NEW METHODS FOR DISHWARE IDENTIFICATION AND INSPECTION

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Abstract: We propose automatically identifying dishes in mixed batches by using statistics of shape descriptors of dish pieces. Experiments were conducted on 725 images of ceramic and plastic dishes taken in different lighting conditions using different positions of 84 separate dishes of 5 different styles and shapes. In order to find the minimum set of descriptors to produce fast, adaptable and efficient automatic dish recognition, we employed several shape-based properties, including area, perimeter, ratio of length to width, extension, and minimum bounding box, together with some properties based on gray level and color. For dish inspection, we propose a new technique using partitioning and adaptive thresholding, combined with global thresholding. For practical purposes, the algorithm should be fast, simple, and produce results invariant with lighting conditions and dish rotation about the camera-dish axis. Such an algorithm is described in this work. Matlab® R14 and Image Processing Toolbox V5.0 were used.

1 INTRODUCTION

Commercial dishwashing systems currently involve human loading, sorting, inspecting, and unloading dishes and silverware pieces before and after washing in hot and humid environments. In such difficult working conditions, leading to high turn-over of low-paid employees, automation is desirable, especially in large-scale kitchens of hospitals, navy ships, schools, hotels and other dining facilities. Our project is a part of developing an integrated machine vision sorting and inspecting system for mixed dish pieces and silverware exiting a flight-type commercial dishwashing machine, coupled with automatic loading and unloading.

Johnson (1993), working on the same dish set as used in this project, employing area and radius of the corner of the dish in using machine vision identification of dish pieces exiting commercial dishwashing machines. His method required an invariant position of a dish under the camera axis, which required a locating mechanism for each dish piece. Even with pre-location, he reported poor repeatability of results under small lighting variations, such as those due to normal small fluctuations in power supply voltage. For inspection of dishes for cleanliness, his algorithm used simple global thresholding, which is insufficient in accuracy for actual implementation. We present a much improved method for both dish identification and inspection, yielding much better results.

Other investigators studied identification and inspection of mixed silverware pieces exiting a commercial dishwashing machine. Yeri (2002) used blob analysis to recognize silverware pieces, using indirect illuminaiton in a light tent to weaken specular reflections. Lolla (2005) identified silveware objects by their perimeters, symmetric and asymmetric properties, and area moment of inertia measurements. He used edge detection algorithms together with template matching to inspect recognized silverware pieces. Zhou (2008) proposed an algorithm to recognize silverware pieces with incomplete (truncated) images and a fusion-based method for silverware inspection, producing very good results.

The objective of this project is to develop algorithms and procedures for on-line dishware identification and inspection of certain types of dish pieces exiting a commercial dishwasher. Figure 1 illustrates the overall process.

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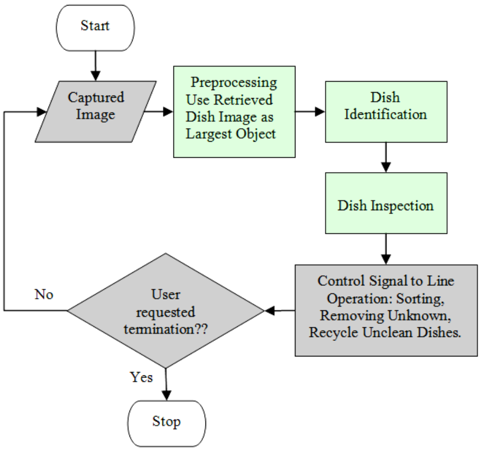

Figure 1: Processing Flow Chart.

2 EXPERIMENTAL APPROACH

2.1 Experimental Setup

The experimental setup, inherited from Zhou (2008) is shown in Fig 2, with our modifications in lighting.

