AUTOMATIC ADJUSTMENT OF THE CUTTING POSITION OF A VISION-BASED FISH PROCESSING MACHINE

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Abstract

Accurate detection of positions of features in an image is required in many machine vision applications. This paper describes several algorithms that can be used to locate the gill position where mechanical operations take place. The effect of adjustable parameters that are inherent to the hardware components and software algorithms, on the performance of the vision system is discussed. Next, to significantly improve the accuracy of the detection rate, a fuzzy-decision maker is developed. This procedure can generate more reliable outputs by using information from different algorithms.

1. Introduction

A vision-based fish processing machine is described in [1]. An important feature of the machine is that it utilizes a real-time vision system to aid the accurate positioning of the cutter. The objective of the image analysis in the head-removal machine is to locate the collarbone of a fish where the cutting takes place. As will be described in the next section, several methods have been developed to detect features related to the position of the collarbone in an image. However, it has been found that none of these methods individually can provide a uniformly satisfactory performance when large and random samples of fish are processed continuously. This paper will show that the performance of each method can be enhanced by tuning the system, by choosing proper parameters for the algorithm and the system. Also, the reliability of the overall system can be improved by combinatorics of results from different algorithms.

2. Gill-Position-Detection Algorithms

In analysing the images, it was apparent that three features could be significant for determining the position of a collarbone. These are: (1) the shadow generated by the gill plate using structured lighting, (2) the end of the pectoral fin, and (3) the variation of texture between the gill plate and the fish body. These are highlighted in Figure 1.

Figure 1: Highlights of Significant Features for Gill-Position Detection.

The geometric position of any one of these three attributes will provide a good estimate for the location of the collarbone. Several methods to detect the position of these features are briefly described below [1,2].

<u>**Binary Density Projection (BDP) Method:**</u> This method is based on the idea that the shadow of the gill plate edge will generate more edge pixels than from the other parts of the fish. It has four basic steps: (1) reverse the intensity of the image, (2) perform the Sobel filter along the x direction, (3) project the thresholded image on to the x axis, and (4) smooth the projected histogram and detect the largest peak of the smoothed histogram to find the gill position.

<u>**The Labeling Method:**</u> Unlike most image processing implementations where labeling is applied to binary images, in this application labeling algorithm is applied to structures formed by object edges. In this way, most of the unwanted structures would be eliminated

by the edge enhancement and smoothing operations. The largest structure that is present after performing these operations is usually the shadow formed by the gill plate. Once the largest structure is detected in this manner, locating the cutting position is a trivial task; for instance, the extreme point on the gill boundary in the lengthwise direction of a fish may be used as the position for cutter placement.

The Fin Detection Method: The method used to detect the fin is quite similar to the labeling method that is employed for detecting the gill. However, the Sobel operation is applied along the y direction here in order to enhance the edges in the lengthwise direction of the fish and to suppress the edges in the orthogonal direction. After the Sobel operation and the subsequent smoothing, two structures become quite clear: the upper longitudinal profile of the fish and the pectoral fin. By applying some heuristics, the pectoral fin can be detected from this information and its extremity in the direction of the fish nose gives a reasonably accurate location for positioning the cutter along x axis.

The Gill Plate Location (GPL) Method:
This method takes a novel approach to locating the position of the collarbone. It is based on the idea that with structured lighting, only those pixels generated by the gill plate have a very low gradient magnitude after Sobel operation, due to its relatively smooth surface. Some of the operations in this method are similar to those as in the BDP method. But in order to show the procedure as a whole, all the major steps involved are described below.

- Perform Sobel filtering in the x direction and binarize the resulting image with a small threshold value T_{bn}. After this step, most pixels, particularly the ones other than those on the gill plate, will be given an intensity value of 255 and those with low gradient magnitude (probably on the gill plate) are given an intensity value of 0.
- Smooth to remove isolated points. This operation will eliminate most of the isolated points, and therefore make the succeeding steps more reliable, as will be shown.
- Project the resulting image onto the x axis.
- The projected histogram is then smoothed by convolving with a one-dimensional Gaussian kernel $g(l, \sigma)$ of zero mean and standard deviation σ,

$$g(l,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-l^2}{2\sigma^2}} . \qquad (1)$$

Figure 2(a), (b) and (c) respectively show a frame of raw image, the result after the Sobel enhancement and binarization with a low threshold (T_{bn}) value, and the histogram that has been smoothed by the Gaussian filter. The rightmost point of the curve indicates the end of the gill plate in the fish body direction. The figure shows, with the use of a low threshold value, the projected number of non-edge points in the gill-plate area is high and that in the main body of the fish is nearly zero.

