A PHOTOGRAMMETRIC METHOD FOR ENHANCING THE DETECTION OF BONE FRAGMENTS AND OTHER HAZARD MATERIALS IN CHICKEN FILETS

S. Barnea[a,*]   V. Alchanatis [b]   H. Stern[a]

[a] Dept. of Industrial Engineering and Management, Ben Gurion University of the Negev, 84105 Beer-Sheva Israel – (barneas, helman)@bgumail.bgu.ac.il
[b] Inst. of Agricultural Engineering, The Volcani Center - ARO, 50250 Bet Dagan, Israel – victor@volcani.agri.gov.il

Commission TS, WG V/I

KEY WORDS: Close Range, DEM, Automation, Color, Industry, Photogrammetry

ABSTRACT:

The research suggests a system that automatically generates Digital Elevation Model (DEM) of a chicken filet. The DEM is generated by close range photogrammetry methods, using stereoscopic images of the chicken filet. A major problem of the photogrammetric process is the uniformity of the chicken filet's color and texture, which makes it hard to find matching-points in the two stereo images. The research suggests a method to enhance the accuracy of the photogrammetric process, based on the projection of a continuous multi-color pattern on the chicken filet. The projected pattern is iteratively designed based on the object's optical and textural features and on the image acquisition and projection systems color definition abilities. System measurement accuracies were within the specified limit of .5 mm in height.

1. INTRODUCTION

Accurate detection of bone fragments and other hazards in de-boned poultry meat is important to ensure food quality and safety for consumers. Automatic machine vision detection can potentially reduce the need for intensive manual inspection on processing lines.

Current X-ray technology has the potential to succeed with low false-detection errors. X-ray energy reaching the image detector varies with uneven meat thickness. Differences in X-ray absorption due to meat unevenness inevitably produce false patterns in X-ray images and make it hard to distinguish between hazardous inclusions and normal meat patterns. Although methods of local processing of image intensity can be used, varying meat thickness remains a major limitation for detecting hazardous materials by processing X-ray images alone.

An approach to overcome the aforementioned difficulties is to use an X-ray imager in conjunction with the chicken filet thickness algorithm, yielding a thickness-invariant pattern recognition system

2. PROBLEM DEFINITION AND OBJECTIVE

The present work addresses the problem of automatically generating a 3D model of a chicken filet when it passes under an imaging system on a conveyer. The 3D model of the chicken filet is expressed in terms of a digital elevation model (DEM). The DEM should satisfy the following specifications.

1. The DEM should represent an area of 300 square millimeters. This is the area represented by the X-ray imaging system.
2. Every number of data in the DEM matrix will represent 1 mm^2 in world coordinates, which means that the DEM matrix dimensions will be 300 by 300. This resolution is satisfactory for detection of most hazardous materials.
3. The DEM error at each point should be less then 0.5mm in height.
4. The speed of the conveyor is 1 feet (304.8mm)/sec, which means that the time required generating a single DEM must be less then a second.

3. METHODS FOR GENERATING A DEM

3.1 Moiré Pattern

A powerful way of describing a three-dimensional shape is to draw contour lines. A Moiré pattern is an interference pattern resulting from two superimposed gratings. The geometry of the moiré fringes is determined by the spacing and orientation of the grids. If we know the grids and can image the moiré pattern formed on the surface, we can determine the topography of the surface.

There are number of ways to produce moiré patterns and to use them to determine object topography. In the shadow moiré technique, a reference grid is placed close to the object and illuminated so that it casts a shadow on the object. The shadow of the reference grid is distorted by the object's topography. If the light source and viewing point are at the same distance from the reference grid, the moiré fringes represent contours of depth with respect to the reference grid.

In a projection moiré, a reference grid is projected onto the object. The projection is distorted by the object topography. This distorted version of the grid is imaged through the reference grid, and a moiré pattern is formed on the image plane.