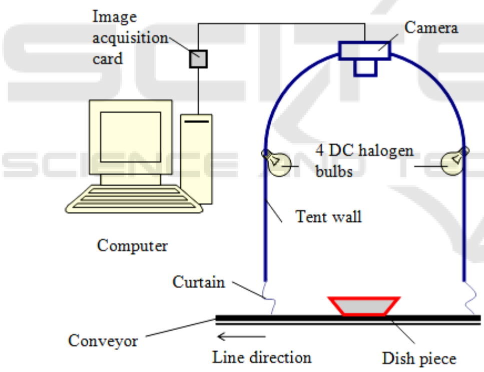

Figure 2: Experimental Setup.

After washing, it is anticipated that dish pieces will be automatically placed on the conveyor. However, in this project, dried dishes were placed manually. While wet dishes can be easily handled with this technique, dried dishes were much easier to handle experimentally. A dish image is captured by the camera when the dish is inside the light tent in the camera field of view. In full implementation, image taking will be triggered by appropriately placed sensors, but in the work herein, this triggering was done manually. This image is transmitted to a computer for image processing. The tent wall and curtains are used to eliminate uncontrolled illumination from the outside environment. In actual implementation, after processing, a signal identifying the type of dish piece will be sent to a sorting mechanism to sort the dish into a stack of like dishes. Unidentified objects will be automatically sent to a bin for such objects, and if the dish is determined by the vision system to be unclean, a signal will be sent to convey said dish into a bin for re-washing, as indicated in Figure 1.

The camera used in this project was an area scan, color digital industrial camera, Basler Co. model A102kc, directly connected to an image processing board in a personal computer, described later, for real time image processing. Sensor size in the camera was approximately 17 mm square. Resolution was set to 1392 by 1038 pixels, which is sufficient to discern a small dirty spot of SFS mm square. The lens was a Fuji model CF35HA-1, 35mm focus length, with 14°26'x10°46' aperture view cone.

Let sensor size SS= 17mm, sensor resolution SR= 1038 pixels, and focal length FL= 35mm. Choose working distance WD= 600mm, which is large enough to avoid distortion when the lens is focused on an object within the working distance (Zhou, 2008). Then we calculate the smallest feature size, SFS, that the camera can detect (Edmund Industrial Optics) by:

$$SFS = \frac{2 \times FOV}{SR} \tag{1}$$

where FOV= 200mm is the field of view, given by

$$FOV = \frac{SS \times WD}{FL} \tag{2}$$

Subtituting FOV from (2) in (1) yields:

$$SFS = \frac{2 \times SS \times WD}{SR \times FL} \tag{3}$$

Using the above numerical values in (3) gives SFS= 0.38mm, which is sufficiently small for detection of food particles in our project.

For inspection purposes, we desire an even illumination across the dish piece, as well as a minimum of specular reflections and shadows. The white mat-finished cardboard forming the inside surfaces of our light tent provided some diffuse lighting of our dish pieces and reduction of specular reflections, while the choice and placement of our lights reduced shadowing. Acceptable lighting was achieved by trial and error. After considerable experimentation, we selected as our light sources four 12V-20W DC halogen light bulbs surrounding the dish piece and placed as indicated in Figure 2, which provided sufficient illumination for both identification and inspection. These lamps were powered by a Switch Mode Power Supply (SMPS) fed by 110V 60Hz building supply. Camera exposure time was set at 20 µs, which was found by experiment to yeild the best dish image details.

2.2 Dish Set

The dish set used in this project is shown in Fig 3.

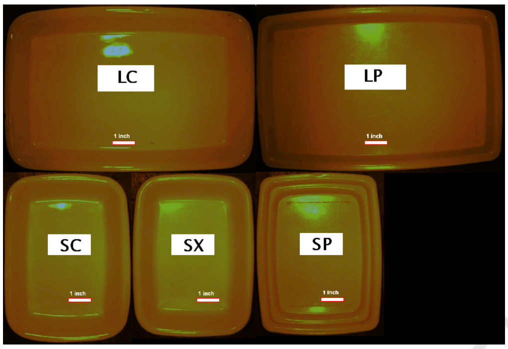

Figure 3: Dish Set Consisting of 5 types and 3 Colors of Dishes.

