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A robust fruit image segmentation algorithm against varying illumination for vision system of fruit harvesting robot

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ABSTRACT

Vision system is the crucial component of fruit harvesting robot for recognising fruit, however, which is seriously affected by varying illumination when the robot works in real natural environment. A robust fruit segmentation algorithm against varying illumination for vision system was proposed with the aim of effectively extracting fruit object in the natural environment. The method involved the application of improved wavelet transform to fruit image to normalise illumination of object surface. Then Retinex-based image enhancement algorithm was used to highlight fruit object of illumination normalised image. Finally fruit image was segmented by implementing *K*-means clustering. Three kinds of fruit images of different colour under sunny and cloudy days were segment using the proposed method respectively and the experimental results showed that the proposed algorithm could be robust against the influence of varying illumination and precisely segment different colour fruits.

1. Introduction

Manual fruit harvesting is a time-consuming and high labour-costs job, which urges that many fruit harvesting robots have been developed [1–4]. A typical fruit harvesting robot consists of a manipulator, an end-effector, a mobile device, a vision system and a control system, in which vision system plays a vital role in producing images for the robot to recognise fruit. Normally, shape based analysis and colour based analysis are used for the vision system to segment fruit image [5]. Circular Hough transform algorithm based on fruit shape information was applied in segmenting fruit image, however, the interference of background, leaves, or curvature contributed to low fruit detection rate [6,7]. The method of threshold segmentation or colour indices was considered as a common method of fruit image segmentation based on colour analysis. The fruit object was extracted by adjusting spectral distribution or setting up colour index [8–12]. But due to uneven illumination on the surface of objects causing by varying light, light spots or shadows can easily form on the surface of fruit and other objects, which causes serious errors in segmentation based on colour analysis.

In this paper, a robust fruit image segmentation algorithm against varying illumination for vision system of fruit harvesting robot was proposed. The fruit colour image was obtained in real natural environment, surface illumination of which was

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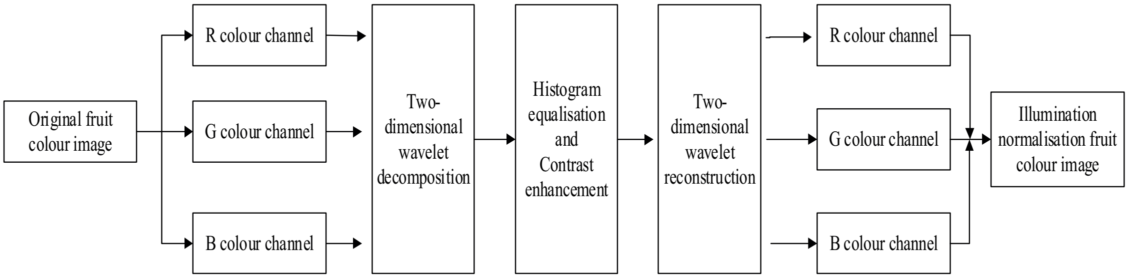

Fig. 1. Flow chart of improved wavelet-based fruit colour image illumination normalisation.

normalised using an improved wavelet transform. And then Retinex algorithm was used to highlight fruit object. Fruit was finally segmented by implementing *K*-means clustering. Three kinds of fruit images of different colour under sunny and cloudy days were used to test the performance of the proposed algorithm.

2. Materials and methods

2.1. Image acquisition

In order to evaluate the effect of the proposed fruit image segmentation algorithm, 300 fruit images under outdoor conditions captured in three orchards were tested. The image acquisition conditions were as follows: grape, 100 images in a grape orchard in Tianjin; dates, July 21, 2014 to July 25, 2014; litchi, 100 images in a litchi orchard in Guangzhou; dates, June 20, 2015 to June 25, 2015; citrus, 100 images in a citrus orchard in Hengyang; dates, October 10, 2015 to October 15, 2015; weather, cloudy and sunny. The images were captured by a CCD colour camera (model MV-VD120SC) which had a digital video output of 1280 by 960 effective pixels, and were stored in a PC with 4 GB RAM, an Intel Core i5-2500 CPU, a Windows 7 operating system. The images were processed using both the proposed segmentation algorithm under Matlab 8.3 programming environment and image editing software Photoshop 13.0 by manually labelling fruits for artificial criteria. The artificial criteria used from the method of the reference [5] was stated: the remaining fruit portion in the difference image between the manual segmentation image and the image segmented by the proposed algorithm was labelled manually, and the pixels were calculated. If the pixel rate of the remaining portion to that manually labelled was less than 0.05, then the fruit segmented by the proposed algorithm could be considered as successful and its segmentation rate could be calculated.

