DEFECTS DETECTION METHOD BASED ON K-MEANS WITH PRIOR KNOWLEDGE FOR BIOMASS PARTICLES

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基于先验知识的 Kmeans 聚类生物质颗粒缺陷检测方法

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ABSTRACT

Biomass particle is one of the most important solid briquette fuels for agricultural and forestry biomass energy. Temperature, pressure, moisture and discharge holes are important factors to control biomass particle forming. The inappropriate setting of the parameters or blocking of the discharge hole will lead to the defects of the biomass particles, such as too short or poor roundness or pits or cracks. In order to detect these defects automatically, this paper proposes a method based on K-Means with prior knowledge. Firstly, the inner boundary tracking region detection algorithm and filling algorithm are combined to extract the regions in the backlight image. The regions are divided into debris, independent biomass particle regions and adhesive biomass particle regions. Secondly, K-Means with prior knowledge is used to segment the adhesive regions to get the independent biomass particle regions. Finally, the features of the biomass particles are extracted to judge the type of defects. The proposed method has been tested on images acquired from the vision system of the ring roller pellet mill. Experimental results show the efficiency of the proposed method in high detection accuracy and short detection time.

摘要

生物质颗粒是农林生物质能源的一种重要的农林生物质能源固体成型燃料。温度、压力、水分和模孔是控制生物质颗粒成型的重要因素。如果参数设置不合适或者模孔堵塞，会造成生物质颗粒长度过短、圆度欠佳、凹坑、裂缝等缺陷。为了自动检测这些缺陷，本文提出一种基于先验知识的 Kmeans 聚类方法。首先，采用基于行扫描的内边界跟踪区域检测和填充算法提取生物质颗粒图像各独立区域。根据区域面积将各独立区域划分为秸秆碎屑、单独的秸秆颗粒区域和粘连的秸秆颗粒区域。其次，使用基于先验知识的 KMeans 算法将粘连的秸秆颗粒区域分割，得到独立的秸秆颗粒区域。最后，对各独立秸秆颗粒提取特征，并据此判断是否存在缺陷。算法在从秸秆颗粒生产线上采集的图片集合中进行验证。实验结果证明本文算法具有较快的检测速度和较快的检测正确率.

INTRODUCTION

It is recommended that farming and forestry resources be reformed into solid briquette fuels to become clean energy *(Zhang and Guo, 2016)*. The biomass particles, which are made of loose biomass by the ring roller pellet mill, are typical solid briquette fuels. The shape and density of them are set by the users according to the specific applications (*Ullah et al, 2019; Rudolfsson et al, 2017*). The production process needs to control the appropriate temperature, pressure, water and the discharge hole should be normal (*Shen L.L., 2016*). If there is something wrong with the parameters and the discharge hole, the defects such as short length, poor roundness, pits, cracks will appear. The traditional method to judge the problems rely on human eyes. As the ring roller pellet mill needs to be installed on the harvester, it is difficult for the users to repeatedly get on and off to check the status of the biomass particles *(Jackson et al, 2016)*. In addition, the users cannot analyse the status of every biomass particle intuitively. Machine vision is an effective way to detect defects, especially biomass particles which are not easy to observe directly *(Sabzi et al, 2020; Bhargava and Bansal, 2020)*. The vision system acquires the images of the biomass particles and judges whether the biomass particles are normal or defective. Because there is a lot of dust in the working condition,

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the lens in the vision system are easy to be polluted, and the images will have a lot of noise, the vision system is put in a black box.

The vision system acquires images with backlight and front light. The images obtained by backlight and front light are used to extract independent biomass particles and features of them respectively. The proposed method is based on the imaging characteristics of biomass particles. Firstly, extract each region with the combination of inner boundary tracking region detection algorithm and filling algorithm. Secondly, get independent biomass particles by K-Means with prior knowledge. Finally, extract the features of the biomass particles and judge the status of biomass particles.

