Intelligent Fusion of Sensor Data for Product Quality Assessment in a Fish Cutting Machine

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Abstract
This paper presents two intelligent sensor fusion techniques, which have been implemented in an automated machine for mechanical processing of salmon, to determine the level of product quality (i.e., the quality of processed fish). An automated fish cutting machine with advanced sensor technology is employed in the present work. The fish cutting process is complex, and ill-defined, and quality assessment methods are subjective. Two knowledge-based fuzzy fusion methods based on: a) regular Mamdani dot-max composition, b) the degree of certainty are implemented to achieve improved results. The data available from disparate sensors like CCD cameras, optical encoders and ultrasonic displacement sensor of the machine are fused using the two methods. An illustrative example for a good and a bad cut is presented. The results indicate that the two methods are equally effective, but method (a), which is more sophisticated, has a slight advantage in performance over the other, at the expense of added complexity.

Index Terms– quality assessment, fuzzy measure, sensor data fusion, fish processing.

1. Introduction

Fish processing involves head removal/cutting of fish at the position of collarbone, with the objective of optimizing the quality and yield of meat. The challenges include, accurate positioning of cutter blades and smooth cutting of fish. The assessment of the quality of processed fish is dependent on the skillful but subjective evaluation by experienced plant operators. The cost of expertise, scarcity of experienced operators, increasing cost of fish and associated processing have led the industry to develop alternative, computer automated techniques and advanced sensor technology for assessing the quality [1]. The prototype machine, as developed in the Industrial Automation Laboratory, is an automated version of an industrial fish cutting machine. It considerably reduces wastage of fish meat during processing, by sensing the position of collarbone (desired position of cut) using a vision system, and by means of a controller which automatically. adjusts the position of cutter blades according to the sensory measurements

In the present context, sensor fusion is considered as the synergistic use or combination of data from multiple sensors to increase the capabilities of industrial machines and systems by improving the quality of the output information [2]. Conventional statistical methods such as Kalman filter can be used when the analytical relationship between the input and the output data is known. Yager proposed a fuzzy data fusion method with the concept of compatibility for fusable degree of data using the ordered weighted averaging (OWA) operator, and fuzzy measures [3]. The present paper implements two fuzzy fusion methods based on: a) regular Mamdani *prod-max* composition [4] and b) the degree of certainty [5] for product quality assessments in fish processing.

The sensory data from disparate sensors are uncertain, incomplete, and sometimes contradictory. It is a challenge to fuse such conflicting data. In this paper a fuzzy fusion method based on the degree of certainty of measured data is implemented, for the specific application. The degree of certainty is related to the concept of measure of fuzziness. In a fuzzy set the membership values (μ) of the elements have a range [0,1]; μ = 1 indicates total agreement with sensors, and μ = 0 shows total disagreement. Furthermore, μ = 0.5 means the sensor data is of no relevance to the hypothesis, and it represents the state of highest fuzziness. The measurements having membership values near the region of maximum fuzziness should have the least effect on the fused output, while those near crisp values should be given high weighting.

Another fusion method is implemented as well, as the basis of comparison, using the conventional *prod-max* fuzzy inference. For a complex and ill-defined process like fish cutting, fusion techniques employing fuzzy logic [6] provide a systematic way of integrated assessment of the available knowledge and human expertise in evaluating the product quality. Preprocessing transforms the crisp sensory information into a linguistic form within the rule-base. The membership functions are defined for the input and output variables. The developed rule-base gives the fuzzy inference (*prod-max* or *dot-max*) on product quality, which is defuzzified to obtain a numerical value for product quality index.

The paper is organized as follows: a description of the fish cutting machine and sensors used is presented in Section 2; the two fuzzy fusion methods, one based on degree of certainty and the other based on Mamdani *prod-max* composition are described in Sections 3 and 4, respectively; fuzzy fusion implementation which includes, fuzzification, rule-base generation, fusion, and defuzzification is discussed in Section 5; an illustrative example for the two cases showing the effectiveness of the two fusion methods is presented in Section 6; and a summary and conclusion are given in Section 7.

