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Fruit shape detection by level set*

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Abstract: A novel approach for fruit shape detection in RGB space was proposed, which was based on fast level set and Chan-Vese model named as Modified Chan-Vese model (MCV). This new algorithm is fast and suitable for fruit sorting because it does not need re-initializing. MCV has three advantages compared to the traditional methods. First, it provides a unified framework for detecting fruit shape boundary, and does not need any preprocessing even though the raw image is noisy or blurred. Second, if the fruit has different colors at the edges, it can detect perfect boundary. Third, it processed directly in color space without any transformations that may lose much information. The proposed method has been applied to fruit shape detection with promising result.

Key words: Machine vision, Shape detection, Level set, Fruit sorting
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INTRODUCTION

Applications of machine vision in automated inspection and sorting of fruits have been widely studied by scientists and engineers, and the promise of this technology for improving grading efficiency was proved (Chen *et al*., 2002; Gui *et al*., 2004; Cheng and Ying, 2004). Among these processes, edge detection, segmentation and shape recovery are difficult problems (Zhang *et al*., 2005). Consider a fruit image, in which the goal is to isolate a fruit from a background image. We can imagine that the fruit corresponds to a region whose pixels are of different grayness intensities or different colors. The goal is to locate this shape within the image, and then not only perform fruit shape analysis and perhaps classification but also detect the fruit size accurately.

In many literature, this problem in fruit sorting has not been paid much attention to by scientists and engineers. The most straightforward approach was to set up a good environment whose background is obviously different from fruit, and then use some sort of threshold method (or based on gradient), which simply decides that the boundary of the desired shape corresponds to pixels whose values lie between the values on the inside and outside. For regions with very sharply delimited contrasts between the interior and the exterior, this works well. In some complicated instances, e.g., the raw image contains noise, or the image is blurred by the fruit motion, preprocessing steps are usually adopted before using the threshold method (Li *et al*., 2002; Shatadal and Tan, 2003). In many cases, however, this method is not unified and does not work well.

Active contours have been widely used recently to detect objects in a given image I_0, using techniques of curve evolution. The basic idea is, starting with an initial curve C, to deform the curve to the boundary of the object under some constraints from the image I_0. In curve evolution, the level set method has been extensively used, which was first introduced by Osher and Sethian (1988) for capturing moving fronts, because it allows for automatic topology changes, cusps and corners. Moreover, the computations of level set were processed on a fixed rectangular grid.

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Most of the classical level set approaches used the edge-function to stop the curve on the edges where the edge-function vanishes (Malladi *et al*., 1995; Caselles *et al*., 1997; Liu and Hwang, 2003). A typical example of edge-function used is given by

$$g(|\nabla I_0|)=\frac{1}{1+|\nabla(G_\sigma I_0)|^2}, \tag{1}$$

where g is a positive and decreasing function, such that $\lim_{t\to\infty}g(t)=0$, ∇ is a gradient operator. The image I_0 is first convolved with the Gaussian $G_\sigma(x,y)=\sigma^{-1/2}\cdot\exp[-(x^2+y^2)/(4\sigma)]$. That is, these models use the gradient of a smoother version of the image to detect the object shape boundary. But, if the image is noisy, the smoothing in the edge-function has to be strong, thus blurring shape boundary, or a preprocessing has to be implemented to remove the noise.

In contrast, Chan *et al*. proposed a new model in (Chan *et al*., 2000; Chan and Vese, 2001), which did not use the stopping edge-function g to find the boundary. Instead, the stopping term is based on Mumford-Shah segmentation techniques. This model has some advantages: (1) it partitions the image into two regions, one formed by the set of detected objects, while the other gives the background; (2) there is no need for a priori noise removal; etc. But in this model, a traditional level set was adopted, so re-initialization was used to keep the evolving level set function close to an assigned distance function. From the practical viewpoint, the re-initialization process can be quite complicated, expensive, time-consuming and have subtle side effects, obviously not suitable for fruit sorting. Luckily many fast level sets without re-initialization procedure were proposed (Peng *et al*., 1999; Gomes and Faugeras, 2000; Li *et al*., 2005), which could speed up the curve evolution.

We proposed here a novel approach for fruit shape detection in RGB space based on fast level set and Chan-Vese model. We called it Modified Chan-Vese model (MCV). This new algorithm is fast because it does not need re-initialization procedure, so it is suitable for fruit sorting. MCV has three advantages compared to the traditional methods. First it provides a unified framework for fruit shape boundary detection, which does not need any preprocessing even though the raw image is noisy or blurred. Second it can detect perfect boundary when the fruit has different colors at edges—in contrast, traditional methods fail in this case. Third it processes directly in color space without any transformations, thus avoids the information loss.

