces, flowers have more color difference than the other parts and background, so they have rise accuracy rate.

Imaging in shadow

The change of light intensity is one of reasons for mistake identification of different parts of image. Imaging in controlled condition caused the uniform distribution of light intensity in all parts of plant. So, pixel intensity will be real. Figure7 shows images histograms. R, G and B histograms related to RGB space show uniform distribution. S and V histograms related to HSV space have the same behavior as components of RGB space conditions, but H histogram has two pike that is useful for separating. Y component in YCbCr space has the same distribution as NTSC space and they are not useful for next actions. Cb component in YCbCr has sudden change in intensity, so it's useful for flowers identification from other parts of plant. For this space, threshold Cb<150 was selected. Figure 8 and Table3 compare sensitivity and precision related to four color spaces. As shown, the acceptability sensitivity and precision rates were obtained in two color spaces of HSV and YCbCr. The reason of high accuracy in two color spaces is unchanged of light intensity related to sunbeam in different parts of image.

Imaging under black background

There are various types of things in field such as soil, stubble and etc. So, captured images consist of these. The volume of calculation will rise at the time of image processing. If images are captured using favorite background, the volume of calculation will reduce. Figure9 shows image with black background. As showed in Figure 9, in all color spaces separation background from plant is possible. We can use Cb component of YCbCr for identification of flowers from other parts, since, as it has been showed, the dominant color in image is green that related to flowers. For this state threshold was Cb>150. The final image is showed in Figure10. Figure 10 shows separated flowers from other parts. Sensitivity and precision rate related to four color spaces is showed in Table 4. Because of one color background (black) and controlled light intensity, three color spaces (RGB, HSV and YCbCr) have high Sensitivity and precision rate. Because the used method in this study is new and hasn't performed by other researcher until now over oxtongue, so there is no possibility to direct comparison the used method in this study with other researches. However, table 5 compare the best result based on used method in this study with two other researches. . The first study is corresponding to Hlaing and Khaing, (2014). They recognized four type weeds (*Pigweed*, *Kyaut kut*, *Lanchon* and *Rape plant*) in each image using Area Thresholding Algorithm. As you can see from 35 samples, 6 samples misclassified, this means that correct classification rate is 82.85%. The second study is corresponding to Zho and Zho (2009). They classified different plants based on texture and shape features. As you can see in this table 35 samples misclassified from 224 samples (correct classification rate was 84.4%).So, by comparing mentioned results and the results of present study the superiority of used method in this study was demonstrated. So, using this method the possibility of making a machine vision system to Oxtongue detection in agricultural field is provided.

Table 6 shows the time required to implement algorithm in three different conditions. We implement these experiments in MATLAB (Version R2014a), and run on a PC with 2.27, GHz Intel(R) Core(TM) i3 CPU and 4 GB of RAM memory.

Conclusions

In this work, image processing method used for identification of flower from other parts of oxtongue. The research presented five overall results as follow:

1- There isn't possibility of identification flower from other parts of Oxtongue in all condition by NTSC color space.

2- In plants that have parts with different color, the suitable method for separation parts is using color.

3- To raise the speed of algorithm, background have to be in minimum, namely major of image space be consist of plant.

4- Algorithm speed dependents on distribution of light intensity, namely uniform light intensity result rise speed.

5-Identification accuracy rate for imaging under direct sunshine, in shadow and under black background were obtained100%, 94% and 97.37%, respectively.

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Table1. Imaging conditions for three different states

	With black background	In shadow	Under direct sunshine
The distance between crop and camera	25cm	25cm	25cm
time	11:30AM	11:30AM	11:30AM
light intensity	407	407	1800

Table2. The Sensitivity and precision of identification in different color spaces for Imaging under direct sunshine state

Color space	Number of samples	Number of Correct identified	Sensitivity (%)	Precision (%)
RGB(R<50,G<50,B>80)	115	47	40.87	41.37
HSV(H<0.5,S<0.3,V<0.45)	115	115	100	100
NTSC(Y<0.5)	115	42	36.52	37.07
YCbCr(Y>150)	115	78	67.83	68.1

Table3. The Sensitivity and precision of identification in different color spaces for Imaging in shadow state

Color space	Number of samples	Number of Correct identified	Sensitivity (%)	Precision (%)
RGB(R<80,G<70,B>110)	115	90	78.26	78.44
HSV(H>0.5,V>0.6)	115	45	39.13	39.66
NTSC(Y<0.4)	115	21	18.26	18.99
YCbCr(Cb<150)	115	108	94	93.96

