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APPLICATION OF FPA TEST SYSTEM TECHNOLOGY TO COMMERCIAL INSPECTION/MEASUREMENT SYSTEMS

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Abstract

Research conducted for the Army has recently developed an FPA (focal plane array) integrated test and evaluation system to provide a testbed for evaluating FPA characteristics and resulting object detection effectiveness. The system design offers various combinations of image processing algorithms with real–time display of raw and processed (i.e., resulting from the application of each chosen algorithm) FPA data. Because this design does not restrict itself to one particular processing scheme, it can be used for a variety of non–military applications requiring object detection within image frames. This paper investigates application of the FPA test system to commercial inspection/measurement tasks, presenting experimental results for product classification by size and color and for product grading by size, features, and quality.

Introduction

Image processing for object recognition can be accomplished through a variety of filtering and signal processing techniques. For a given application system designed and deployed to detect a specific type of object within an image, its underlying processing methodology determines its recognition effectiveness. Since the process of generating images for the system dictates how target objects are represented, the characteristics of the input process affect system effectiveness as well. Thus, for applications requiring specialized image gathering hardware whose operational characteristics are unknown or cannot be compared easily among vendors, producing an optimal object recognition system requires the investigation of both image generating and image processing issues.

Additionally, real–time object recognition at high frame rates requires a high–performance system. To support a wide range of image/object scenarios, general–purpose processors fall short of the performance needed in providing the necessary variety and combination of signal processing techniques. Thus, for applications with varied image/object characteristics at high frame rates, producing an optimal object recognition system requires specialized, high–performance image processors.

The following section describes the existing FPA test system technology. The next sections introduce the commercial inspection/measurement problems investigated with the system and present their results. The last section analyzes the results and discusses application possibilities and limitations.

FPA Test System

The Computer Engineering Research Laboratory (CERL) at Georgia Tech (GT) has developed the FPA (focal plane array) Integrated Test and Evaluation System, GT–FITES, to provide a real–time object detection testbed for evaluating both image generating and image processing issues for the case of FPAs. Incorporating custom high–performance VLSI signal processors (GT–VSP) developed by CERL, GT–FITES is a heterogeneous parallel image processing system that can interface to various image–generating hardware (FPAs) or can emulate them, providing a graphical user interface. It provides a platform for the analysis of the characteristics and quality of an FPA sensor as well as its effectiveness when applying various image processing functions. The primary features supported by GT–FITES are the ability to:

1. Interface to a wide range of FPAs;
2. Display a raw FPA image live on a color monitor so that a user can locate visually bad detectors and characterize the image quality for comparison to other FPAs;
GT–FITES is designed to support FPA frame sizes up to 1024x1024 with real-time display of any 128x128 or 256x256 segment. The system design incorporates both hardware and software. The hardware consists of four board designs (see Figure 1): GT–SIB (SBus Interface Board), GT–FIM (FPA Interface Module), and GT–FFE (FPA Frame Emulator). The software is a graphical user interface (GUI), GT–XSPI (X Windows-based Signal Processing Interface).

FPA frames in GT–FITES are processed in parallel such that the heterogeneous image processors (i.e., SP filtering and feature extraction hardware) are working simultaneously with a computational

Figure 1. FPA Integrated Test and Evaluation System (GT–FITES)
capability of 653 MOPS (2.4 GIPS) at 100 frames per second (fps). Within each FPA frame, individual pixels are treated in a pipeline fashion. The system scales by replicating (up to the limits of the chosen host) the core system presented here. For example, using a SPARCstation 20 host with four available SBus slots, up to four GT–FITES systems may be combined to process different image data streams in parallel, giving an aggregate computational capability of 2.6 GOPS (9.8 GIPS) at 100 fps. Such an extended GT–FITES system could then be used to process different image spectra of the same scene (e.g., visible spectrum image, infrared (IR) spectrum image, etc.) with the host integrating the processed spectra for the user into a single GUI representation.

The following subsections describe GT–FITES hardware and operation in more detail. The first subsection discusses the image input streams appropriate for GT–FITES. The next subsection describes the functionality of each of the image processors. Finally, the last subsection explains the operation of GT–FITES for object detection from the input image stream using the image processors.

References 2 and 3 give more detailed descriptions of the system and its operation.

