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Estimation of Tomato Ripening Stages Using Three Color Models

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Summary : This research was carried out to compare the effectiveness of three color models in estimating the ripening of tomato fruits using features from image histograms and linear discriminant analysis as the statistical classification model. Digital color images were taken from nine tomatoes for each five maturity classes for a total of 45 samples. In each class, five samples were used for model development while the remaining four samples for model verification. Using Matlab (version 6.0 Release 13 Image Processing Toolbox), the images were processed to compute their histograms using the RGB, HSV and CIE L*a*b* color models at different bin sizes. Linear discriminant analysis using a statistical analysis software (SPSS) was performed on the histogram features to determine a multi-variate classification model.

While all the color models had successfully classified 80 to 100% of the model development samples, they did not performed so well in the verification samples. The average classification success rates of HSV (62.5 %) and CIE L*a*b* (60.0 %) were almost the same and much better than in RGB (35.0 %). Increasing the number of bins did not, however, result to a better classification model.

Key words : Image processing, RGB, HSV, CIE L*a*b*, Tomato

Introduction

Tomato fruit is one of the more economically important vegetables in Japan. While the fruits are more popularly taken fresh in salads and sandwiches, they are also processed into paste and other preparations. Recently in Japan, however, with the increasing demand of the produce and the decline in agricultural labor (Gejima et al. 2003), there is a need to automate the grading and sorting post-harvest operations. It will not only address the labor problem but also ensure food safety and achieve more consistent quality.

Recently, a machine vision system had been used to automate the grading process with marked success. While mostly based on an RGB color system and simple grading rules, this computer based system cannot respond well to changing operational conditions such as fluctuating illumination levels. Because of this, more robust techniques are now being explored to improve the performance of such systems.

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Of the many color space models available, RGB, HSI and CIE L*a*b* are more popularly used for machine vision. The RGB (red, green and blue) color model is used in most electronic systems such as in digital cameras and computer monitors (Russ 1995). It resembles the tri-stimulus model of the human eye. However, this system fails to achieve a consistent and reproducible description of color. On the other hand, the HSI (hue, saturation and intensity) color model was used because it does not only closely resembles how humans perceive color but also decouples the intensity component from the color information to minimize the effects of illumination intensity fluctuations (Chen and Ling 1995; Choi et al. 1995; Tao et al. 1995; Russ 1995). Using the HSI color model, Choi and others (1995) developed a Tomato Maturity Index for classification to six classes based on the aggregated percent surface area below certain hue angles. Their classification results agreed with manual grading in 77.5 % of tested tomatoes. Tao and others (1995) used the same HSI color system for color inspection of potatoes and apples. They achieved a 90 % accuracy using hue histograms as features while applying a multi-variate discriminant analysis. Moreover, they found out that changes in lighting intensity affected the results of classification by shifting pixel colors toward green. However, Chen and Ling (2001) confirmed that hue and saturation are stable features for color classification when object irradiance intensity varied. Similar to HSI, the HSV (hue, saturation and value) color system offers the same features particularly the invariance to changing illumination levels.

CIE L*a*b* is an internationally accepted color model standard established by the *Commission Internationale de L'Eclairege* that can accurately describe colors. Gejima and others (2003) evaluated the RGB and CIE L*a*b* color systems as tomato ripeness indicators using linear correlation analysis. They found out that the gray pixel value of 36 in the green channel had highest correlation with ripening, and the a* channel alone can be used for ripening judgement. In an earlier work, Cao and others (1998) found the intensity levels of R, G and B in an RGB color system were significantly affected by changes in illumination, while the levels of a* and b* in CIE L*a*b* were not affected.

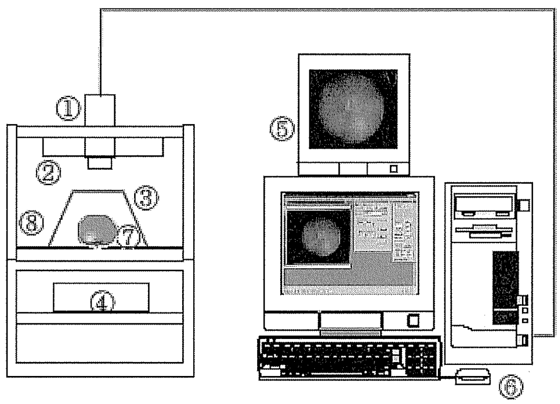
This research was primarily aimed to compare and assess the effectiveness of the RGB, HSV and CIE L*a*b* color models for estimation of ripening of tomatoes. Using the image histograms as object features, statistical classification models were developed based on the linear discriminant analysis.

