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Image Processing in Automated Pattern Classification of Oranges

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Abstract

A rapid method for automated classification of oranges in living trees by size has been developed. It is based on image processing with correlation analysis in the frequency domain. This technique has the advantage of being a direct measurement method that automatically identifies and counts oranges for quality control. Calibration was performed using standard image with known orange sizes. Orange's sizes, ranging from less then 2 cm to over 10 cm in diameter have been automatically recognized and successfully measured. Error was not larger than 1.4%. In addition, practical examples of use of the method for determining characteristics of oranges are presented.

Keywords: Machine Vision, Agricultural Instrumentation, Orange Measurement.

Introduction

During the past 30 years, considerable interest has developed in problems of pattern recognition, pattern identification and image processing with application to vision systems. This interest has created an increasing need for theoretical methods and experimental software and hardware for use in the design of vision systems (Duda and More, 1973; Fukunaga, 1985; Fukunaga, 1990; Fonga, 1996; Giacinto et al, 1997). Drawing on its roots in traditional signal processing and systems theory, early image processing depended mainly on linear filters and convolution masks. Recently, image processing has applied frequency analysis, non-linear analysis, space-variant filtering, and model-based analysis, which are much more powerful than traditional techniques for handling varied and challenging image processing tasks.

Within this context, the Fourier transform has been widely used, mainly because of its computational efficiency. The discrete Fourier transform in two dimensions is typically used in image processing, i.e., the classical definitions establish the two-dimensional discrete Fourier transform of f(k,l) as:

$$F(h,i) = \frac{1}{p}\sum_{k=0}^{p-1}\sum_{l=0}^{p-1} f(k,l)e^{-j2p(kh+li)/p} \qquad 0 \le h,i \le p\text{-}l \qquad (1)$$

and the inverse transform as:

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$$f(k,l)=\frac{1}{p}\sum_{h=0}^{p-1}\sum_{i=0}^{p-1}F(h,i)e^{j2p(kh+li)/p} \qquad 0 \le k,1 \qquad (2)$$

where p is the number of pixels in the image, and j= $\sqrt{-1}$. There are limitations on the function f(k,l) for its transform to exist. If it is a continuous function, it must be piece-wise with left and right-hand derivatives at every point. A complete study of the Fourier transform, its properties, and particularities may be found, for example, in Young and Sun Fu (1986), or in Gonzales & Wintz (1987). Many imaging and optical systems can be analyzed by using Fourier methods. In addition, it is a natural choice for use in applications requiring both image filtering and pattern matching, in which case, several applications can be made to determine where a pattern image best fits within another.

Material and Methods

In this study, the correlation analysis technique was developed by means of the correlation theorem in the Fourier domain. In the developed algorithm, the correlation operation, using the standard symbol o, was obtained by using the inverse Fourier transform (F^{-1}) of the product of an input image, having patterns of orange to be recognized, and the standard image with known patterns. Thus, by using the notation figXX(k,l) to represent an input image in the spatial domain, with Cartesian coordinates (k,l) and the notation figHH(k,l) to represent an image with a known pattern, it is possible to write the following equation:

figXX(k,l) o figHH(k,l) = F^{-1} {FigZZ*(h,i).FigRR(h,i)} (3)

where FigZZ*(h,i) is the conjugate of the Fourier transform of the input image and FigRR(h,i) is the Fourier transform of the image with a known pattern in the frequency domain. The (h,i) coordinates represent the frequency domain coordinates. The Fourier transform was chosen to decrease processing time. In addition, to represent the quantified values of the images, a 256-gray level scale was used.

To generate standard orange for calibration of the method, several spheres with known diameter, as a complete calibration standard, was derived for use in correlation analysis, and recognition. Moreover, in order to avoid dependency of the digitized image scale on the distance between the video camera and the oranges, a visual calibration pattern was included. This visual calibration pattern consists of a known sphere (10cm in diameter) that allows determination of (cm/pixel) ratio after a digitizing process.

To digitize the images, a conventional video camera (model Sony TR50BR) and a video capture board were used. It is possible to use any image-capturing system for image digitalization.

Figure 1 shows the algorithm for analysis outlined in block diagram form. The notation used in the block diagram, which is presented in figure 1, is as follows:

figXX(k,l) : image to be analyzed;
figHH(k,l) : image of a pattern to be recognized, in figXX(k,l);

FigRef(k,l) : image of the reference pattern, i.e., a pattern having an uniform circular shape with a known radius that allows determination of the (cm/pixels) ratio in a digitized image;
figCor(k,l) : image resulting from correlating an image of a standard sphere of known diameter (or radius) with the image under analysis;
figAX(k,l) : auxiliary image used in an intermediate process of the recognition procedure;
Radius : an integer variable, which defines the standard radius used during a pattern recognition procedure;
RealRadius : an integer variable, representing true radius value of the biggest orange in the image under analysis;
K is the (mm/pixels) ratio, which allows the conversion of the radii, measured in number of pixels, to centimeters.

The algorithm assumes the use of a table for obtaining correct searching conditions for the next orange of known radius, as well as for making corrections in the digitizing process and assuming a sphere geometry. This task is repeated recursively until the last raindrop with the smallest radius is found and identified.

Table 1 shows an example of a calibration table used with the algorithm where radii values are given in number of pixels, calibrated in diameter by linear measurements.