Image Input

GT–FITES accepts an input stream of digitized pixels accompanied by pixel and frame synchronization signals. It expects 16–bit, two’s complement integer pixel intensities streaming in at a rate of up to 20 MHz with each pixel indicated by a pixel synchronization signal and each frame by a frame synchronization signal. The pixels may be in any order as long as the system user specifies them in the pixel address map (PAM) of the GT–FIM. Thus, the FPA test system can interface to almost any digital imaging hardware.

Image Processors

Image processing and object detection are provided by six types of image processors, each a custom ASIC (VLSI processor): non–uniformity compensation (GT–VNUC); temporal filtering (GT–VTF); spatial filtering (GT–VSF); thresholding (GT–VTHR); clustering (GT–VCLS); and, centroiding (GT–VCTR). The chips were designed using the Genesil Silicon Compiler and fabricated by HP using a 1–μm CMOS process. GT–VNUC and GT–VTF support frames of 128x128 or 256x256 pixels, and the rest support frames of 128x128 pixels. The pixel format for all processors is 16–bit, unsigned intensity.

From the GT–XSPI GUI, the user programs each of GT–VNUC, GT–VTF, GT–VSF, and GT–VTHR for image conditioning prior to object detection using GT–VCLS and two GT–VCTRs. In this manner, the GT–FITES user can select individually any or all of GT–VNUC, GT–VTF, GT–VSF, and GT–VTHR to participate actively in processing, configuring them appropriately for the intended images and objects. The following sub–subsections describe the functionality of each VLSI processor.

Non–Uniformity Compensation. GT–VNUC provides a pixel–by–pixel correction of the actual pixel response of an FPA to the desired response using up to a five–point, piecewise–linear correction to pixel intensity. Up to five calibration frames (stored in local memory provided for GT–VNUC), which are the pixel responses to known intensities, determine the correction. For a given image pixel, the section of the piecewise–linear correction is determined by comparison with the corresponding pixel position in the calibration frames, and then GT–VNUC performs a linear interpolation between the desired responses. At 100 fps, GT–VNUC computes at 13 MOPS (350 MIPS).

Temporal Filtering. GT–VTF provides pixel–by–pixel infinite impulse response (IIR) filtering of frames, (or finite impulse response [FIR] filtering, if the feedback coefficients are set to zero). This processing can be used to eliminate noise, extract important object behavior, and discriminate objects based on frequency components. GT–VTF can realize up to a fourth–order filter via user–specified coefficients. Its filter state information is stored in local memory provided on the board. It operates at 24 MOPS (936 MIPS) at 100 fps.

Spatial Filtering. GT–VSF implements a nine–point, bi–symmetric filter. It is used to eliminate or suppress noise in the image frame. GT–VSF can handle arbitrary frame sizes from 5 x 5 to 128 x 128. The user determines the filter by specifying a four–point symmetric mask. Separate masks are used for edge pixels since not all of the pixels needed are defined, allowing a more general application of boundary conditions. At 100 fps, GT–VSF computes at 20 MOPS (294 MIPS).

Thresholding. GT–VTHR limits image pixels to intensities of interest by providing three thresholding modes for image pixels: simple, adjusted, and adaptive. The lower threshold intensity is determined according to the thresholding mode, and an optional upper threshold intensity is fixed by the user. Pixels
in the threshold range(s) (i.e., less than the lower threshold or [optionally] greater than the upper threshold) are zeroed. In simple mode, the lower threshold intensity is fixed as specified by the user. In adjusted mode, if the number of pixels lying outside the threshold is above/below a user-specified upper/lower limit, the lower threshold intensity for the following frame is decreased/increased by a decrement/increment specified by the user. In adaptive mode, the lower threshold intensity is determined by the average and first central absolute moment of the surrounding eight pixels. At 100 fps, GT–VTHR operates at 3.3 MOPS (90 MIPS) in simple mode, 4.9 MOPS (95 MIPS) in adjusted mode, or 53 MOPS (358 MIPS) in adaptive mode.

Clustering. GT–VCLS identifies connected sets of pixels (clusters) based on the surrounding pixels. Two non-zero pixels are considered connected if they are nearest neighbors. Thus for a 128 x 128 frame, there can be at most 4,096 clusters. This cluster information is used by GT–VCTR to form object information.

Centroiding. GT–VCTR computes the desired object information for the image. For each cluster identified by GT–VCLS, it computes: the geometric center of the object (area centroid); the intensity center of the object (object centroid); the total intensity of the object; and, the total area (number of pixels) of the object. One GT–VCTR is used for calculating x-axis information, and another is used for the y axis. Together GT–VCLS and two GT–VCTRs at 100 fps compute at 543 MOPS (501 MIPS).