The main disadvantage of the methodology is that the depth of the surface under test is limited to not more than several tens of the wavelengths of light used. (Yu et al. 1997; Paakkari et al. 1998; Mikhail et al. 2001; Karara 1989)

3.2 Light Stripping

Light stripping is a particular case of the structured light technique for range sensing. A light striping range sensor consists of a line projector and a camera that is displaced from the light source. The line projector casts a sheet of light onto the scene. The projection of the plane on the surface results in a line of light. This line is sensed by the camera. The light plane itself has known position in world coordinates that can be determined by measuring the geometry of the projection device or by direct measurements of the resulting plane of light. Every point in the image plane determines a single line of sight in three-dimensional space upon which the world point that produces the image point must lie.

This methodology requires a large amount of images. In this method each image contributes a single profile of the object. Generating a DEM with the desired resolution and speed requires capturing and processing of 300 frames per second (Mikhail et al. 2001; Karara 1989).

3.3 Coded Light Projection Techniques

Among all the ranging techniques, stereovision is based on imaging the scene from two or more known points of view and then finding pixel correspondences between the different images in order to triangulate the 3D position. Triangulation is possible if cameras are calibrated (Salvi 2001). However, finding the correspondences poses difficulties even after taking into account epipolar constraints. Coded structured light consists of substituting one of the cameras by a device that projects a light pattern onto the surface. Since each point in the pattern is encoded in a way that identifies its coordinates, the correspondence problem is solved with no geometrical constraints. With an appropriate light pattern, correspondences of a large number of pixels can be found. Thus, coded structured light may be used as a solution to simplify the inherent problem of finding correspondences in classical stereovision systems. (Pag`es 2004)

4. OBJECTIVE

Considering the advantages and disadvantages of the methodologies presented above, the specific objective of the present work was to develop a DEM generation system for chicken filets using a coded light projection technique.

5. DESCRIPTION OF THE SYSTEM

The imaging system contains several major hardware parts (Fig. 1) (a) a projection unit including the projector itself, (b) a computer which creates patterns that are projected on the object and (c) two cameras to capture a stereoscopic view of the object. The images from the two cameras are sent to frame grabber in the host computer where the analysis is preformed.

Figure 1 Major hardware parts

In order to calculate the object's height the first task is to determine the point in the space, where the cameras center of projection is located, and its orientation. This process is essential in order to build the 3-D model of the object and for finding the epipolar lines. The aim of this calibration process is to find the six extrinsic parameters for each of the cameras. These parameters contain three location parameters (Xt, Yt, Zt) in millimeters, and three orientation parameters (phi, epsilon, kappa) in radians. In order to calculate the parameters, an image of a calibration object with marked points of known world coordinates was acquired by each one of the cameras. SPR (Single Photo Resection) method was used to estimate the extrinsic parameters of each camera. (Mikhail et al. 2001)

After obtaining an estimate of the cameras' extrinsic parameters, the height of any point on the object is calculated by finding its corresponding pixels in the two images and the principle of triangulation. In order to overcome the correspondence problem a continuous color pattern is projected on the object.

6. THE PROJECTED PATTERN

Several methods for overcoming the correspondence problem using projected color patterns can be found in the literature (Tajima et al. 1990; Geng 1996; Sato 1997; Wust and Capson 1991). Those researches present global methods to use a projection that will fit any object. Those objects may be multi-color and multi-texture bodies. Caspi et al. (1998) analyze the illumination model of a structured light system. This model takes into account the light spectrum of the LCD projector, the spectral response of a 3-CCD camera and the surface reflectance. The main benefit of this model is that it assumes a constant reflectance for every scene point in the three RGB channels (Pag`es 2004). Preliminary tests showed that when transforming an image of a color projection captured in RGB to HSL (Hue Saturation Lightness) the hue channel contains most of the information, while the other two channels contain mostly noise. Caspi's work also defined a noise immunity factor α, and presented the relationship between α and the number of possible strips. The number of possible strips in the projected pattern depends on the maximum accuracy under constrains of the projection / sensors equipment.

The structured light technique that is presented in the present work can cover different values of α, across the different RGB intensity values. The sensitivity of the CCD sensors changes across the spectral range. The projected patterns can be

squeezed or extended in order to include the regions where the system can efficiently differentiate between color levels.

