

BONES DETECTION FROM CHICKEN BREAST MEAT USING A COMPETITIVE HOPFIELD NEURAL NETWORK AND FUZZY FILTERING

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Abstract

The contaminant detection process of a food product is an important stage of a modern food production factory. The automatic detection of bones in raw chicken breast meat is a major problem. This paper presents a fuzzy reasoning algorithm for post-processing the segmented images of dual-band X-ray images of raw chicken breast. The results show that bone detection rates are considerably improved over non-fuzzy or crisp methods without increasing the false negative rate. Further work is proposed and recommendations made for improving the method.

Keywords: image segmentation, Hopfield neural network, fuzzy reasoning.

1. Introduction

Because there is an increase in demand for larger assortments of food products there was a need for automation of the processes involved in the preparation of the meat, fish or other food products. One of the most important processes is the removal of bones. Many fast and automated systems have been developed and are being used in the food industry to separate the meat and bones. During the automated meat processing stage, foreign bodies can remain in the meat. At a later stage the meat has to be inspected and the foreign bodies removed. The most important type of image used in commercial inspection systems is the X-ray image [4,5]. A summary of the process of detection of foreign bodies within the meat, based on acquisition of X-ray images of the products is depicted in figure 1. In meat production, the largest complaint and problematic area is that of the presence of fragments of bones in supposed bone-free products. Poultry bone-free meat is of particular interest to the industry because chicken carcass is much softer than

beef or pork and the occurrence of bone fragments within the products after the automated excision of bones process has a very high rate. Image segmentation is the first and the most important step in a contaminant/defect detection/inspection system used in the food industry. Most segmentation methods currently rely on simple thresholding algorithms [8,9,10]. The thickness of the meat is usually a function of a random variable and therefore simple thresholding algorithms cannot be applied to segment chicken X-ray images into objects. Our system uses a Competitive Hopfield Neural Network (CHNN) for the segmentation process of a dual-band image of raw chicken breast meat products [1,2]. The segmentation results need to be post-processed in order to eliminate segments, which indicate obvious non-bone objects. This paper describes a fuzzy reasoning algorithm that is used to discriminate between possible bone objects and non-bone objects from the segmentation process results.

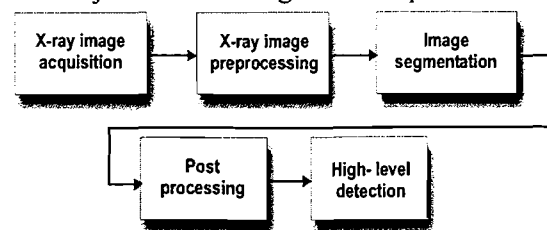


Fig.1: The process of detection of foreign bodies in meat products

2. Example Images for segmentation

A dual-band image was taken from chicken-breast meat: one high-energy image and one low-energy image from the same product (figure 2). The segmentation process is difficult due to the fuzziness of the X-ray images and the random thickness of the meat. Often, pieces of meat overlap creating a zone of high grey-level which masks the bones that might be present. The number of classes for the CHNN should be large enough that it eliminates the possibility of false negatives as much as possible but small enough to be computationally efficient. Thus the bones are guaranteed to be in the

segments found but the processing is computationally fast and the post processing is not going to produce too many false positives. It was determined experimentally that the number of classes for the segmentation process was 7. Segmentation into 7 classes is depicted in figure 3. The segmentation process generates objects of different sizes and shapes some of which are possible bones. Large areas are present along with very small areas that may contain "air". Thus, the segmented image needs to be post-processed in order to facilitate high-level object detection



Fig.2: Example of the low-energy and high-energy X-ray images for a chicken breast meat product containing 4 bones



Fig.3: Segmentation result

3. Fuzzy determination of objects indicating the presence of bones

Our proposed architecture consists of two fuzzy filtering Mandami-type modules [3,11] (figure 4). First module is in charge of deciding whether a region or area corresponds from the geometrical point of view. The second module is used only if the output of the first module confirms the possibility of the current area being a bone. It consists of a second fuzzy decision based on statistical grey-level characteristics of the region in question.

A first step was to define the standard fuzzy sets describing the generated areas geometrical properties. From each region, five measures were taken. The first and the most important one is the number of pixels contained in that area: **AREA_SIZE**. The second measure was the size of the air holes contained within the object: **HOLE**.

This reflects the homogeneity of the area in question. These measures were defined as fuzzy sets using a trapezoidal membership function. **PERIMETER** was another important measure computed. It consists of the number of pixels at the edge of the region in question. The **SHAPE** feature is a measure of the shape of an individual region.