Image Processing

The available image processors enable object detection throughout a wide range of image and object characteristics. The essence of the system’s detection methodology is to define a dichotomy among image pixels: object pixels and non-object pixels. Therefore, image processing (i.e., NUC, TF, SF, and/or THR) is applied to change the intensities of non-object pixels to an out-of-range intensity. Following this dichotomous image processing, object detection processing (i.e., CLS and CTR) is applied to quantify object area and intensity characteristics.

Technology Transfer:
Commercial Inspection/Measurement

The interface and processing versatility of GT–FITES make it suitable for a wide range of image object detection applications. Its ability to interface to various FPAs translates to an intrinsic support for almost any imaging hardware. Furthermore, its suite of available image processing algorithms along with its capacity to combine them for processing allows it to detect desired objects in images having various characteristics.

Preliminary research has been conducted on the application of GT–FITES to the commercial technology of visual product inspection/measurement. Commercial inspection and measurement require object detection and orientation information. Given a fixed frame of reference such as a camera at a fixed point on an assembly line, the system would generate orientation information from the object area and intensity values and centroids. In its current form, GT–FITES can serve as a research testbed to identify successful inspection/measurement techniques which could be implemented subsequently in a more compact and cost-efficient system in the field.

In this research, not only does the nature of GT–FITES’ use change from its military design, but its image source changes as well. Rather than obtaining images from an FPA, for these investigations, the system processed CCD (charge-coupled device) images. Common to the consumer market in video cameras, CCDs are used also in industrial assembly line situations for still-frame product imaging. Thus, CCD-generated images are appropriate for evaluating the industrial suitability of GT–FITES.

For these preliminary investigations, a 324x242 CCD was used to generate a still image of each product, individually. Since GT–FITES has no CCD data acquisition system, a PC (personal computer) running CCD acquisition software captured grayscale product images to a standard 8-bit, unsigned PC bitmap (.bmp) format. Next on GT–FITES’ Sun host, the image was converted to a 128x128 16-bit, two’s complement raster-scan pixel stream for compatibility with GT–FITES’ image input format:

1. 324x242 8-bit, unsigned .bmp cropped to square 242x242 size, (for preservation of aspect ratio in reduction to 128x128);
2. 242x242 8-bit, unsigned .bmp reduced to 128x128 size;
3. 128x128 8-bit, unsigned .bmp converted to 8-bit portable gray map (.pgm) format, (the lowest common denominator grayscale file format); and,
4. 128x128 8-bit, unsigned .pgm converted to 128x128 GT–FITES 16-bit, two’s complement raster-scan pixel stream (.2sc). Each 8-bit, unsigned pixel $p_{54}$ in the .pgm file was
converted to a 16-bit, two's complement pixel \( P_{16|2} \) in the .2sc file by the relation,
\[
P_{16|2} = (P_{8|u} - 2^7) \times 2^8 ,
\]
which incorporates the following operations:
(a) 8-bit unsigned converted to 8-bit two's complement, \([0, 255] \rightarrow [-128, 127]\); and,
(b) 8-bit two's complement converted to 16-bit two's complement, multiplying by 256 to maintain intensity range \([-128, 127] \rightarrow [-32768, 32512]\).

The product imaging characteristics for these preliminary investigations places certain restrictions on the industrial situations to which their results can be applied directly. (However, these restrictions do not necessarily reflect limitations of GT–FITES applicability to other situations but rather result from simplified experimental control for the preliminary investigations.) First, still images imply that products can be imaged at rest or that the imaging speed is significantly faster than the product speed. This condition is reasonable for: (1) a “stop and go” conveyor that stops at regular intervals for every individual product to be added/removed; or (2) a conveyor that moves several times slower than the maximum product imaging speed. Secondly, individual product images imply that the imaging system can capture a single product image within a frame. Products placed single-file on a conveyor and separated by some uniform distance satisfy this condition for a fixed camera. Thus, the preliminary GT–FITES investigations are reasonable for common track-oriented conveyor systems (i.e., individual products on a conveyor placed at uniform distances indicated by track notches).