MATERIALS AND METHODS

Diagram

The diagram of the proposed method is shown in Fig. 1. As there is more than one region in the images, the inner boundary tracking algorithm *(Latson et al, 2001)* and filling algorithm are combined to improve the detection speed. The area of debris is much smaller than that of the biomass particle, so the debris can be abandoned if its area is smaller than a set threshold. For the adhesion regions, the segmentation is performed by K-Means *(Soua et al, 2017; Song et al, 2017)* with prior knowledge to get the independent biomass particles. The standardization and feature extraction are performed to the biomass particles in the images obtained under front light to judge their status. The ratio of different defects is computed to speculate the problem with the parameters and discharge hole. The parameters used in the method, such as the range of the permitted length and roundness, the parameters of convolutional neural network *(Moeskops et al, 2016)*, and so on, are obtained offline.

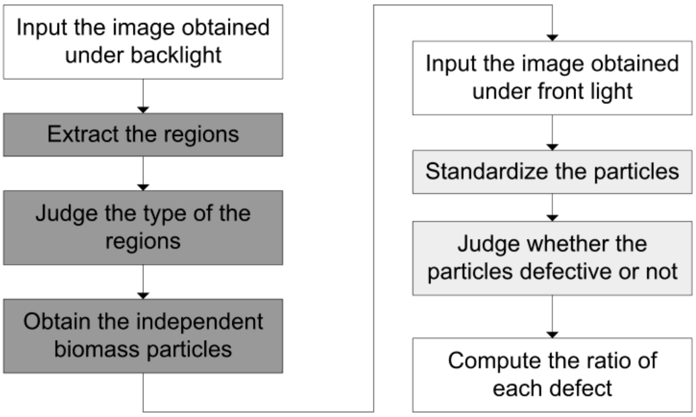


Fig. 1 - Outline of the proposed method

Image acquisition

The images are acquired with the vision system which is shown in Fig.2. There is a controller which can gather the biomass particles and put them on the backlight panel. The camera captures two times with backlight and front light respectively. The image captured under backlight gives clear boundaries which are suitable for region segmentation of the biomass particles. The image captured under front light provides detail textures that help extract the features of the biomass particles.

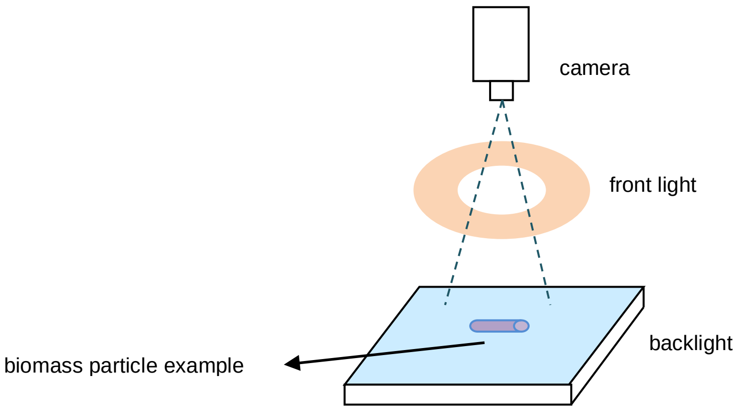


Fig. 2 – The vision system

Extraction of independent biomass particles

The contours of the regions are clear in the image acquired under backlight which is shown in Fig. 3. There are two problems: The first one is that the region should be filled once it was found to avoid being searched again as there are several regions in the image; The second one is that the biomass particles may stick together, so the segmentation should be done to get the independent ones.

For the former problem, the combination of the region extraction algorithm and filling algorithm is proposed. For the latter one, the K-Means with prior knowledge is used.

Fig. 3 - Image under the backlight

Region extraction

The combination of the region extraction algorithm and filling algorithm is as follows:

Step1: denote the number of the point of the inner boundary as n, set n = 0; denote the area of the region as a, set a = 0.

