A Real-time Computer Vision System for Biscuit Defect Inspection

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Abstract: This paper presents a computer vision system for biscuit defects inspection which contains both hardware and software. By utilizing the system with two cameras, we focus on the detection of biscuit partial deletion and cream overflow. For detecting partial deletion, a new algorithm with a membership function for calculating feature descriptor is proposed. It's convenient and efficient to extract feature of textons. For cream overflow detection, a chemical property of enantiomers under polarized light is made use of distinguishing cream from background. The proposed system has been implemented on the production line. Groups of on-line experiments show that our system can achieve accurate defect detection with low missing detection rate and false alarm.

1 INTRODUCTION

With the development of automation in industry, the application of on-line detective equipment which focuses on quality detection increases in a fast growing speed. The detection equipments achieve the accuracy and efficiency which automated production requires. Moreover, they can reduce the dependence on human at the period when it's hard to employ labors. Computer vision plays an increasingly important role in the field of on-line detection. Coffee roasting is evaluated by the changes of brightness and surface area with image processing on-line (Hernandez, J.A. 2007). Foreign bodies in biscuits are inspected through computer vision by infrared thermography (Senni, L. 2014). A real-time computer vision system is implemented to detect defects in textile fabric (Mak, K.L. 2005).

Mondellez International is a famous food company which produces tons of Oreo cookies through automatic line every day. Oreo cookie consists of three parts: two chocolate biscuits and a piece of cream between them. One of the procedures is to put cream on the back biscuit and put top biscuit on the cream on line. With this procedure, it's easy to product defective cookies which could be partial deletion and cream overflow. Our computer vision system is aimed at inspecting defective cookies which may give rise to block on automatic line and picking them out automatically.

Oreo cookies have uniform texture on biscuit. The biscuit border textures are either peak stripes or valley stripes which scatter from center to edge. Under light, the peak stripes show brighter than valley stripes as the shadow of peak stripes falls on valley stripes. As the partial deletion or fray always appears from biscuit edge to center, we can judge the biscuit is intact or not by the integrity of border texture. Since the width and length of stripes is not uniform strictly, the method of template matching (Mahalak-shmi, T. 2012) (Liu, C. 2012) or Fourier transformation is not suitable. Histogram of textons (Hoang, M. 2005) is a kind of classic texton descriptor. As the detected area has some other texture besides the stripes discussed above, histogram of textons is not effective. Co-occurrence matrix and local binary patterns (Heikkila, M. 2006) could not describe stripe feature. Scale-invariant feature transform (Mikolajczyk, K. 2005) and speeded up robust features (Herbert, B. 2008) (Chenbo, S. 2010) are so complicated that they are not appropriate for online inspection. In section 2, we propose an algorithm which is to extract the texture of biscuit to inspect partial deletion or fray. Firstly, the ring area is unfolded to a long strip for feature extraction. Secondly, we introduce a membership function to calculate pixel's label (Perrot, N. 1996) (Johannes, A.R., 2001). Then, we define lines and make up of feature vector with lines.

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The cookies are produced on metal production line. It's hard to distinguish white overflow cream from the metal background in images. Chirality is a kind of structure characteristic for molecules. A chiral molecule is a type of molecule which has a non-superposable mirror image like an asymmetric carbon atom. A chiral molecule and its non-superposable mirror molecule are defined as enantiomer (Mcnaught, A. D., 1997). The preponderance of right or left hand enantiomers will change the linearly polarized light to a net circular birefringence.

As the cream contains enantiomers while background metal does not, under polarized light, the characteristic of reflected light from biscuit is changed to a net circular birefringence. (Eugene, H., 2002) (Vollhardt, K. P. C., 2003). When we put a polaroid ahead of camera, the reflected light from cream will filter through polaroid while the reflected light from metal won't. We design a set of optical device which consists of two cameras to detect overflow cream and partial deletion respectively.

2 BISCUIT PARTIAL DELETION INSPECTION ALGORIGHM

2.1 Unfolding the Ring Area

Partial deletion of biscuit usually appears at the border of biscuit. The inspection of partial deletion can be simplified by unfolding biscuit border. To get an unfolded region of biscuit border, two steps are needed as follows: firstly, biscuit has to be located accurately; secondly, the region of biscuit border should be unfolded to a long stripe.