Table4. The Sensitivity and precision of identification in different color spaces for Imaging under black background state

Color space	Number of samples	Number of Correct identified	Sensitivity (%)	Precision (%)
RGB(R<50,G<90,B>110)	115	79	68.69	68.97
HSV(H>0.4, S>0.2 ,V>0.6)	115	97	84.34	84.48
NTSC(Y<0.5)	115	16	13.9	14.66
YCbCr(Cb>150)	115	112	97.37	97.41

Table.5 Compare correct classification rate of present study and two other studies

Method	The number of samples	The number of samples misclassified	Correct classification rate
Best result based on used method in this study	115	0	100%
Hlaing and Khaing, (2014)	35	6	82.85%
Zho and Zho (2009)	224	35	84.4%

Table 6. Comparison of time of image processing in different condition

Condition of imaging	Time(s)
imaging under direct sunshine	8.999
imaging in shadow	7.284
imaging under black background	7.204

Figure1: Images of an oxtongue plant acquired at three different lighting conditions: (a) under direct sunshine (b) in shadow (c) with black background

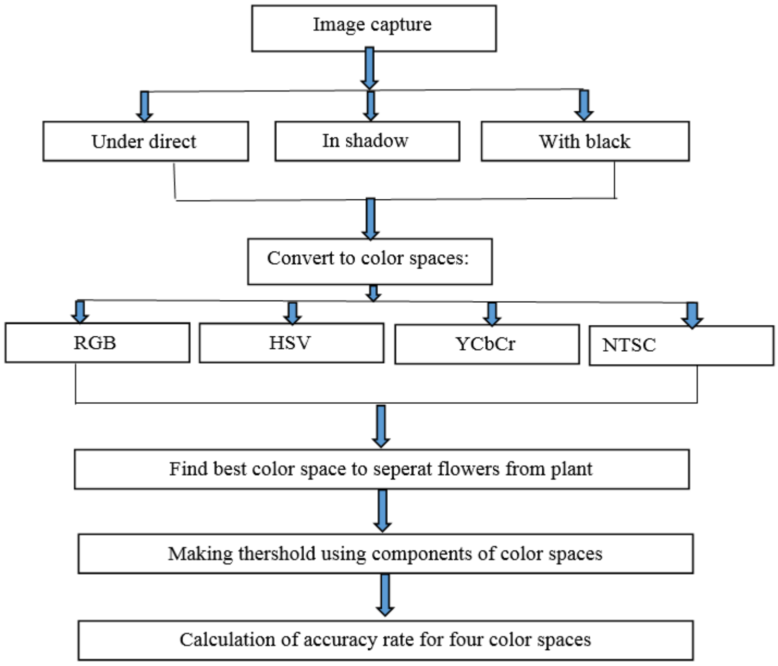


Figure 2: work algorithm

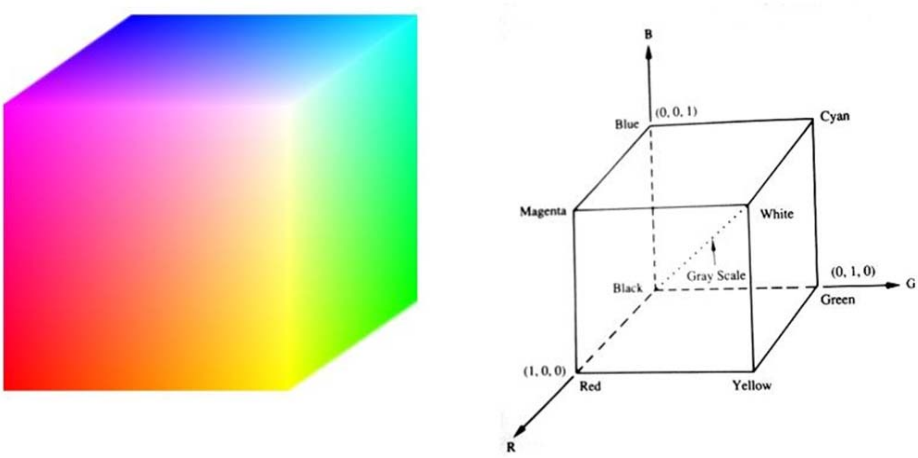
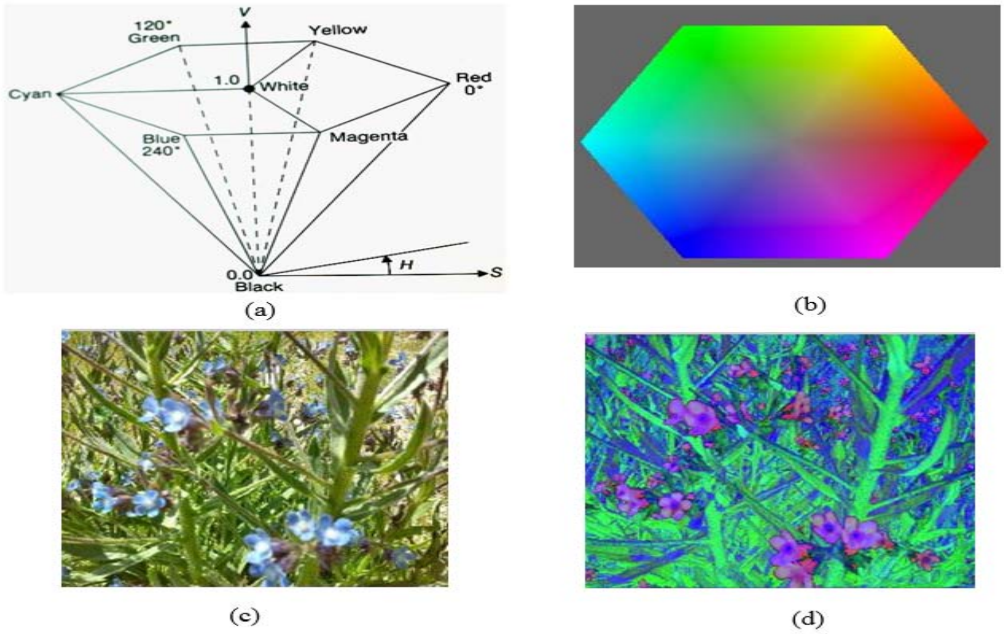


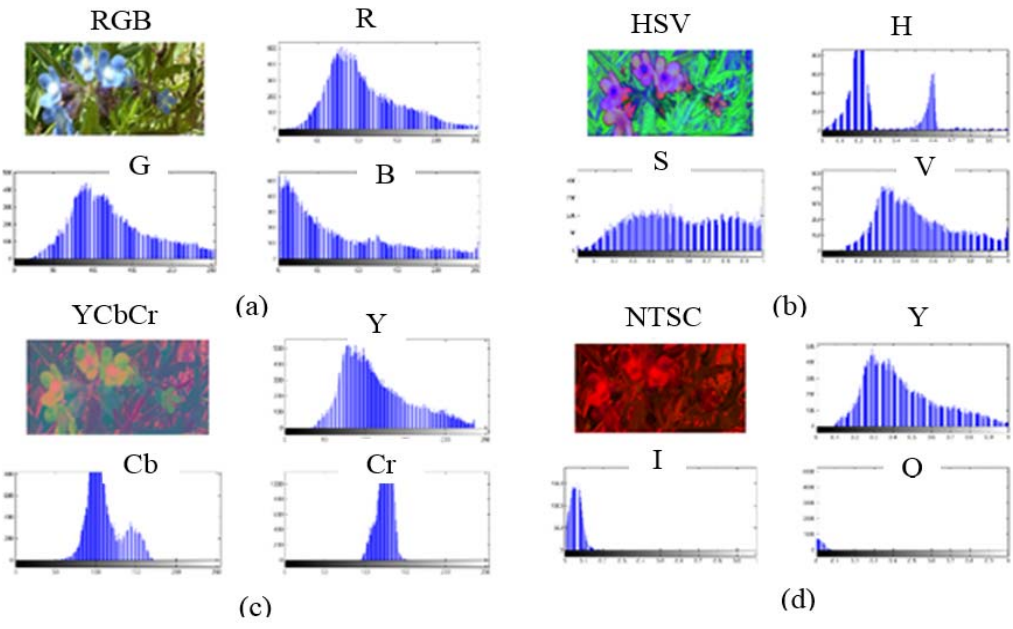
Figure 3: RGB color cubic



(a) (b)

(c) (d)

Figure 4: HSV color hexagonal (a, b), RGB image(c) and HSV image(d)



(a) (b) (c) (d)

Figure 5: The difference between color spaces and theirs histogram under direct sunshine