The preliminary commercial visual product investigations can be divided into two types of inspection/measurement processes: product classification and product grading. Product classification is a process applied to heterogeneous lots of products, whereas grading is applied to homogeneous lots. For each process type, one subsection follows to describe the task and to present the research example(s).

Product Classification

The process of identifying a product’s type from among several manufactured types is product classification. Such a sorting process is needed if products of various types are placed on the same conveyor line for distinct handling according to product type. GT–FITES has been used to classify products by size and by color as discussed in the following sub-subsections.

**Size.** The size of a product can be used to classify it when each of the possible product types is a different size. For this investigation, consider a plastic bottle manufacturer that makes two types of dark brown, opaque bottles of similar height: circular hydrogen peroxide bottles (as in Figure 2) and elliptic squeezable chocolate syrup bottles (as in Figure 3). The biggest differences between these two bottles are their shape and size.

**Color.** When different product types are colored differently, color can be used to classify products. The scenario for this investigation is that of a vitamin pill manufacturer whose different types of pills are different colors (as in Figures 4–6) and which requires sorting of the pills for packaging. Since the pills are essentially all the same size, color is their most distinguishing feature.
Product Grading

Whereas product classification distinguishes among products differing by at least one major characteristic, product grading distinguishes among very similar products. Thus, the same differentiation concepts apply but on a much finer scale since there is less difference. For example, size and color product classification, are analogous to size and color grading of the same type of product. GT–FITES has been used to grade product types based on size, features, and quality as discussed in the following sub–subsections.

Size. If the same product made in different sizes is to be sorted according to size, then the grading process of product sizing must be used. For this investigation, consider a manufacturer of different sized roller bearing outer races (shown in Figures 7–9) which uses the same conveyor to transport all sizes for packaging. To package them by size, the correct size must be determined.

![Figure 7. Small Roller Bearing Race](image1)
![Figure 8. Medium Roller Bearing Race](image2)
![Figure 9. Large Roller Bearing Race](image3)

Features. Sometimes products of the same type and same general size and shape have small distinguishing features that make them different. For this investigation, consider again the roller bearing race manufacturer from the size grading experiment. As shown in Figures 10 and 11, some of the races produced have notches in them, while others do not. The notches introduce changes in both the overall area and intensity of the race images. Thus, the area and total intensity of races can distinguish among them according to their notch features.

![Figure 10. Large Roller Bearing Race, with Notches](image4)
![Figure 11. Large Roller Bearing Race, without Notches](image5)

Quality. Commercial product quality assurance (QA) programs require identifying defective products to prevent their being sold and shipped as first–quality merchandise. For this task, it is necessary to distinguish defects among “identical” products to within some established, acceptable degree of tolerance. Thus, the task of quality product grading has the potential for being one of the most difficult commercial visual inspection/measurement tasks in terms of demand for accuracy.

For a GT–FITES QA investigation, again consider the roller bearing race manufacturer. When a notch is machined in a race, the stress placed on the tiny area of the side sometimes causes a defect by shearing off an excess portion (as shown in Figures 12–15). Since

![Figure 12. Small Roller Bearing Race, Good](image6)
![Figure 13. Small Roller Bearing Race, Defective Shear](image7)
![Figure 14. Small Roller Bearing Race, Defective Shear](image8)
![Figure 15. Small Roller Bearing Race, Defective Shear](image9)
defective notches differ from normal notches in volume and in surface characteristics, the area and total intensity of good and defective races differ and thus can be used to distinguish between them.

As another example of visual product differentiation by quality, consider the roller bearing races of Figures 16 and 17. Because one race is scratched and damaged, it’s surface characteristics are different from the other, normal one. These surface differences result in different total intensities for the two races and hence can be used to differentiate them.

Results

Each of the GT–FITES commercial visual product inspection/measurement technology transfer experiments was conducted as described in the previous section. The GT–XSPI GUI was used for all inspection/measurement experiments to load the product images, program the GT–FITES processors, process the images, and obtain crucial product image data. As an example of GT–XSPI use, Figure 18 shows the display from inspection of the circular bottle for the product classification by size investigation. In this captured display image, the “FPA Display Panel” shows the raw, unprocessed image of the cylindrical bottle (which is identical to Figure 2), the “THR Programing Panel” shows GT–VTHR’s programming parameters, and the “THR Display Panel” shows the image after the resulting GT–VTHR simple thresholding. A visual comparison of the two display panels verifies that the background pixels of the original image have been removed (i.e., zeroed). In the “THR Display Panel,” the “+” mark indicates the bottle’s area centroid, and the “x” mark indicates its intensity centroid. The pixel coordinate window in the lower left corner of the display panel gives a pixel coordinate (selected with the host’s mouse) from the image and the numerical value of any area and/or intensity.
intensity centroids there. For the pixel listed in the pixel coordinate window, the pixel value window (above the pixel coordinate window in the display panel) gives its intensity and the intensities of its nearest neighbors.

