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Fusion of Visible and X-Ray Sensing Modalities for the Enhancement of Bone Detection in Poultry Products

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ABSTRACT

The U.S. demand for deboned chicken has risen greatly in the past 5 years, with the expectations that this demand will only continue at an accelerated level. The standard inspection process for bones in meat is for workers to manually feel for bones. It is clear that this time-consuming manual inspection method is insufficient to meet the increasing demand for deboned meat products. Georgia Tech Electrical Engineering faculty and Research Scientists in conjunction with a leading x-ray equipment manufacturer are working together on the development of a system to fuse information from visible images and x-ray images to enhance the accuracy of detection. Currently there are some bones that x-ray systems have difficulty detecting. These are usually relatively thin and are located near the surface of the meat. A primary example is a fanbone (so called because of its shape). We will describe and present results from work geared towards the development of an integrated system that would fuse visible and x-ray information. Significant benefits to the poultry industry are anticipated in terms of reduced processing costs, improved inspection performance and increased throughput through the use of the integrated system to be described. Additionally, generic aspects of the proposed technologies may be applicable to other food processing industries.

Keywords: Machine vision, x-ray, sensor fusion, color, food processing

1. INTRODUCTION

Cut up and further processed products are the fastest rising segment of the U.S. poultry industry's product lines. Figure 1 illustrates the fact that since 1990 the production of whole birds has dropped from over 90 percent of overall production to less than 20 percent. The result is that more products are now being deboned or cut up in order to better meet consumer demand.

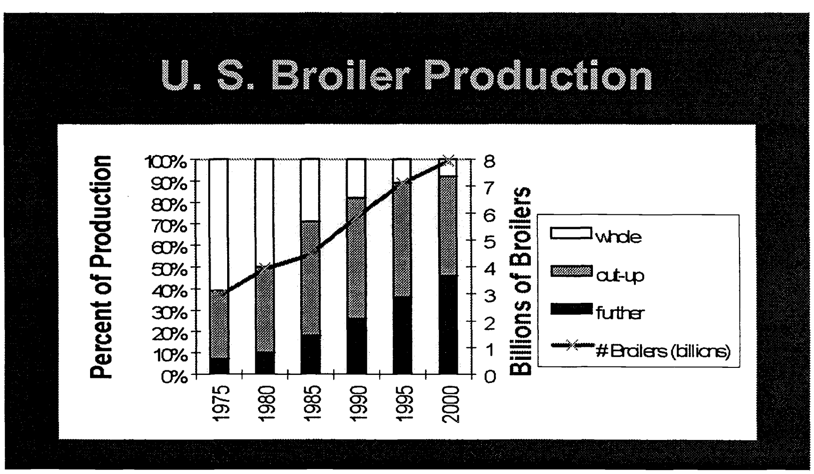

Figure 1: U.S. Broiler Production

With the increased consumption of these products, bones, have now become the third most common complaints for all chicken products.[1] Data on insurance claims are not readily available but one U.S. facility had an average of 50 complaints per year in which they made settlements due to claims on bones.[1] There are other costs that are difficult to quantify such as

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the cost of rework in terms of lost product as well as labor to conduct the rework. This is a significant enough problem however that plants rely either on people to do visual and tactile inspection, or other kinds of automated inspection systems to minimize the possibility of bones ending up in the products that reach the consumer.

Deboning is currently conducted in three ways: manual deboning, semi-automated deboning and fully automated deboning. Manual deboning lines are cone lines in which there are several stations where people make a sequence of cuts to allow for removal of the desired portions of meat. This process has the attendant problems of cumulative trauma disorders (CTDs) along with excessive labor costs, which can be problematic in a tight labor market. The semi-automated systems utilize humans to make some of the key initial cuts and to conduct a variety of trimming operations. The fully automated systems utilize a human just to load the machine with the front halves. The latter systems are not as popular in the U.S. as it is felt that the yield of these machines is lower than acceptable for current market conditions.

One study has found that there are 25% fewer bones in the manual method than in the automated techniques.[2] This implies that as we continue to use automation the need for more reliable inspection systems will continue to be a major requirement. This is representative of a more general problem in food processing, however, where the problem of foreign bodies in produce is a serious concern and the need for intelligent sensing and detection systems will be more pressing in the future. [2]

2. PROBLEM DESCRIPTION

X-ray based equipment has been used as a viable but expensive means to address the problem of automated inspection of deboned meat. Performance evaluation criteria are unfortunately not uniform for these systems and manufacturers claim a wide range of performance specifications for their product. Feedback from customers using data derived mostly from beta testing of purchased systems; indicate false positive rates anywhere where from 3-4% to 12-13%. It is evident that both equipment manufacturers and meat processors generally agree on a need for improved performance to meet their customer's strict specifications. It is also recognized that, although x-raying can deliver a certain level of performance and that new developments might make it easier to distinguish soft tissue[3], other sensing strategies may be required to complement and enhance this technology in order to improve performance without exceeding cost constraints.