Our dish set was commercially available and used by a large, 700 bed hospital in Oklahoma. It consisted of 5 types and 3 colors of dishes. It was selected not only because it is in wide commercial use, but also because the colors, shape, and size of different types of dishes are very similar. However, each dish piece had uniform color, with no decorative markings (i.e. they were "plain"). Other commercially available "plain" dish sets present much lower challenges for the identification problem because their sizes are often easily distinguishable. For easy reference, we name each dish piece using size (large or small), and its material or function (ceramic, plastic, or spacer). Then LC and LP represent, respectively, the large ceramic dish and the large plastic dish, while SC, SP and SX represent, respectively, the small ceramic dish, the small plastic dish, and the small plastic spacer dish.

2.3 Pre-processing

We developed a pre-processing algorithm for thresholding, computing areas, and choosing the largest object (or particle) in a dish image, rejecting all other particles. This process removed noise and reliably retrieved a good dish image from the camera image, which was then ready for identification and inspection, illustrated in Figure 4.

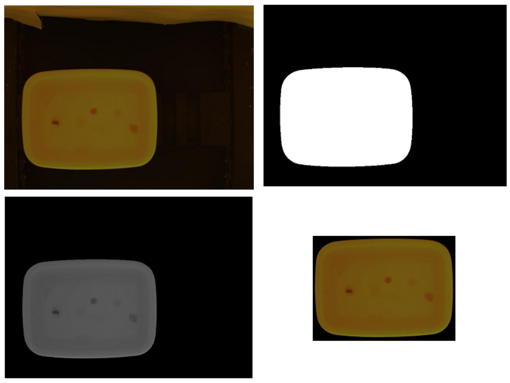

Figure 4: Example of SX Pre-processing. Original camera image (top-left); Binary mask for largest object (top-right); Gray image (bottom-left); and Dish retrieved image (bottom-right).

3 DISH IDENTIFICATION

The implemented automatic system should at least be comparable in performance to what can be achieved manually. Accordingly, from our observations in actual commercial dishwashing operations, our automatic system should be able to accurately recognize and inspect 5 types of dishes in real time at a minimum rate of 30 dishes per minute. While this task is easily accomplished manually, it poses a significant challenge for automation. We desire an algorithm that works flawlessly under varying dish positions beneath the camera and with varying illumination.

3.1 Possible Approaches

A human can quickly recognize each type of dish based on the weight, corner curvature, size, edge pattern, color, and/or a mix of these properties. In an attempt to imitate these capabilities, we experimented with several approaches based on edge detection, color recognition, and statistics of shape descriptors, such as area and perimeter. When using the area of a bounding box around the dish image axes, we found poor repeatability, due to slight dish non-alignment with the box (rotation), which produced pixel counting errors. Methods based on color or gray level intensity were found to be overly sensitive to small lighting variations. Edge detection methods, using Matlab and its Image Processing Toolbox, were not only computationally expensive and slow, but also proved difficult in selecting appropriate threshold values (Duong, 2008).

3.2 Identification Algorithm

We propose using statistics of shape descriptors of dish pieces to solve the identification problem. Three easily calculated statistics of shape descriptors are the dish image area, the ratio of dish image length to width, and the ratio of the dish image area to the area of the image oriented bounding box. The area of the dish image is already available from the pre-processing step.

In order to classify dish types, we used a training set of 500 images, with 100 images for each dish type, in varying position and orientation under the camera, to estimate the distributions of dish image properties. Examining the dish image area, we observe from Figures 5 and 6 that two groupings readily appear: large areas representing LC and LP, and small areas representing SC, SP and SX. By considering only dish area information, Table 1 shows that it is straightforward to identify SC, since none of the image areas of SC overlap with any other dish piece. However, there clearly is overlap in image areas of LP and LC, and of SP and SX.