2.2. Improved wavelet-based illumination normalization

Varying illumination mainly affects the low-frequency components of fruit colour image by changing brightness and contrast of image [5]. Due to ability of combining space domain and frequency domain to analyze, wavelet is a potential tool for extraction details and other approximate composition of image.

As shown in Fig. 1, original fruit colour image was firstly decomposed into R, G, B three colour channels in RGB colour space. These colour channels were two-dimensional gray scale images. Using formula 1, which was the two-dimensional discrete wavelet transform (two-dimensional Mallat algorithm) in the first layer, three colour channels were decomposed into low-frequency component and high-frequency component respectively. Then, in this paper, the low-frequency component and the high-frequency component were processed using histogram equalisation and contrast enhancement respectively. The processed low-frequency component and high-frequency component were reorgnised into three different colour channels using two-dimensional wavelet reconstruction using formula 2 respectively. Finally, improved wavelet-based illumination normalisation was accomplished by reorganisation of the three illumination normalised colour channels of the fruit colour image.

$$\begin{cases} d_{j+1}^{V}(x,y)=\sum\limits_{k}\sum\limits_{l}g(k-2x)h(l-2y)c_j(k,l) \\ d_{j+1}^{H}(x,y)=\sum\limits_{k}\sum\limits_{l}g(k-2x)h(l-2y)c_j(k,l) \\ d_{j+1}^{D}(x,y)=\sum\limits_{k}\sum\limits_{l}g(k-2x)h(l-2y)c_j(k,l) \\ c_{j+1}(x,y)=\sum\limits_{k}\sum\limits_{l}g(k-2x)h(l-2y)c_j(k,l) \end{cases} \tag{1}$$

$$
\begin{aligned}
c_j(x,y) = {} & \sum_l \sum_k h(k-2x)h(l-2y)c_{j+1}(k,l) \\
& + \sum_l \sum_k g(k-2x)h(l-2y)d_{j+1}^H(k,l) \\
& + \sum_l \sum_k h(k-2x)g(l-2y)d_{j+1}^V(k,l) \\
& + \sum_l \sum_k g(k-2x)g(l-2y)d_{j+1}^D(k,l)
\end{aligned} \tag{2}
$$

Where x, y presented the coordinate of the pixel point, k, l were both integers, and g and h were high-pass filter and low-pass filter respectively. c_j was the original image, d_{j+1}^V was vertical high-frequency component, d_{j+1}^H was horizontal high-frequency component and d_{j+1}^D was diagonal high-frequency component. c_{j+1} was low-frequency component.

2.3. Retinex-based image enhancement

Retinex that simulates regulation mechanism of human vision system according to actual illumination situation is an adaptive enhancement algorithm. Its basic aim is that decomposing an input image $S(x, y)$ into a reflection image $R(x, y)$ and an illumination image $L(x, y)$, as shown in formula 3, therefore, enhancing image by changing the ratio of incident illumination and reflected illumination.

$$S(x,y) = R(x,y) \cdot L(x,y) \tag{3}$$

After wavelet-based illumination normalisation, the classical single scale Retinex algorithm was applied to fruit colour image for enhancing image. Its decomposition formula is as follows:

$$\log R(x,y) = \log S(x,y) - \log[F(x,y) * S(x,y)] \tag{4}$$

Put the input image $S(x, y)$ (in this paper, it was the illumination normalised fruit colour image) into the formula 4, and $F(x, y)$ was the Gauss convolution function as shown in formula 5:

$$F(x,y) = \lambda \exp(-(x^2+y^2)/n^2) \tag{5}$$

Where λ was a normalized constant that enabled $\iint F(x,y)dxdy$ be equal to 1. n was a scale constant for controlling domain scope, in this paper, the value of n was 15. Thus, the reflection image $R(x, y)$ was obtained, and it was just the enhanced image of the illumination normalised fruit colour image.