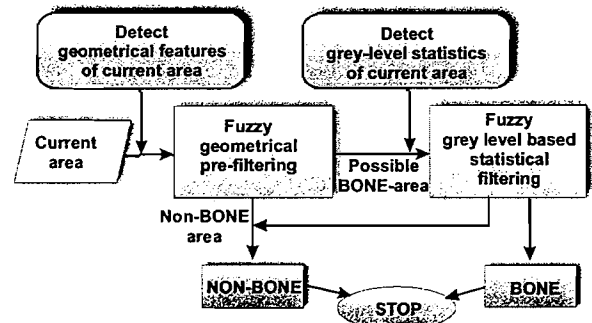


Fig.4: Proposed fuzzy filtering system

The compactness of a shape is derived from the ratio of the perimeter length of the shape divided by its area:

$$SHAPE = \frac{PERIMETER}{AREA} \quad (1)$$

The **ROUNDNESS** measure [7] is defined as follows: if the region is a circular one then it has a high roundness measure, if it is an ellipse or of a different shape it has a low roundness measure. In defining this concept a reference circle was used with its centre in the centre of gravity of the current region and with a similar area size. Therefore the concept was defined as the difference between the two areas (pixels that do not belong to the region but belong to the reference circle- A_1 ; and pixels that belong to the region but do not belong to the reference circle- A_2):

$$ROUNDNESS = 1 - \frac{A_1 + A_2}{2 \cdot region_area} \quad (2)$$

Examples for calculation of different measures are presented in table 1.

A Mandami-type fuzzy system with 5 inputs, a single output and 11 rules that apply geometrical constraints was built [10], [11]. The crossover points between neighbouring membership functions were determined experimentally. The linguistic variables defined for the concepts presented above are presented in table 2. Their corresponding fuzzy sets are also presented in figure 5. Examples of the rules used are presented below:

1. if **SHAPE** is **IRREGULAR** then **OUTPUT** is **NO_BONE**

2. if **AREA_SIZE** is *MEDIUM* and **HOLE** is *SMALL* and **SHAPE** is *SMOOTH* and **PERIMETER** is *SHORT* and **ROUNDNESS** is *HIGH* then **OUTPUT** is *NO_BONE*
3. if **AREA_SIZE** is *SMALL* and **HOLE** is *SMALL* and **SHAPE** is *SMOOTH* and **PERIMETER** is *SHORT* then **OUTPUT** is *POSSIBLE_BONE*
4. if **AREA_SIZE** is *BIG* and **HOLE** is *SMALL* and **SHAPE** is *SMOOTH* and **PERIMETER** is *SHORT* and **ROUNDNESS** is *HIGH* then **OUTPUT** is *POSSIBLE_BONE*

Table 1: Roundness measure examples




Roundness	Image	Output
31.18%		Possible bone area
72.80%		Non-bone area
88.54%		Non-bone area

Table 2: Linguistic variables defined for the system

Geometrical features	Grey-level based features
AREA_SIZE: <i>tiny, small, medium, big, large</i>	BRIGHTNESS: <i>low, high</i>
HOLE: <i>small, big</i>	DIFFERENCE: <i>big, small, negative</i>
PERIMETER: <i>short, long</i>	TOGETHERNESS: <i>loose, close</i>
SHAPE: <i>smooth, irregular</i>	
ROUNDNESS: <i>low, medium, high</i>	

The basic principle for the area in question was: if the area is within its accepted size and it does not contain big holes and it has an accepted measures of shape and roundness, then the object is treated as being a possible bone; otherwise, the object is considered as being non-bone and it is eliminated from later high-level detection (second fuzzy grey-level statistics module is not necessary).

The second fuzzy-filtering module consists of 3 inputs and 5 rules, derived by summarizing the knowledge gathered from direct observations and human experts. The statistical measures computed here were the **BRIGHTNESS** of the area in question, the **DIFFERENCE** between area intensity and its neighbourhood intensity and the **TOGETHERNESS** (RMS intensity) of the region (their membership functions are presented in figure 6). The first measure corresponds to the mean intensity of the grey-levels for the current region. The second measure is defined as the difference between the mean intensity for the region and the mean intensity for the neighbourhood of the same area. Both high- and low energy images were used when computing those two measures. The third measure was taken only as a safety feature for the segmentation process

and it refers to the homogeneity and heterogeneity of the region [8]. Small variations of grey level within the same region make it homogenous, whereas high transitions make it heterogeneous. Even if the segmentation process should provide only homogenous areas, as a safety feature, the **TOGETHERNESS** concept was used:

$$TOGETHERNESS = \sqrt{\frac{\sum_{\text{pixel}(i,j) \in \text{Area}} (I_{\text{pixel}(i,j)} - \text{Brightness})^2}{\text{Area_size}}} \quad (3)$$