Step2: searching from the top and left of the image until a seed point, which is smaller than the threshold, is found; denote the seed point as P_n, n = n + 1; denote the moving direction from the former inner boundary point to the current one as d_{n-1}, set $d_{n-1} = 7$;

Step3: searching the eight neighbour of P_{n-1} from i until a point smaller than the threshold is found, otherwise, go to Step 8, in which, the starting number i is computed as Eq. (1):

$$i = \begin{cases} (d_{n-1}+7) \bmod 8 & \text{when } d_{n-1} \text{ is odd} \\ (d_{n-1}+6) \bmod 8 & \text{when } d_{n-1} \text{ is even} \end{cases} \tag{1}$$

where, d_n represents the moving direction from P_{n-1} to P_n.

Step4: judge whether Pn-1 is left inner boundary point or right inner boundary point: P_{n-1} is left inner boundary point when ($d_{n-1} = 5$) or ($d_{n-1} = 6$ and $d_n \neq 1$) or ($d_{n-1} = 7$ and $d_n \neq 1$and $d_n \neq 2$); P_{n-1} is right inner boundary point when ($d_{n-1} = 1$ and $d_n \neq 7$) or ($d_{n-1} = 2$ and $d_n \neq 5$) or ($d_{n-1} = 3$ and $d_n \neq 1$ and $d_n \neq 6$);

Step5: fill to the right if P_{n-1} is left inner boundary point and to the left if P_{n-1} is right boundary point, otherwise, go to Step6; During the filling process, set a value larger than the threshold for the points smaller than the threshold and update a = a + 1 in turn until the last point is smaller than the threshold, set it as a boundary point and press it in stack;

Step6: set n = n + 1;

Step7: repeat Step2 – Step5;

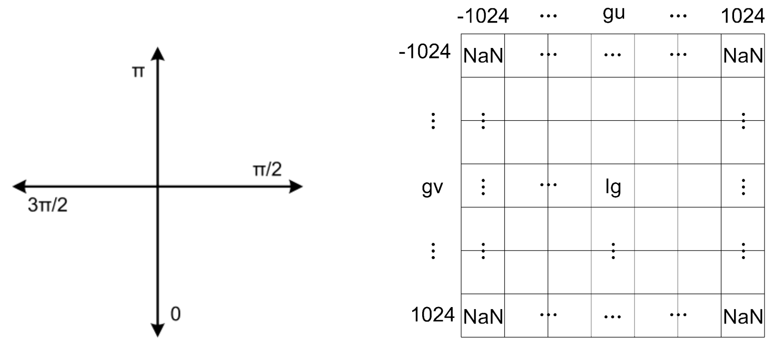
Step8: take the boundary point in the stack as the seed point P_n in turn, repeat Step2 – Step7;

As the boundary points in the stack are used as the seed points, the inner boundary points are P_0 - P_{n-1}. These points are reordered in adjacent order to get the sequence of the inner boundary points. The area of the region is a + n. The regions with areas smaller than a threshold are abandoned as debris. The regions with areas larger than a threshold are considered as the adhesion biomass particles. The regions of the independent and adhesion biomass particles are shown in Fig.4.

Fig. 4 - Region of the independent and adhesion biomass particles

Extraction of independent biomass particles

Adhesion is inevitable as the biomass particles are cylindrical and they are free to move arbitrarily. The regions are segmented based on the K-Means with prior knowledge. The segmentation will use the gradient direction of the inner boundary points. So, the gradient lookup table shown in Fig.5 is used to save time. Fig.5a is the direction diagram and Fig.5b is the lookup table in which the abscissa and ordinate represent the horizontal and vertical gradient respectively. The detailed procedure is as follows:



a. gradient direction diagram *b. lookup table*

Fig. 5 - Gradient direction look up table

Step1: calculate the horizontal and vertical gradients of inner boundary points, and obtain the gradient direction of them according to the gradient direction lookup table;

Step2: calculate the number of clustering centres according to the area of the region, and select K clustering centres; initialize K sets to store the points of each class.