Spectral Fusion Technologies (SFT) Limited provides such a system with high detection accuracies for most of the bones of concern. The machine however has difficulties with the detection of fanbones, which are given that name because they have the shape of a fan. Currently the system detects fanbones with accuracy rates around 30%. Fanbones are typically less dense and of lower thickness perpendicular to the x-ray beam making it difficult to detect these bones using the same settings that are needed for the other bones normally found in the meat. This is because the machine needs to be optimized to detect embedded bones and also to handle the variety of meat thickness to be accommodated. An approach using a dual energy system could be considered but this would serve to increase overall system costs and complexity. Fanbones are visible however, and typically occur on the surface. One approach toward enhancing the performance of such a system is to use another mode of sensing; such as color machine vision to identify these fanbones, and then to fuse the information from both modalities to make the final decision.

3. APPROACH

Example images of both the visible and x-ray images for the same part are shown in Figure 2 and Figure 3. It can be observed that the fanbone in the visible image is barely noticeable in the x-ray image. Additionally, it can also be observed that in the visible image there are parts of the breast meat that due to blood spots, bruising or the efficiency of killing that could appear as a fanbone due to their color and shading.

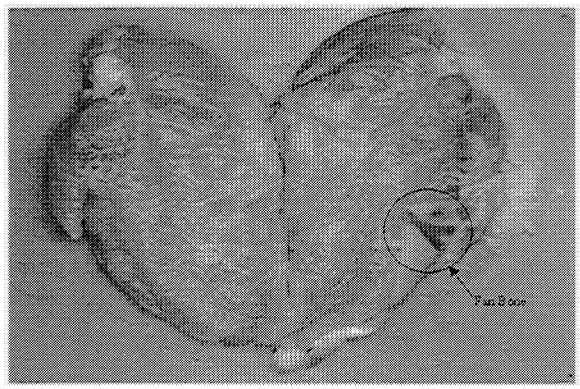


Figure 2: Example image of a breast with fanbone

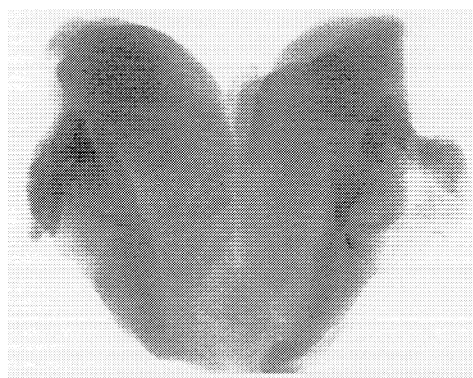


Figure 3: Example x-ray image of breast with a fanbone.

The strategy to be employed would be to process both the visible data along with the data from the x-ray image and to fuse this information. There are probably three levels at which fusion could occur. These would be the report, decision and pixel levels. Initially it would be easier to fuse at the report level where if the result of the visible processing says that there is fanbone the x-ray system would be notified and could then report the presence of bones of either type. The decision level would directly use the information from both systems in concert to decide on the type of bone present. The pixel level determination would take this one step further where it would use pixel features in the determination. This paper will look at the approaches for visible image processing to identify and locate the fanbones.

4. VISIBLE DATA PROCESSING

The first stage in this process is to attempt with a high rate of accuracy to locate the presence of fanbones in the visible images. This task is complicated by the fact that there are aspects of the surface that could look visually like fanbones, which result as noise in the processed images. Additionally there are changes in the color properties of the product with time and the system within limits should be able to accommodate these changes. The change in R, G, and B color for sample breast meat is presented in Figure 4 as a function of time. Especially with the move to continuous processing where the aging is conducted in the chiller it is likely that we would be operating on the transient portion of the curve shown in Figure 4.[2] An approach robust enough to surmount these problems is necessary.

