Machine Vision based Citrus Mass Estimation during Post-Harvesting Using Supervised Learning Algorithms

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Introduction

A machine vision system was investigated as a means of estimating citrus fruit mass during post-harvesting. An estimation of the amount of citrus fruit can be made by analyzing images that contains citrus fruit at the process of debris removal. Image acquisition for previous machine vision based yield monitoring system took place during or before harvesting. This type of sensing could lead to the decrease in estimation accuracy since sensed object might include debris or non-fruit objects. Hence, image acquisition after the removal of those unnecessary objects would increase the estimation accuracy. For a proposed machine vision system, image sensing after the disposal process of a citrus debris cleaning machine corresponds to such image acquisition.

Objectives

- Develop a image segmentation algorithm based on supervised machine learning algorithms.
- Design and develop a machine vision system for citrus mass estimation at the time of post-harvesting.

Materials and Methods

Hardware:

- CCD color camera with high frame rates (206 fps) featured camera
- Incremental encoder was installed on the rotating axis of the conveyor for synchronization.
- Housing covers the camera and the lightning devices in order to remove the effect of sunlight variation.
- Two Exo-lights, DAQ card

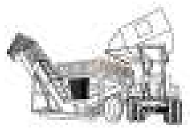

Fig. 1. Schematic image of citrus debris cleaning machine

Fig. 2. Housing

Fig. 3. CCD camera

Fig. 4. Incremental encoder

Software:

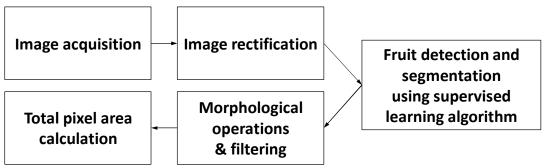

Fig. 5. Block diagram of image processing algorithm

Image acquisition

- Two field experiments conducted at Lykes grove in Fort Basinger, Florida
- Each experiment has several sets which represent the different yield amount, abscission usage, and harvesting conditions.
- The machine vision system captures images of citrus fruit sliding over the conveyor belt of the cleaning machine.

Table 1. Field experiment summary

	Set number	Actual fruit mass (kg)	Number of images acquired
1st experiment	1	1,492.3	2084
	2	979.8	917
	3	1,628.4	1947
2nd experiment	1	2,004.9	2640
	2	1,217.9	1787
	3	1,510.5	2394
	4	1,614.8	1733

Image rectification

- Camera's geometry and lens distortion models are derived through the process of camera calibration. Two models are used to correct for intrinsic deviations and lens distortions.

Fruit detection and segmentation

- Binary classification problem : classify pixels as fruit or non-fruit
- Supervised machine learning algorithms were utilized to solve the binary classification problem.
  - Naïve Bayes classifier : Parameter extraction using Maximum Likelihood Estimation
  - Artificial Neural Network : Multilayer feed-forward with 2 hidden layers
  - Decision Tree : Pruning to avoid over-fitting problem
- Feature vector = [Hue Saturation Cb Cr]
- Morphological operations with disk-shaped structural element was used to remove a noise and segmentation errors.
- Binary image as an output of the segmentation

Mass calibration

- Calibration image sets which consist of 8 images containing 5 fruit samples with varying size and mass were taken at the field.
- Regression analysis on the pairs of mass and pixel area for individual fruit
  - $\text{Estimated mass (kg)} = p_1 \times \text{pixel area} + p_2$

Results

Image segmentation

Fig. 6. Image taken during the field experiment

Fig. 7. Binary image created using naïve Bayes classifier

Fig. 8. Binary image created using Artificial Neural Network

Fig. 9. Binary image created using Decision Tree

Mapping equation $\text{Estimated mass (kg)} = p_1 \times \text{pixel area} + p_2$

Table 2. Results of regression analysis on the calibration sets

Experiment number	Error sum of squares (SSE, kg)	Coefficient of determination (R^2)	RMSE (kg)	p_1	p_2
1	0.0322	0.924	0.0291	0.0000686	-0.0273
2	0.0303	0.929	0.0282	0.0000718	-0.0659

Mass estimation

Table 3. Summary of mass estimation results

Experiment	Set number	Actual mass (kg)	Naïve Bayes		Neural Network		Decision Tree	
			Estimated mass (kg)	Error (%)	Estimated mass (kg)	Error (%)	Estimated mass (kg)	Error (%)
1st	1	1,492.3	1,549.4	-3.8	1,560.7	-4.5	1,346.2	9.8
	2	979.8	855.2	12.7	883.7	9.8	979.3	0.1
	3	1,628.4	1,599.7	1.8	1,605.8	1.4	1,414.7	13.1
2nd	1	2,004.9	2,222.8	-10.8	2,197.5	-9.6	2,222.2	-10.8
	2	1,217.9	1,224.5	-0.5	1,250.2	-2.6	1,324.0	-8.7
	3	1,510.5	1,590.9	-5.3	1,597.8	-5.7	1,694.2	-12.1
	4	1,614.8	1,427.3	11.6	1,430.0	11.4	1,479.2	8.4

- Regression analysis between the actual fruit mass and the fruit estimated mass

Table 4. Comparison of mass estimation results

	RMSE (kg)	R-square
Naïve Bayes	121.7	0.929
Artificial Neural Network	120.5	0.924
Decision Tree	187.1	0.804

Problems

- Fruit missing or overlapping in image capturing
  - Synchronization problem: varying conveyor speed, sensor noise
  - Fruit overfeeding, housing blocking the camera view in part

Conclusions

- A machine vision system for citrus mass estimation during post-harvesting was designed and implemented.
- For the image segmentation, pixel classification algorithms were implemented based on supervised machine learning algorithms, such as naïve Bayes, artificial neural network and decision tree.
- The naïve Bayes and the neural network model performed better than the decision tree model in pixel classification, which led to R-square more than 0.92 in conducting mass estimation. Even if considering rather high RMSE, it can be concluded that the mass estimation was performed reasonably well using the two methods.