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Using Entropy Based Meanshift Filter and Modified Watershed Transform for Grain Segmentation

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Abstract: Life science research aims to continuously improve the quality and standard of human life. One of the major challenges in this area is to maintain food safety and security. A number of image processing techniques have been used to investigate the quality of food products in the last decade. In this paper, we propose a new algorithm to effectively segment connected grains so that each of them can be inspected in a later processing stage. One family of the existing segmentation methods is based on the idea of watersheding, which has shown promising results in practice. However, due to the over-segmentation issue, this technique has experienced poor performance in various circumstances, such as inhomogeneous background and connected targets. To solve this problem, we present a combination of two classical techniques to handle this issue. In the first step, a mean shift filter is used to eliminate the inhomogeneous background, where entropy is used as a converging criterion. Secondly, a color gradient algorithm is used in order to detect significant edges, and a marked watershed transform is applied to segment the cluttered objects out of the previous processing stages. The proposed framework is capable of compromising among execution time, usability, efficiency and segmentation outcomes in analyzing ring die pellets. The experimental results demonstrate that the proposed approach is effective and robust.

Keywords: Robust segmentation, cluttered grains, mean shift filter, entropy, modified marked watershed transform

1 Introduction

Inspection of grains is a very important task for ensuring food safety and security. An inspection process consists of segmentation of grains and quality evaluation of each piece of grains. Currently, segmentation of grains is manually handled and hence time consuming. In the meantime, it is very difficult to maintain the quality of segmentation across different inspectors. With the development of image processing and machine vision techniques, the nondestructive inspection of grains can be achieved at a high speed and accuracy [1-3]. However, it is also recognized that the segmentation becomes a challenge in the presence of clutters or inhomogeneous backgrounds.

Traditional low level image segmentation processing approaches, for example, thresholding [4], region growing [5], clustering [6] and evolutionary algorithms [7], require a considerable amount of human-computer interaction in order to attain satisfactory results. Making these systems hand-free is difficult because of ambiguity, uncertainty, and variability of individual objects. Furthermore, inhomogeneous background or connected target can cause over-segmentation of images.

Many segmentation techniques have been presented in the literature in order to effectively separate grains. For example, Shatadal used an erosion method for segmenting cluttered grains [8]. Shatadal used ellipse fitting to segment touching grains [9]. Van den Berg developed an algorithm to detect characteristic grains edges along the detected contours [10].

These approaches are not effective in case a large number of grains are connected [11]. Connected grains are especially prominent in severe cases [12]. In the field of connected objects segmentation, watershed transform is one of the most commonly used techniques. Images' gray distribution corresponds to geographic altitudes, and water basin corresponds to a separable region. The growing process starts from a local minimum, and each of the minimum points generates an individual region after transformation [13]. Watershed transform can be used to produce wide continuous edges and homogeneously closed regions [14]. This mechanism is consistent with human being's perception. However, watershed methods suffer from the over-segmentation problem due to the presence of a large number of local minimums. These local minimum points are due to image noise. Meanwhile, its computation is of high complexity that makes it not feasible for real-time process. To our knowledge, many solutions have been proposed in order to reduce the noise's effect on this technique:

1) Vincent proposed a fast watershed algorithm based on immersion simulation [15]
2) Bentsson proposed a robust watershed algorithm based on H-minima mark to overcome the problem of over-segmentation[16]
3) Gaoli proposed an improved marked watershed using a low-pass filter to eliminate fake local minima regions[17]

To solve these problems, we propose in this paper an improved Watershed transform combining mean shift filtering with entropy. Entropy is used as a stopping criterion to regulate the convergence of mean shift. Color gradient image is directly calculated in the RGB space to obtain higher accuracy than the methods using gray gradient calculation. After we extract markers and water basin information, over-segmentation can be greatly reduced. Experiments show that the proposed approach provides consistent and robust segmentation performance

with satisfactory efficiency; in addition, our new approach is noise immune with good edge-location capability.

The rest of the paper is organized as follows: In section 2, as a well-known algorithm, we briefly introduce watershed methods, mean shift and the entropy concept. In section 3, we describe our segmentation algorithm into two parts. Finally, in section 4, we show the experimental results. Section 5 concludes this paper.