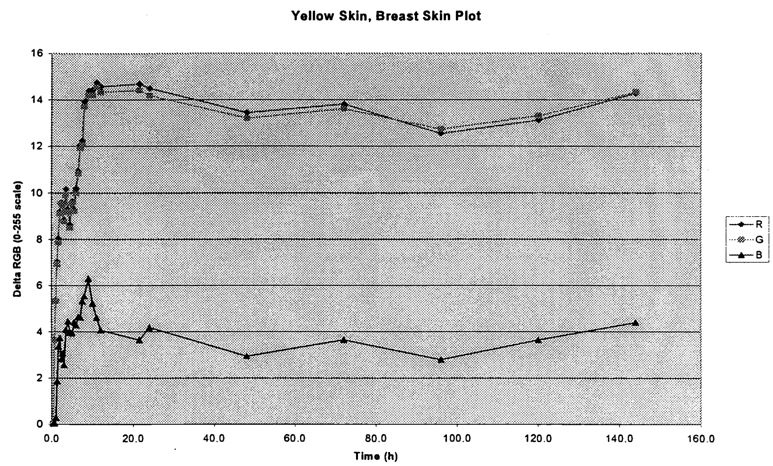


Figure 4: Color Changes vs. Time For Breast Meat[4]

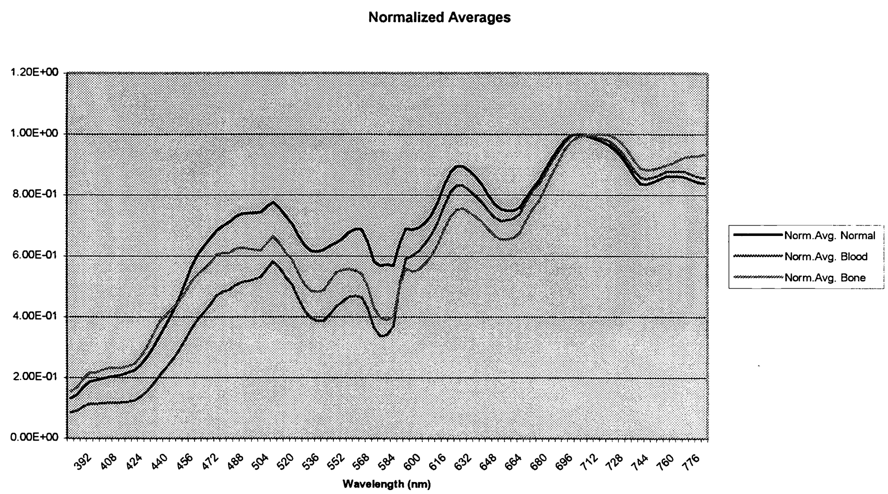


Figure 5: Normalized Averages of Spectral Responses

Color Image Processing

Using an internally developed program called VIPER, which provides an environment for testing and developing color machine vision algorithms; we were able to evaluate an approach towards the location of fan bones. This was accomplished by looking at the relative changes in the color values as we transitioned from bone to meat and meat to bone and developed heuristics based on these transitions. Heuristics were obtained by looking at the spectral data from the different parts of the surface of the breast in Figure 5. Using a model for the spectral response of a color camera the output energy for each color band can be obtained using Equation 1.

$$e_i = \int_{\lambda vis} Si(\lambda)R(\lambda)D\lambda \qquad (1)$$

where $i = R, G, B$

e_i = band energy

λvis = visible part of the electromagnetic spectrum

$S(\lambda)$ = the camera sensor response

$R(\lambda)$ = the spectral distribution of the energy for the parts under consideration.

Expected photometric band energy for bone and normal breast meat are shown in Tables 1 and 2.

Bone Source Power lumen/m^2			
	Sample 1	**Sample 2**	**Sample 3**
r	0.75	0.44	0.73
g	0.51	0.35	0.55
b	0.46	0.36	0.52

Table 1: R, G, B Power Bone Samples

Meat Source Power lumen/m^2				
	Sample 1	**Sample 2**	**Sample 3**	**Sample 4**
r	1.02	0.97	1.11	0.94
g	0.72	0.62	0.74	0.61
b	0.60	0.46	0.56	0.46

Table 2: R, G, B Power Breast Meat Samples.

From this data it is observed that these are overall lower red values for the fanbones and closer relationships between the g and b values for the bones, as compared to the meat.

It is expected that the RGB values in the image would be directly proportional to the energy and these general heuristics were used to develop the algorithm. In order to speed up the processing we computed the RGB values averaged over blocks of data 5x5 pixels wide. This is much smaller than the averaged sized fan bone and so there is a low probability that we will miss fanbones using this technique.

Output images processed using this approach are shown in Figure 6 and Figure 7. The first one shows an image with no fan bone and the designation clean to denote the fact that this piece of meat was found to be bone free. (Figure 6) The second image shows the processing for a breast that actually has a fanbone with the fanbone area circled. (Figure 7) The computational times using this approach are on the order of a half a second so we should be able to easily match speeds of up to 60 pieces per minute which is the average speed of the current machines.