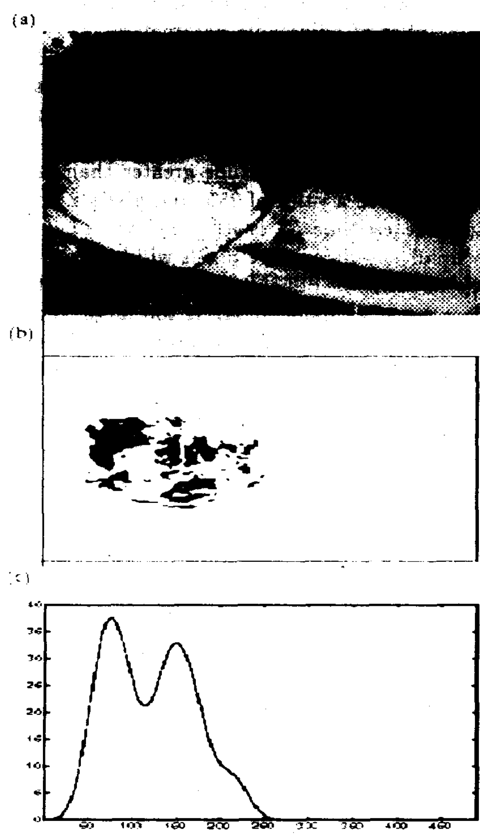

Figure 2: Gill-Position Detection Using GPL Method. (a). A Greylevel Image. (b). The result after Sobel enhancement. (c). The Gaussian-Smoothed Histogram.

3. Parameters versus Performance

As described in Section 2, most image processing algorithms have one or more adjustable parameters. In fact, in an industrial machine vision system, not only parameters in software algorithms need to be adjusted, but also the parameters in the hardware system, such as the aperture of the camera, and the illumination level of the lights. Undoubtedly, all these parameters affect the performance of a vision system. The adjustable parameters in software algorithms are referred to as *algorithmic parameters*, and parameters in the hardware system and those associated with the application environment are referred to as *system parameters*. The following sections qualitatively analyse the effect of the adjustable parameters inherent to the software algorithms.

Algorithmic Parameters

In the gill-position detection algorithms described in Section 2, a number of adjustable parameters are involved. The effect of a few significant ones are discussed here. The first one, which is used in all the algorithms and is referred to as T_{bn}, is the threshold value used to binarize the image after the Sobel enhancement. Typically, pixels with an edge magnitude greater than or equal to T_{bn} is assigned a value of 255, and pixels with an edge magnitude less than T_{bn} is assigned a value of 0. If T_{bn} is too small, too many edge pixels will be generated and consequently it is difficult to locate the largest structure. On the other hand, if T_{bn} is too large, too few edge pixels are generated and the largest structure may not represent the accurate position of the feature because it might have been broken into several pieces.

However, different algorithms may require different thresholding levels. For example, in the BDP Method, a high T_{bn} value is used and those pixels with high gradient magnitude values are relevant, and in contrary the GPL method uses a low T_{bn} value and those pixels with low gradient magnitude values are relevant.

The second adjustable parameter, which is the standard deviation σ of the Gaussian kernel, determines the level of smoothing on the projection histogram. A larger σ gives a heavier smoothing, and vice versa. Thus depending on the noise level in the image, the smoothing factor should be adequately set.

4. Methods Combinatorics

A perfectly accurate detection rate is difficult to achieve with the use of a single image processing algorithm, and quite possibly, the accuracy of detection will improve with the appropriate use of information from several algorithms. The most important step in trying to use information from multiple sources is that of determining which particular algorithm has resulted in an accurate or nearly accurate detection. For this purpose, a fuzzy decision making system may be employed, as discussed below.

The Basic Idea

Four methods have been developed to detect the position of a collarbone as outlined before. A degree of merit can be assigned to each method in terms of its output parameters. For example, if the peak projection value that corresponds to the gill position in the BDP method is within a certain range (this range can be determined using *a priori* knowledge), a high degree of merit (belief) is assigned to this method; otherwise if it is outside this range, a low degree of merit (belief) is assigned. Once this is done, a fuzzy decision-making system can be employed, which will determine which method is more reliable and consequently the corresponding output position can be used for cutter positioning.

The Fuzzy Decision Algorithm

Let $A = [A1, A2, A3, A4]$ be the set of algorithms for detecting the gill position. To evaluate the performance of each algorithm for a specific frame of image, a number of criteria are developed and an example of these criteria is described as follows.