2. Automated Fish Cutting Machine

A schematic diagram of the over all system is shown in Figure 1. The prototype machine, as developed in the Industrial Automation Laboratory, is an automated version of an industrial fish-cutting machine [1]. It considerably reduces the wastage of fish meat and improves the quality of cut. Fish is fed through a hopper to the conveyor and a low-level CCD camera (primary) captures its image. This image provides the position of collarbone (desired position of cut), and simultaneously an ultrasonic displacement sensor measures the thickness of the fish in the gill region. The information from the CCD camera and the ultrasonic sensor is used for adjusting the cutter blades in the horizontal and the feeding platform in the vertical direction, respectively. Two DC servomotors, with optical encoders, controlled by the two-drive axes of a controller are used for the lateral positioning the cutter, and the vertical placement of fish with respect to cutter, using the feeding platform. The two cutter blades are arranged in V-shape and driven via flexible shafts by two, three-phase AC induction motors, whose load is measured by sensing the "slip", using optical encoders. A high-level CCD camera (secondary), placed at the exit side captures the image of the cut section of the fish. The image captured by this camera indicates the accuracy and the smoothness of cut. It is used for the direct monitoring and assessing the cutting quality. The conveyor is driven by a variable speed DC motor complete with a feedback having optical encoder and a drive controller.

3. Fusion Method 1 - Based on Degree of Certainty

The data fusion method as described in [4] used here, is based on degree of certainty associated with each

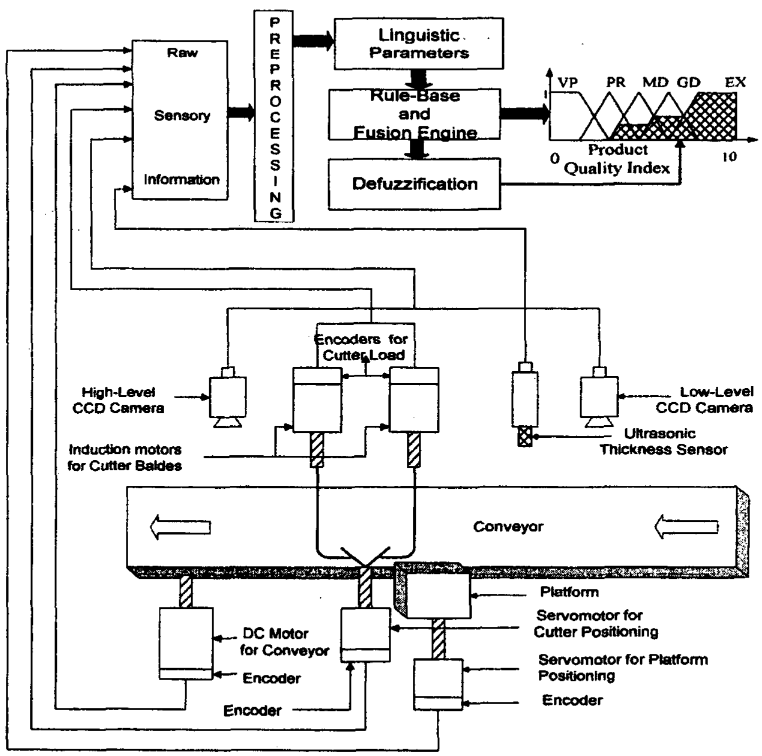

Figure 1. Schematic Diagram of the Overall System.

given assessment (measurement). Suppose that μ_1, μ_2, ... ,μ_n are the membership values related to the proposition $\theta \subset \Theta$, where $0 \le \mu_i \le 1$, for i = 1, 2........,n and n is the number of evidences to be fused. The membership values can have a range [0,1], and $\mu = e = 0.5$ corresponds to maximum fuzziness, meaning that the data is of no relevance to the hypothesis and thus its degree of certainty is zero. The degree of certainty of a measurement depends on how far the committed support is from the maximally fuzzy location. The combined deviation of μ_1, μ_2, ...,μ_n from the location of maximum fuzziness is obtained by calculating the average Minkowski distance given by following equation:

$$d = \left[\frac{1}{n} \sum_{i=1}^{n} (\mu_i - e)^{\alpha} \right]^{\frac{1}{\alpha}}, \qquad (1)$$

where α is odd; i.e., α = 1, 3, 5, ...,∞, and represents a normalization factor that preserves the degree of certainty associated with each μ_i. The fused value can be calculated as the sum of the combined deviations, d, and the location of maximum fuzziness i.e., $\mu = e = 0.5$, and is given by following equation:

$$\mu = e + \left[\frac{1}{n} \sum_{i=1}^{n} (\mu_i - e)^{\alpha} \right]^{\frac{1}{\alpha}}, \qquad (2)$$

As α is an odd integer, the value of $(\mu_i - e)^{\alpha}$ is negative if μ_i is less than e = 0.5, i.e., non-supportive evidences, and is positive for supportive evidences. The parameter α determines the weight of each evidence, which in turn expresses the relative importance of the combined effect of all the evidences. The fusion function as defined in equation (3) adjusts the weights related to each evidence in such manner that a support that is closer to the maximum fuzziness location, has only a small effect in the fused output value, while those near the crisp values have a quite large effect. The characteristics of the fusion function changes with the parameter α. If α = 1, then fusion function acts as an arithmetic mean. For $\alpha \ge 3$, the evidences with higher fuzziness have less effect on the fused output, and for $\alpha = \infty$ the fusion function acts as a *max* operator. In this paper, the value of α = 3 is used for obtaining the fused output

4. Fusion Method 2 – Based on Prod-Max Composition

Mamdani [4] proposed the compositional rule of inference for decision making in fuzzy logic control. The same method can also be used for fusing (combining) the fuzzified data from different sensors. Amongst various types of composition methods, *min-max* and *prod-max* are commonly used in engineering applications. If A_1 and A_2 are fuzzy sets with membership functions $\mu_{A1}(x_1)$ and $\mu_{A2}(x_2)$ then *prod-max* composition of A_1 and A_2 is given by following equation:

$$A_1 \circ A_2 \equiv \mu_{f(A_1,A_2)}(y) = \max_{x_1,x_2} prod[\mu_{A_1}(x_1), \mu_{A_2}(x_2)], \quad y = f(x_1,x_2) \qquad (3)$$

where the symbol " ∘ " denotes the *prod-max* composition. The decision making process comprises five steps: a) fuzzification of inputs, b) aggregation of fuzzified input variables, c) implication, d) aggregation of output fuzzy sets and e) defuzzification. In each rule that is fired there are multiple number of fuzzified input values, which are aggregated by applying fuzzy operators such as AND (*min*) or the OR (*max*). An implication operator such as *min* or *prod* is applied to establish the output fuzzy set. The output fuzzy set is clipped by the *min* operator and scaled by the *prod.* All the outputs generated by the rules in the rule-base are aggregated using the *max* operator. The last step is the defuzzification, which produces a crisp numerical value from the aggregated output fuzzy sets. Defuzzification using the centroid method produces the fused output; i.e., the product quality index; as given by:

$$u^* = \left[\frac{\sum_{i=1}^{n} u_i \cdot \mu_{out}(u_i)}{\sum_{i=1}^{n} \mu_{out}(u_i)} \right], \qquad (4)$$

for i = 1, 2,.......,n, where u^* is the crisp output value.

5. Implementation of Data Fusion

The implementation consists of four steps 1) Fuzzification of raw data; 2) rule-base generation; 3) fusion; and 4) defuzzification.

5.1 Fuzzification

The sensors involved in the fish cutting process are the CCD Cameras, the optical encoders, and the ultrasonic displacement sensor. Raw (crisp) signals from these sensors are preprocessed through specific filters to extract context based fuzzy sets (linguistic variables). The quality of processed fish is not amenable to simple quantification based on few dimensions, shape, or surface defects. The captured image is filtered to indicative parameters in the form obtain an arc-length profile and from it quality of linguistic variables are extracted. The quality indicative parameters are *Cut_depth* (D_c), *Cut_contour* (S_c) and *Cut_surface* (S_r). As shown in figure 2 (a), these parameters can take the three fuzzy states: *Poor (PR), Moderate (MD),* and

Good (GD). A larger value of D_c indicates a better cut, a larger value of S_c indicates a smoother cut, and a larger value of S_r indicates a smoother cut over the cutting region.