The results of the experiments are presented in the following subsections which follow the format and order of their descriptions in the previous section. A captured image of the GT–XSPI “THR Display Panel” for each product type serves as an example of the processed image from which the experimental results were collected. For each inspection/measurement investigation, a table summarizes the relevant GT–FITES output information.

**Product Classification**

**Size.** To differentiate between the circular and elliptic dark plastic bottles, GT–VTHR was programmed for simple thresholding mode with the optional upper threshold enabled and set to 45056, zeroing out the background pixels. All other image processors were programmed in “pass–through” mode, not altering the image. Then GT–VCLS and GT–VCTR identified the bottles and computed the total area for each. Figure 18 includes the GT–XSPI display for the circular bottle.

**Table 1. Bottle Classification Data**

<table>
<thead>
<tr>
<th>Bottle Type</th>
<th>Area (pixels)</th>
<th>Total Intensity (16-bit unsigned)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Circular</td>
<td>5,226</td>
<td>120,542,540</td>
</tr>
<tr>
<td>Elliptic</td>
<td>5,793</td>
<td>149,495,296</td>
</tr>
</tbody>
</table>

Table 1 lists the GT–FITES output that can be used to distinguish between the two bottles. The area of a bottle is a measure of its size in pixels. Since the areas of the bottles differ by around 500 pixels, area is a sufficient metric for differentiation. Otherwise if a metric with a larger difference is desired, total bottle intensity, could be used, because the average pixel intensity,

\[ \text{Average Intensity} = \frac{\text{Total Intensity}}{\text{Area}}, \]  

(2)

for both bottles is similar since they are made of identical material.

**Color.** As in the case of the plastic bottles, GT–VTHR was programmed for simple thresholding to zero the background pixels. Since the white pill is lighter than the background, it required use of a lower threshold (45055, shown in Figure 19), whereas the brown and grey pills needed an upper threshold because they are darker than the background. Thus, GT–FITES could not accommodate pills lighter than the background on the same conveyor with those darker than the background without additional programming. Furthermore, the brown and grey pills (shown in Figures 20 and 21, respectively) needed different upper thresholds (43265 and 42241, respectively) because of their unique contrast characteristics with respect to the background. Hence, an industrial deployment for automatic color classification would require an improved background compatible with all pill colors such that a single thresholding paradigm and value could be employed.

![Figure 19. Thresholded White Pill Image](image_url)

![Figure 20. Brown Pill, Thresholded](image_url)

![Figure 21. Gray Pill, Thresholded](image_url)

Table 2 summarizes the GT–FITES operation and output for pill classification by color. From the area and total intensity outputs, the average intensity (computed according to equation 2) is the basis for identifying pill color. Thus although the background used in acquiring the images presented difficulties that would prohibit automated processing in an industrial setting, the results show that, given a suitable background for uniform processing, GT–FITES is able to classify the pills by color.
Table 2. Pill Classification Data

<table>
<thead>
<tr>
<th>Pill Type</th>
<th>Threshold Type (fixed)</th>
<th>Threshold Intensity (16–bit unsigned)</th>
<th>Area (pixels)</th>
<th>Total Intensity (16–bit unsigned)</th>
<th>Average Intensity (16–bit unsigned)</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>Lower</td>
<td>45,055</td>
<td>996</td>
<td>47,918,080</td>
<td>48,111</td>
</tr>
<tr>
<td>Brown</td>
<td>Upper</td>
<td>43,265</td>
<td>1,631</td>
<td>62,137,600</td>
<td>38,098</td>
</tr>
<tr>
<td>Gray</td>
<td>Upper</td>
<td>42,241</td>
<td>1,919</td>
<td>67,112,960</td>
<td>34,973</td>
</tr>
</tbody>
</table>

Product Grading

Size. For grading the roller bearing races by size, GT–VTHR was programmed for simple thresholding to zero the background pixels using the lower threshold (24575). The other processors were placed in “pass–through” mode. Figure 22 shows the final processed image of the large race from the GT–XSPI “THR Display Panel.” (Although race pixel intensities were not altered, they may appear different than in Figure 9 because an alternate color display spectrum was used to allow the black centroid markers to be visible in the zero–intensity background.) As in the product classification by size, GT–VCLS and GT–VCTR computed the total area and total intensity of each race, which are listed in Table 3.