2.4. K-means clustering-based fruit image segmentation

Some colour indices have been applied in segmenting fruit image. A colour index 3R − (G + B) with high contrast value was used for segmenting red apple image [10]. Another index R − B was applied in segmenting citrus image [11]. Most job objects of fruit harvesting robot are ripe fruits, the colour of which is different from branches, leaves and background, for example, tomato, litchi, strawberry, citrus, grape, and so on. But there are exceptions that the colour of the fruit is similar to leaf colour such as watermelon, cucumber, and so on. This paper applied *K*-means clustering that was a commonly used clustering algorithm to the enhanced fruit image for segmentation of fruit. *K*-means clustering needs to specify the number of clusters to be partitioned and a distance metric to quantify how near the two classes are to each other. The ripe fruit had its own colour, the leaves are green and the peduncles and branches are other colours, thus the number of clusters should be determined as three.

3. Results and discussions

3.1. Performance of fruit segmentation algorithm

Colour images of three kinds of fruits (litchi, grape and citrus) were used to test the performance of the proposed algorithm, and these images were all acquired under sunny and cloudy days conditions. Fig. 2(b) and (h) showed the illumination normalisation results of litchi images that were Fig. 2(a) and (g) under sunny and cloudy days conditions by the improved wavelet transform, and surface illumination of litchi image was apparently uniform. Especially, in Fig. 2(h), the portion of litchi image in shadowed areas was obviously seen after illumination normalisation. Using Retinex algorithm, ripe red litchis were apparently enhanced as shown in Fig. 2(c) and (i). Thus, litchi images were segmented using *K*-means clustering as shown in Fig. 2(d) and (j). Compare with the result processed by only *K*-means clustering shown in Fig. 2(e) and (k) and the result processed by only 3R − (G + B) shown in Fig. 2(f) and (l), the litchi fruits were completely segmented in the result processed by this paper, however, the segmented litchis of other results were not complete and there many holes in the surface of the segmented litchi fruits due to the uneven lighting. Similarly, after illumination normalisation shown in

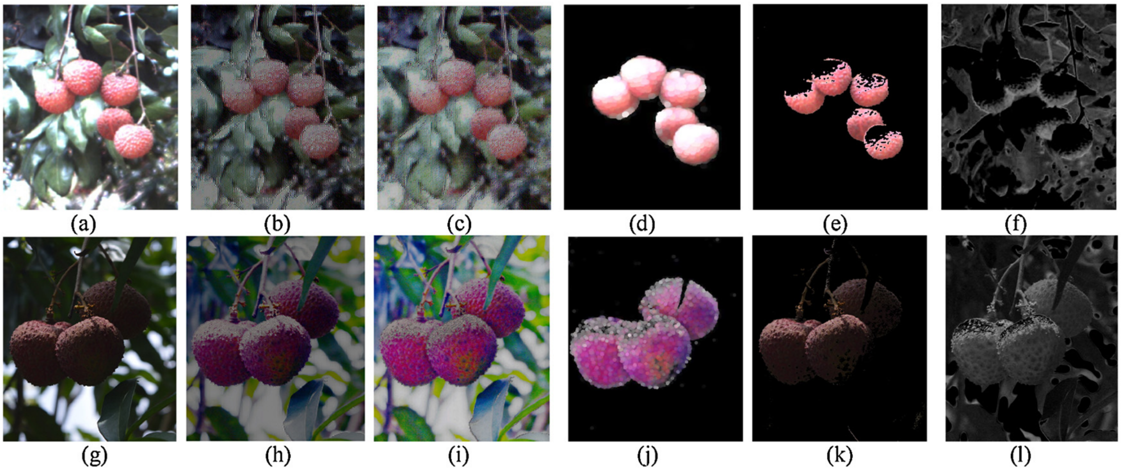

Fig. 2. Litchi image and processed results (a) Litchi image under sunny days, (b) Processed result of (a) by wavelet, (c) Processed result of (b) by Retinex, (d) Result processed by this paper, (e) Result processed by only *K*-means clustering, (f) Result processed by only 3R – (G + B), (g) Litchi image under cloudy days, (h) Processed result of (g) by wavelet, (i) Processed result of (h) by Retinex, (j) Result processed by this paper, (k) Result processed by only *K*-means clustering, (l) Result processed by only 3R – (G + B).