2 Preliminaries

2.1 Watershed using geomorphologic distance

Watershed transform is considered as a segmentation approach based on regions [17, 18]. There are two major classes of watershed transforms, one was proposed by Vincent & Soille, and the other by Meyer [19]. We focus on the Meyer's algorithm, and the reader can refer to [20] for details.

We assume that y is a gray image. The gradient $S(e)$ is defined as the maximal gradient and decent to its neighborhood in a low altitude. $S(e)$ is written as:

$$S(e) = max_{v \in n(e) \cup e}(\frac{y(e) - y(v)}{d(e,v)}) \tag{1}$$

Where $n(e)$ is a numerical set of a neighbor pixel e, and $d(e,v)$ is the Euclidean distance, which is bound up with $edge(e,v)$. When $e = v$, $S(e)$ is equal to zero. The pixels whose neighborhoods are of higher gray levels than others will be assigned zero intensity. So we have a lower gradient where e is a local minimum pixel. Eventually, the loss from pixel e to the neighborhood v is described as:

$$loss(e,v) = \begin{cases} S(e) \cdot d(e,v) \ if \ y(e) > y(e) \\ S(c) \cdot d(e,v) \ if \ y(v) < y(v) \\ \frac{1}{2}(S(e) + S(v)) \cdot d(e,v) \ if \ y(e) = y(v) \end{cases} \tag{2}$$

The geomorphologic distance along $\pi = (e_0,...,e_l)$ between $e_0 = e$ and $e_n = v$ is defined as:

$$T_c^{\pi}(e,v) = \sum_{i=0}^{n-1} d(e_i,e_{i+1})loss(e_i,e_{i+1}) \tag{3}$$

Following the geomorphologic distance's definition, we define the basin of the local minimum pixels as a data set, and it has smaller geomorphologic distances than the other local minimum values. Finally, the pixels data sets that do not belong to any of the basins are set to be the watershed.

The purpose of watershed transform is to extract watershed basins from an image, and its performance relates closely to a gradient image. Classical gradient methods will obtain many regional basins due to image noise. The result of the classical gradient based watershed transform methods includes a large number of tiny local regions, which severely affects the post-processing.

2.2 Mean shift filter

The following is the concept of the classical mean shift approach [21]: Let x_j be a numerical sample of n in a d dimensional space. The basic mean shift is defined as

$$M_h(x) = \frac{1}{k} \sum_{x_i \in g_h} (x_i - x) \tag{4}$$

Where g_h is a window with center x and radius h. k is the sample set number in g_h. $(x_i - x)$ is an relative offset of center x.

Eq. (4) is a monotonic form and not effective in practical applications. The Kernel based mean shift algorithm is to minimize the following function:

$$M_h(x) = \frac{\sum_{i=1}^{n} Q(\frac{x_i - x}{h})\alpha(x_i - x)}{\sum_{i=1}^{n} Q(\frac{x_i - x}{h})\alpha(x_i)} \tag{5}$$

$\alpha(x)$ is the self-impact factor, $Q(x)$ is a kernel function.

In a color image of $n \times n$ pixels, each pixel corresponds to a 5 dimension vector R^5 (R,G,B,X,Y). Due to the independence of space and color information, the kernel function is obtained via Eq. (6)

$$Q_{g_s g_r}(x) = \frac{1}{g_s^2 g_r^3} q(\|\frac{x^s}{g_s}\|^2 \ q(\|\frac{x^r}{g_r}\|^2)) \tag{6}$$

Where x^s is the spatial position of an image pixel; x^r is the color information of the pixel; g_s is the spatial window with center x and radius s; g_r is a color window with center x and radius r.

2.3 Entropy

In the image processing, entropy is defined as:

$$F(t) = -\sum_{t=0}^{2^A - 1} q(t)log_2 q(t) \tag{7}$$

Where A is an image with $log_2(0) = 0$; $q(t)$ is a gray value with a probability. Within a homogeneous local area, the minimum value of inhomogeneity can be found using entropy. The theoretical probability of $q(t)$ is the one used in a homogeneous local area. In practice, due to image noise, the entropy value cannot equal to zero. Thus, if we try to apply entropy to a measurement of confusion, it can be used as a down stopping rule for the iteration of a mean shift algorithm.