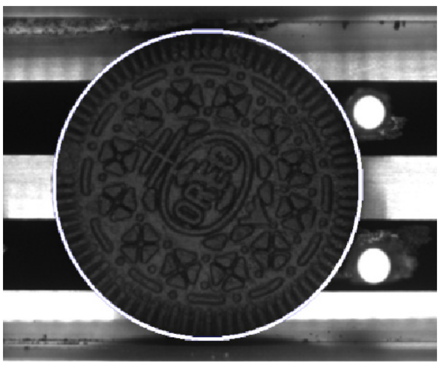

Figure 1: The result of locating cookies.

In our method, we use random sample consensus (RANSAC) (Hossam, I. 2012) (Shi, C. 2012) to calculate biscuit's center and radius. Since the value of biscuit edge is much lower than the value of metal, we select 200 pixels from the edge of biscuit after thresholding the original image. The location result is shown in Fig.1. According to the result of locating, a ring area from the edge to inside part is unfolded to a long strip to form a new image.

In order to get a clear image efficiently, trilinear interpolation is applied to unfold the ring area. We unfold 390 degrees of the ring region to avoid truncation defects in the new image. The unfolded image is shown in Fig.2. We define the unfolded image as a region of interest (ROI) for feature extraction.

Figure 2: The unfolded image of ring area.

2.2 A Membership Function for Pixels

By observing the unfolded image, it's obvious that gray values of biscuit pixels are not uniform except for the influence of light. One of the reasons is that biscuit is made up of flour, chocolate and sugar which won't be uniform completely. With an experiment, we can get a distribution of pixel values without texture which is shown in Fig.3. However, the main reason for the difference of pixel values is the shadow caused by peak stripes and valley stripes on biscuit. So from Fig.2, we can find the texture which bright stripes alternate dark stripes clearly. The distribution frequency of dark and bright stripe pixel values is shown in Fig.4.

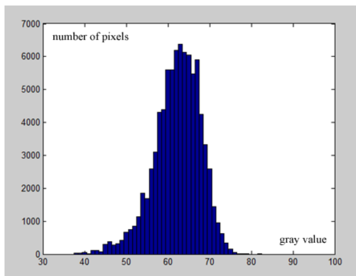

Figure 3: the histogram plot of biscuit without texture.

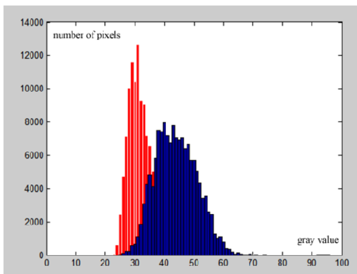

Figure 4: the histogram plot of dark and bright stripes.

In Fig.4, the red part is the distribution of dark stripe pixel values and the blue part is the distribution of bright stripe pixel values. For each pixel value, we can calculate the probability belong to dark stripes or bright stripes with the distribution of pixel values. However in order to process efficiently, we use a segmented function to fit the distribution of possibility approximately. We call the segmented function as a membership function. And the probability is considered as a membership for bright or dark. The membership function can be expressed as:

$$T_w(x) = \begin{cases} 0 & (x \le T_L) \\ a(x) & (T_L < x < T_H) \\ 1 & (x \ge T_H) \end{cases} \tag{1}$$

where T_H denotes the middle value of bright stripe pixel values and T_L represents the middle value of dark stripe pixel values. $T_w(x)$ is the membership to dark strip. While $a(x)$ can be calculated according to following equation:

$$a(x) = \begin{cases} \mathrm{round}(10 \times \frac{x - T_L}{T_M - T_L}) \times 5\% & (T_L < x \le T_M) \\ \mathrm{round}(10 + 10 \times \frac{x - T_M}{T_H - T_M}) \times 5\% & (T_M < x < T_H) \end{cases} \tag{2}$$

where T_H and T_L are same as the variables in Eq.(1). T_M is the middle value in which the number of dark stripe pixels is equal to the number of bright stripe pixels. $\mathrm{round}()$ is a round function. With the membership to dark strip, we can calculate the membership to bright strip as follows:

$$T_b(x) = 1 - T_w(x) \tag{3}$$

where $T_w(x)$ can be calculated by Eq.(1). $T_b(x)$ is the membership to bright strip.

2.3 Feature Extraction for ROI

With the membership of each pixel, we propose a method of feature extraction in ROI for partial deletion inspection. Continuous pixels in a column are defined as a line. For texture part of ROI, long bright or dark lines exist. We can find the longest line in each column as a feature.

