Level Set Methods and Auto-Relation for Detection of Objects

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Abstract

This paper presents a framework for detecting objects in images. The motive of this research can be found in onsite requirements. We focus on the practical need on distinguishing salt called purity from impurities, which are sand, soil, and other substance in the heaped salt on a conveyer belt. In this work, basing on image energy, we formulate the auto-relation function on image energy to construct a piloting set which includes possible elements to classify objects and the impurity object in order to lead the front propagation. We use level set method to detect the topologic changes for evolution curves and to catch the objects/impurity.

1. Introduction

Image vision technology has matured substantially in the last decade to be successfully applied to a variety of industrial tasks. Three methods, optical device-based, algorithm-based technology and special image deice-based are the main in industrial applications. In the field of factory automation, successful applications of image technology are roughly divided into assembling and inspection. For example to decide a 2D positions as analogical robot sensor or 3D positions when measuring automobile's body, surface inspections, inspecting LSI pattern, and mask and printing board etc [1][2][3][4]. With the development of cheaper color cameras, more people have been more and more interested in digital image application or algorithm technologies [5][6][9]. There are many successful industrial applications in the past years, but the past works mostly depend on the constraints of possible pattern matching. Image technologies for applications, especially in industry, are strong case-dependence. Because we want to solve our problem by image technology instead of paying more cost to some special material inspection sensor device, it is our intelligent selection to develop the image algorithm.

The aim of this paper is to introduce level set methods based on the auto-relation techniques and provide a basic framework for applications. The key idea of Level set methods in image plane is implicit curve evolution in the planer image. We notice the fact that when purity and impurity are mixed in an images, their different textures and gray values are certainly bringing about gradients changes. These changes show us a lot of clues for image classification and recognition. We induce the propagating interfaces by those high image energy parts to label the object from their background. The evolving surface of impurity is presented as the zero level function. To reduce the computation cost required by level set formulation scheme, a new approach exploited by image auto-relation is proposed. Making a piloting set is a process calculating image energy. It supports level set function a limited domain and speed up evolving front effectively.

The present approach is described as followings. The image pre-process is at the first. This will take us the advantages that the changes we are interested in will not be suppressed by some smoothing, which tends to suppress the effects of noise. We introduce the important auto-correlation method to pilot the interest point in an image. Such a fact has been noticed that the border between and soil certainly cause an obviously image energy changes i.e. gray value changes. We will illustrate either how the auto-correlation algorithm catches these changes or how its results give us a coarse pilot on the objectives we are interested in. We want to classify the coarse positions by some local windows, to inspect the detail changes and compare the results with our preset models, which are the features of their Gaussian distributions. Based on the similarities between the results and the models, we judge whether a class is accepted as an object soil or not [14] and these are our following works.

In this paper, we give the auto-relation model in next section. The pre-process and classification are also introduced in the section 2. Section 3 describes the principle of curve evolution based on level set methods. Some experimental results and discussions are at the last.

2. Auto-relation Model

2.1 Image pre-precess

In general, any change of significance to us has effects over a pool of pixels. For many kinds of noise model, large image derivatives due to noise are an essentially local event. This means that smoothing a differentiated image tends to support the changes we are interested in and to suppress the effects of noise. In a pre-process, the smoothing filter can be chosen by taking a model of an edge and using some set of

Fig. 1: The soil grains image for test.

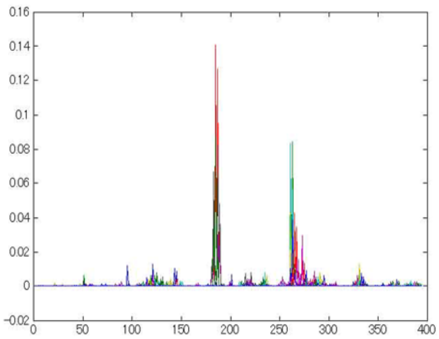

Fig. 2: The horizontal is the horizontal coordinate in Fig.1, the vertical is $\mathcal{M}(X)$ in Eq. (6).

criteria to choose a filter that gives the best response to that model. It is difficult to pose this problem as a two-dimensional problem because edges in 2D can be curved. Conventionally, the smoothing filter is chosen by formulating a one-dimensional problem and then using a rotationally symmetric version of the filter in 2D. In our case, we select a nonlinear rank-value median filter for image pre-process. We take all the gray values of the pixels which lie within the filter mask and sort them by ascending gray value. The rank-value filter only differs by the position in the list from which the gray value is picked out and written back to the center pixel, well known as median filter. Let $\mathcal{M}_1$=$\{M_1(n,n)\}$ (n is odd) be those gray values around a pixel. To an array $\mathcal{M}_2 = \{M_2(k)\}$ ($k = 1, 2, \ldots, S = n \times n$), this filter use the value $M_2(S/2)$ as it responses. This made us easily adjust the smoothing scales to different size of objects.