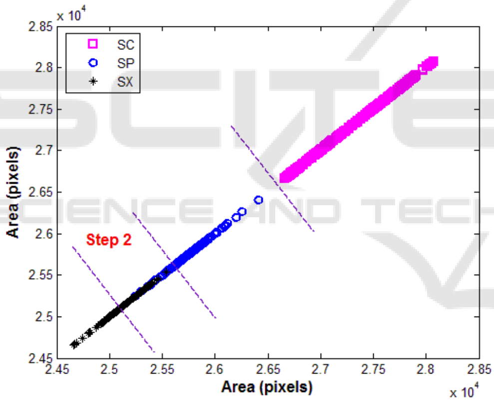

Figure 5: Small Dish Image Area Group.

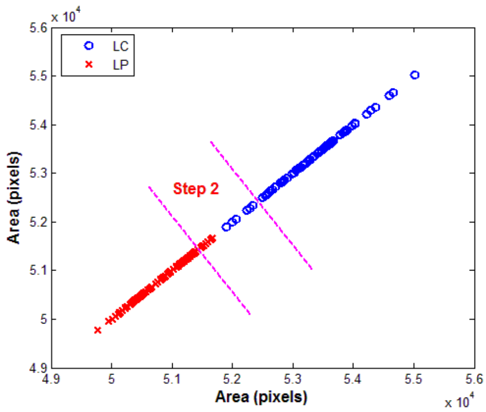

Figure 6: Large Dish Image Area Group.

Table 1: The area contribution.

Dish type	SX	SP	SC	LP	LC
Area (10^4 pixels)	2.45-2.58	2.53-2.66	2.69-2.83	4.96-5.28	5.16-5.51
Overlap region	2.53- 2.58 **SX or SP**?		x	5.16- 5.28 **LP or LC**?	

Accordingly, we employ other properties to distinguish between them. Consider the ratio of dish image area to the area of the oriented image bounding box, called O_EXT, which can be thought of as indicating the curvature of the dish corner. This ratio is much faster to calculate, with more repeatable results, than calculating the radius of curvature of the dish corner, as attempted by Johnson (1993). Consider further the ratio of bounding box length to width, called O_REC, which can be calculated quickly with repeatable results. Using these two properties together, as indicated in Figure 7, we can easily distinguish SP from SX. Using area and length-to-width ratio, Figure 8 illustrates how LC is easily distinguished from LP.

The optimal lines to separate SP and SX, and LC and LP are given in Table 2. To save time, the two

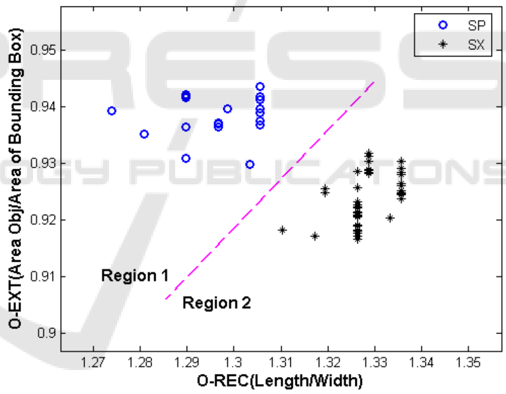

Figure 7: Separating SP and SX Dish Types.

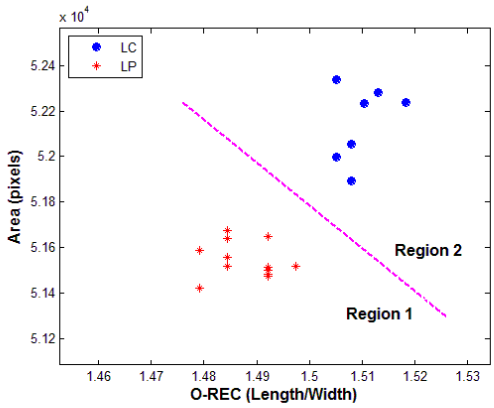

Figure 8: Separating LC and LP Dish Types.

properties, O_REC and O_EXT, are computed only if the area property is insufficient to make a reliable decision. Otherwise, the algorithm stops at Step 1 below.

Table 2: Lines separating SP and SX, LC and LP.