Some of the 5 rules used in the second fuzzy module were:

1. if **DIFFERENCE** is *SMALL* and **BRIGHTNESS** is *LOW* then **OUTPUT** is *NO_BONE*
2. if **TOGETHERNESS** is *LOOSE* then **OUTPUT** is *NO_BONE*
3. if **DIFFERENCE** is *BIG* and **TOGETHERNESS** is *CLOSE* then **OUTPUT** is *BONE*

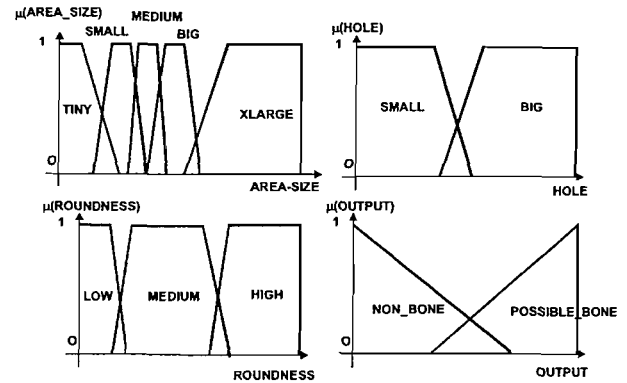


Fig.5: Membership functions for Area, Hole, Roundness and Output concepts

A crisp input was also added as a method to set the sensitivity of the detection process. This was used in the second fuzzy module to decrease or increase the weight of rules 1 and 5. There is a trade-off between the sensitivity of the detection process and the false positives (area that are not bones but reported by the system otherwise). For a high sensitivity, the system will detect all of the bones, but also false-positives will be generated. In contrast, for normal detection sensitivity, no false positives appeared, but bones that are of a high brightness surrounded by a low contrast neighbourhood, were not detected. One can set their own sensitivity parameter in order to meets their specific detection criteria.

Results are shown in figure 7. As it can clearly be seen from the figure 7 and 8, there is a significant decrease of the number of **POSSIBLE_BONE** areas. The fuzzy approach to detection was tested on 50 images and the average decrease in the number of possible bone areas was 85.7% with the worst figure at 25% and the best figure at 100%.

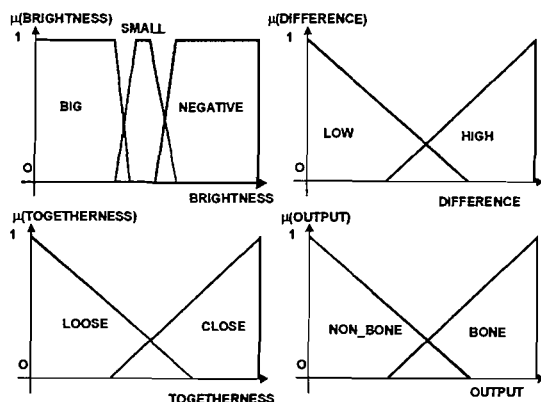


Fig.6: Membership functions for Brightness, Difference, Togetherness and Output concepts

4. Conclusions

This paper concerns the detection of bones of dual-band X-ray images from chicken breast meat by means of image segmentation and fuzzy post-processing reasoning. The overall number of computations associated with the proposed system is lower in comparison with other segmentation techniques proposed, i.e. morphological filtering [5]. The major advantage of these techniques is that only the histogram information of both images is used in the CHNN as opposed to spatial constraints that will lead to increased overhead. This study proved the applicability of a fuzzy rule-based post-processing approach for the detection of foreign bodies within a dual-band X-ray image. Future work will concentrate on minimizing even further the computational overhead involved and on the improvement of the fuzzy-post processing

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reasoning. This may be achieved by adding other measures such as fuzzy inputs. Automatic generation of the number of classes that now needs to be known *a priori* for the CHNN, is currently under investigation by the use of fuzzy logic processing of the histograms. The present architecture can be easily extended to colour-image segmentation and it has a great deal of potential for hardware implementation (VLSI parallel hardware implementation).



Fig.7: Results of fuzzy reasoning for high sensitivity (left) and normal sensitivity (right)

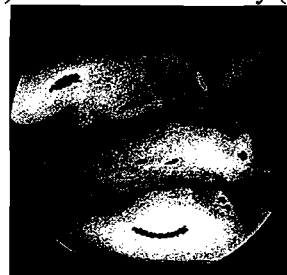


Fig.8: Results of crisp approach to detection