The value of the histogram peak: This peak can usually give a good indication of how reliable a particular algorithm has performed. For example, the value of the peak for the BDP method should be around 60 to 100. If this value is too low or too high, say less than 20 or greater than 150, the algorithm is no longer reliable for the particular frame of image. Thus by using statistical method, a different degree of merit can be derived for a particular algorithm in terms of the peak value it has generated. It should be noted that the evaluation method is different for each algorithm. For example, the highest belief value (i.e., a membership of 1) is given to the BDP method when the peak value of the histogram is from 70 to 80, and to the GPL method when the peak value is from 35 to 50. The histogram-peak evaluation generates a fuzzy subset S_1:

$$S_1 = [\frac{\mu_{S_1}^{r_{S_1}^1}(A1)}{A1_{S_1}}, \frac{\mu_{S_1}^{r_{S_1}^2}(A2)}{A2_{S_1}}, \frac{\mu_{S_1}^{r_{S_3}^3}(A3)}{A3_{S_1}}, \frac{\mu_{S_1}^{r_{S_4}^4}(A4)}{A4_{S_1}}] \quad (2)$$

where $A1$, $A2$, $A3$, and $A4$ represent the four alternatives, $\mu_{S_1}^{r_{S_1}^1}(A1)$, $\mu_{S_1}^{r_{S_1}^2}(A2)$, $\mu_{S_1}^{r_{S_3}^3}(A3)$, and $\mu_{S_1}^{r_{S_4}^4}(A4)$ are the respective membership values of these alternatives with respect to the current evaluation, and $r_{S_1}^1$, $r_{S_1}^2$, $r_{S_1}^3$, and $r_{S_1}^4$ are the positive numbers assigned to each algorithm to indicate the relative importance of the current evaluation on the decision-making.

In a similar way, several other criteria can be obtained. These include the dynamic range of the projection data, the total number of structures, the area difference between the largest and the second largest structures, and the difference between the default position and the gill position as reported by each algorithm, which may be denoted as S_2, S_3, S_4, and S_5. Once all the criteria are established, the fuzzy decision process can be formulated. The objective of the fuzzy decision making process here is to select an alternative (algorithm) that best satisfies "all" the criteria as the output of the decision-maker. This is achieved by using a sup-min composition, i.e., the optimal alternative is A^* such that

$$\mu(A^*) = \sup_{a \in A} \min_{i=1,m} \mu_{S_i}(a) \tag{3}$$

where m is the number of criteria used in the evaluation process, and A denotes the set of alternative algorithms. Equation 3 shows that for each alternative, the criterion with the lowest membership value is first selected (because, all criteria have to be treated simultaneously, as a cross product), and the alternative algorithm with the highest membership in the resulting fuzzy subset is then selected as the optimal decision (because, the appropriateness of the algorithm has to be maximized).

To show how the fuzzy decision making algorithm works, an example is presented here. Three images are used in the experiment. They are the images shown in Figure 1, Figure 2(a), and Figure 3.

Figure 3: Another Test Image.

Table 1 shows the membership values of the evaluation attributes, and the decisions made by the fuzzy decision maker. The on-line tests show that the cutting positions thus produced are accurate.

Table 1. The Membership Values of the Evaluation Attributes and the Fuzzy Decisions

img	A	μ_{S_1}	μ_{S_2}	μ_{S_3}	μ_{S_4}	μ_{S_5}	D
img1	$A1$	0.9	0.9	-	-	0.9	A1
	$A2$	-	-	0.8	0.9	0.8	
	$A3$	-	-	0.9	0.7	0.9	
	$A4$	0.6	0.9	-	-	0.8	
img2	$A1$	0.5	0.8	-	-	0.8	A2 or A4
	$A2$	-	-	0.9	0.9	0.9	
	$A3$	-	-	0.9	0.9	0.8	
	$A4$	0.9	0.9	-	-	0.9	
img3	$A1$	0.5	0.6	-	-	0.9	A4
	$A2$	-	-	0.8	0.7	0.8	
	$A3$	-	-	0.7	0.7	0.8	
	$A4$	0.9	0.9	-	-	0.8	

It should be pointed out that despite every effort made, occasional off-position cutting may still occur due to factors such as variations in fish size, the machine errors, and the feeder error. To account for this, a default position may be necessary. Fixed position in this case is usually not satisfactory, and an automatic default-setting scheme is more desirable. This could be achieved by using a statistical learning scheme. Learning may be incorporated for the purpose of updating the default position, by keeping track of the cutting position for the most frequently used detection algorithm. Other aspects worth noting include the use of ***a-priori*** knowledge to remove background structures and fix the region of interest, and the incorporation of a dynamic calibration scheme to compensate for the variations of the height thickness of the fish.

5. Conclusion

Machine vision can be successfully used to guide mechanical operations in an automatic food processing workcell. The accuracy and the reliability of the particular image processing algorithm that is employed, has a direct effect on the success of the operation. This paper presented several gill-position detection algorithms that have been implemented in a prototype fish processing workcell. It is argued that, in a complex application as the one considered here, a perfect detection rate is difficult to achieve with the use of a single image processing algorithm. To reduce this problem, a fuzzy decision-making system for a multiple-algorithm scenario has been proposed. The tests show that the performance of the workcell can be significantly improved with the use of the methodology described in this paper.

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