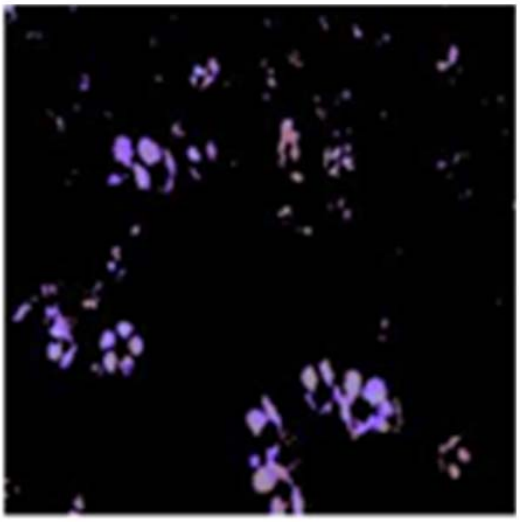


Figure 6: Identification of flowers under direct sunshine

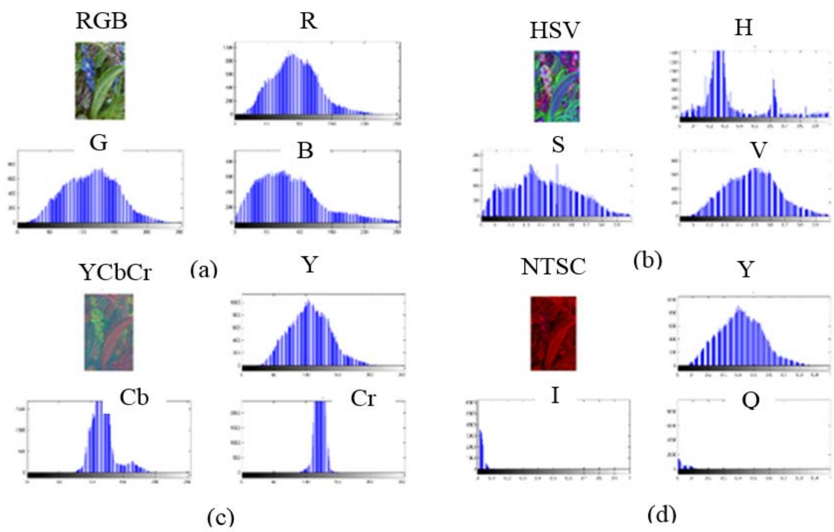


Figure 7: The difference between color spaces and theirs histogram in shadow

Figure 8: Identification of flowers space in shadow

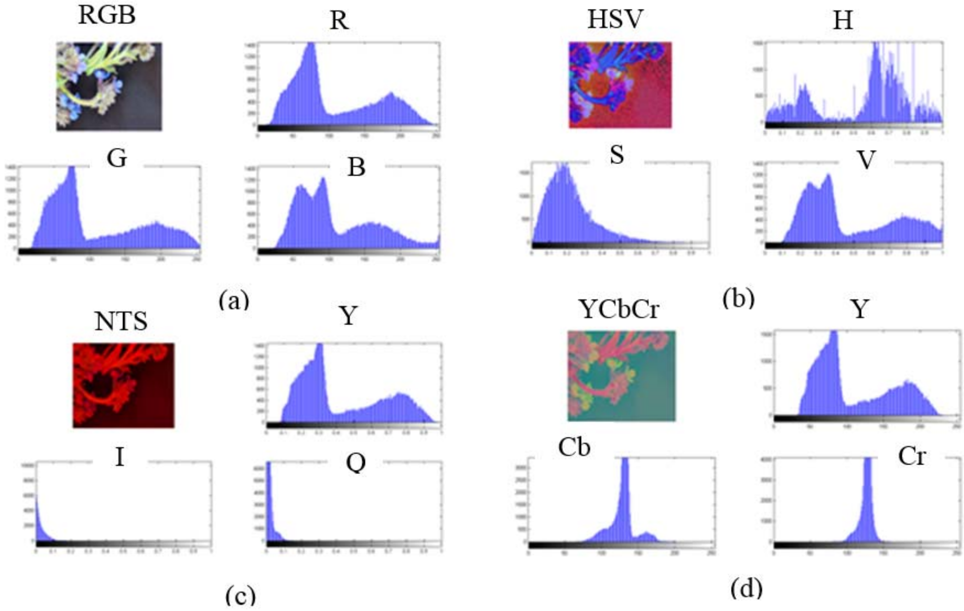


Figure 9: The difference between color spaces and theirs histogram in black background

Figure 10: Identification of flowers in black background

REFERENCES

Ahmed, F., Al-Mamun, H.A., Bari, A.S.M.H., Hossain, E., Kwanb, P., 2012. Classification of crops and weeds from digital images: A support vector machine approach. ***Crop Protection*** 40: 98-104.