Table 3. Roller Bearing Race Size Grading Data

<table>
<thead>
<tr>
<th>Race Size</th>
<th>Area (pixels)</th>
<th>Total Intensity (16–bit unsigned)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>6,571</td>
<td>143,466,982</td>
</tr>
<tr>
<td>Medium</td>
<td>7,841</td>
<td>363,351,014</td>
</tr>
<tr>
<td>Large</td>
<td>8,315</td>
<td>365,454,848</td>
</tr>
</tbody>
</table>

Among the race sizes, the least difference in area is around 500 pixels. Thus, area can be used to distinguish among the three sizes. As an alternative metric of size, the total intensities here vary by at least 2,000,000. However, as seen in results to follow, total intensity depends on bearing features and quality as well as size, so it may not be a desirable metric to use.

Table 4. Roller Bearing Race Notch Feature Grading Data

<table>
<thead>
<tr>
<th>Large Race Notches</th>
<th>Area (pixels)</th>
<th>Total Intensity (16–bit unsigned)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>8,505</td>
<td>260,313,779</td>
</tr>
<tr>
<td>4</td>
<td>8,315</td>
<td>365,454,848</td>
</tr>
</tbody>
</table>

Since the bearing races are the same physical size, their areas are fairly close, differing by the pixels removed by the notches. However, their total intensities varied by a much larger amount, with the notched race’s intensity being 5,000,000 more than the unnotched one. Thus, GT–FITES can distinguish notched races by their total intensity.

Quality. For grading small roller bearing races for notch defects (i.e., excess shear), again GT–VTHR applied a lower threshold (24575) to the images with the other image processors in “pass–through” mode. Table 5 lists the object feature information returned by GT–VCLS and GT–VCTR. The differences in good versus defective races were similar to those in unnotched versus notched bearings. The areas of the defective bearings were around 500 pixels less than the good one, and the defective total intensities varied greatly from the good one, (by at least 100,000,000).

Table 5. Roller Bearing Race Notch Quality Grading Data

<table>
<thead>
<tr>
<th>Small Race Condition</th>
<th>Area (pixels)</th>
<th>Total Intensity (16–bit unsigned)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>6,571</td>
<td>143,466,982</td>
</tr>
<tr>
<td>Defective</td>
<td>5,995</td>
<td>293,146,368</td>
</tr>
<tr>
<td>Defective</td>
<td>5,987</td>
<td>322,128,895</td>
</tr>
<tr>
<td>Defective</td>
<td>5,964</td>
<td>243,561,344</td>
</tr>
</tbody>
</table>

To grade small roller bearing races on surface quality, the same threshold–based processing was applied. Table 6 summarizes the resulting object information along with the average intensities.
(calculated according to equation 2). Relative to the preceding results, the small differences observed here in area (40 pixels) and total intensity (400,000) reveal the relatively fine-grained measurement nature of this visual inspection task.

Table 6. Roller Bearing Race Surface Quality Grading Data

<table>
<thead>
<tr>
<th>Small Race Surface</th>
<th>Area (pixels)</th>
<th>Total Intensity (16-bit unsigned)</th>
<th>Average Intensity (16-bit unsigned)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>6,571</td>
<td>143,466,982</td>
<td>21,833</td>
</tr>
<tr>
<td>Scratched</td>
<td>6,611</td>
<td>143,893,606</td>
<td>21,766</td>
</tr>
</tbody>
</table>

Conclusions

The results from these preliminary investigations indicate that GT–FITES can be used in commercial product inspection/measurement tasks. Given images of distinct objects on a contrasting background, object data from GT–FITES can be used to classify products by: (1) size, from area (and/or total intensity if the average intensity of the products are the same); and, (2) color, from average intensity (calculated from area and total intensity). Furthermore, GT–FITES output can be used to grade products based on: (1) size, from area and total intensity; (2) features, provided they generate significant and consistent area, total intensity, or average intensity characteristics; and, (3) quality, given a uniform measure of acceptability.