The colors and texture of chicken filets are relatively constant among filets, and are also uniform across the filet itself. The system presented in this work addresses the problem of matching points in stereoscopic images for objects with uniform color and texture. The main idea is to project a non-uniform varying color pattern. In some wavelengths the spectrum of the reflected color pattern will change rapidly, but in some ranges the color spectrum will change slowly. This change depends on the object, on the imaging system and on the projection system.

Projection of a monotonic linear increasing hue value pattern on the object does not result in the same linear increasing pattern on the captured image. This is due to the object's chromatic characteristics and the features of the capturing / projection systems. Analysis of the captured pattern showed that the hue values, which are absorbed by the object, look similar on the captured pattern. Wavelengths, which are reflected by the object body, are well detected as changing on the captured pattern. The ability to detect small amounts of change depends on the projection / capturing systems. The systems sensitivity is also not constant and may change from one wavelength to another.

Assuming that the best-fit projection will be the one that is captured as linearly changing across all the hue values, the specific objective of this work was then narrowed down to develop the methodology for constructing a projection pattern that will be captured as linearly changing across all the hue values. For a given projection system, image capturing system and chromatic / textural object characteristic a projected pattern that leads to a linear captured pattern can be found.

To find the best projection pattern an iterative method was implemented. Let i be the iteration number. Let L be a pattern with linearly varying hue values. Let P_i be the projected hue pattern at iteration i. Set i =1 and P1 = L.

The stages of the iterative method:
1. Project (P_i).
2. Capture the pattern of the hue values as reflected by the object (C_i).
3. Compute the differences between the captured pattern, C_i, and the linear pattern, L. Denote the difference pattern as the delta pattern D_i where $D_i = C_i - L$.
4. If all elements of D_i are smaller than a small value ε then stop.
   else $P_{i+1} = P_i - \alpha D_i$, where α is the learning rate, go to 1.

7. EXPERIMENTAL RESULTS

The method was initially tested on a white board plane. A linearly varying hue pattern was projected on the surface of the board and two cameras captured the scene. Figure 2 shows the result of the reflected color pattern after the first iteration. The X-axis is the pixel number across one cycle of the varying hue pattern (from red too violet) and the Y-axis is the hue value. In the first iteration L = P1 which means that the projected pattern is the desired linearly varying pattern. C1 is the resultant pattern captured by the imaging system. P2 is calculated according to P2 = P1 - α D1. The learning rate was set to be 0.7. In the next iteration the projection pattern was P2. Figure 3 shows the results at iteration 11 after the process converged. One can see that the captured pattern almost coincides with L,

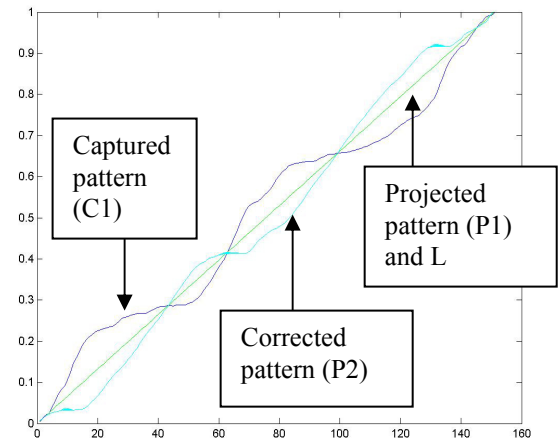which means that the hue of the captured pattern varies almost linearly.
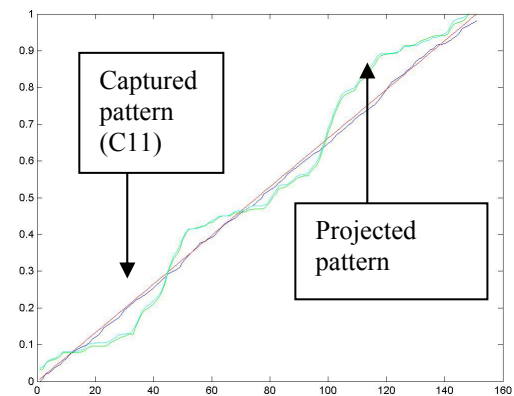