Entropy can be used to reduce noise in each local area, and when the entropy value reaches a stable value, the entire image tends to be more homogeneous than the original image.

3 Proposed Algorithms

The classical marked watershed transformation algorithm usually consists of the following four steps:

Step1: low-pass filtering to a color image

Step2: calculation of the gray image gradient ∇I

Step3: extraction of markers in ∇I with $H - minima$ and imposing them as local region minima on the gradient image

Step4: taking watershed transform of the marked gradient image.

Based on the classical watershed transform, we generate our proposed approach.

1. Using the entropy based mean shift filter to improve the image edge identification.
2. Calculate the color image gradient ∇I_c
3. Apply $H-minima$ parameters based on basin information

Fig.1 illustrates the proposed algorithm.

In this section, we show two improved algorithms. The first one is for image filtering and the second one is for the watershed segmentation process, which is the extension of the standard filtering approach.
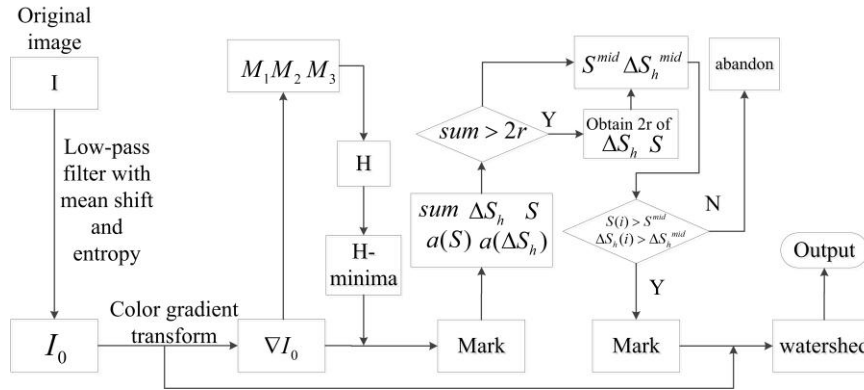

Fig.1 The process flowchart of the proposed approach

Algorithm 1:   entropy based mean shift filtering algorithm

Let x_i $i=1,...,n$ be the input image. Let O_i $i=1,...,n$ be the filtered image. Pixel $p \in x_i$, $p=(R,G,B,x,y) \in \square^5$. Let $ent.0$ be the entropy initial value, $ent.1$ be the next iteration of $ent.0$, and $ent.2$ be the next value of $ent.1$. Let $erras$ be the absolute value of the difference between the first two iterations. Let $edset$ be the thresholding as the iteration's stopping criteria. Our algorithm comprises the following steps:

1 Initialize $h=1$, $y_{h,1}=p_h$, $ent.2=1$, $erras=1$, $edset=0$.

2 While $erras > edset$, then

   2.1 Filter the image using mean shift. Store the result in $O^{[K]}$.

   2.2 Calculate entropy from the $O^{[K]}$ and store the result in $ent.1$.

   2.3 Entropy is used to calculate the absolute difference which is obtained in the previous step; $erras = |ent.1 - ent.2|$.

   2.4 Update the parameters; $ent.1 = ent.2$ and $O^{[k+1]} = O^{[k]}$.

   2.5 Continue to apply mean shift which is carried out till the image entropy converges.

3 Store at Z_i which is calculated as $Z_i=(x_i^s, y_{i,c}^r)$. Where x_i^s is the spatial information and $y_{i,c}^r$ is the color range information.

Algorithm 2:   Modified marked watershed transform:

Let M_1 be the gradient image's mean value, M_2 be the gradient image's local minimum mean value and M_3 be the gradient image's local maximum mean value . Let S be the local minimum region area, ∇S_h be the local minimum region ratio between an area and a depth. $a(s)$ and $a(\nabla S_h)$ are the sequence of S and ∇S_h respectively. S^{mid} and ∇S_h^{mid} are the middle values of S and ∇S_h.

sum is the number of a local minimum region, and r is the threshold of the maximum number of the segmented region.