	Line to separate SP and SX		Line to separate LC and LP	
	Point 1	Point 2	Point 1	Point 2
Area (10^4 pixels)	x	x	5.22	5.13
O_REC	1.28	1.35	1.48	1.52
O_EXT	0.91	0.95	x	x

Hence, our identification algorithm is as follows:

- Pre-processing: retrieve dish image as the largest object in camera image.
- Step 1: Classify using dish area.
- Step 2: Separate SP and SX using O_REC and O_EXT. Separate LC and LP using O_REC and area.

3.3 Identification Results

Results were collected from 725 images of all types of dish pieces, not including any of the 500 training set images. All training and testing image sets were produced from 84 dishes of all types, clean and dirty, under different lighting conditions (produced by changing the exposure time of the camera) and under different dish positions and orientations under the camera axis.

The results in Table 3 show accurate identification for all images, with an average computation time of 0.21 sec. This is deemed acceptable to allow identification and inspection of dishes at our target dish processing rate of 30 dish pieces per minute. The variability from min to max computation time is explained because the amount of rotation among dish pieces varied with dish position, causing variability in times to compute classification parameters.

Table 3: Results of Dish Identification.

	No.	Correct	Time* (sec)		
			Min	Average	Max
LC	85	100%	0.18	0.22	0.57
LP	120	100%	0.18	0.33	0.59
SC	200	100%	0.17	0.18	0.23
SP	167	100%	0.17	0.20	0.49
SX	153	100%	0.16	1.24	0.48
All dishes	725	100%	0.16	0.21	0.59

(*) Matlab® R14, Image Processing Toolbox V5.0, Window Vista, dual core 1.6GHz, 2GB RAM.

4 DISH INSPECTION

Automated dish inspection following commercial dishwashing using image processing presents some unique challenges. First, the intensity of dish images is sensitive to changes in lighting, normal power fluctuations, and camera sensitivity drift (Lolla, 2005). Second, even with reasonable attempts to establish uniform illumination of dish pieces, uneven illumination persists in the camera field of view. This non-uniform color and gray intensity across a clean dish varies as the position of the dish varies in the field of view. Third, because of the non-flat geometry of the dish surface, the gray intensity of the image drops significantly at the dish side wall, especially for a deep dish with steep sidewalls, such as LC, SC and SX. Moreover, glare and shadows increase the difficulty of discerning clean from dirty dishes, even for human manual inspection. Fourth, food particle images vary in gray level, depending on food type, size, and location. Certain food particles, such as dried egg yolk, can be especially difficult to detect. Fifth, the definitions of a “clean dish” and a “dirty dish” are subjective and ill-defined (Zhou, 2008).

4.1 Previous Work

Zhou (2008) proposed a fusion based technique for silverware inspection. His key idea was based on the observation that shadows will move, but dirt will not, between two images of a silverware piece captured at two different positions under fixed illumination. Zhou’s technique combines relevant information from two images, which reduces noise and recovers information in regions obscured by lighting glare and shadows. His method could be used in pre-processing before inspection, as long as the computation time is sufficiently small. After fusion of two images of one piece, Zhou applied simple global thresholding to the three color (R, G and B) channels. While this approach worked well for silverware, it will not work for dish inspection, because the gray level of a clean spot on the dish wall is comparable to or less than a dirty spot on the dish floor, and Zhou used only global thresholding.

Lolla (2005) used template edge matching for silverware inspection. This approach is not only time consuming, but also suffers from lacking the ability to deal effectively with glare and shadows.

One approach we considered was to create targeted illumination on the dish walls based on their inclination angle, and then apply global thresholding to the entire modified image. The problem was that modifying illumination of the wall was time consuming, and was difficult to adapt to inside corners. A more promising approach was to treat the dish floor region and dish wall region differently during image processing. This is the essence of our proposed method, in which we use partitioning and adaptive thresholding, which is much simpler and more efficient.