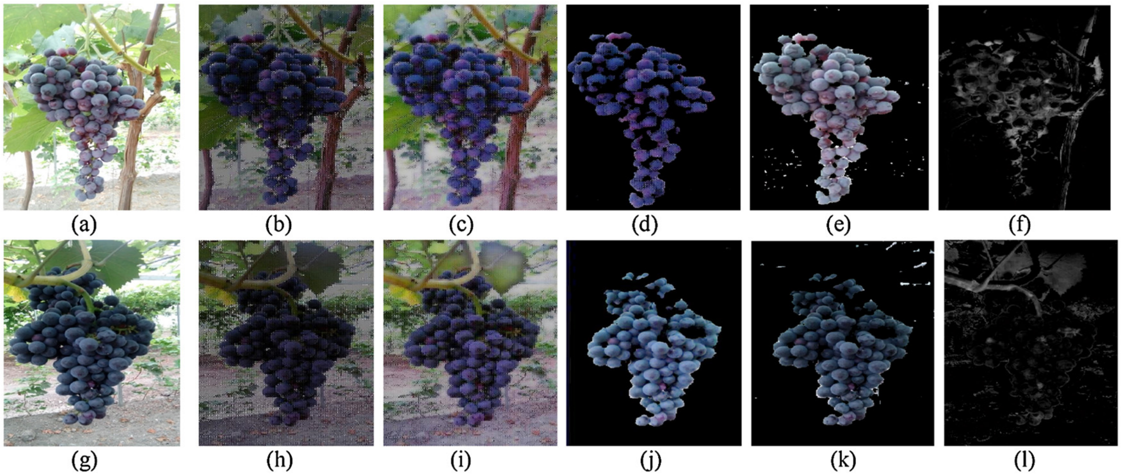

Fig. 3. Grape image and processed results (a) Grape image under sunny days, (b) Processed result of (a) by wavelet, (c) Processed result of (b) by Retinex, (d) Result processed by this paper, (e) Result processed by only *K*-means clustering, (f) Result processed by only 3R – (G + B), (g) Grape image under cloudy days, (h) Processed result of (g) by wavelet, (i) Processed result of (h) by Retinex, (j) Result processed by this paper, (k) Result processed by only *K*-means clustering, (l) Result processed by only 3R – (G + B).

Fig. 3(b) and (h) and Fig. 4(b) and (h), the surface illumination of grape images and citrus images under sunny and cloudy days conditions shown in Fig. 3(a) and (g) and Fig. 4(a) and (g) were even, in which fruits and the surface colour were enhanced by Retinex algorithm shown in Fig. 3(c) and (i) and Fig. 4(c) and (i). Thus, grape fruits and citrus fruits were segmented by *K*-means clustering shown in Fig. 3(d) and (j) and Fig. 4(d) and (j) respectively, which showed the proposed algorithm was more suitable for segmenting fruits in the real natural environment than the algorithm only *K*-means clustering shown in Fig. 3(e) and (k) and Fig. 4(e) and (k) and R – B shown in Fig. 3(f) and (l) and Fig. 4(f) and (l).

As shown in Table 1, the performance of the proposed algorithm in segmenting the different colour fruits under different lighting conditions was illustrated by comparing the segmentation data with artificial criteria. For sunny days, the average fruit segmentation rates (hit rate) of litchi and grape were 95.3% and 97.2% respectively, and the hit rate of citrus declined to 89.2%. However, for cloudy days, the average fruit segmentation rates of three kinds of different colour fruits were 91.6%, 93.6% and 87.3% respectively. The colour of the background (i.e. soil) was similar to the litchi and grape colour. It was difficult to distinguish the litchi and grape and the soil based on colour analysis. The rates of background mistakenly recognised as fruit (i.e. false positive rates) under this condition were (1.5%,0.6% and 4.6%) much higher than under sunny days conditions (0.5%,0.3% and 3.7%). The rates of fruit mistakenly recognised as background (false negative rates) were much lower than the false positive rates and under the two conditions were 0.8%, 0.4% and 2.5% and 0.9%, 0.5% and 1.6% respectively. Light could be compensated under sunny and cloudy days conditions using improved wavelet-based illumination normalisation algorithm