2.2 Auto-relation on image energy

Let $I(X)$(also denoted as I) be the image function in an image frame. Given a shift $(\Delta x, \Delta y)$ and X=(x, y), X$\in \mathcal{R}^2$. The auto-correlation function is defined as:

$$f(x,y) = \sum_w \big(I(x_k, y_k) - I(x_k + \Delta x, y_k + \Delta y)\big)^2 \tag{1}$$

where (x_k, y_k) are the points in the working local widow w . Based on the Taylor expansion:

$$\begin{aligned} &I(x_k + \Delta x, y_k + \Delta y) \\ &\quad = I(x_k, y_k) + I_x(x_k, y_k)\Delta x + I_y(x_k, y_k)\Delta y +, \cdots \\ &\quad \approx I(x_k, y_k) + \big(I_x(x_k, y_k) \;\; I_y(x_k, y_k)\big)\begin{pmatrix}\Delta x \\ \Delta y\end{pmatrix} \end{aligned} \tag{2}$$

where I_x=$\partial I(X)/\partial x$, I_y=$\partial I(X)/\partial y$. Substituting the above approximation (2) into Eq.(1), we obtain:

$$\begin{aligned} &f(x,y) \\ &= \sum_w \left(\big(I_x(x_k, y_k) \;\; I_y(x_k, y_k)\big)\begin{pmatrix}\Delta x \\ \Delta y\end{pmatrix}\right)^2 \qquad (3) \\ &= \sum_w (\Delta x \;\; \Delta y)\begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix}\begin{pmatrix}\Delta x \\ \Delta y\end{pmatrix} \\ &= (\Delta x \;\; \Delta y)\left[\sum_w \begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix}\right]\begin{pmatrix}\Delta x \\ \Delta y\end{pmatrix} \\ &= (\Delta x \;\; \Delta y)\big[\Gamma(x,y)\big]\begin{pmatrix}\Delta x \\ \Delta y\end{pmatrix} \qquad (4) \end{aligned}$$

To $I(X)$=$G * \mathcal{I}$, $*$ is the convolution operation, we change $\Gamma(x,y)$ as $\bigtriangledown I(\bigtriangledown I)^T$, build up a transform relation $\mathcal{H}(X)$ in a local window about X.

$$\begin{aligned} \mathcal{H}(X) &= \mathcal{T}(X) * \sum \left\{\bigtriangledown I(\bigtriangledown I)^T\right\} \\ &= \mathcal{T}(X) * \sum \begin{Bmatrix} (G_x * \mathcal{I})^2 & (G_x * \mathcal{I})(G_y * \mathcal{I}) \\ (G_x * \mathcal{I})(G_y * \mathcal{I}) & (G_y * \mathcal{I})^2 \end{Bmatrix} \end{aligned} \tag{5}$$

where G is a Gaussian with standard deviation one, G_x=$\partial G/\partial x$, G_y=$\partial G/\partial y$. $\mathcal{T}(X)$ is a weight mask to weight the derivatives over the window. In Eq. (5), there relations $\partial I/\partial x$=$\partial/\partial x * I$, $\partial/\partial x*(G*\mathcal{I})$=$(\partial/\partial x* G)*\mathcal{I}$=$\partial G/\partial x*\mathcal{I}$. This matrix captures the local structure. The eigenvectors of this matrix are the principal curvatures of the auto-correlation function. We consider a cost function M(X) :

$$\mathcal{M}(X) \;\; = \;\; \mathcal{E}[H(X)] + \mathcal{C}[H(X)] \tag{6}$$

where $\mathcal{E}[*]$, $\mathcal{C}[*]$ are the determinant and trace of $\mathcal{H}(\mathcal{X})$ respectively. For example, $\mathcal{M}(X)$ is shown in Fig. 2.