4.2 Inspection Algorithm

Our inspection method is inspired by observing how human eyes inspect a dish piece. Humans focus locally, and are very sensitive to relative changing in color or intensity. The human visual system also easily learns, and appears to eliminate glare and shadows, as well as adapts the background intensity.

In our inspection algorithm, a “dirty spot” is defined as a connected component that is (1) sufficiently dark, and (2) darker than the immediately surrounding area. The algorithm first separates the dish image into a dish floor region and a dish wall region. Then for each region, we automatically locate all components that are darker than the near surrounding area, employing adaptive thresholding, and discard those components that are not sufficiently dark, employing global thresholding. After these steps, we combine the floor and wall regions and carry out post-processing to remove small noise.

The steps of our inspection algorithm are as follows:

- Identify the dish piece, so that we have a template for partitioning.
- Start from a gray image of a dish piece which is the result of pre-processing.
- Partitioning: Detect and separate floor region and wall region of a dish image by using the appropriate floor template image.
- Adaptive and global thresholding: work with the floor region and wall region separately. Adaptive finds potential spots; global retains only those with gray levels less than the global threshold.
- Combine the two regions.
- Post processing: remove tinny spots that most likely are produced by noise rather than dirt.

Our experimental results showed that it is unnecessary to use a color image, such that even though we took color images with our camera, we employed only the corresponding gray scale image. A sample result of the partitioning process based on a dish floor template is shown in Figure 9.

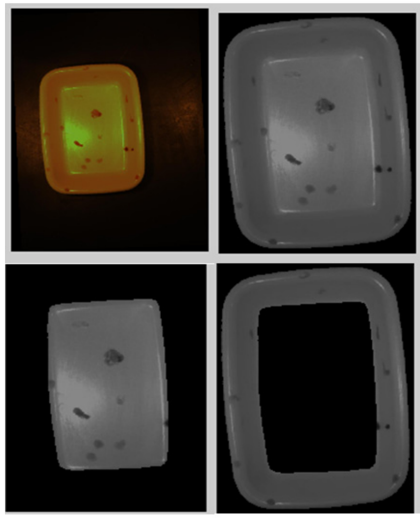

Figure 9: Partitioning process (SC Dish): Original Camera Image (top-left), Gray Scale Pre-processed Dish Image (top-right), Dish Floor Region (bottom-left), and Dish Wall Region (bottom-right).

For the dish in Figure 9, results of adaptive thresholding combined with global thresholding for floor region and wall region are shown in Figure 10.

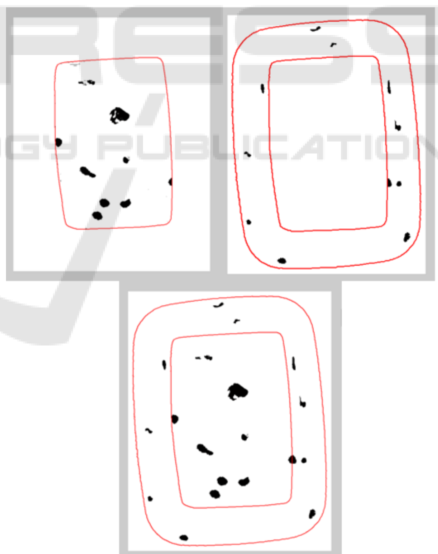

Figure 10: Adaptive and Global Thresholding for Floor Region (top-left) and Wall Region (top-right). Combination of the Two Regions and Post-processing (bottom).

For all tested images in our inspection process, the values of parameters for adaptive thresholding and global thresholding, found by trial and error, are given in Tables 4 and 5 respectively.

Table 4: Adaptive Thresholding Parameters.

	Dish floor region		Dish wall region	
	Window size (pixels)	Threshold value (%)	Window size (pixels)	Threshold value (%)
SC	60	3	30	5
SX	50	5	30	3
SP	50	5	12	3

Table 5: Global thresholding parameters.