Step3: The inner boundary points are divided into each set corresponding to the nearest clustering centre points according to the gradient direction;

Step4: calculate the average gradient direction of each class and use them as new clustering centres;

Step5: repeat Step3-Step4 until the error is less than the set value;

Step6: the boundary points in each class are fitted with straight line; use the least square to eliminate the error points; the fitted straight segments with right length are saved;

Step7: select the straight line segment with parallel direction; calculate the distance of the straight line segment with parallel direction respectively; classify the straight line segments, that are closest and the distance of them is about the integral multiple of the average distance, into a group.

Step8: segment the region into several sub-regions according to the distance and length of straight line segments in each group.

Due to that, there are two straight line segments of each biomass particle, the number of clustering centre is calculated as $(A / avrA + m) * 2$, in which, A and avrA denote the area of current region and the average area of the regions, m denotes the surplus. As Step 6 does not consider the position of the points, the least square is used to eliminate the points that are not on the same line. Different cases should be considered in Step 8 according to the length and distance as follows and the examples in each step are shown in Fig. 5 in which the blue lines are the line segments L1, L2 in each group in Step 8 and the black lines are the supplemental lines and the dotted lines are the other line segments of the region:

Step1: calculate the distance of the two lines in the same group; if the distance meets the allowable distance of an independent biomass particle, go to Step 2, otherwise, go to Step 5;

Step2: if the length of the two lines meets the allowable length of an independent biomass particle, then connect the end points of the lines near each other to get an independent biomass particle region. The example is shown in Fig. 6a. Otherwise, go to Step 3;

Step3: if there is one line L1 which meets the allowable length, then extend another line so that the lines obtained by connecting its two end points with the end points of L1 be perpendicular to L1 to get independent sub-regions; The example is shown in Fig. 6b; otherwise go to Step 4;

Step4: if there are other lines intersected with the two lines, then connect their closer endpoints separately, otherwise, extend the line segment to the boundary of the region to obtain the independent sub-region; The example is shown in Fig. 6c;

Step5: supply line segments which are parallel to the lines of the group and the distance is multiple of average distance between the two line segments of the biomass particle to obtain the independent sub-region; The example is shown in Fig. 6d;

Step6: Search the boundary points around the sub regions; if there are boundary points, the supplied segments of the sub regions are replaced by them, otherwise, the supplied segments are saved.

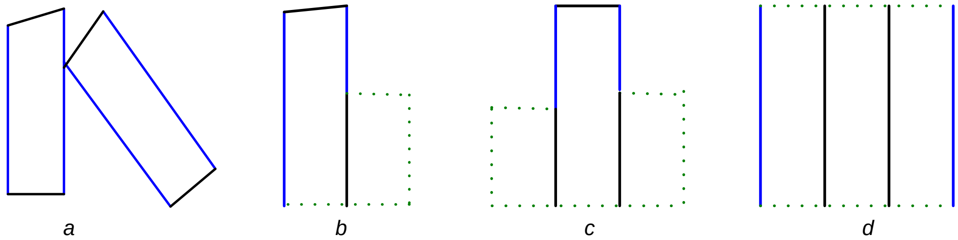


Fig. 6 - Examples of the different cases

The regions obtained with the steps above correspond to the independent biomass particles in the image acquired under front light. They are shown in Fig. 7 with different colour.

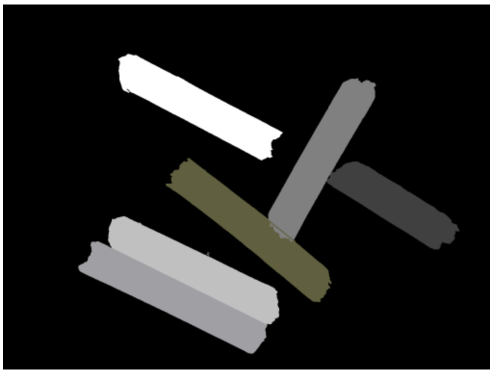


Fig. 7 - Regions of independent biomass particles

Defect detection

The defects are manifested in length, roundness, pits, cracks. The detection of the defects uses the image acquired under front light that is shown in Fig. 8 with boundary points drawn on. Firstly, judge whether the length and roundness meet the requirement; secondly, standardize biomass particles; finally, use convolutional neural network to extract the feature of the biomass particles and estimate the status of them. The detailed steps are as following:

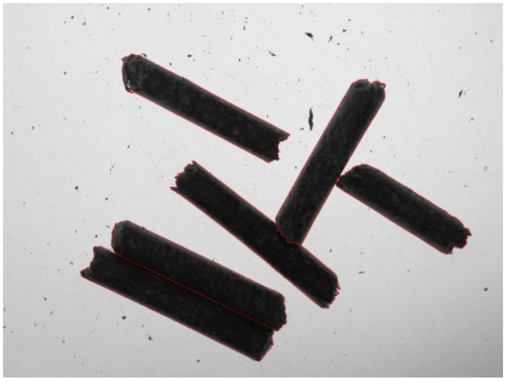


Fig. 8 - Image acquired under front light with boundary points drawn

Firstly, judge whether the length and roundness meet the requirement. The requirement is that the length and roundness of the biomass particle is within the allowable error range around the average length and average roundness. Average length refers to the average length of the two line segments of a single biomass particle. Roundness refers to the ratio of points on one line segment whose distance from another line segment meets the threshold. Average roundness refers to the average roundness of the independent biomass particle.

Secondly, biomass particles meeting the requirements of length and roundness are standardized. The biomass particle is rotated to the vertical state. The rotation angle is the angle between the straight line and the line segments of the biomass particle, as shown in Fig. 9. The rotated biomass particle is scaled according to the average distance of the line segments of the biomass particles offline.

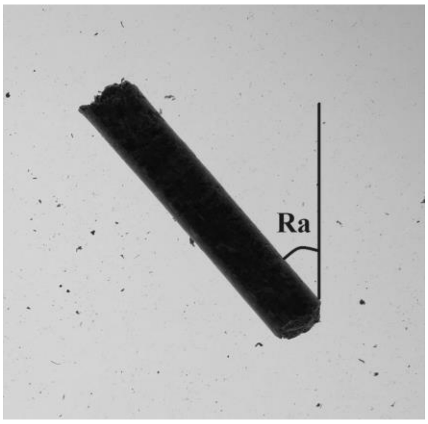


Fig. 9 - Rotation angle diagram

Finally, use the convolution neural network to extract the features of the single biomass particle and classify them. As the position and length are indefinite, overlap block is adopted to avoid the pits and cracks being divided into multiple blocks. The convolutional neural network is adopted to extract feature of each block. As long as one of the blocks is defective, the biomass particle is considered to have the same defects. The ratio of each defect of the image is computed after all biomass particles are detected. And the ratios will be sent to the controller to infer the problem.

RESULTS

Experimental results and discussion

Experimental setup

To verify the performance of the proposed method, the controller is equipped with 2.5 GHz CPU and 8.00GB RAM. The biomass used in this experiment is corn stalk. The images were acquired under different conditions by the vision system installed in the ring roller pellet mill of Liaoning Ningyue Agricultural Machinery Equipment Co., Ltd.. The number and type of different images are shown in Table 1. The pits are caused by the blocking of the discharge hole.

Table 1

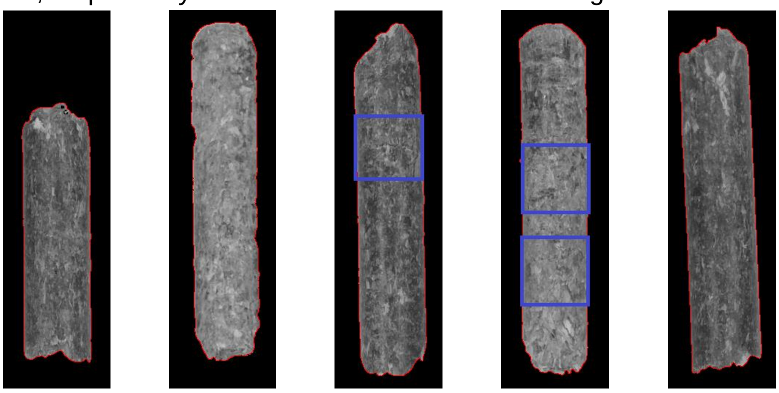
Number and type of images

Type	Num	Main defect
a	5010	Length
b	5000	Roundness
c	5100	Crack
d	5000	pit
e	5000	No defect