The other major item of note about this approach is that while its detection accuracy is very high (close to 100%) tested on approximately 60 images. One potential problem is that the approach does not always accurately represent the morphology of the bone and in some cases the areas represented are much less in area than the total area of the fanbone. This would lead one to think that noise might be factor that could affect its performance in the field. In these cases we should look at the use of other techniques to enhance and support this approach. The use of the snake routines that we are currently developing would serve this purpose.

Figure 6: Processed sample image without fanbone..

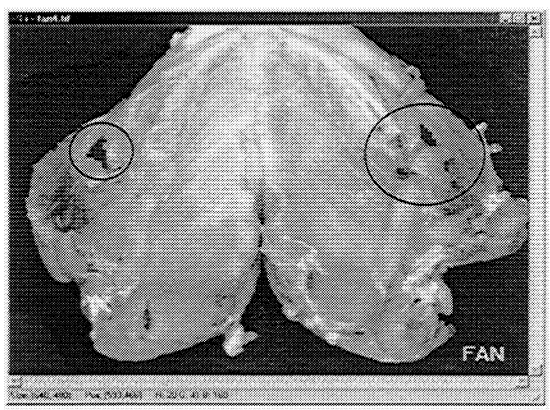


Figure 7: Processed sample image with fanbone identified..

5. POST PROCESSING

As mentioned earlier, even with the algorithms above, there will still be situations in which we might not be completely certain about the determination of a fanbone using strictly color processing; this implies there will be times when we will need supporting information. One useful feature is shape, as it is somewhat distinctive, and might be obtained through the use of snakes.

Snakes

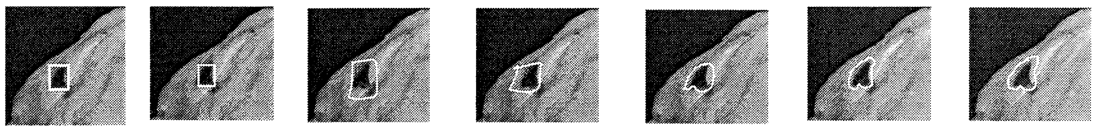
Since the introduction of the snake methodology active contours have become particularly popular for segmentation applications. The snake method we used in this project is the fully global segmentation algorithm using coupled curve evolution equations.[3] This method combines curve evolution and statistics in a natural way for images consisting of a known number of region types. Multiple sets of contours, each with its own curve evolution equation, are employed to segment an image into multiple region classes. This approach is fully global in that the evolution of each boundary depends on the pixels within the two regions on either side.

The key idea behind the coupled curve evolution model is to design curve evolution equations, which "pull apart" the values of one or more image statistics (e.g. means, variances, textures) within each set of contours and the background. A global constraint is added to dictate that the flows not only separate the relevant statistics but also prevent the statistics to evolve in the same direction.

The level set methods of Osher and Sethian are adopted for numerical implementation of the coupled curve evolution model. This implementation handles topological changes (merging or splitting) of the boundaries and was the viscosity solution at nondifferentiable points (e.g. corners) in a natural and seamless way. More details on the approach are given in the Appendix and associated reference.

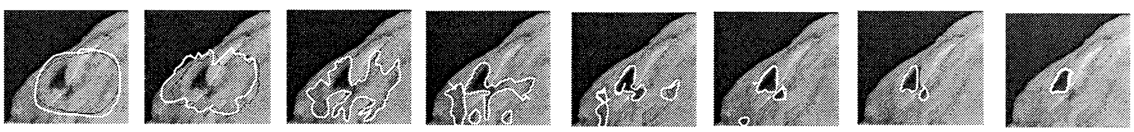
Simulation

We applied the coupled curve evolution models with global constraint on the suspected regions on the chicken images. As long as the initial contour captures part of the fan bone area and there is a fair contrast between fan bone and meat the boundary can be correctly located as shown in Figure 8 and Figure 9.



a) initial contour   b) i = 5   c) i = 10   d) i =15   e) i = 20   f) i = 25   g) i = 30

Figure 8: Evolution of the snake outline with a rectangular arbitrary initial contour.



a) initial contour b) i = 50   c) i = 150   d) i =200   e) i = 225   f) i = 250   g) i = 400   h) i = 850

Figure 9: Evolution of the snake outline with an arbitrary initial contour.

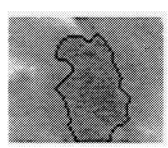


Figure 10: False contour located in a dark portion of the meat.