To determine a line whether belong to dark or bright, we defined a sum function of pixels membership. The function is shown as the following two equations:

$$K_b(m,n) = \sum_{i=m}^{n} T_b(x) \tag{4}$$

$$K_w(m,n) = \sum_{i=m}^{n} T_w(x) \tag{5}$$

where $K_b(m,n)$ is the sum of membership to dark and $K_w(m,n)$ is the sum of membership to bright from pixel m to pixel n in a column. $T_b(x)$ and $T_w(x)$ are calculated by Eq.(1), Eq.(2) and Eq.(3). And we can find the longest line in a column as follows:

$$L = \max(L_b, L_w) \tag{6}$$

where

$$L_b = \max\left\{ l_{mn} \,\middle|\, K_w(m,n) \le K_T, K_b(m,n) > K_T \right\}$$
$$L_w = \max\left\{ l_{mn} \,\middle|\, K_b(m,n) > K_T, K_w(m,n) \le K_T \right\}$$
$$l_{mn} = n - m + 1$$

$m = 1, 2, \ldots N$; $n = m, m+1, \ldots N$. K_T is a threshold. L_b is the longest line of which the sum of membership to dark is larger than K_T while the sum of membership to bright is smaller than K_T. If it not exists, L_b is set to 0. L_w is the longest line of which the sum of membership to bright is larger than K_T while the sum membership to dark is smaller than K_T. If it not exists, L_w is set to 0. L is the longest line in a column.

In this method, we can find the longest line in each column. If the longest line is longer than threshold N_T, the column is labeled white or black, otherwise the column is labeled gray. We define several continuous black, white or gray columns as a black, white or gray stripe respectively. According to the process above, we can get the longest black, white and gray stripes in each part. The procedure of statistical process can be described as following pseudo-code:

```
For(column j from 1 to M)
begin
    Lj=FindLongestLine();
    if(Lj >= NT)
        column label to black or
        white;
    else column label to gray;
End
WBlackStripe=WidestContinuesC(B);
WWhiteStripe=WidestContinuesC(W);
WGrayStripe=WidestContinuesC(G);
```

L_j (j =1, 2, 3,... M) is defined as the value of L in column j . L_j is small in defective area meanwhile it's would be a large number in intact area. The last 3 items in feature vector consist of width of the widest black, white and gray stripes: W_B, W_G, W_W. It would not be a large number in texture area. Feature vector can be described by following equation:

$$V = [L(1) \quad ... \quad L(M) \quad W_B \quad W_G \quad W_W]^T \tag{7}$$

2.4 Classify with Feature Vector

We choose adaptive boosting (Adaboost) (Freund, Y., 1997) as our classifier. The classification and regression tree is the weak learner in Adaboost. Usually, the intact biscuits have a small value of W_B, W_G and W_W which will influence the weak learner first. The first N items of feature vector can improve the accuracy for further iterations. Iteration time is set to a small number to satisfy the request for speed for online detection.

3 DESIGN AND PROCESS OF OVERFLOW DETECTION

3.1 Hardware Structure

In order to detect cream overflow, we utilize the chemistry character of enantiomer. We put a polaroid below camera to filter the reflected light from metal. Because the intensity of polarized image is low, it's impossible to detect texture with the polarized image. So we try to design a set of device with two cameras to deal with the problem. The structure of optical device is shown in Fig.5 schematically.

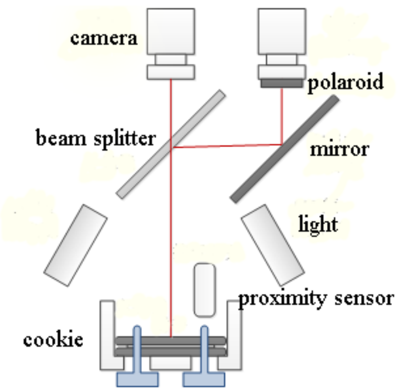

Figure 5: Schematic of optical device.

There are two CCD cameras to take photos: one is a mono camera which can take 640×480 pixels, 8-bit per pixel images, the other one is an RGB camera which can take 640×480 pixels, 24-bit per pixel images. A polaroid is below the RGB camera which can detect various creams. Below the mono camera, there is a beam splitter which transmits half light to mono camera and reflects half to RGB camera with another mirror. Two stripe polarized lights are set along the both sides of production line. We utilize a proximity sensor to trigger two cameras to take photos when cookie reaches the best location. Fig.6 shows the equipment on production line.

Figure 6: Schematic of optical device.

3.2 Calibration of Original Image and Polarized Image

We need to detect the defect of cream overflow. The polarized image of biscuit is shown in Fig.7 as follows. With Fig.7, it's hard to locate the position of biscuit.