Then, the segment algorithm comprises the following steps:

1. Calculate color image gradients according to literature[22]

2. Extract markers in the gradients, and adopt H that has been defined as

$$H = \alpha \cdot (M_3 - M_2), \quad \alpha = \frac{(M_3 - M_1)^3 + (M_1 - M_2)^3}{(M_3 - M_2)^3}$$

3. If the sum is larger than $2r$, we obtain first $2r$ of S and ∇S_h. Finally, update S and ∇S_h.

4. Apply the watershed transform

5. End

4 Experiments and analysis

The proposed algorithm has been evaluated against a number of pellet images. The pellet samples are collected with the help of a company located in Shandong Province of China with 70 images which are captured using a Basler CCD sensor (A601f) and the images are then resized to be of 640*480 pixels. Experiments have been carried out on the ring die pellet images with different conditions to evaluate the feasibility and efficiency of the proposed algorithm. These experiments were carried out on an Intel dual-core 3.0GHz PC with 4 GB RAM. The first two of the computations were performed with Matlab 7.0, and the other experiments were performed with visual studio 2010.

4.1 Analysis of major effect issues

As mentioned above, inhomogeneous background and cluttered objects are the major issues affecting the outcome of image segmentation. Firstly, the experiment shows the segmentation results of the traditional algorithms in different situations. The results are shown in Fig. 2, and

Fig.3. Fig. 2(a) is the origin image collected in a homogeneous background and non-clutter environment, and Fig.3 (a) is of inhomogeneous background with a noisy and cluttered environment. Fig. 2(b) , Fig.3(b), Fig.2(c) , Fig.3(c), Fig.2(d), and Fig.3(d) show the segmentation

results from several state of the art methods: Canny, Sobel and improved Canny. From the comparisons, we observe that these classical segment methods perform poorly in the challenging conditions.
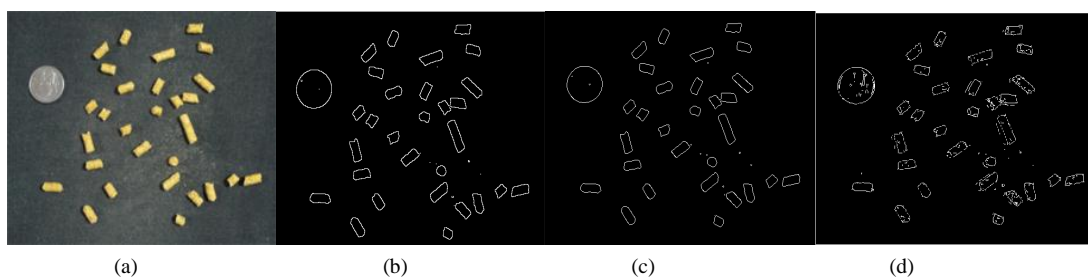

(a)   (b)   (c)   (d)

Fig.2. (a):original image (b) :canny method (c):sobel method (d) improved canny method

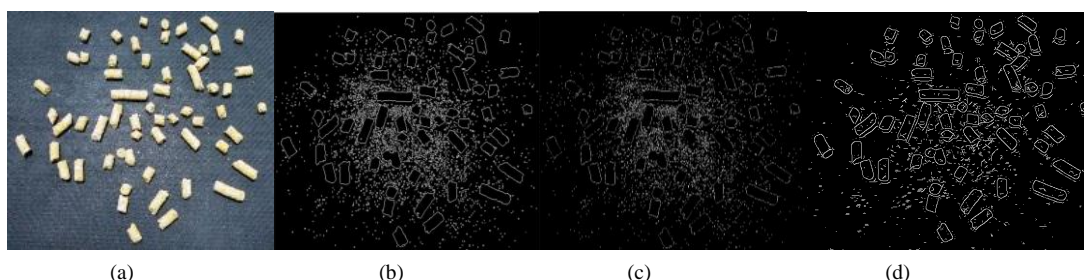(a)   (b)   (c)   (d)

Fig.3. (a)oOiginal image, (b) Canny method, (c) Sobel method, (d) Improved canny method

4.2 Analysis of the entropy based mean shift filter

In image deniosing, a classical low-passing filter can be used to suppress high frequency noise [23-25]. However, it is hard for them to preserve the edges of images due to the mixture in some frequency bands. Here, we use discrete Fourier energy density spectrums to illustrate the outcomes of different filters. Discrete 2D Fourier transform is based on the following definitions:

$$F(u,v) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n) exp\left[-2\pi i(\frac{mu}{M} + \frac{nu}{N}) \right] \quad (8)$$
$$u = 0,1,...,M-1, v = 0,1,...,N-1$$

