Research and application of uniform material counting method based on machine vision*

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Manufacturing and agricultural industries use manual methods to count materials. This leads to low accuracy and inefficiency. This paper proposes a secondary counting method that combines main and differential counting. The area-fill identification algorithm is applied to mark the counted materials. To verify the effectiveness of the proposed counting algorithm, numbers of countings are conducted for different materials, such as the screws, hole gaskets, beans, jujube, etc. The results show that the counting accuracy reaches 98% for materials with size of 2—20 mm. The method has delivered a high-efficiency and high-accuracy automatic intelligent counting, with a wide range of application prospects and reference value.

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Accurate counting of hardware, electronic components, seeds, and tablets of uniform materials is required in industries such as manufacturing, electronics, agriculture, medicine, food, and others. Of the methods currently in use, the traditional manual counting is not only inefficient, but also leads to higher labor costs, subjective judgment, and psychological pressure[1]. The optoelectronic sensor counting method has strict requirements on the counting conditions of the materials, and a gap must be included during the design of material structure for accurately counting. Besides, this method takes a long time and leads to high costs[2]. The above two mainstream counting methods cannot meet the requirements of high speed, efficiency, and accuracy.

In recent years, continual development of machine vision has allowed for a greater judgment ability in visual inspections, for high efficiency, high accuracy, and for wide use in small particle detection and product quality grading[3]. Machine vision has been widely used in manufacturing and agriculture[4-7]. Image processing technology allows measuring high-resolution images based on phenotypic parameters[8,9]. In addition to image processing technology, machine learning technology is more and more applied in the field of material phenotype extraction and measurement[10]. Up till now, researchers have counted materials by using the end-point refinement algorithm target tracking, neural networks, and image analysis. Of those, the difficulty of image analysis is the segmentation of adhesive materials, where main algorithms are corrosion expansion method [11], the watershed algorithm[12], active contour model method[13] and the feature point matching method[14]. Most of the above methods count materials of large sizes, and their algorithms are quite complicated. When counting materials of small sizes, it is impossible to accurately determine the amount of overlapping or sticking materials, which leads to such problems as wrong or missing counts.

Machine vision is a fast-developing technology that combines machine vision and motion control technology. It combines main counting and differential counting, where the main counting provides high efficiency, and differential counting provides high accuracy. The amount of overlapping materials is determined based on the frame counting algorithm, to provide an automatic count of uniform materials.

The counting equipment is integrated into the machine vision, and with the assistance of software on INDUSTRIAL PC end, so the precision motion control of materials is achieved. The diagram of the equipment structure is shown in Fig.1. The working principle of the system is shown in Fig.2. The target value of the count and the main count value are set on the software system, with the differential count being computed automatically according to the set value. When the motion control module starts, the material is fed from the main counting hopper to the primary counting vibration zone through

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the opened stop valve, and the vibration conveyor belt sends the material to the secondary vibration belt of the primary counting. It drops from the secondary conveyor belt in an orderly manner from the blanking tank. An industrial camera with the light source is used to acquire the real-time image of materials. And the image is processed by the system's software for counting purposes. After reaching the master count value, two-stage vibration conveyor movement for the main count stops, and also the main count baffle valve is closed. The difference complement counting is performed. Then, the material enters the vibration conveyor belt of the differential complement counting from the vibration plate and is transported to the blanking tank and then dropped. With the assistance of machine vision, the differential counting of materials is performed. When the differential counting limit is reached, the whole counting procedure is finished.