Arribas, J.I., Sanchez-Ferrero, G.V., Ruiz-Ruiz, G., Gomez-Gil, J., 2011. Leaf classification in sunflower crops by computer vision and neural networks. ***Computers and Electronics in Agriculture*** 78: 9-18.

Burgos-Artizzu, X.P., Ribeiro, A., Guijarro, M., Pajares, G., 2011. Real-time image processing for crop/weed discrimination in maize fields. ***Computers and Electronics in Agriculture*** 75: 337-346.

Chowdhury, S., Verma, B., Stockwell, D., 2015. A novel texture feature based multiple classifier technique for roadside vegetation classification. ***Expert Systems with Applications*** 42: 5047-5055.

Gonzalez, R.C., Woods, R.E., Eddins, S.L., 2004. Digital Image Processing Using MATLAB. Prentice Hall.

Hlaing, S.H., Khaing, A.S., 2014. WEED AND CROP SEGMENTATION AND CLASSIFICATION USING AREA THRESHOLDING. ***International Journal of Research in Engineering and Technology*** 3: 375-382.

Liu, X., Du, H., Wang, G., Zhou, S., and Zhang, H., 2015. Automatic diagnosis of premature ventricular contraction based on Lyapunov exponents and LVQ neural network. ***Computer Methods and Programs in Biomedicine*** 122: 47-55.Mursalin, M., Hossain, M.M., Noman, M.K., Azam, M.S., 2013. Performance Analysis among Different Classifier Including Naive Bayes, Support Vector Machine and C4.5 for Automatic Weeds Classification. ***Global Journal of Computer Science and Technology Graphics & Vision 3***.

Peng, Z., and Jun, C., 2011. Weed recognition using image blur information. ***BIOSYSTEMS ENGINEERING*** 110: 198-205.

Rumpf, T., Römer, C., Weis, M., Sökefeld, M., Gerhards, R., Plümer, L., 2012. Sequential support vector machine classification for small-grain weed species discrimination with special regard to Cirsium arvense and Galium aparine. ***Computers and Electronics in Agriculture*** 80:89-96.

Swain, K.C., Nørremark, M., Jørgensen, R.N., Midtiby, H.S., Green, O., 2011. Weed identification using an automated active shape matching (AASM) technique. ***BIOSYSTEMS ENGINEERING*** 110: 450-457.

Wisaeng, K., 2013. A Comparison of Decision Tree Algorithms For UCI Repository Classification. ***International Journal of Engineering Trends and Technology*** 4: 3393-3397.

Zhu, W., Zhu, X., 2009. The Application of Support Vector Machine in Weed Classification. **IEEE International Conference on Intelligent Computing and Intelligent Systems**, China, pp. 532-536.

تعريف ازهار نبات لسان الثور (Oxtongue) باستخدام تقنية معالجة الصور

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ملخص

نبات لسان الثور oxtongue لديه خصائص غذائية وفيرة، ويستهلك في جميع انحاء العالم. إن تعريف وتمييز الأزهار من الأجزاء النباتية الأخرى للنبات باستخدام معالج الصور تعتبر خطوة رئيسية في تصنيع آلة حصاد نبات oxotongue الاتوماتيكي. هدفت هذه الدراسة إلى إيجاد مسافات الألوان المناسبة لتعريف الزهرة بواسطة اللون.حيث تم خلال هذه الدراسة التقاط الصور تحت ثلاثة ظروف مختلفة وهي: تحت اشعة الشمس المباشرة، تحت الظل وتحت خلفية سوداء، حيث كانت المسافة بين النبات والكاميرا للحالات الثلاثة 25سم وكانت شدة الإضاءة 1800، 407 و 407 لوكس للحالات الثلاثة على التوالي. بعد إجراء عملية التصوير تم استخدام أربعة مسافات لونية RGB, HSV, YCbCr, NTSC لتحديد المسافة اللونية المناسبة لتعريف وتمييز الازهار. بينت النتائج بان المسافات اللونية المناسبة للتصوير تحت اشعة الشمس المباشرة، تحت الظل وتحت خلفية سوداء هي HSV RGB, , YCbCr, على التوالي. حيث كانت العتبة وخوارزمية وقت التشغيل لهذه المسافات هي: H<0.5, S<0.3, V<0.45 و 8.999s, Cb<150 و 7.284s و Cb>150 و 7.204s على التوالي. تم حساب معدل دقة التصوير تحت ظروف التصوير الثلاثة 100% و 94% و97.3% على التوالي.

الكلمات الدالة: oxtongue ،معالجة الصور، تعريف، آلة الرؤية.

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