Inverse Fourier transform is defined as follows

$$f(m,n) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(U,V) exp\left[2\pi i(\frac{mu}{M} + \frac{nu}{N}) \right] \quad (9)$$
$$m = 0,1,...,M-1, n = 0,1,...,N-1$$

For the convenience of calculation, Eq.(8) can be turned into Eq.10

$$F(u,v) = \frac{1}{M} \sum_{m=0}^{M-1}\left[\frac{1}{N} \sum_{n=0}^{N-1} exp\left(\frac{-2\pi inv}{N}\right) f(m,n) \right] exp\left(\frac{-2\pi imu}{M}\right) \quad (10)$$
$$u = 0,1,...,M-1, v = 0,1,...,N-1$$

The item in the square bracket corresponds to the one-dimensional Fourier transform of line m . The one-dimensional Fourier transform is easy to be calculated by standard fast Fourier transform (FFT). Each row is calculated by Fourier transform, followed by the calculation of one-dimensional Fourier transform for each column.

The result of 2D Fourier transform is a complex frequency spectrum. The value of the real part and the image part of the frequency spectrum are very large, and sometimes they can reach millions. For the convenience of data storage, we usually use a monotone function to reduce its value range such as $\left|\sqrt{F(u,v)}\right|$ or $log\left|\sqrt{F(u,v)}\right|$.

In Fig. 4(a), this is the energy spectrum of the original image, where the yellow-orange color indicates the major energy of symbol "+" and this area is easily contaminated by the background noise (i.e. blue and green areas). Fig. 4(b) shows the outcome of a low-pass filter, where only the central area of the symbol is kept but the edges of symbol "+" are mixed with the background. In Fig. 4(c), based on mean shift, the filtering result shows that the central area of the symbol is outstanding and the edges are also kept well. The results show that the traditional low-pass filter has good performance on image smoothing but affects the edge details.

Fig.5. (a) is the output of 27 iterations before it reaches convergence with mean shift. Fig.5. (b) is the result of involving 7 iterations to reach convergence with the entropy based mean shift. In Fig. 6, the entropy value gradually descreases before the convergence. We calculate the entropy value at each iteration. The mean shift iteration stops at a given thresholding. Fig. 7 shows the result of using a mean shift based method. Fig. 7(a) illustrates the energy distribution of the original image with many spikes (noise) on the background. Fig. 7(b) is the outcome of mean shift, where the background contains much less spikes than Fig. 7(a) and this attributes to the strong filtering capability of mean shift.
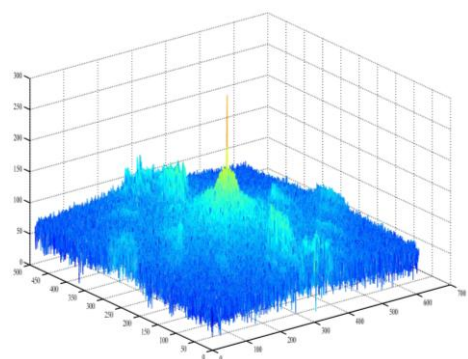
The performance of mean shift filtering can be measured using the Mean Square Error (MSE) defined as

$$MSE = \frac{1}{BG}\sum_{x=0}^{B-1}\sum_{y=0}^{G-1}[(I'(x,y) - I(x,y))^2] \qquad (11)$$
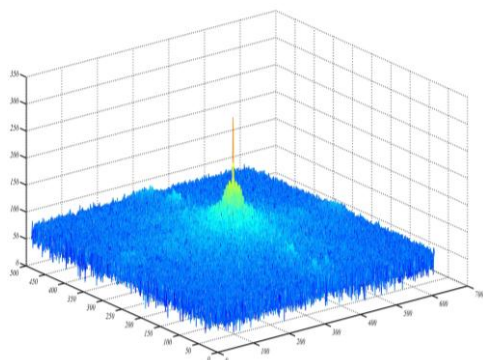
Where, $I'(x, y)$ is denoted as the filtered output image. $I(x, y)$ is denoted as the original input image. Table.1 shows the performance of the three different filtering approaches.