This paper is organized as follows. In Section 2 we address the background of our method and propose the MCV. Section 3 presents and discusses experimental results. Some conclusions are derived in Section 4.

MODIFIED CHAN-VESE MODEL

Let C be the evolving curve. We denote c_1 and c_2 as two constants representing the average intensity of I_0 inside and outside the curve C respectively, with this model being the minimization of the energy-based segmentations. The basic idea can be explained with a simple case. Assume that the image is binary and formed by two regions of background and object which have different constant intensities I^b and I^o. When objects are detected, the region inside the object boundary C is $I_0\approx I^o$, and outside the object boundary C is $I_0\approx I^b$. So we can define a fitting energy formed by two terms:

$$F_1(C)+F_2(C)=\int_{inside(C)}|I_0-c_1|^2\,\mathrm{d}x\mathrm{d}y+\int_{outside(C)}|I_0-c_2|^2\mathrm{d}x\mathrm{d}y, \tag{2}$$

where C is any other variable curve. When C is the object boundary, the value of $F_1(C)+F_2(C)$ is minimal.

In the level set methods, this evolving curve C is represented by the zero level set of a Lipschitz continuous function $\phi{:}\Omega\to\mathbb{R}$. So $C=\{(x,y)\in\Omega|\phi(x,y)=0\}$ and we choose ϕ to be positive inside C and negative outside C. Therefore, we introduce a modified energy model in RGB space by level set formulation:

$$E(\phi)=\int_{\Omega}\frac{1}{2}|\nabla\phi-1|^2\,\mathrm{d}x\mathrm{d}y+\mu\cdot length\{\phi=0\}+\int_{\phi\ge0}\frac{1}{3}\sum_{i=1}^{3}\lambda_1^i\cdot(I_0^i-c_1^i)\mathrm{d}x\mathrm{d}y+\int_{\phi<0}\frac{1}{3}\sum_{i=1}^{3}\lambda_2^i\cdot(I_0^i-c_2^i)\mathrm{d}x\mathrm{d}y, \tag{3}$$

where $\lambda_1=\{\lambda_1^1,\lambda_1^2,\lambda_1^3\}$, $\lambda_2=\{\lambda_2^1,\lambda_2^2,\lambda_2^3\}$, with the superscripts 1, 2, 3 representing the R, G and B components, respectively; μ are positive.

In Eq.(3), the first term is an internal energy, which penalizes the deviation of the level set function from an assigned distance function and the level set function was naturally and automatically kept as an approximate signed distance function during the evolution. Therefore, the re-initialization procedure is completely eliminated, which speeds up the curve evolution. The second term is a regularizing term that computes the length of the curve C and smoothes the curve. The third and fourth terms are the fitting energy computed from RGB space.

Instead of Heaviside function H, we use the C^∞-regularized versions defined by

$$H_\varepsilon(x)=\frac{1}{2}\left[1+\frac{2}{\pi}\arctan(x/\varepsilon)\right],$$

ε is a prior parameter, the value of ε is set to 1 in this research. And the derivative of H is denoted by $\delta_\varepsilon(x)$:

$$\delta_\varepsilon(x)=\frac{\mathrm{d}}{\mathrm{d}x}H_\varepsilon(x)=\frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2+x^2}.$$

Now some terms in Eq.(3) can be expressed as follows:

$$\begin{cases} length\{\phi=0\}=\int_\Omega|\nabla H(\phi)|\mathrm{d}x\mathrm{d}y=\int_\Omega\delta(\phi)|\nabla\phi|\mathrm{d}x\mathrm{d}y, \\ \int_{\phi\ge0}\frac{1}{3}\sum_{i=1}^{3}\lambda_1^i\cdot(I_0^i-c_1^i)\mathrm{d}x\mathrm{d}y=\int_\Omega\frac{1}{3}\sum_{i=1}^{3}\lambda_1^i\cdot(I_0^i-c_1^i)H(\phi)\mathrm{d}x\mathrm{d}y, \\ \int_{\phi<0}\frac{1}{3}\sum_{i=1}^{3}\lambda_2^i\cdot(I_0^i-c_2^i)\mathrm{d}x\mathrm{d}y=\int_\Omega\frac{1}{3}\sum_{i=1}^{3}\lambda_2^i\cdot(I_0^i-c_2^i)[1-H(\phi)]\mathrm{d}x\mathrm{d}y, \end{cases} \tag{4}$$

where $c_1^i=\int_\Omega I_0^iH(\phi(x,y))\mathrm{d}x\mathrm{d}y\Big/\int_\Omega H(\phi(x,y))\mathrm{d}x\mathrm{d}y$, $c_2^i=\int_\Omega I_0^i[1-H(\phi(x,y))]\mathrm{d}x\mathrm{d}y\Big/\int_\Omega[1-H(\phi(x,y))]\mathrm{d}x\mathrm{d}y$ represent the ith average component of I_0 in $\{\phi\ge0\}$, $\{\phi<0\}$, respectively.