Primary sources of product quality information are the cameras; however, fusion of information related to the quality of cut from the other sensors such as encoders can increase the reliability of the output. The speeds of the induction motors that drive the cutter blades, is provided by optical encoders and used to calculate the slip and the cutting load. Preprocessing of these parameters provides a cutter load profile and from it performance parameters such as *Average_load (AL)* and *Assymetry_index (AI)*, are calculated. As shown in figure 2 (b) and (c), these parameters are given the three fuzzy states: *Small (SM)*, *Medium (MD)* and *Large (LG)*. The parameter *Average_Load (AL)* indicates the load on the induction motors over a single cutting cycle, and *Assymetry_index (AI)*, indicates the level of asymmetry in feeding a fish into the cutter (platform error). Assymetry is represented by the difference of loads between the top and bottom blade and alternatively by the offset of the platform position. Small values of these parameters indicate a better quality of cut.

Similarly, a quality indicative parameter is extracted from the responses of the DC servomotors, used for the horizontal positioning of the cutter unit and the vertical positioning of the platform. Quality of cut can then be deduced from the *Cutter_offset (CO)* and *Platform_offset (PO)*. As shown in figure 2 (d) and (e), these parameters are given three fuzzy states: *Small (SM)*, *Medium (MD)* and *Large (LG)*. A large value of offset will represent the wastage of meat and a small value will indicate a high accuracy of cut; i.e., the distance between the desired and actual positions is small. The smaller the offset the better the quality of cut.

The single output of the fusion process is the parameter, *product_ quality_index (PQI)*. It indicates the grade or level of product quality, calibrated on a scale of one to ten. As represented in figure 2 (f), it is assigned to take the five fuzzy states: *Excellent (EX)*, *Good(GD)*, *Medium(MD)*, *Poor(PR)* and *Very Poor(VP)*. The membership functions have been defined for the input and output parameters, the shape

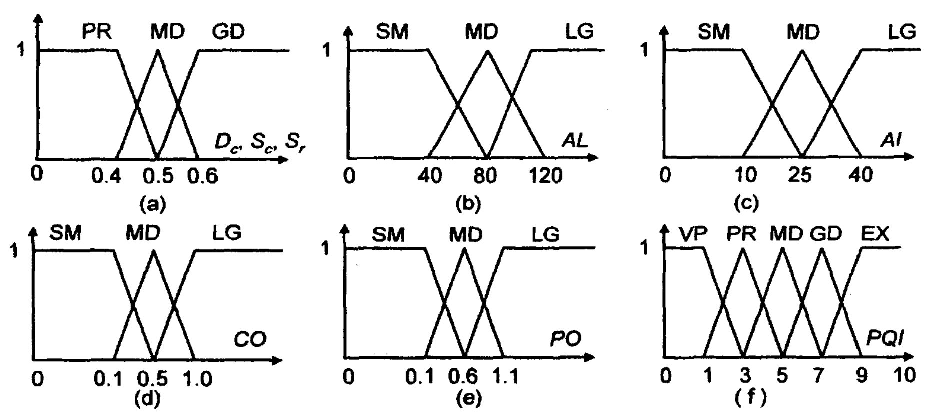

Figure 2. Membership Functions: (a) Cut_Depth (D_c); Cut_Contour (S_c); Cut_Surface (S_r) (b) Average_Load (AL); (c) Assymetry_Index (AI); (d) Cutter_Offset (CO); (e) Platform_Offset (PO); (f) Product_quality_Index (PQI).