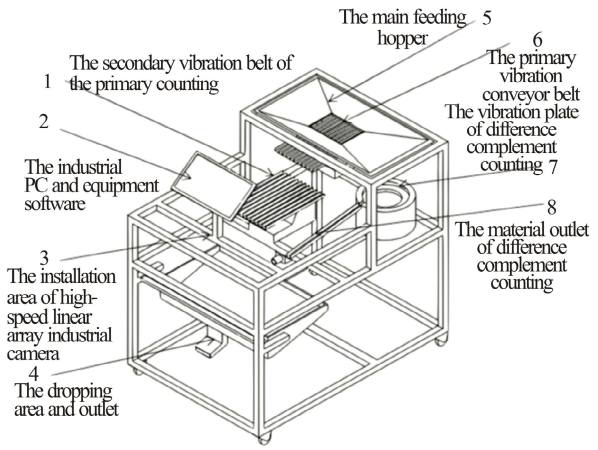

Fig.1 Schematic diagram of counting equipment

In high-speed counting, if only one counting target value is set, the movement of the vibration conveyor stops when the target value is reached. Some materials near the blanking trough may fall to the receiving plate due to inertia, resulting in the actual value of the count exceeding the set target value. Therefore, two levels of the counting method are proposed for automatic counting, including the main count and differential count. When the master count is implemented, the vibration band moves at a high speed to achieve the high-speed counting target of most quantities. When difference complement counting is implemented, the vibration conveyor belt slows down, effectively avoiding the error caused by the inertia problem, and producing high accuracy and high reliability of the overall value. The two-level counting method is presented below.

Definition 1: The two-level counting method is calculated as follows:

$$N1>N2,$$

$$N1=N2+N3, \qquad (1)$$

where $N1$ is the target count value, $N2$ is the master count value, and $N3$ is the difference complement count value.

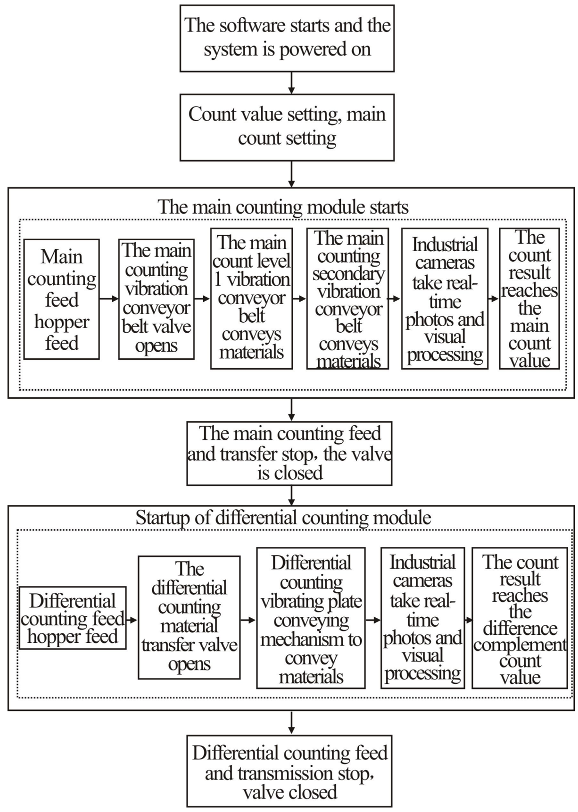

Fig.2 Flow chart of the working principle of the system

Generally, $N2$ is set to be slightly less than $N1$. For example, when $N1$=1 000, $N2$ is set to 980, and then $N3$ is set to 20. 980 and 20 are counted in stages to achieve high speed and accuracy of counting. The diagram of the two levels of the counting principle is shown in Fig.3.