Thus, the technology for the FPA test system developed from research conducted for the Army can be transferred easily to visual object inspection technology. This transfer is facilitated by GT–FITES’ versatile design to support FPAs and images of varying characteristics. Its flexible interface and programmable image processors provide an avenue to almost any type of object detection research. Furthermore, its high throughput capability enables it to handle real-time inspection in current production scenarios.

Implications

The product color classification using the pills demonstrates the importance of consistent background contrast trend and lighting. A more suitable background choice for imaging the pills would have allowed a single processing strategy (necessary for automated industrial settings). A better lighting strategy for image acquisition would have avoided the product reflections into the background that become successively more pronounced from Figures 19 to 20 to 21.

In regard to product grading by size for roller bearing races, the results of the surface quality grading give an example of size tolerance among “same–sized, identically–featured” races. The area difference in these small races of 40 pixels is significantly less than the differences in area observed among the various race sizes. Hence, the surface quality data seem to reinforce the validity of the size grading application.

The feature grading and notch quality grading results demonstrate how material characteristics produce visual inspection metrics. The total intensities of the notched and defective roller bearing races are significantly greater than the unnotched or good races (respectively). Thus it appears that the notched or sheared surfaces are more reflective than the normal race surface.

Regarding surface quality grading, more data needs to be collected to establish GT–FITES’ capability. Although detectable differences were observed in the surfaces, the metrics were still similar, and therefore tolerances among “normal” surfaces should be established. GT–FITES output will be sufficient for successful grading only if these tolerances are always less than differences between normal and unacceptable (e.g., marred) surfaces.

Applications

These investigations have concentrated on commercial product inspection/measurement tasks based on product total area and total intensity metrics obtained following simple (upper or lower) threshold processing of a single still, grayscale product image. While this methodology is suited to many potential applications (as demonstrated in this paper), other types of applications require different metrics and/or processing. GT–FITES offers two additional metrics and many processing modes which may be useful for such applications.

Two visual metrics output by GT–FITES but not investigated here are the product area centroid and product intensity centroid. The area centroid can be used for product grading based on shape or orientation. For example, crookedly capped bottles could be detected by variations in the cap centroid. On the other hand, a product’s area centroid could be used to grade positioning of critical intensity–dependent (i.e., color–based) elements. If a product label affects its intensity characteristics, such a metric could be useful for label grading. If processing can isolate a product’s label, then GT–FITES will return a label cluster if and only if the product is labelled, and the corresponding
intensity centroid of the label cluster will reflect its positioning. Otherwise, for labels not separable from the product but with different intensity characteristics, the total product intensity and intensity centroid could be used to verify labelling and label positioning, respectively.

Only one of the four image processors, GT–VTHR, has been fully utilized for these investigations. The other processors and their combinations could be incorporated to compensate for linear imaging anomalies in pixel intensities (GT–VNUC), to eliminate time–dependent effects for moving–frame product inspections (GT–VTF), and to enhance or reduce the impact of individual pixel intensities with respect to their nearest neighboring pixels (GT–VSF). Therefore, these investigations leave unexplored some fundamental GT–FITES processing modes and their numerous combinations for application to commercial visual product inspection/measurement.

Limitations

The maximum GT–FITES processing rate is 100 fps. This speed should be more than adequate for most commercial product inspection tasks. The GT–VSF and GT–VTHR processors are limited to frame sizes of 128x128 pixels, whereas GT–VNUC and GT–VTF can process frames of either 128x128 or 256x256 pixels. Although, some manufacturers make CCDs in these square array sizes, many CCDs are not square. Thus in the general case, images will have to be cropped and perhaps decimated for input to GT–FITES. Furthermore, the GT–FIM expects 16–bit, two’s complement pixels per its design specification for FPA input, and hence most available imaging formats require conditioning for compatibility (such as was done for these investigations). For an industrial deployment, a custom CCD (or other camera) interface to replace the GT–FIM likely would be desirable.

The cluster and centroid processing generates all of the metrics for product inspection/measurement. GT–VCLS is unable to divide connected sets of pixels into separate clusters. Therefore, GT–FITES will be successful only on product images where processing can isolate pixels of the product being measured from those of the background or of other objects in the image. To handle other types of images, the GT–VCLS and GT–VCTR processing would have to be replaced with processing not based on blob analysis.5

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References


*Available via anonymous ftp to cerl.gatech.edu from the “pub/gtfites/manual” directory.