“Type”, “Num”, represent “image type”, “number of defective images”

Performance of proposed method

For the images in Table 1, the four defects were detected with the proposed method, namely, an image may have several defects. The image is considered to have length defect, roundness defect, crack defect, and pit defect when the ratio of biomass particles with length defect, crack defect, and pit defect exceed 3%, 2%, 5%, 3%, respectively. Different defects are shown in Fig. 10.



a. length *b. roundness* *c. crack* *d. pit* *e. normal*

Fig. 10 – Examples of different defects

The experimental results are shown in Table 2, in which, “Type”, “Num”, “Ra” represent “image type”, “number of defective images”, “ratio of defective images”. For the images whose main defect is length, the length defect detection accuracy is 100 percent and the roundness defect detection accuracy is 24.35% and there are some cracked images, which indicates that the main problem may be too much water and this can cause the collapse of the biomass particles to make the roundness unsatisfactory. For the images whose main defect is roundness, the roundness defect detection accuracy is 100 percent, and there are a few images that have length defect and crack defect, which indicates that the pressure may be unsuitable. For the images whose main defect is crack, the crack defect detection accuracy is 99.35 percent, and the problem may be too little water. As the crack can make the surface rough, the roundness defect accuracy reached 31 percent. The main reason for pit defect is the wear and blocking of the discharge hole. The surface of biomass particle may be rough when it has pit defect, so accuracy of the roundness defect reached 36 percent. The biomass particle may be detected as crack defect when the pit is too long. And the biomass particle will increase its length to meet the free-falling condition when the pit defect is serious. Hence, pit defect is also accompanied by length, roundness, and crack defect. It can be seen from table 2 that the detection accuracy does not reach 100 percent. Through the analysis of the wrongly detected images, the pit and crack defects are relatively few and in the other side of the camera so these defects cannot be detected. For the normal images, no defects are detected by the proposed method. In addition, the average time to detect an image is about 50.43 milliseconds which can meet the real time detection as to the ring roller pellet mill. It shows that the proposed method has a high accuracy and fast detection speed. The proposed method is suitable for the defect detection of the biomass particles made by different biomass. It can avoid the complicate manual operations and help the user improve work efficiency.

Table 2

Results of the experiment

Type	**Length**		**Roundness**		**Crack**		**Pit**		**Avr. time (ms)**
	Num	**Ra (%)**	**Num**	**Ra (%)**	**Num**	**Ra (%)**	**Num**	**Ra (%)**	
a	5010	100.00	1220	24.35	122	2.44	0	0.00	50.35
b	100	2.00	5000	100.00	150	3.00	0	0.00	50.89
c	66	1.29	1581	31.00	5067	99.35	15	0.29	50.38
d	9	0.18	1800	36.00	21	0.42	4992	99.84	50.23
e	0	0.00	0	0.00	0	0.00	0	0.00	50.33

CONCLUSIONS

An effective method is proposed to detect the defects of the biomass particles. It can assist the user to judge the problem of the ring roller pellet mill. The proposed method has three unique features:

(1) The first one is the combination of boundary tracking algorithm and filling algorithm which can run simultaneously to improve the detection speed.

(2) The second one is that the features of the biomass particles are used as prior knowledge of K-Means to divide to adhesive biomass particles.

(3) Finally, the process of the images under the backlight and front light is separate to extract the independent biomass particles’ regions and detect defects. This benefit comes from the clear contour and texture of the images acquired under the backlight and front light respectively.

Experimental results reveal that the proposed method is effective for the defect detection of the biomass particles. The first one can also be used in other cases similar to the images of the biomass particle.

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