Materials and Methods

1. Tomato collection and Image acquisition

Nine samples of tomatoes (cv. Momotarou) for each of the five maturity classes according to JA Miyazaki tomato grading standards (less than 20 % ripening, 30 to 40 percent ripening, 50 to 60 percent ripening, 70 to 80 percent ripening, and full ripening) were collected locally. Five of the nine samples in each class were used for statistical classification model development, and the remaining four were used for model evaluation.

Images of tomatoes were taken using the set-up shown in Figure 1. A circular white fluorescent light driven by a high-switching power



1. CCD camera, 2. Fluorescent lamp, 3. Paper diffuser, 4. High frequency switching power source, 5. Monitor, 6. personal computer, 7. Tomato, 8. Stage with black mat.

Fig. 1 The image acquisition set-up

supply provided uniform illumination through a diffusive filter. To capture images, a Sony DXC-151A single chip RGB color video camera was attached to an 8-bit HIMAWARI 50 frame-grabber board at 512 x 512 pixels resolution, and installed to an NEC, PC-9821 Xv20, 200MHz computer.

2. Preliminary Image processing

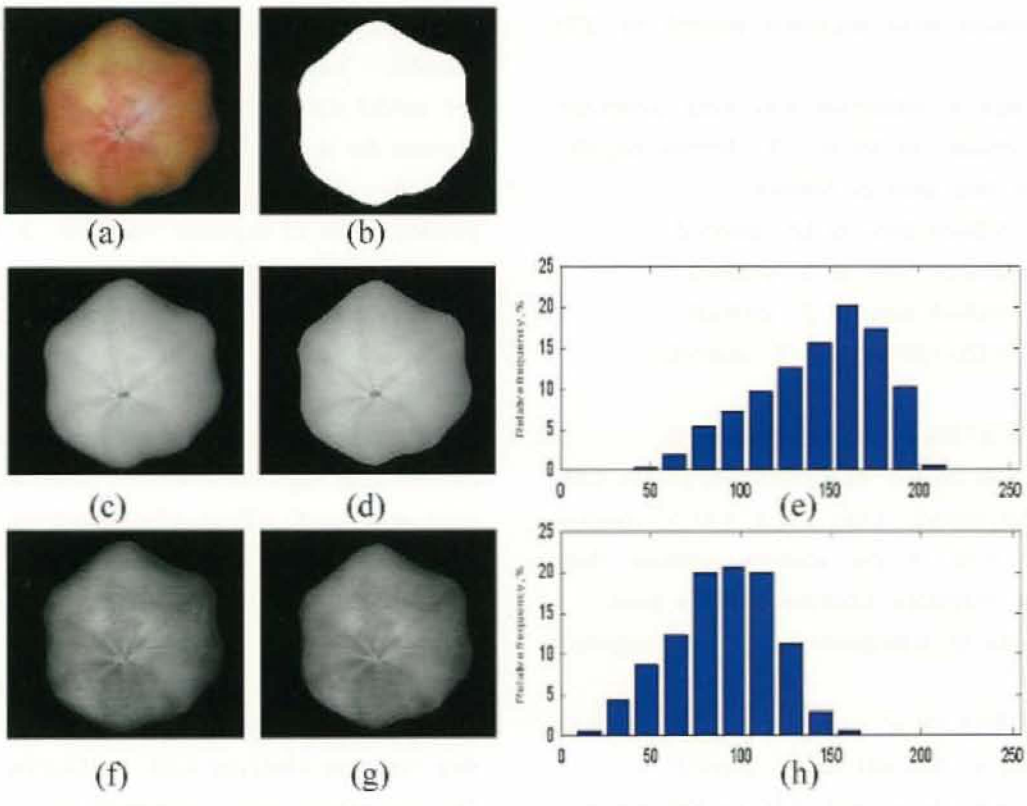
Image processing was carried out using Matlab version 6.5 (Release 13) and its Image Processing Toolbox. To create the mask binary image, a general threshold at 20 grayscale pixel value was used for the red channel. Next, to remove any holes from the fruit object, the mask was morphologically dilated using a disk structuring element with a radius of 5 pixels. Additionally, to reduce the edge effects caused by the background, the mask was morphologically eroded using a disk structuring element with a radius of 10 pixels. The mask was then pixel-wise multiplied to the original image to isolate the fruit from its background. Figure 2 shows an example of the results of the operation.

3. RGB Model Histogram Processing

The blue channel data was taken out from the analysis set because it had been found out (after a preliminary analysis run) that it can contribute very little information to assess tomato ripeness, which was, intuitively more explained by the red and green channels data. Figure 2's (e) and (h) show an example of the histograms for the red and green channels, respectively.

Five sets of histogram bins were computed using Matlab's *hist* function as follows:

V1 to V16 for red and V17 to V32 for green-16 bins, at 16 grayscale interval



(a) original image, (b) binary image mask
(c) red channel image, (d) masked red channel image
(e) red channel histogram (f) green channel image,
(g) masked green channel image, (h) green channel histogram.