Keeping $c_1=\{c_1^1,c_1^2,c_1^3\}$ and $c_2=\{c_2^1,c_2^2,c_2^3\}$ fixed, and formally minimizing the energy $E(\phi)$ with respect to ϕ by calculus of variations, we obtain the Euler-Lagrange equation for ϕ, with the evolution formula being

$$\frac{\partial\phi}{\partial t}=\mathrm{div}\left[\left(1-\frac{1}{|\nabla\phi|}\right)\nabla\phi\right]+\delta_\varepsilon(\phi)\left[\mu\cdot\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)-\frac{1}{3}\sum_{i=1}^{3}\lambda_1^i\cdot(I_0^i-c_1^i)^2+\frac{1}{3}\sum_{i=1}^{3}\lambda_2^i\cdot(I_0^i-c_2^i)^2\right] \tag{5}$$

in Ω, and with the boundary condition

$$\frac{\delta_\varepsilon(\phi)}{|\nabla\phi|}\cdot\frac{\partial\phi}{\partial\boldsymbol{n}}=0$$

on $\partial\Omega$, where $\boldsymbol{n}$ denotes the unit normal at the boundary of Ω.

To solve this partial difference equation (PDE), a finite difference scheme is used. All the spatial partial derivatives $\partial\phi/\partial x$ and $\partial\phi/\partial y$ are approximated by the central difference, and the temporal derivative $\partial\phi/\partial t$ is approximated by the forward difference, with the initial condition set being as follows:

$$\phi(x,t=0)=\pm d, \tag{6}$$

d is the distance from x to boundary $\partial\Omega$. If x is inside Ω, $d>0$; if x is outside Ω, $d<0$.

Therefore, the solution of PDE Eq.(5) is the shape boundary that must be detected.

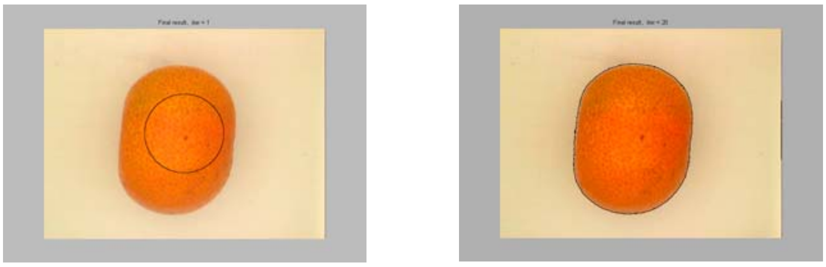
RESULTS AND DISCUSSION

The proposed method has been applied to a variety of fruit images in different modalities, such as containing noise, motion blur, bad illumination condition and different colors on the edges. All the experimental results are shown, as well as the results compared to traditional shape detection (see Figs.1~4). Note that, in our experiments, all the fruit image sizes are 480×640, which is larger than the image in many other literature.

In the process of solving PDE Eq.(5), the time step can be chosen significantly larger than those in traditional level set methods. Here, a variable time step was used as

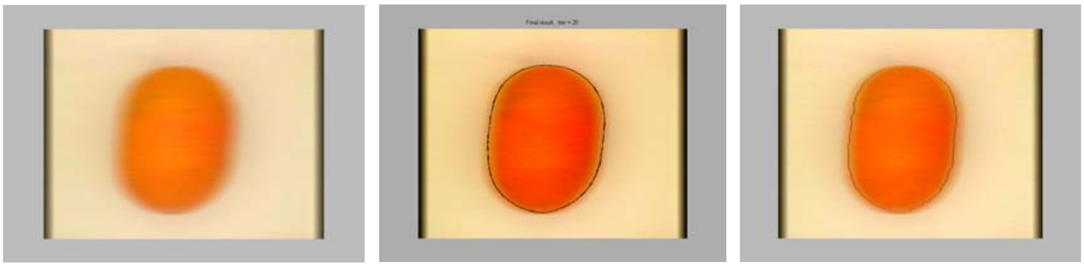
$$\Delta t=\begin{cases}30, & iter<20, \\ 0.1+30/iter, & iter\ge20,\end{cases} \tag{7}$$

where $iter$ is the number of iterations. By this manner the solution can rapidly converge. For example, in