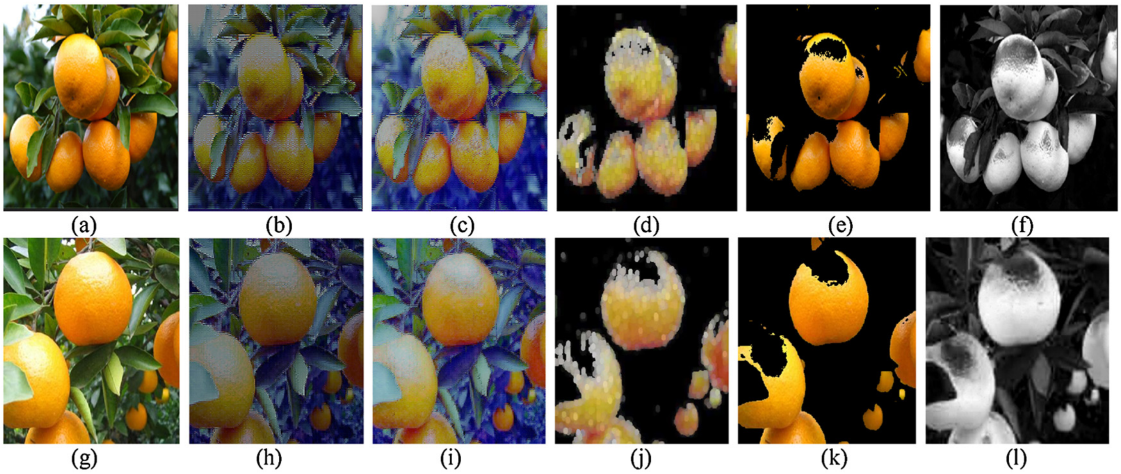

Fig. 4. Citrus image and processed results (a) Citrus image under sunny days, (b) Processed result of (a) by wavelet, (c) Processed result of (b) by Retinex, (d) Result processed by this paper, (e) Result processed by only *K*-means clustering, (f) Result processed by only R − B, (g) Citrus image under cloudy days, (h) Processed result of (g) by wavelet, (i) Processed result of (h) by Retinex, (j) Result processed by this paper, (k) Result processed by only *K*-means clustering, (l) Result processed by only R − B.

Table 1
Performance of fruit segmentation algorithm.

		Hit rate (%)	False positive rate (%)	False negative rate (%)
Litchi	Sunny days	95.3	0.5	0.3
	Cloudy days	91.6	1.5	0.9
Grape	Sunny days	97.2	0.3	0.4
	Cloudy days	93.6	0.6	0.5
Citrus	Sunny days	89.2	3.7	2.5
	Cloudy days	87.3	4.6	1.6

and object fruits could be enhanced by Retinex-based image enhancement. Thus, fruits could be better differentiated. Using the proposed algorithm, the proposed image segmentation algorithm yielded very satisfactory results and was effective.

3.2. Real time performance of the proposed algorithm

The real time performance of algorithm is vital to vision system, which affects real time working performance of fruit harvesting robot. The proposed algorithm included improved wavelet-based illumination normalization, retinex-based image enhancement and *K*-means clustering-based fruit image segmentation. The time consumed by the proposed algorithm mainly occured during improved wavelet-based illumination normalisation. And it required three colour channels of a fruit colour image and each colour channel to be decomposed into different frequency images. The average time of processing achieved was 1097 ms. And the average time of the proposed algorithm was 1365 ms, which should be sufficient to meet the needs of fruit robotic harvesting controlled in real-time.

4. Conclusions

A robust fruit image segmentation algorithm against varying illumination was developed for vision system of fruit harvesting robot. According to the results, some conclusions can be made: (1) The proposed fruit algorithm was more suitable for segmenting different colour fruits in the real natural environment than *K*-means clustering, 3R − (G + B) and R − B; (2) The proposed fruit image segmentation algorithm was very satisfactory under sunny days conditions. Even on cloudy days, the average hit rates for litchi, grape and citrus were 91.6%, 93.6% and 87.3%, respectively; (3) The average time of processing achieved of the proposed algorithm was only 1365 ms. This showed that the proposed algorithm was robust to variable illumination and met the needs of fruit robotic harvesting controlled in real-time.

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