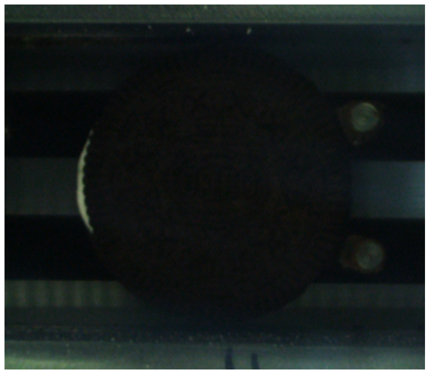

Figure 7: Polarized image of biscuit.

As original image and polarization image are formed by a splitter light, calibration of two images can achieve through training. Just taking translation and scale into consideration, 3 variables need to be solved: ΔX , ΔY and K . When training, the polaroid is taken off, the center coordinate and radius of two image's biscuit can be solved by random sample consensus. These 3 variables can be calculated as following equation:

$$\begin{bmatrix} K_i \times X_{Oi} + \Delta X_i \\ K_i \times Y_{Oi} + \Delta Y_i \\ K_i \times R_{Oi} \end{bmatrix} = \begin{bmatrix} X_{Pi} \\ Y_{Pi} \\ R_{Pi} \end{bmatrix} \tag{8}$$

where

$$\left[\Delta X \ \Delta Y \ K\right]^T = \frac{1}{N}\sum_{i=1}^{N}\left[\Delta X_i \ \Delta Y_i \ K_i\right]^T$$

$i = 1,2,3...N$. In Eq.(8), N means the number for training images. X_{Oi} means the x-coordinate value of biscuit center in original image i , X_{Pi} stands for the x-coordinate of biscuit center in polarized image i .

With the result in Eq.(8), we can calculate the location of biscuit in polarization image with center and radius of biscuit in original image.

3.3 Calculate the Area of Cream Overflow

With the data of biscuit center and radius in polarized image, we calculate the area of cream overflow. The polarized image is transformed from RGB to HSV color space. Three threshold bands are set for hue, saturation and value component to get a binary image. The noises in binary image are removed by morphological operating. Then the number of white pixels in binary image is counted in the region which is a ring area from edge of biscuit to outside. If the number is larger than threshold, the biscuit is considered cream overflow. Otherwise, it's a biscuit with no cream overflow.

4 EXPERIMENTS

The method has been implemented in Visual Studio 2008 and all experiments are going on a Nuvo-1005b IPC, core i5 540M and 2G RAM. We conduct experiments on production line in Mondelez International Suzhou Food Co.LTD Huxi Branch.

We make four groups of experiments as follows: three groups for accuracy test, the last group for stability test of system. Results of four groups are shown from Fig.8 to Fig.10 and the data are shown in Table 1 and Table 2.

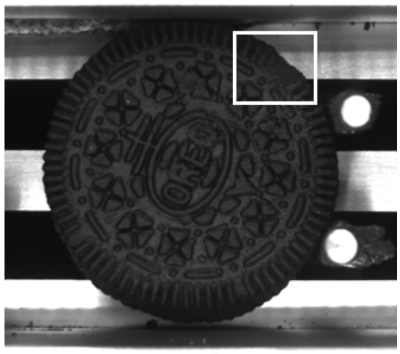

Figure 8: The result of partial fray biscuit.

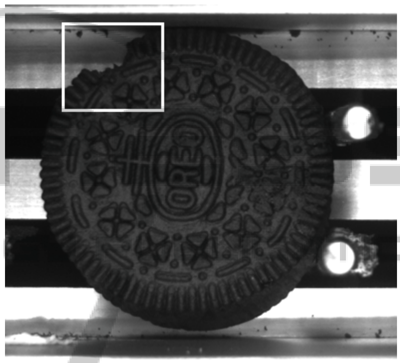

Figure 9: The result of partial deletion biscuit.

From Table 1, we can get the result of inspection partial deletion or fray biscuit. The false positive proportion is range from 0.09‰ to 0.14‰. The false negative rate is range from 0.09‰ to 0.27‰. The total error rate in the four groups of experiments is 0.33‰. The precision of partial deletion or tray is 0.3 mm^2.

Table1: The proportion of FP and FN in partial deletion or fray detection.

Group	Number of biscuits	Proportion of false positive	Proportion of false negative
1	21756	0.09‰	0.18‰
2	22052	0.14‰	0.09‰
3	22034	0.14‰	0.27‰
4	126843	0.13‰	0.22‰

The result of cream overflow detection is shown in Table 2. The false positive rate is range from 0.05‰ to 0.14‰. The false negative proportion is range from 0.14‰ to 0.32‰. The total error rate in the four groups of experiments is 0.32‰. The precision of overflow detection can reach to a 0.5 mm width cream overflow. The fourth experiment lasts 6 hours, so the system has been proved stable.