The number of iterations varies with the size of the image, the position of the initial contour, and the parameters of the algorithm. Figure 8 and Figure 9, shows the evolution of the contour using initial contours of two different shapes. It is seen that in both cases the curve collapses to the shape of the fanbone where it would then be possible to perform shape analysis on the contour to see if it matches the expected shape of a fanbone. We also show in Figure 10 the evolution of a contour around a dark portion of meat, which would result in a false contour. We will, however; use the color processing to choose target regions for the operations thereby reducing this possibility.

6. RESULTS AND CONCLUSIONS

The techniques presented using color processing are able to detect the presence of surface fanbones at relatively high rates of speed and high accuracy. To handle a situations where our confidence level on the presence of a fanbone is low we propose to locate the contours using snakes to further solidify the determination based on its shape features. Further enhancements to this approach could be obtained by the definition of different functionals, which could reduce the potential of error identified previously. Investigations into those other approaches are underway.

With these outputs we are now capable of fusing the results with the x-ray system at the report level, to make the decision on the status of a given part. Further work will look into the integration of test bed for real time evaluation and also to look at the possibilities of fusing of the decision and pixel levels.

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APPENDIX

The coupled curve evolution equations

The chicken images can be considered a bimodal image I (x, y) (Figure 2) which consists of fan bone R (foreground) and meat Rc (background). The intensity of the foreground Ic is smaller than that of the background Ir: Ic < Ir. We wish to determine an evolution that will continuously attract an initial closed curve toward the boundary ∂R of R. Given that the curve will enclose some portion of R and some portion of Rc, the average intensities u and v inside and outside the curve respectively are bounded above and below by Ir and Ic. Consequently, using the distance between u and v to measure how well the curve has separated the fanbone from the meat will ensure an upper-bound of | Ir - Ic | that is uniquely attained when the contour = ∂R. A related strategy would be to descend along the following quadratic energy functional:

$$E = -\frac{1}{2}(u-v)^2 \tag{2}$$

Now consider the global constraint that u and v must evolve in the opposite direction, that is, $u'v'<0$, which leads to the following condition

$$\Gamma(u, v)(\Gamma(u, u)+ \Gamma(v, v))< \Gamma(u, u)\, \Gamma(v, v)+ \Gamma^2(u, v) \tag{3}$$

where

$$\Gamma(u,u) = \frac{1}{A_u A_u} \oint_{\vec{C}} (I-u)(I-u)ds \tag{4}$$

$$\Gamma(u,v) = \frac{-1}{A_u A_v} \oint_{\vec{C}} (I-u)(I-v)ds \tag{5}$$

$$\Gamma(v,v) = \frac{1}{A_v A_v} \oint_{\vec{C}} (I-v)(I-v)ds. \tag{6}$$

where Au = area of the defect region inside the contour.

where Au = area of the non - defect region inside the contour.

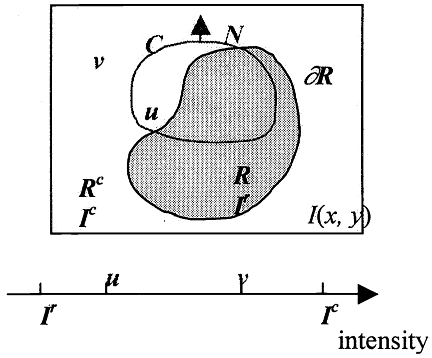

Figure 11: Bimodal image and the closed curve.

Then a flow which optimally separates the mean intensities inside and outside the evolving curve while keeps them separating in the opposite direction is:

$$\frac{d\vec{C}}{dt} = -\nabla E = (u-v)\left(\frac{I-u}{A_u} + \frac{I-v}{A_v}\right)\vec{N}, \text{ when Equation 3 is satisfied,} \tag{7}$$

otherwise,

$$\frac{d\vec{C}}{dt} = \begin{cases} \dfrac{u-v}{A_v}((I-u) + \gamma_u (I-v))\vec{N}, \text{ fix u.} \\ \dfrac{u-v}{A_u}((I-v) + \gamma_v (I-u))\vec{N}, \text{ fix v.} \end{cases} \tag{8}$$

where the constants γ_u and γ_v are defined by

$$\gamma_u = \frac{\oint_{\vec{C}} (I-u)(I-v)ds}{\oint_{\vec{C}} (I-u)(I-u)ds} \quad \text{and} \quad \gamma_v = \frac{\oint_{\vec{C}} (I-u)(I-v)ds}{\oint_{\vec{C}} (I-v)(I-v)ds} \tag{9}$$