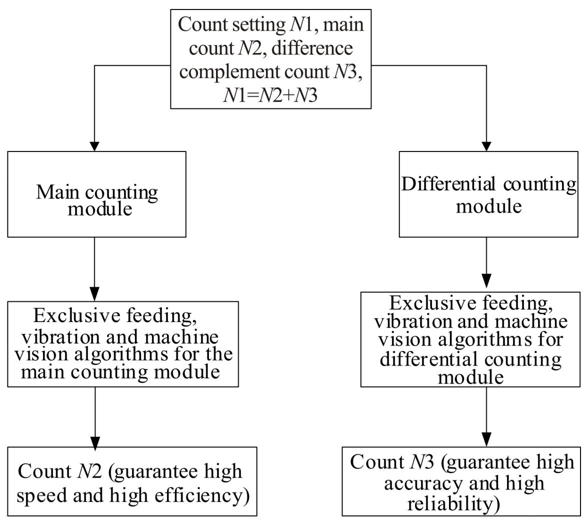

Fig.3 Diagram of the two-stage counting working principle

In the intelligent counting algorithm, the uniform material enters the main counting module or the differential counting module of the system through the vibrating conveyor belt. The industrial camera in front of the blanking trough obtains the material image in real-time with the cooperation of the light source. The image is processed by the machine vision algorithm to achieve the purpose of automatic counting of materials. The steps of the automatic counting algorithm are shown in Fig.4.

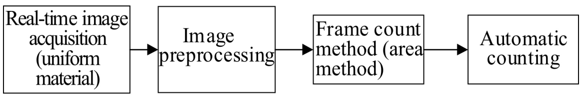

Fig.4 Flow chart of the automatic counting algorithm

Field tests have to deal with the interference of many factors, such as environmental light, vibration, and power fluctuation. Therefore, after the image is acquired by the linear array camera, it has to be preprocessed. The image pretreatment process is shown in Fig.5. Image noise filtering, graying, and binarization are carried out to get the segmentation image, which is easy to obtain a segmented image that is easy to identify material characteristics.

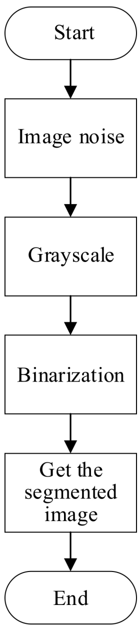

Fig.5 Image preprocessing flow chart

If there is a "salt and pepper" noise in the image, it can be filtered by a single-mean filtering method. However, a median filter can accomplish that very well. The interference of the noise on the image processing analysis links is minimized by adopting a combination of the mean and median filtering methods in the real-time image filtering processing and then graying and binarizing the processed image. The *dyn_threshold* algorithm based on the local adaptive threshold segmentation is adopted for the review of the complex illumination situation of the application scene of the counting equipment. The algorithm is defined as *dyn_threshold* (*Orig*Im*age*, *Threshold*Im*age*: Re*gionDynThresh*: *Offset*, *LightDark*:), where *Orig*Im*age* represents the input grayscale image, *Threshold*Im*age* represents the input pre-processed image for local grayscale comparison, Re*gionDynThresh* represents the output threshold region, and *Offset* represents the value set after comparing the original image with the input pre-processed image. *LightDark* represents the parameter that determines which part of the region is extracted, and it offers four options: 1. *light*, leading to the selection of the pixel value in the original image that is greater than or equal to the pixel point value of the pre-processed image minus the *Offset* value; 2. *dark*, leading to the selection of the pixel value in the original image that is less than or equal to the pixel point value of the pre-processed image minus the *Offset* value; 3. *equal*, leading to the selection of the pixel point value of the pre-processed image plus the *Offset* value because the pixel value in the original image is greater than that of the pre-processed image minus the *Offset* value; 4. *notequal*, which means that the extraction scope is outside the scope.

Taking bolt count as an example, the image after the local threshold segmentation, where black represents the target and white represents the background, is shown in Fig.6. After the threshold segmentation, the target and background are separated, which is helpful for the system software to further recognize and count the target, reduce any counting error caused by the confusion between the target and background, and ensure accuracy of the automatic count.

Fig.6 Image after segmentation

The camera captures an image of a uniform material falling with a high speed. When the current frame material image is not complete, the frame rate should be slightly higher than the falling velocity of materials. In other words, through the adjustment of vibration frequency of secondary vibration band during the primary and differential count procedure, the falling speed of materials can be controlled precisely, which guarantees the integrity of captured images.