2.3 Image classification

$\mathcal{M}(X)$ in Eq. (6) gives the distributions of image energy clearly. We classify those points by $M(X)$ further. Assume the i_{th} point P_i(X) be presented by a complex OP_i, the j_{th} point P_j(X) by OP_j, to a constant ϵ_1, if it is true that

$$|OP_i - OP_j| < \epsilon_1 \tag{7}$$

$P_i(\mathbf{X}(\mathrm{i}))$ and $P_j(\mathbf{X}(\mathrm{j}))$ are put into same set C^k, $C^k \subset C$. C is defined as the classification set.

$$C = \bigcup_{k=1}^{s} C^k \tag{8}$$

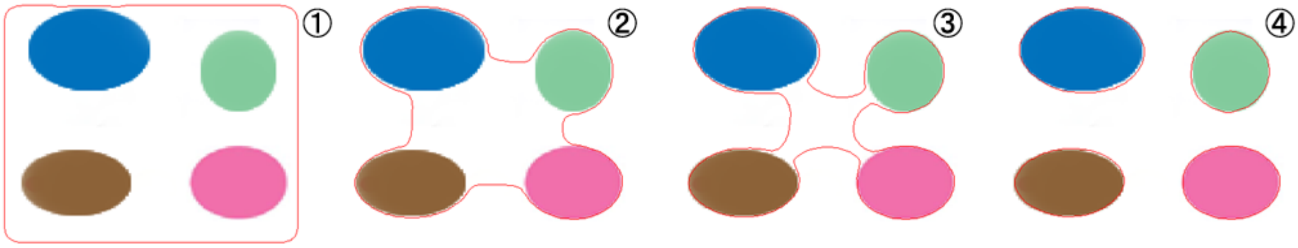

Fig. 3: 1: the initial curve; 2 and 3: the evaluating curve; 4: The entire objects are caught.

where s is a preset constant to decide the subsets in C. The elements in C^k are coarse results classified. Assume the center of gravity of the elements in C^k be $P_c(X)$, $M(X)$ will be recalculated by Eq. (5) and Eq. (6) with a smaller preset constant ϵ_t ($\epsilon_t < \epsilon_{t-1}$, $t \leq constant$) around $P_c(X)$ in a smaller local window several times. If the results under ϵ_t will be treated as the part of the soil, the calculations finish. The reason we did this is that it is hardly to get complete pixels about the object, for the reasons that the surface of any object reflects light in all direction, smaller ϵ_t can use more fine resolutions to analyze objectives.

3. Skeleton of Level Set Methods

Level set methods add dynamics to implicit surfaces. The key idea that started the level set fanfare was the Hamilton-Jacobi approach to numerical solutions of a time-dependent equation for a moving implicit surface. Given a moving closed hypersurface $\mathcal{G}$(t), we wish to produce an Eulerian formulation for the motion of the hypersurface propagating along its normal direction with speed $\mathcal{F}$, where $\mathcal{F}$ can be a function of various arguments, including the curvature, normal direction, etc. This propagating interface is embed as the zero level set of a higher dimensional function $\phi(\mathbf{x}$, t) (also denoted as ϕ in this paper). Let $\phi(\mathbf{x}$, t=0), where $\mathbf{x}$ is a n-dimension space, be defined by

$$\phi(\mathbf{x}, t = 0) = D \tag{9}$$

where D is the signed distance from $\mathbf{x}$ to $\mathcal{G}$(t=0), and plus/minus sign is chosen if the point $\mathbf{x}$ is outside/inside the initial hypersurface $\mathcal{G}$(t=0). Thus, we have an initial function $\phi(\mathbf{x}$, t=0) with the property that

$$\mathcal{G}(t = 0) = (x|\phi(\mathbf{x}, t = 0) = 0) \tag{10}$$

Our goal is to produce an equation for the evolving function $\phi(\mathbf{x}, t)$ which contains the embedded motion of $\mathcal{G}$ as the level set $\phi = 0$. Let $\mathbf{x}$ be the path of a point on the propagating front. That is, $\mathbf{x}$(t=0) is a point on the initial front $\mathcal{G}$(t=0), and d$\mathbf{x}$/dt=$\mathcal{F}$ ($\mathbf{x}$) with the vector d$\mathbf{x}$/dt normal to the front at $\mathbf{x}$. Since the evolving function $\phi(\mathbf{x}$, t) is always zero on the propagating hypersurface, we must have the constraint

$$\phi(\mathbf{x}, t) = 0 \tag{11}$$

By the chain rule,

$$\phi_t + \bigtriangledown(\mathbf{x}, t)\mathbf{x}_t = 0 \tag{12}$$

We then have the evolution equation for $\phi(\mathbf{x}$, t)