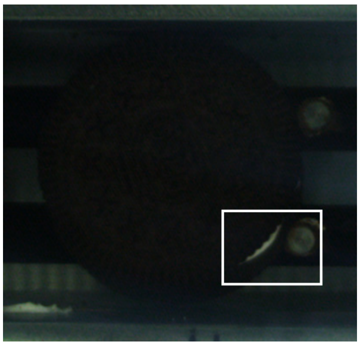

Figure 10: The result of cream overflow biscuit.

Table 2: The proportion of FP and FN in cream overflow detection.

Group	Number of biscuits	Proportion of false positive	Proportion of false negative
1	21756	0.05‰	0.14‰
2	22052	0.14‰	0.18‰
3	22034	0.09‰	0.32‰
4	126843	0.12‰	0.21‰

The time consuming of detecting a biscuit is less than 40 ms in on-line experiments, which can satisfy the speed of production. The experiments demonstrate that our system is effective and efficient.

5 CONCLUSIONS

In this paper, a biscuit inspection system is proposed in on-line detection. The feature extraction algorithm can be described to three steps: locate and unfold the ring area; calculate the membership for pixels; find the longest line in each column and compose the feature vector. The application of polarized light can detect cream overflow of biscuit. The result of experiment shows that our method is accurate and can meet real-time demands. The system has been implemented on biscuit production line.

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REFERENCES

Chenbo, S., Guijin, W., Xinggang, L., Yongming, W., Chao, L., Quan, M., 2010. Topology based affine invariant descriptor for MSERs. *IEEE Conference on Image Processing, 133-136.*

Eugene, H., 2002. *Optics*, Addison Wesley. United States of America, 4th edition.

Freund, Y. and Schapire, R. E., 1997. A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences, 55,* 119-139.

Heikkila, M., Pietikainen, M., 2006. A texture-based method for modeling the background and detecting moving objects. *IEEE Transactions on pattern analysis and machine intelligence, 28*(4), 657-662.

Herbert, B., Andreas, E., Tinne, T., Luc, V.G,. 2008. Surf: Speeded Up Robust Features. *Computer vision and image understanding, 110*(3) 346-359.

Hernandez, J.A., Heyd, B., Trystram, G., 2007. On-line assessment of brightness and surface kinetics during coffee roasting. *Journal of food engineering,* 87(3), 314-322.

Hoang, M., 2005. Energy-based geometric multi-model fitting. *International Journal of Computer Vision,* 97(2) 23-147.

Hossam, I., Yuri, B., 2012. Color texture measurement and segmentaion. *Signal Processing,* 85(2) 265-275.

Johannes, A.R., Magne, Setnes., Janos, A., 2001. Learning fuzzy classification rules from labeled data. *Information sciences,* 150(2003) 77-93.

Liu, C., Wang, G., Lin, X., Li, L., 2012. Person re-identification by spatial pyramid color representation and local region matching. *IEICE Trans. Information & System. E95D, 2154-2157.*

Mahalakshmi, T., Muthaiah, R. and Swaminathan, P., 2012. Review Article: An Overview of Template Matching Technique in Image Processing. *Research journal of applied sciences, engineering and technology.* 4(24): 5469-5473.

Mak, K. L., Peng, P., Lau, H. Y. K., 2005. A real-time computer vision system for detecting defects in textile fabrics. *ICIT'05, IEEE International Conference on Industrial Technology.,* 469-474.

McNaught, A. D., Wilkinson, A., 1997. *Compendium of Chemical Terminology*, International Union of Pure and Applied Chemistry. Zürich. 2nd edition.

Mikolajczyk, K., Schmid, C., 2005. A performance evaluation of local descriptors. *IEEE Transactions on pattern analysis and machine intelligence,* 27(10), 1615-1630.

Perrot, N., Trystram, D., Guennec, F. And Guely, F., 1996. Sensor fusion for real time quality evaluation of biscuit during baking. *journal of food engineering,* 29(3-4), 301-315.

Senni, L., Ricci, M., Palazzi, A., 2014. On-line automatic detection of foreign bodies in biscuits by infrared thermography and image processing. *journal of food engineering,* 128, 146-156.

Shi, C., Wang, G., Pei, X., He, B., Lin, X., 2012. Stereo matching using local plane fitting in confidence-based support window. *IEICE Trans. Information & System. E95D, 699-702.*

Vollhardt, K. P. C., Schore, N. E., 2003. *Organic Chemistry*, W. H. Freeman. American.4th edition.