If there is a repeating area between the two adjacent image frames, a real-time area filling identification is performed on the materials that have been counted. The floodwater filling method is essentially a seed filling method that judges the neighborhood pixels of the seed point to determine whether a connected domain with the seed should be formed to fill it until all pixels in the area are found or until the boundary of the contour line is reached[15]. As shown in Fig.7, for the bolts that are counted effectively, a circular outline is drawn at the center of the area for effective identification. The area at the lower left corner in Fig.7 shows that the previous frame has been counted successfully. In this frame, the counting is repeated. Neither counting nor counting marks are drawn. Therefore, the system will not repeat counting even if there are duplicate areas between two adjacent frames.

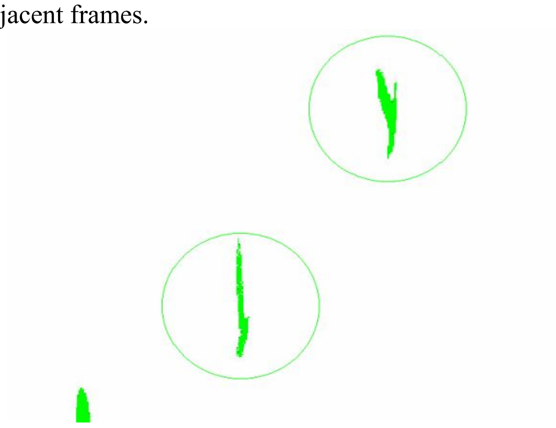

Fig.7 The area filled with logo image

Counting the overlapping materials is the key to ensuring accuracy. A two-stage method combines main counting and differential counting. The vibration frequency of vibration belt can be adjusted precisely, and thus the material appears in the best field of vision of the array camera and remains in a more uniform position throughout the two-stage conveyor belt movement, thereby reducing the possibility of the overlapping and adhesion of the material.

The frame counting method is adopted to divide the total area of the material image in a single frame binarization diagram (no corrosion operation is required) by the area of the unit material to obtain the total amount of the material in a single frame image. The algorithm principle for the process is shown in Fig.8.

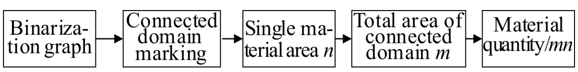

Fig.8 Schematic diagram of the area method principle

The material connected to the domain R is marked and the area S_i of each connected domain is calculated in the following manner:

$$S_i=\sum_x\sum_y f(x,y)(x,y)\in R. \tag{2}$$

To remove the influence of impurities, the average value of a single material is selected as an area of a single material n in all the images, and the binary connected domain whose area is significantly smaller than the average area of a single material is removed. After that, the total area of the connected domain m is calculated. The total area of the connected domain is divided by the area of a single material to obtain the material quantity T_1. The following algorithm is used to calculate the quantity of materials in a single frame image without overlap:

$$T_1=\frac{m}{n}. \tag{3}$$

The counting process continually collects images online in real time. A multi-frame counting algorithm is proposed based on the single-frame counting algorithm. First, the material quantity of the current frame is calculated, then the material quantity of the next frame is calculated, and finally, the total material quantity is obtained by accumulation.

(1) When the material is counted without the overlap phenomenon, the value of N is calculated as follows:

$$N=\sum T_i\,(i\geq 1), \tag{4}$$

where i is the frame sequence, T_i is the number of materials in the frame with a serial number i, and the value of materials can be obtained through accumulation.

(2) When material is counted with the overlap phenomenon, the average area algorithm of a single material is designed as follows.

Definition 2: The average area algorithm of a single material is calculated in the following manner:

$$n=\frac{1}{T}S_i, \tag{5}$$

where S_i is the area of a single connected domain, n is the average area of a single material, and T is the total amount of all materials in the image.

The vibration frequency of the motion control function module is adjusted to allow the material to have an even appearance within the range captured by the camera. If the material overlaps, the algorithm for discriminant analysis of the overlapping material is designed as follows.