$$\phi_t + \mathcal{F}| \bigtriangledown \phi| = 0 \tag{13}$$

with a given value of $\phi(\mathbf{x}$, t=0). This is referred as Hamilton Jacobi "type" equation because, for certain forms of the speed function $\mathcal{F}$, we obtain standard Hamilton Jacobi equation. Because $\phi(\mathbf{x}$, t) remains a function as it evolves, we may use a discrete grid in the domain of $\mathbf{x}$ and substitute finite difference approximations for the spatial and temporal derivatives. We use a uniform mesh of spacing h, with grid nodes ij, and employing the standard notation that ϕ_{ij}^n is the approximation to the solution $\phi(ih, jh, n\delta t)$, where δt is the time step, we may write

$$\frac{\phi_{ij}^{n+1} - \phi_{ij}^n}{\delta t} + (\mathcal{F})(\bigtriangledown_{ij}\phi_{ij}^n) = 0 \tag{14}$$

Here, we have used forward differences in time, and let ϕ_{ij}^n be some appropriate finite differences in time, and let $\bigtriangledown_{ij}\phi_{ij}^n$ be some appropriate finite difference operator for the spatial derivative. To a given speed function $\mathcal{F}$, we update the front by the modified version of an Engquist-Osher scheme [11]. The front propagation is illustrated in Fig. 3.

4. Experiments and Discussions

We compute a practical images, which was taken onsite, by the proposed algorithm. In Fig. 4, using the original images on the left, we indicated the processes. Based on the result of Eq. (5) and Eq. (6), the positions of image energy are detected. We have gotten two positions or two significant M(X). Locating the two positions, we give the closed initial front curve for evolution. This decrease the computation cost obviously. The results in Fig. 4 also show us that M(X) bring us less image noise in the closed front curve and, this is very helpful for the recognition using the finished evolution results. Fig. 4-4 show that the contour of the objects are caught perfectly. This is one of successful applications by means of the advantage of the level set based active contour technique.

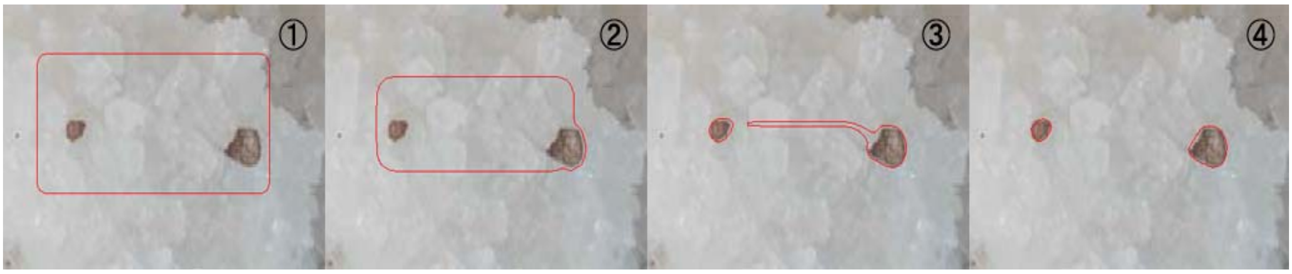

Fig. 4: 1: starting contour based on the image auto-relation; 2 and 3: the evaluating curve; 4: the objects are caught.

5. Conclusions

We proposed in this work a piloted level set methods. This approach uses traditional rank-value median filter as pre-processor, creates an image energy auto-relation function to lead an initial front propagation in order to perform classification and calculate features about their textures and so on for the purpose of recognition. When different kinds of objects/grains appear on the same image, most of them will bring about image energy changes presented by the form of gray gradients. The auto-relation function is excellent way to describe these features, especially in the case of objectives have the global dominant positions in an image, just like the case of the soil-in-salt. The finished front propagation can give more information for recognition. We can adjust the cost constants from coarse to fine in a widow around piloted positions dynamically. Then those features can be compared with their models made in advance. Not limited by this application, the developed technique will be also available when the environment is changed, with some modification. Though this approach faces the problem of computation cost, it still is a basic frame work.

In this algorithm, if the objects don't have an obvious energy features in a global detection, it will cause s in Eq.(8) increased, and hard to be classified. We suggest s should be maximum three, number constrain companies it, or it is an intelligent way to consider this problem from other bases.

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