Figure 2. Iteration 1of the iterative process

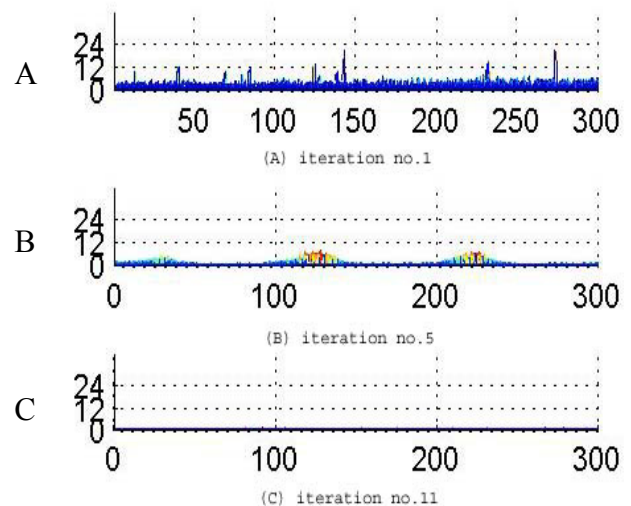Figure 3. Iteration 11 of the iterative process

Figure 4. Error rate of phases 1, 5 and 11 of the iterative process

Figures 4 A, B, C show the DEM profiles, generated at iterations 1, 5 and 11 respectively. X-axis is the DEM profile and Y-axis is the pixels height in millimeters. The improvement of the DEM accuracy of the flat white board along with the iterations is clearly seen: as the iterative process

progresses, the height of more pixels is closer to zero (flat board). The overall accuracy of the algorithm was evaluated in each iteration by the percent of pixels that their height was within the required accuracy of 0.5mm. At iterations 1, 5 and 11 the accuracy was 64%, 81% and 98% respectively.

The same process was done to a real chicken filet. The number of iterations until conversion using the same parameters (ε, α) was similar. The resulted projected pattern after the 11th iteration was different than the one resulted in the white board experiments. As expected, because of the chromatic characteristics of the chicken filet, the span of the red band, is short across the pattern when comparing it to its span along the pattern in the white board experiment (Fig. 5). In the white board pattern it's below the linear line, which means slow change – good differentiation ability of the sensor, whereas in the chicken filet experiment most of it above the line (increase sharply in the beginning of the pattern) which means poor differentiation ability.
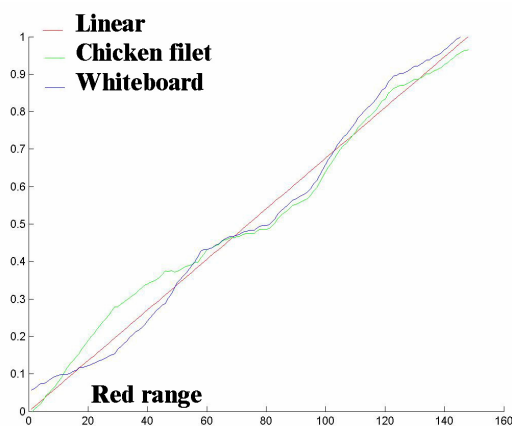

Figure 5. Color projection pattern after 11 iterations for the white board (blue line) and the chicken filet (green line)

Figure 6 shows the chicken filet with the color pattern projected on it. The cyan line is the sampling line across this line the hue values are measured during the iterative process.

