Method for Detecting Visible Impurity in Oral Liquid Based on Improved SURF Algorithm

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Abstract. In order to solve the problems that the visible foreign objects in the large bottle oral liquid are small, the detection speed is low and the single feature would be easy to cause the mis-tracking. In this paper, the speed-up robust features (SURF) algorithm is improved and applied to the detection of visible foreign objects. Firstly, features from accelerated segment test (FAST) detection algorithm is used instead of the Hessian matrix for feature point detection to avoid the extraction of numerous and useless feature points in the edge region. Secondly, two-way fast library for approximate nearest neighbours (Flann) algorithm is adopted for the feature matching to accelerate the matching rate and improve the accuracy of matching. The related experiment shows that the proposed algorithm can accurately match the target and effectively improve the detection speed, which meets the requirements of online detection.

1. Introduction
Oral liquid is a common type of health care products. However, in the production and bottling process, various impurities may occur in the oral liquid, which may cause the serious harm to consumers. At present, the detection of visible foreign matters still utilizes the artificial light inspection in China. The method has low efficiency and large human factors, which lead to the missed and false detection.

In recent years, owing to the rapid development of image processing technology, various detection algorithms have been proposed and achieved good results. For example, the SVM algorithm proposed by Jiao S H [1] and the neural network algorithms used by Zhang Y [2] both need a lot of training that cause the low detection speed; Ou Q [3] adopted the nearest neighbour matching algorithm, it needs to find the nearest measurement as the prediction point, and the feature is single, which easily leads to the false tracking. The SURF algorithm adopted by Liu X F [4] is time-consuming and may cause the mismatch.

Based on the above problems, this paper intends to use the maximum entropy three-frame XOR composite frame difference method (ME-XOR) to extract the foreign objects target. Then, the improved SURF algorithm is applied to match the extracted foreign objects. Finally, based on the physical characteristics and the motion characteristics of the foreign matters, the foreign matters are distinguished from the bubbles to sort out the unqualified products.

2. The detection and matching of visible foreign matters

2.1 Detection of visible foreign bodies
In order to obtain moving foreign objects, it is necessary to conduct the grayscale and the GAUSSIAN filtering for the collected sequence images to eliminate noise interference resulted from external
environment and internal factors. And then we identify the foreign objects by the ME-XOR. Now there are lots of methods for detecting foreign matters including the optical flow, the background difference and the frame difference. The first one is complex and time-consuming and, the second one is efficient but is limited by the background. For the third one, it is efficient and can detect moving targets accurately. Nevertheless, there are two problems as following: 1). Voids would be easily generated in the difference process. 2). The secondary interference would be caused by the influence of the threshold T. Consequently, this paper proposes the ME-XOR method to realize the detection of foreign objects. The relevant flow chart is as below.

The ME-XOR method selects information entropy to show the gray distribution of the images after the difference between two adjacent frames. When the sum of the information entropy of the foreign objects and the backgrounds takes the maximum value, the obtained value is the optimal binarization threshold. The main steps are as follows.

1) A sequence image is obtained by first difference between the two adjacent frames of the denoised image.

\[
f_{(n,n-1)}(x,y) = f_{(n)}(x,y) - f_{(n-1)}(x,y)
\]

2) Calculate the gray value distribution of the foreign objects and the background.

\[
k_n = \sum_{n=0}^{255} f(x,y)(n)^{-1}
\]

The probability can be worked out as the following formula.

\[
p_n = k_n(w \times h)^{-1}
\]

The gray values of foreign objects and background are as below.

\[
y_n = p_n(\sum_{i=0}^{T} p_i)^{-1} \quad (1 \leq n \leq T)
\]

\[
bg_n = p_n(1 - \sum_{i=0}^{T} p_i)^{-1} \quad (T \leq n \leq 255)
\]

Where \(k_n\) represents the number of pixels with a pixel value of \(n\), \(p_n\) is the probability that a pixel with a pixel value of \(n\) appears in the entire image, where \(w, h\) represents the width and height of the image pixel, \(y_n\) and \(bg_n\) respectively represent the distribution of the gray value of \(n\) in the foreign objects and the background, where \(T\) is the threshold for binarization.

3) Calculate the total entropy

\[
\gamma(s) = \sum_{m=5}^{255} p_m(1 - Z_m)^{-1} \ln (p_m(Z_m)^{-1}) + \sum_{m=1}^{5} p_m(Z_m)^{-1} \ln (p_m(Z_m)^{-1})
\]

According to the equation (6), the binarization performs the best if \(\gamma(s)\) is taken as the maximum value. Then the images of the first difference are binarized by the following equation.

\[
B_{(n,n-1)}(x,y) = \begin{cases} 
0 & f_{(n,n-1)}(x,y) < T \\
255 & f_{(n,n-1)}(x,y) \geq T 
\end{cases}
\]

The foreign objects detected by the ME-XOR method are shown as follows.
2.2 The matching of visible foreign bodies

The SURF [6] algorithm is a detection and matching algorithm with highly robust for a feature point. It is not affected by rotation and scale. There are three main steps including feature point detection, feature description and feature matching. However, in the first step, it is easy to extract a large number of useless feature points at the edge of the region, which increases the computational complexity. And in the third step, the algorithm adopts a one-to-one correspondence matching, which is time-consuming and cause the mismatch.