Table 1. Rule-bases: (a) D_c = GD;

S_c \ S_r	GD	MD	PR
GD	EX	GD	GD
MD	GD	GD	MD
PR	MD	PR	PR

(b) D_c = MD;

S_c \ S_r	GD	MD	PR
GD	GD	MD	MD
MD	MD	MD	PR
PR	MD	PR	PR

(c) D_c = PR

S_c \ S_r	GD	MD	PR
GD	GD	MD	MD
MD	GD	PR	PR
PR	MD	PR	VP

Table 2. Rule-bases: (a) AL and AI

AL \ AI	SM	MD	LG
GD	EX	GD	GD
MD	GD	MD	PR
PR	MD	PR	VP

(b) CO and PO

AL \ AI	SM	MD	LG
GD	EX	GD	MD
MD	GD	MD	PR
PR	MD	PR	VP

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of these functions being either triangular of trapezoidal, and the overlaps have been decided on the basis of sensor variances.

5.2 Rule-base Generation

A fuzzy rule-base is characterized by a collection of linguistic statements expressed in the form of *if-then* rules. The rules for the fish cutting machine have been generated by making use of the experience and the knowledge gained by operators in the fish processing industry and extensive experiments performed in the laboratory [7]. In the present work, there are 45 rules, which relate the preprocessed inputs from the sensors to the fused output, i.e., the product quality index (PQI). Table 1 indicates the 27 rules in the form of linguistic matrices (a), (b) and (c). These rules relate the input parameters from the CCD cameras, such as *Cut_depth* (D_c), *Cut_contour* (S_c) and *Cut_surface* (S_r), to the product quality index. Matrices (a), (b) and (c) in Table 1 represent the rules for the condition that *Cut_depth* (D_c) is Good, Medium, and Poor, respectively.

Table 2 matrix (a) represents the 9 rules, which relate the input parameters from the induction motors, such as *Average_Load (AL)* and *Assymetry_index (AI)*, to the fused output, i.e., the PQI. Similarly, Table 2, matrix (b) represents the 9 rules, which relate the input parameters from the cutter servo and the platform servo, such as the *Cutter_offset (CO)* and the *Platform_offset (PO)*, to the fused output, i.e., the PQI.

5.3 Fusion

In the present application, there are three sets of rules within the rule-base. The first set comprises 27 rules, which relate the three input parameters from the CCD cameras specifically, *Cut_depth* (D_c), *Cut_contour* (S_c) and *Cut_surface* (S_r), to the *product_ quality_ index (PQI)*. Each rule that is fired, for a given input, provides an output (PQI), with a support $\mu(PQI)$. The following fusion formula combines the degree of support $\mu(PQI)$ of each output provided by all the fuzzy input values (D_c, S_c, and S_r), that make up this rule:.

$$\mu_i(PQI) = e + \left[\frac{(\mu_i(D_C)-e)^3 + (\mu_i(S_C)-e)^3 + (\mu_i(S_r)-e)^3}{3}\right]^{\frac{1}{3}} \quad (5)$$

where i = 1, 2,.......,27.

For the second set of 9 rules corresponding to cutter load data provided by the induction motors, there are two fuzzy inputs: *Average_Load (AL)* and *Assymetry_index (AI)*. The following formula combines the degree of support $\mu(PQI)$ of each output provided by the rules that fire:

$$\mu_i(PQI) = e + \left[\frac{(\mu_i(AL)-e)^3 + (\mu_i(AI)-e)^3}{2}\right]^{\frac{1}{3}}, \quad (6)$$

where i = 1, 2,......9. Similary, for the third set of 9 rules corresponding to the cutter and platform servo, there are two fuzzy inputs: *Cutter_offset (CO)* and *Platform_offset (PO)*. The following formula combines the degree of support $\mu(PQI)$ of each output provided by the rules that fire:

$$\mu_i(PQI) = e + \left[\frac{(\mu_i(CO)-e)^3 + (\mu_i(PO)-e)^3}{2}\right]^{\frac{1}{3}}, \quad (7)$$

where i = 1, 2,......9. By adding the equations (3), (4) and (5) the cumulative degree of support of the fused output $\mu(PQI)$ is obtained.