Fig. 2 Sample result of preliminary image processing:

V1 to V32 for red and V33 to V64 for green-32 bins, at 8 grayscale interval
V1 to V48 for red and V49 to V96 for green-48 bins, at 5.3 grayscale interval
V1 to V64 for red and V65 to V128 for green-64 bins, at 4 grayscale interval
V1 to V80 for red and V81 to V160 for green-80 bins, at 3.2 grayscale interval

4. HSV Model Image Processing

The RGB images were converted to HSV using MatLab's *rgb2hsv* function. Only the hue channel data were used in the analysis because it contains the pixel's chromatic information. Because the hue data were in decimal value, they were multiplied by 360 to convert them into angular degrees. Since some colors near the red color angle (0 degree) were in the vicinity of less than 360 degrees and to make the colors around the Red color angle rather contiguous, the hue values were circularly rotated by 120 degrees.

Four sets of histogram bins were computed that each divide the 60 to 300 degrees angular values. The bins were as follows:

V1 to V24-24 bins, at 10° interval
V1 to V30-30 bins, at 8° interval
V1 to V48-48 bins, at 5° interval
V1 to V120-120 bins, at 2° interval

5. CIE $L^*a^*b^*$ Model Image Processing

The RGB images were converted to the CIE $L^*a^*b^*$ color model. Only the a^* and b^* channel data were used in the analysis because they contain the chromatic information of a pixel.

Five sets of histogram bins were computed as follows:

V1 to V20 for a^* and V21 to V40 for b^*-20 bins, at 10.0 chromatic interval
V1 to V40 for a^* and V41 to V80 for b^*-40 bins, at 5.0 chromatic interval
V1 to V60 for a^* and V61 to V120 for b^*-60 bins, at 3.3 chromatic interval
V1 to V80 for a^* and V81 to V160 for b^*-80 bins, at 2.5 chromatic interval
V1 to V100 for a^* and V101 to V200 for b^*-100 bins, at 2.0 chromatic interval

6. Statistical Processing of Data

Standard multi-variate Linear Discriminant Analysis classification models were developed using a statistical software (SPSS) for each color model and bin size. A selection variable, however, was added to distinguish between the samples for model development and for model verification.

Results and Discussion

Table 1 shows a summary of classification rate performance and the accountable percent variation in ripening classes for each color model and bin sizes. In general for any color model, the discriminant analysis technique had successfully classified the samples used for model development at a rate of more than 80 %. However, it performed not too well on the verification samples. The limited number of samples used for model development could explain this. To account for a larger variability of images in each maturity class, more samples representing all possible cases of expected variation in the color features must be taken.

Increasing the number of feature variables or bins seemly did not improve the performance of the classification models. This could be apparently explained by the transfer of feature information from one bin to another when smaller bin sizes were used. Thus, the underlying information were still contained in the dataset.

In the RGB color model, increasing the number of bins did not improve the success rate of 96 % for model development samples except for the 64 bins. However, very poor classification rate was observed with verification samples. On the other hand, increasing the number of feature bins in the HSV model had improved the rate of successful classification from 92 % when using 24 bins to 100 % when using 48 bins for the model development samples. However, the

Table 1. Summary of classification model development and verificationfor the different color models and bin numbers.

Color Model / No. of Bins	Successful Classification Rate Performance		Percent of Variation of Maturity Classes Explained by the Models	
	Model Development Samples	Model Verification Samples	Function 1 alone	Functions 1 and 2 combined
RGB Color Model				
16	96%	45%	81.2%	94.5%
32	96%	50%	68.4%	90.9%
48	96%	15%	60.3%	83.4%
64	100%	15%	87.8%	96.3%
80	96%	50%	65.9%	82.4%
HSV Color Model				
24	92%	65%	75.8%	93.8%
30	96%	65%	75.1%	94.4%
48	100%	65%	83.5%	94.7%
120	92%	60%	69.3%	93.3%
CIEL*a*b* Color Model				
20	92%	70%	77.6%	93.4%
40	92%	50%	67.0%	95.6%
60	80%	55%	60.7%	91.5%
80	92%	65%	72.4%	96.1%
100	92%	60%	58.4%	91.7%

success rate for the verification samples was almost uniform at 60 to 65 %. The success rate for the CIE $L^*a^*b^*$ color model for the model development images was about 92 % for most bin ranges except for 80 % in the case of 64 bins. However, the success rate for model verification samples ranged from a low of 50 % to a high of 70 %.

In all color models, two functions were necessary for classification. About 82.4 to 96.3 % of the variability of ripening classes can be accounted by the classification models developed using the RGB color model. On the other hand, by using two determinant linear functions can account for 93.3 to 94.7 % for the HSV model and 91.5 to 96.1 % for the CIE $L^*a^*b^*$ of the variability in the maturity classes.