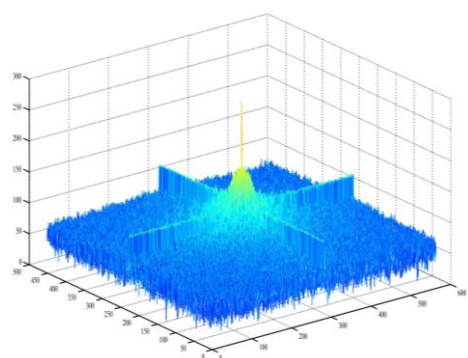Table.1. The filtering performance of three filtering algorithm

Performance Comparison	MSE		
	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.2$
Median filter	28.8642	41.2589	62.2587
Butterworth filter	28.4517	40.6587	62.0639
Proposed filter	26.9695	38.2657	58.6984

(a)　　　　　　　　　(b)

Fig.5. (a) Mean shift filter after 27 iterations. (b) Mean shift filter after 7 iterations
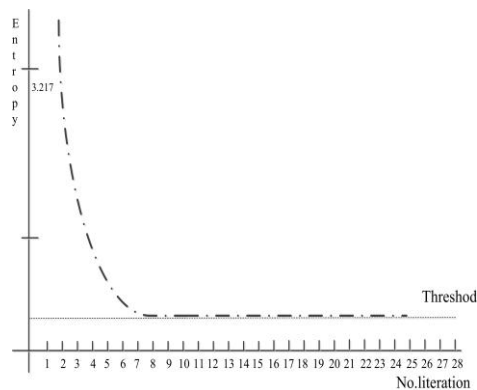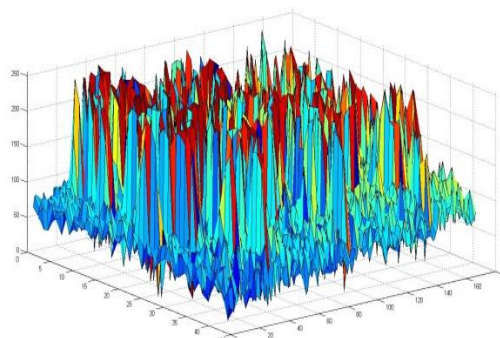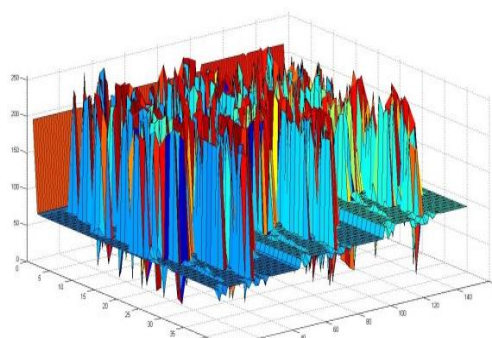

Fig.6. Entropy diminishes until reaching a threshold

(a)

(b)

Fig.7. Comparison of original noisy image (a) and denoised using mean shift (b).

4.3 Analysis of the image gradient transform

Gradient image is more important than an image itself. An color image has three color channels. In this paper, the

(a)

(b)

(c)

Fig.4. DFT transform energy frequency spectrum

Di Zenzo's method [26] is used to calculate gradient ∇I_c directly in the RGB space. The experiment proves that calculating gradient with color vectors can achieve better performance than gray gradient images.

Fig.8.(b) shows the color gradient without filtering, and Fig.8.(c) illustrates the color gradient with a mean shift filter.
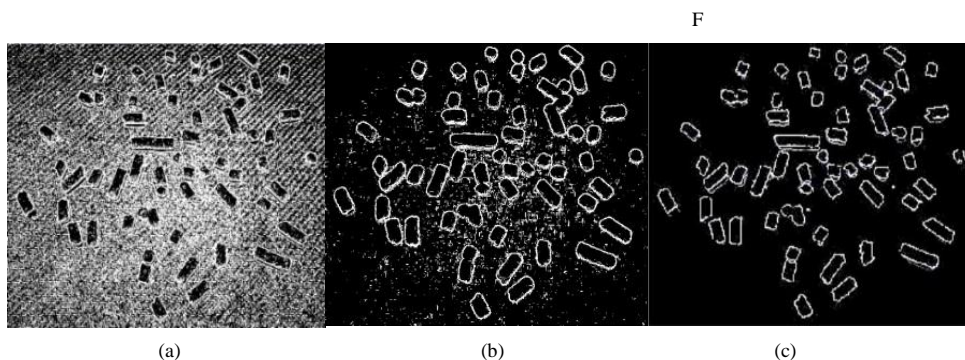
F