5.4 Defuzzification

Defuzzification is used to transform the fused output, i.e., product quality index, into a crisp numerical value. The defuzzification is based on the centroid method. For each fuzzy output value, the crisp value is calculated by the following method:

$$PQI = \left[\frac{\sum_{i=1}^{n} \mu_i(PQI)\mu_c(PQI_{ci})}{\sum_{i=1}^{n} \mu_i(PQI)}\right] \quad (8)$$

where n is the number of rules that are fired for a given input and $\mu_c(PQI_{ci})$ is the centroid of the fuzzy output for the i^{th} rule.

6. Illustrative Example

In this paper, the two fusion methods are applied to assess the determination of the product quality; i.e., the quality of the processed fish. Two cases are considered, one clearly represents a good cut and the other a bad cut. Table 3 indicates the crisp input parameters and the fuzzy set which they belong to, for the good cut and the bad cut.

These input values are fuzzified and corresponding support values, belonging to different fuzzy sets, are obtained.The fusion method based on the degree of certainty uses the fusion equations (5), (6), (7) and the defuzzification equation (8) to provide the product quality index. Similarly, Mamdani *prod-max* composition method uses the fusion equation (3) and the defuzzification equation (4) to determinethe PQI as a crisp numerical value on a scale of 0 to 10. MATLAB's Fuzzy Logic Toolbox with prod implication, max aggregation and centroid defuzzification is employed [8].

Table 3. Input Parameter Values for the example Cases

Inputs	Good Cut		Bad Cut	
	Crisp Values	Fuzzy Set	Crisp Values	Fuzzy Set
(Dc)	0.638	GD	0.384	PR
(Sc)	0.697	GD	0.550	MD, MD
(Sr)	0.730	GD	0.440	PR, MD
(AL)	99	MD, LG	149	LG
(AI)	17.63	SM	21.90	SM, MD
(CO)	0.1	LG	1.1	LG
(PO)	0.1	SM	2.0	LG

Table 4 shows the results obtained for the fused output; i.e., the product quality index, obtained by the two methods, for the good and the bad cut.

Table 4. Results for the Two Cases

Fusion Method Based on	PQI for Good Cut	PQI for Bad Cut
Degree of Certainty	7.0	2.9
Prod – Max Composition	6.7	2.6

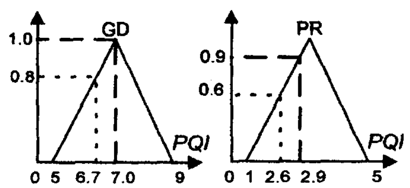

Figure 6 (a) Good Cut Figure 6 (b) Bad Cut

Prod-Max

Degree of Certainty

Figure 6 (a) and (b) indicate the defuzzified values of PQI and the corresponding membership values of the product quality indices for the fuzzy sets *GD(Good)* and the *PR(Poor)*, respectively. Table 4 shows that the results for PQI, obtained by the two methods do not differ to a great extent numerically, even though the degree of certainty method apears to provide crisper results. Figure 6 (a) for the good cut shows that the membership value of the defuzzified PQI for prod-max method is 0.8, and for the degree of certainty method it is 1.0. Similary, figure 6 (b) for the bad cut it is 0.6 for the prod-max method and 0.9 for the degree of certainty method . Analysis of these membership values clearly indicates that the results obtained by the degree of certainty method are more certain for both the good and the bad cut. Whether these results are more accurate from those from *prod-max* method can only be determined if the quality data are available a priori for a set of test measurements, using for example, the opinion of fish cutting experts.

7. Summary and Conclusion

This paper applied two methods of knowledge-based fuzzy sensor fusion for automatic evaluation of product quality of a fish cutting machine. The machine as developed in the Industrial Automation Laboratory, The University of British Columbia employs multiple sensors to reduce the wastage and improve the product quality. The fish cutting process is complex and the product quality assessment methods are subjective. The results in the form of a product quality index were obtained for a good cut and a bad cut of fish from the machine. The comparison of the results by the two methods does not indicate a substantial difference in the numerical values for the product quality, however, the results obtained by the method based on degree of certainty appear to be less fuzzy; i.e., more crisp or reliable. In fish processing industry the quality classification has only two levels, acceptable or unacceptable; however, the present work has extended this to a five level quality classification, thus providing higher resolution.

8. Acknowledgment

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