The radius corresponding to the highest value obtained during the correlation operation, whose result appears in figCor(k,l), can be located in Table 1. For instance, if the greatest correlation value in figCor(k,l) corresponded to a gray level 150 and the integer variable Radius is equal to 35 pixels, then the integer variable RealRadius would be equal to 15 pixels. Following this operation, the frequency of occurrence of the largest gray level intensity in figCor(k,l) is counted and stored.

After that operation the drops most commonly correlated with the drop pattern being recognized are erased from figXX(k,l). However, if the process does not exactly match a result, it is repeated until a result is found.

This procedure is also used to improve the calibration method when using digitized images, whose patterns lack perfect circular shapes. Furthermore, to obtain count numbers of correlated standards from an input image, the procedure employs a mask allowing neighboring pixels to be counted only once.

To implement the fast Fourier transform, (FFT), the radix-2 (Preuss, 1982) with optimizations was used. The algorithm was implemented in C++ language on a PC-Compatible© computer, in a Windows© environment.

Results and Discussion

To demonstrate use of this technique, a set of images, as that presented in Figure 2, having several oranges patterns with different radii were tested. For a 256x256 image, the correlation, FFT calculation, and raindrop identification used a CPU operating at 240 MHz for 5 seconds. The input image had 256X256 pixels with 256 levels of intensity.

After the first identification, the process is repeated, using a second standard image, giving a second result, and so on until identification of the raindrop with the smallest radius. Figure 2 also shows the recognized oranges from the whole-analyzed images obtained from an orange living tree by using a histogram for data interpretation.

Orange images were successfully measured and automatically recognized. Based on the diameter distribution and the factor of conversions into diameters based on values obtained by the calibration process, orange size ranging from 2 cm to 10 cm were recognized.

Accuracy is limited primarily by how accurately calibration standards and the diameter of the circular pattern are established.

Some problems with orange's measurement may occur when either the shaking of the living trees by wind or by shifts of the video camera by as little as 1cm. In this case, the percentage error can vary from 0 to 2% approximately. Increasing image size reduces variation in readings, but decreases orange measurement accuracy. By choosing suitable values for the table required by the method, a range of oranges radii can be identified. It is possible to automatically identify oranges as small as 1 cm in diame

Conclusions

This paper presents an algorithm for automatic oranges in living tree identification based on correlation analysis in the frequency domain. Results show the suitability of the developed algorithm in terms of performance, processing time, and reliability, i.e., its usefulness in studying effects in orange's crop production and quality control by orange size and distribution.

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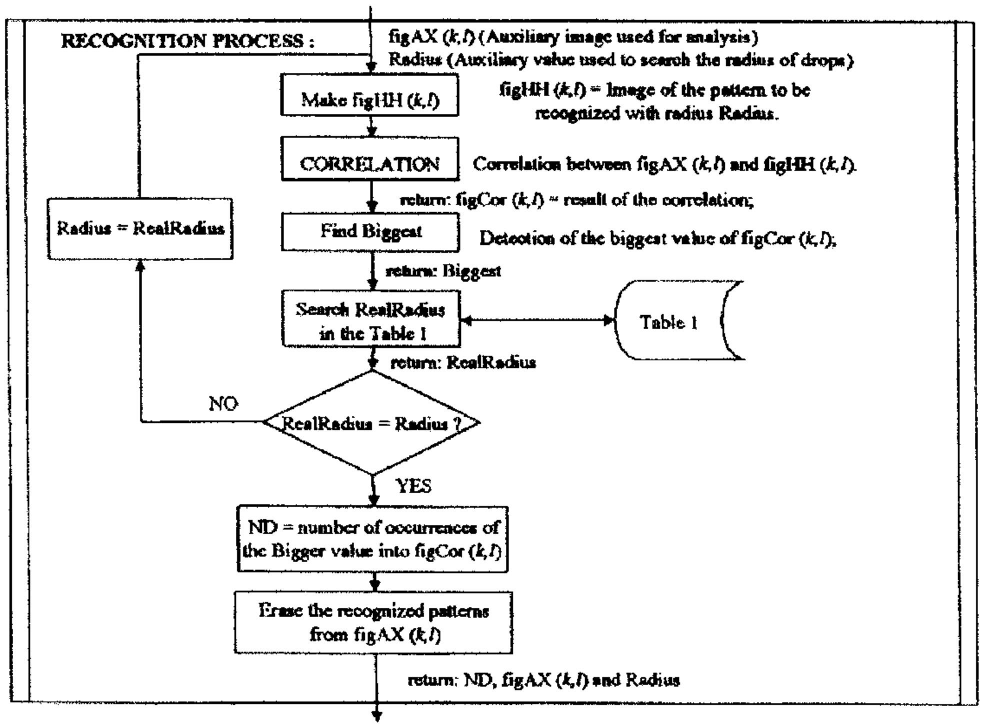
Tables

Table 1 - Example of a calibration table used by the algorithm. The radii values are given in terms of number of pixels.

Largest Autocorrelation Value (gray level intensity)	**Radius (number of pixels)**	**RealRadius (number of pixels)**
225	35	35
150	35	15
140	35	8
120	10	7
42	10	5
20	5	5



(b)

Figure 1 – Algorithm for orange classification outlined in block diagram showing the procedure for recognition process.

Figure 2 – A partial view of an input image and resulting histogram for a whole analysis of a living orange tree. For this practical experiment oranges with diameters of about 7 cm were the most frequent.