For the above problems, this paper uses the FAST detection algorithm to conduct feature point detection to reduce the computational complexity. Feature matching by the bidirectional Flann algorithm not only improves the matching rate, but also improves the accuracy of matching.

2.2.1 Feature point detection. The SURF algorithm uses the Hessian matrix to extract feature points, which is easy to generate a large number of useless feature points. The FAST [7] feature point detection introduced in this paper is simple and fast. If a pixel is quite different from the surrounding pixels, the pixel may be a feature point. In the template shown in Figure 3, the pixel \( p \) is the centre and \( r = 3 \) is the radius. Define a threshold of \( \varepsilon \), 1) Compare the pixel difference between \( p \) and \( p_1, p_9 \). If the absolute values are greater than the threshold, the point \( p \) is selected as the candidate point; 2) If the first step is established, we calculate the pixel difference from \( p_1, p_9, p_5 \), and \( p_{13} \). If at least three absolute values exceed the threshold, the point \( p \) is the candidate point; 3) If the second step is established, we will calculate the pixel difference from the 16 points from \( p_1 \) to \( p_{16} \). If at least 9 of them exceed the threshold, then \( p \) is the feature point. Discriminate feature points by the following equation.

\[
N = \sum_{q \in \text{circle}(p)} |I(q) - I(p)| > \varepsilon
\]

where \( I(q) \) is the pixel value of any point in the circle \( p_1 \) to \( p_{16} \), \( I(p) \) is the pixel value of the candidate point, and \( N \) is the number of points which satisfy the conditions.

For the feature point extraction, if there are multiple feature points detected in the neighborhood centered on the feature point \( p \), we will take the non-maximum suppression method to eliminate the local extreme points. That is, we calculate the response size \( V_i \) for each detected feature point and compare the \( V \) values of two adjacent feature points and retain the larger one.

\[
V_i = \sum_{x=1}^{16} |I(p_i) - I(x)|
\]
where $V_i$ is the sum of the absolute deviation of the feature point $p_i$ and the 16 pixels around it.

2.2.2 Feature point description. To describe a feature point, it is essential to determine the main direction of the feature point at first. Namely, scanning the entire area, the maximum vector direction is obtained by superimposing the Harr wavelet responses of the $x$ and $y$ directions in the area of $\pi/3$. After determining the main direction of the feature point, the square neighbourhood is divided into $4 \times 4$ sub-regions, which is centred on the feature point and the side length is $20s$ ($s$ is the scale value where the feature points are located). And we perform the Harr wavelet filter processing for each sub-area to acquire Harr wavelet features, which are relative to the main direction. The horizontal direction is $dx$ and the vertical direction is $dy$. After weighting the $dx$ and $dy$, we can get a 4-dimensional descriptor as the following formula.

$$V = \{\sum dx, \sum |dx|, \sum dy, \sum |dy|\}$$ (10)

After all the sub-areas are connected, a 64-dimensional descriptor can be obtained.

2.2.3 Feature point matching. The SURF matching algorithm is a one-way matching process which easily leads to the mismatching. In this paper, the bidirectional Flann [8] neighbour matching algorithm is used to optimize the matching process so that we can improve the accuracy of feature point matching. Specific steps are as follows.

a. The distances from the feature point $x$ of the image A to the nearest neighbour feature point $y$ and the next nearest neighbor feature point $z$ in the image B ($d_{yx}$, $d_{zx}$) are respectively calculated based on the Euclidean distance formula.

$$d_{yx} = (\sum_{n=0}^{64}(F_y(n) - F_x(n))^2)^{1/2}$$ (11)

$$d_{zx} = (\sum_{n=0}^{64}(F_z(n) - F_x(n))^2)^{1/2}$$ (12)

where $F_x(n)$, $F_y(n)$, and $F_z(n)$ represent the feature vectors of the feature points $x$, $y$, and $z$, respectively.

b. Calculate the distance ratio $R = d_{yx}/d_{zx}$. If $R < \beta$ (where $\beta$ is the threshold, generally take from 0.4 to 0.8), the feature point $x$ and $y$ match successfully and are stored in the set $M$.

c. Perform steps a and b on all feature points in image B. Store the feature points that match successfully into the set $Q$, finally find the intersection of the set $M$, $Q$, thus obtaining a matching set $U$ after bidirectional neighbour matching.

3. Experimental results and analysis

In order to verify the accuracy of the improved algorithm in this paper, oral liquid with different impurities are taken for matching detection. Figures 4, 5 and 6 are oral liquid sequence images respectively containing white impurities, black impurities and bubbles. The small box marks the foreign matters in the oral liquid.

Figure 4. Sequence image with white impurities.
Figures 5, 6, and 7 are respectively the matching images of a sequence image of white impurities, black impurities and bubbles after image processing by the improved algorithm.

Figures 7, 8, and 9 are respectively the matching images of a sequence image of white impurities, black impurities and bubbles after image processing by the improved algorithm.
4. Conclusion
This paper proposes a new algorithm for detecting visible foreign matters in oral liquid. The algorithm with high accuracy which combines FAST feature point detection, SURF feature description and bidirectional Flann neighbor matching algorithm. The average time required for the matching and tracking of visible foreign objects is nearly 400ms, which demonstrates a high detection rate. And we can accurately distinguish the foreign matters from the bubble so as to sort out the defective products by the algorithm combined with the characteristics of the upward movement of the bubbles.

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