Definition 3: The discriminant algorithm of the overlapping material provides the following area judgment rule for a single connected domain:

$$k_1 n\leq S_i\leq k_2 n, \tag{6}$$

where k_1 is the minimum coefficient of the connected domain, k_2 is the maximum coefficient of the connected domain, S_i is the area of a single connected domain, and n is the average area of a single material.

The setting of the vibration frequency and adjustment of the k_1 and k_2 coefficients for uniform materials of different types and sizes eliminates the overlapping of materials at ≥4, which can satisfy the counting requirements of the uniform materials of different types and sizes.

Based on the different values of k_1 and k_2 coefficients, the number of overlapping materials is automatically judged, and then the total number of materials is obtained. For example, seeds in the agricultural field generally have round shapes, and their coefficients are shown in Tab.1.

Tab.1 Parameters setting

Parameter	k_1	k_2	S_i	Remarks
No overlap	0.4	1.5	$0.4n \le S_i < 1.5n$	Material quantity plus 1
Two overlaps	1.5	3.5	$1.5n \le S_i < 3.5n$	Material quantity plus 2
More than three overlaps	No	3.5	$S_i \ge 3.5n$	Material quantity plus 3

Testing in this study was conducted with the following uniform materials: soybeans, wheat grains, jujube, pills, screws, capacitors, gaskets, and others. Fig.9 demonstrates the software test that sets the minimum size of the material to 10 mm and the maximum size to 600 mm. When the material count reached 500, the number of prompts was the material quantity at master count. When the number of prompts was 410, the value of the difference compensation meter was 90. When the number of prompts was 450, the complement count value was 50, and when the number of prompts was 490, the complement count was 10. Tab.2 shows the test data obtained by this counting method.

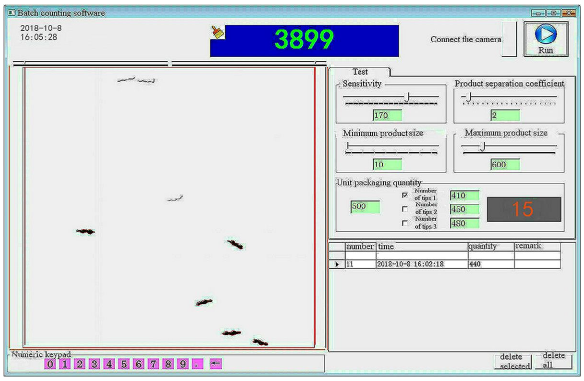

Fig.9 System software test

Tab.2 Experimental test data

Testing material	Size	Actual amount	Master count $N2$	Difference $N3$	Counting result
Wheat grains	2 mm in length	500	456	38	494
Jujube	10 mm in diameter	1 000	986	14	1 000
Soybeans	5 mm in diameter	800	796	4	800
Capacitors with pin	20 mm in length, 8 mm in width	500	488	12	500
Hole gaskets	8 mm in diameter	300	289	11	300
Buttons	10 mm in diameter	500	489	11	500
Pills	4 mm in diameter	1 000	990	10	1 000
Screws	10 mm in length, 3 mm in width	100	95	5	100

The data in the table shows that the proposed counting method and algorithm meet the requirements of high speed and accuracy. It also demonstrates a 100% accuracy and a counting speed of up to 8 000/min for materials with a 2 mm diameter. The equipment system has been mass-produced and marketed in Guangzhou Fu-Wei Electronic Technology Co., Ltd., and has good application value.

Nowadays, manufacturing and agriculture industries still employ manual or photoelectric sensor counting to count their materials. This paper proposes the use of machine vision technology as part of a two-stage counting method and an intelligent counting algorithm for overlapping materials. Conducted tests show that materials in the range of 2—20 mm are not affected by the shape, color, or size, producing an intelligent count with high accuracy, which innovates the current counting method, and provides a good reference for the relevant industries.

Statements and Declarations

The authors declare that there are no conflicts of interest related to this article.

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