Figure 7 shows the error rate of a complex topography body, similar to a chicken filet that was measured both by the proposed system and manually by a 3-D digitizer. The X and Y axis represent world coordinates in millimeters. The bar on the right hand side of the figure represents the error rate. 10,000 sample points were measured across the body, 97.5% were within the error rate of ±0.5mm.
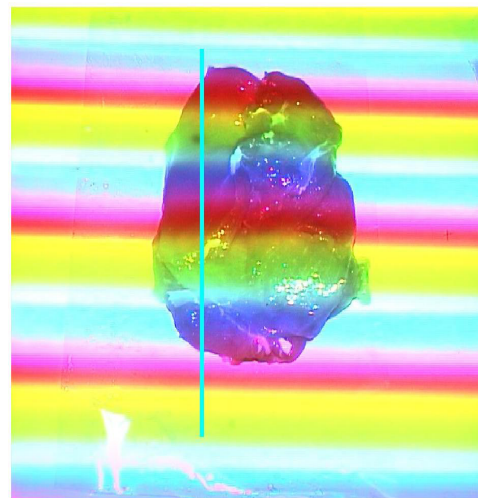

Figure 6. Chicken filet with pattern color projection on it during the iterative process
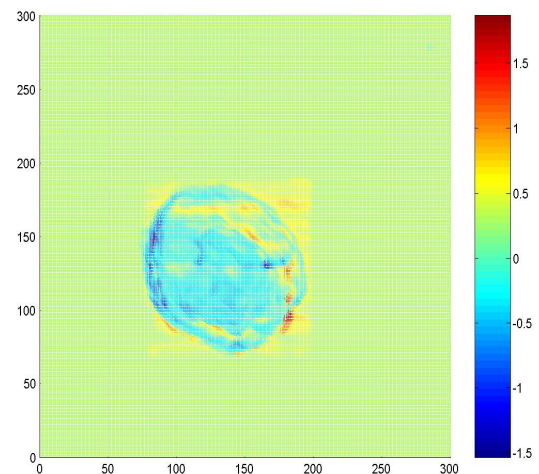

Figure 7. Error rate of a measured body

8. SUMMARY

This research apply photogrammetric / machine vision methodologies in the field of agricultural engineering. Customization of the methods was done as required by the special demands of the field. A method for generating color patterns of structured light was presented. This method can be used for industrial application when the texture and color of the measured object is uniform. Prototype of the suggested system was build and validated. The tests showed that measurement of chicken filet thickness is feasible in the accuracy level required for detecting bones fragments and other hazardous materials.

9. REFERENCES

Caspi, D., Kiryati N. and Shamir, J. 1998. Range imaging with adaptive color structured light. *Pattern Analysis Machine Intelligent* 20 (5) pp. 470–480.

Geng, Z.J., 1996. Rainbow 3-dimensional camera: new concept of high-speed 3-dimensional vision systems. *Optical Engineering*, 35 (2) pp. 376–383.

Karara, H.M. (ed.), 1989. *Non-Topographic Photogrammetry*. Falls Church va: American Society for Photogrammetry and Remote Sensing.

Mikhail, E.M., Bethel, J.S. and McGlone, J.C., 2001. *Introduction to modern photogrammetry*. John Wiley & Sons, New York.

Paakkari, J., 1998. On-line flatness measurement of large steel plates using moiré topography, University of Oulu Finland

Salvi, J., Armangu´e, X., and Batlle, J., 2002a. A comparative review of camera calibrating methods with accuracy evaluation. *Pattern Recognition*, 35(7) pp.1617–1635.

Salvi, J., Pagès, J. and Batl, J., 2004. Pattern codification strategies in structured light systems. *Pattern Recognition*, Volume 37, Issue 4, pp. 827-849

Sato, T., 1999. Multispectral pattern projection range finder. In: *Proceedings of the Conference on Three-Dimensional Image Capture and Applications II*, Vol. 3640, SPIE, San Jose, California, pp. 28–37.

Tajima, J. and Iwakawa, M., 1990. 3-D data acquisition by rainbow range finder. In: *International Conference on Pattern Recognition*, pp. 309–313.

Wust, C. and Capson, D.W., 1991. Surface profile measurement using color fringe projection. *Machine Vision Application*, (4), pp. 193–203.

Yu, W.M., Harlock, S.C., Leaf, G.A.V. and Yeung, K.W., 1997. Instrumental design for capturing three-dimensional moiré images. *Int J Clothing Sci Tech,* 9 pp. 301-310.