(a)   (b)   (c)

Fig.8 Gradient transform of an image

4.4 Comparison of segmentation performance

In this section, comparison results of the segmentation performance are shown for our method, Vincent' method [15], Bentsson' method [16] and Gaoli' method [13]. Fig. 9 shows the segmentation results of cluttered pellet image. Fig. 9(a) shows the result of the Vincent' method. Fig. 9(b) is the outcome of the Bentsson' method. Fig. 9(c) is the result of the Gaoli' method, and Fig, 9(d) is the result of our method. The number of regions obtained by each approach is shown in Table 2. We clearly see that the Vincent and Bentsson's algorithm suffers from over-segmentation. The Vincent's method is sensitive to inhomogeneous background and cluttered targets. The Bentsson' method has better performance than the Vincent's method due to the use of the H-minima marker approach, although it still needs further improvements. The Gaoli's method produces false minimum basin regions with low-pass filtering, but it has poor performance on edge segmentation because of the low-pass filter that only removes weak edges. The proposed method greatly reduces over-segmentation and obtains much better segmentation results than all the other methods. Meanwhile, it locates edges accurately in the inhomogeneous background.

Fig.10 is the result of segmentation. It is clear to find out that pellets can be well separated.

Table. 2 region number and executing time(s)

method	Number	time
Vincent' algorithm	1977	1.75
Bentsson'algorithm	536	2.04
Gaoli' algorithm	173	1.98
The proposed method	70	1.28

Fig.10 Fake-color marked image

(a)   (b)   (c)   (d)
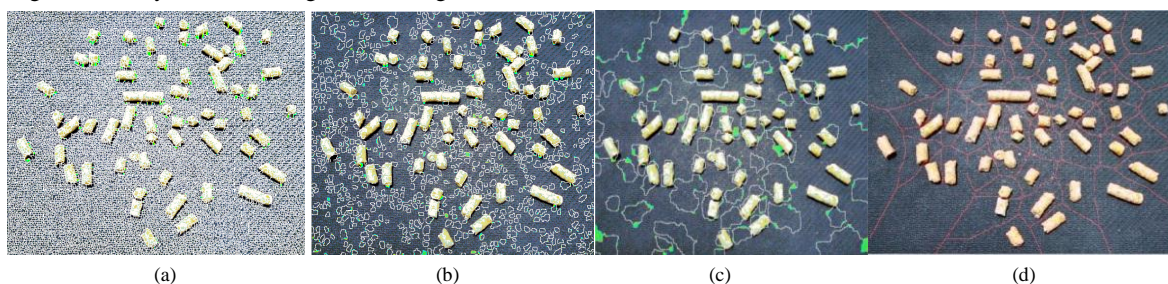
Fig.9. Four segmentation results of cluster pellet image

5 Conclusion and future work

In this paper, a robust segmentation algorithm for cluttered grain images is proposed using an entropy based mean shift filter and modified Marked Watershed Transform. We used the entropy information to improve the mean shift convergence speed. Meanwhile, the H-minimal depth threshold is adaptively obtained to overcome the threshold selection. Experimental results show that the proposed approach can obtain better segmentation results than the classical Watershed algorithms with lower computational consumption. Moreover, it has better performance in terms of anti-noise and edge detection abilities than the other state of the art techniques.

There are several research directions to extend this work

that we are currently considering. The first is to make use of the sparse representation not only for image compression, but also for feature extraction. Additionally, the mean shift filter can be developed using other gradient descent techniques to speed up the convergence.

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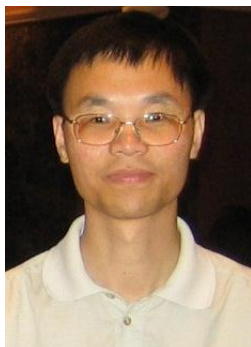
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