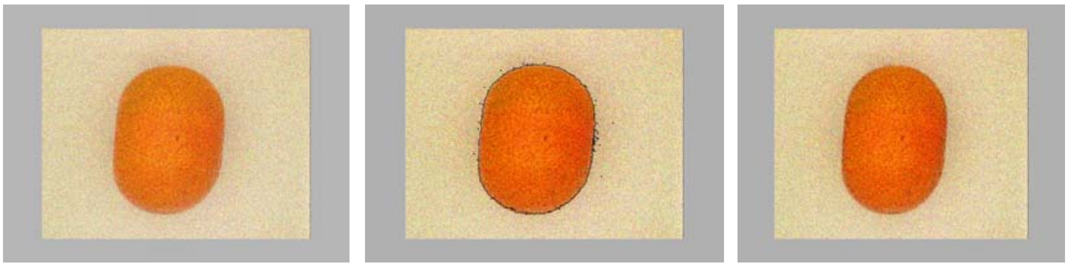
(a) (b)

Fig.1 Using MCV to detect fruit shape boundary. The dark thicker curve is the zero level set
(a) The initial zero level set; (b) The zero level set after 20 iterations



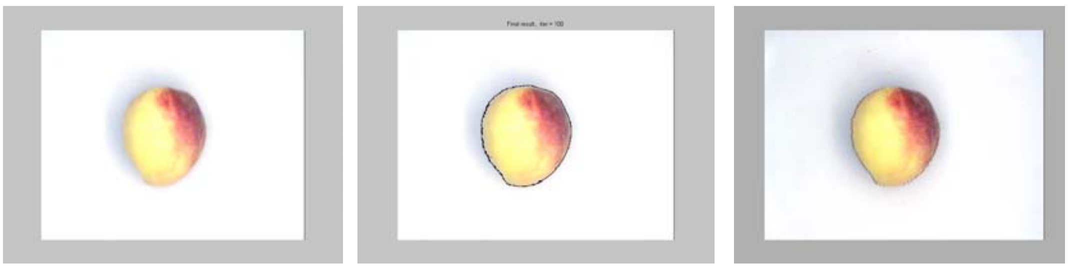
(a) (b) (c)

Fig.2 Comparison between the MCV and traditional threshold method in motion blurred image
(a) Original fruit image; (b) Result detected by MCV; (c) Result detected by the traditional method



(a) (b) (c)

Fig.3 Comparison between the MCV and traditional threshold method in noisy image
(a) Original fruit image; (b) Result detected by MCV; (c) Result detected by the traditional method



(a) (b) (c)

Fig.4 Comparison between the MCV and traditional threshold method in fruit image containing different colors on the boundary. (a) Original fruit image; (b) Result detected by MCV; (c) Result detected by the traditional method

Fig.1, the curve evolution only takes 20 iterations, while the curve converges to the fruit shape boundary precisely.

Fig.2 shows the result of a motion blurred fruit image detected by MCV and by traditional threshold method. Fig.2a is the original motion blurred image; Fig.2b is the detection result by MCV. It is obvious that our method is superior to the traditional methods. Fig.2c is the result of traditional method, where the detected boundary at the top and bottom of the fruit has disappeared, and the edge is very rough, not so smooth as that in Fig.2b. Especially, it is not necessary to deblur the image when using MCV.

Fig.3 shows the result of a noisy fruit image detected by MCV, and by traditional threshold method. Even without any prior noise removal, the detected result is better than that of traditional method. In Fig.3c, the detected edge is dim while it is clear in Fig.3b.

Fig.4 shows the result of a fruit image containing different colors on its edge detected by MCV and by traditional threshold method. It is obvious that the traditional threshold method fails to detect the shape boundary. In Fig.4c, the dark red region edge is false in that it severely deviated from the true boundary, but the MCV can detect completely the fruit shape boundary, which can be seen in Fig.4b.

CONCLUSION

This paper proposes an MCV method for fruit shape detection in RGB space based on fast level set and Chan-Vese model, which is faster than traditional curve evolution method and suitable for real-time fruit sorting. Compared to existing work on machine vision based fruit shape detection, MCV has an important advantage in that it provides a unified framework for detecting fruit shape boundary, and does not need any preprocessing even though the raw image is noisy or blurred. Our proposed approach can detect completely the boundary when the fruit has different colors at edges that the traditional methods fail to deal with. In our research, the quality of the result is related to μ, which controls the weights of regularizing term, and λ, which controls the weights of R, G, B in Eq.(3). The parameter selection needs further research in the future.

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