Not all the computed histogram feature variables were actually used in the analysis. During the development of models particularly those having large number of bins, the feature variables with zero values were manually dropped in the analysis so that SPSS can accommodate the dataset. Likewise, SPSS also automatically performed a tolerance test to eliminate unnecessary variables.

A sample output for linear model development for the RGB colorspace model using 64 bins is shown in Table 2. Mostly the feature variables from the red channel (V1 to V64) were used in the model development while green channel feature variables (V65 to V128) failed the tolerance test except for the V111 and V123 values. This suggests that a model from the RGB colorspace can be developed using the features from the red channel alone.

A sample output for linear model development for the CIE $L^*a^*b^*$ colorspace model using 80 bins is shown in Table 3. In a similar manner to the RGB colorspace classification model development, most of the features were taken from the a^* channel alone. This could be explained by the fact that the surface color of the tomato changes from green to red as the fruits ripened. The green and red pixel data are solely contained in the a^* channel of the CIE $L^*a^*b^*$ color

Table 2. A sample output for a linear discriminant model for RGB color model with 64 bins.

Discriminant Function Coefficients

Feature Variables	Function 1	2	3	4
V8	490.906	368.980	−659.740	−285.045
V9	−42.071	−44.190	73.804	22.794
V12	−9.623	−2.420	2.474	5.848
V17	−15.985	−3.615	.123	2.678
V18	20.924	−.166	3.292	−3.871
V20	−1.301	3.187	−6.240	−5.807
V21	−8.404	−4.953	.486	3.511
V22	−14.600	4.992	5.744	6.973
V23	25.709	2.531	−3.612	−5.038
V32	−3.463	−.223	.857	1.927
V37	2.451	.727	.405	.182
V41	−1.684	−2.441	−.718	−2.002
V42	1.086	1.927	1.077	2.484
V54	−43.883	60.301	60.955	−2.575
V111	3.977	−.555	−.347	.369
V123	−140.645	27.795	70.879	−10.740
(Const)	−15.878	−9.655	−5.114	−7.926

Table 3. A sample output for a linear discriminant model for CIE L*a*b* color model with 80 bins.

Discriminant Function Coefficients

Feature Variables	Function 1	2	3	4
V31	5.669	56.742	−35.427	−34.145
V32	2.410	18.219	2.269	−21.507
V33	−.098	−3.649	−.853	5.239
V34	−.101	−.041	.389	−.413
V37	.330	.440	−.187	.121
V38	−.301	−.601	.242	.109
V40	.351	.341	−.089	.187
V45	.447	−.109	.028	.180
V46	−.571	1.004	.205	−.116
V47	1.328	−1.986	−.404	.197
V48	−1.600	2.581	.688	.114
V49	1.123	−1.301	−.310	.025
V50	.494	−.089	.042	.119
V51	−.294	−.201	−.149	−.211
V53	1.459	−.008	.209	.428
(Const)	−8.818	−.969	−2.257	−5.305

model. Thus, this suggests that the b^* channel may be dropped from future model development.

Conclusion

1. The linear discriminant classification models from all colorspace models can reasonably perform well for ripening classification of tomatoes. The HSV and CIE $L^*a^*b^*$ are attractive to use because of their invariance to lighting level. In the HSV model, moreover, using the single hue channel made it more robust than the other two. However, the research showed that a single channel for RGB color model (red channel) and CIE $L^*a^*b^*$ (a^* channel) can be used to discriminate ripening classes of tomatoes.
2. Increasing the number of bins for feature extractions may not necessarily result to better classification model. However, the lesser the number of feature variables there is, the more computationally attractive it becomes.

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三種類のカラーモデルによるトマトの成熟度評価

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要 約

本研究はトマトの成熟度を評価するために，三種類のカラーモデル（RGB, HSV, CIE L*a*b*）の有効性を比較検討したものである。その方法は，トマトの表面色を各カラーモデルごとにイメージヒストグラムを求めて，その特徴を統計処理（線型判別分析，linear disrimenant analysis）するものである。トマトのデジタルカラーイメージは5段階の成熟度に分類した。各分類ごとに9個のトマトを供試して，そのうちの5個を線型モデル化のために，残り4個は立証のために使用した。トマトの原画像はデジタルカメラを用いて取得し，次にRGB, HSV及びCIE L*a*b* によるイメージヒストグラムはMatLab（イメージプロセシングツールボックス）を用いて作成した。イメージヒストグラムの線型判別分析（線型判別係数予測）には，統計ソフトSPSSを使用し多変量解析を行った。

その結果，各カラーモデルにおける線型モデル化は80から100 %の値となり良好な結果を得た。成熟度の評価率は，HSV（平均62.5 %）およびCIE L*a*b*（同60 %）がRGB（同35.0 %）より高かった。今後は，品種，サンプル数を増やして精度の向上を図る必要がある。