	Dish floor region (gray level 0-255)		Dish wall region (gray level 0-255)	
	Lower bound	Upper bound	Lower bound	Upper bound
SC	20	86	20	70
SX	20	99	20	66
SP	20	99	20	54

4.3 Inspection Results

To obtain experimental results with our proposed inspection method, we manually applied real food particles to a variety of our dish pieces, varying them in type size, shape, and location of food. We used egg yolk, fruit juice, and a variety of sauces, including tomato-based sauces, all of which were allowed to air dry before inspection.

Figure 11 shows an example of results, with the original SC dirty dish image on the left and detected dirt spot boundaries (on the right) overlaid on the original dish image. All dirt spots with variation of gray intensity and location were correctly detected.

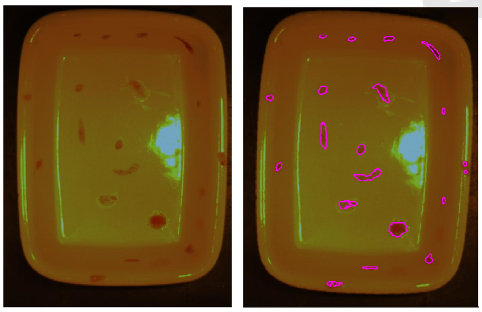

Figure 11: Origin SC (left) and all dirt spots detected (right).

Notice that the glare (specular reflection) due to the shiny surface of the ceramic dish did not produce spurious results.

Inspection results of a dirty SX dish and a clean SX dish are presented in Figures 12 and 13, respectively. Notice in Figure 12 the dirt spot exactly on the boundary of the floor region and wall region of the dish image (near the centre of the left image). This location of a dirty spot could be a significant detection challenge, yet our algorithm did detect it.

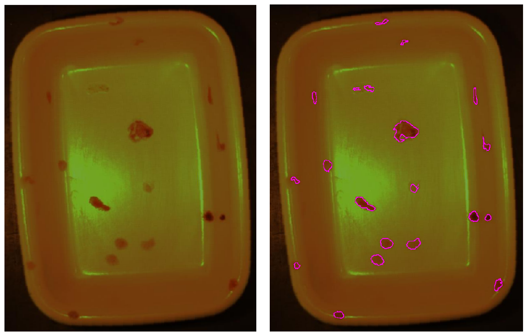

Figure 12: Original SX (left) and All Dirt Spots Detected (right).

Figure 13: Origin Clean SX (left) and Correctly Detected Non-dirt (right).

One inspection result of a dirty SX dish is shown in Figure 14. All dirt spots, even some that are right on the inner edges of multilayers of the dish, are correctly detected. This type of dish with 3 shallow layers was the most difficult case to tune the parameters of the inspection algorithm.

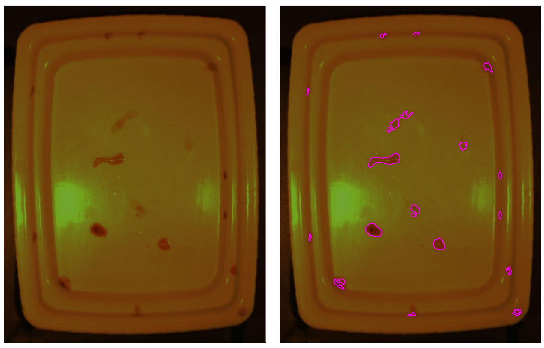

Figure 14: Original SP (left) and All Dirt Spots Detected (right).

A summary of inspection results for all types of dish pieces, SC, SP, SX, LC, and LP is given in Table 6.

Table 6: Summary of Inspection Results for Small Dishes.

	Total	Correct	Miss	Failed Alarm
Clean SC	5	4	-	1
Dirty SC	5	5	0	-
Clean SP	5	4	-	1
Dirty SP	5	5	0	-
Clean SX	5	5	-	0
Dirty SX	5	5	0	-
Clean LC	5	5	-	0
Dirty LC	5	5	0	-
Clean LP	5	4	-	1
Dirty LP	5	5	0	-
All dishes	50	47 (94%)	0 (0%)	3 (6%)

"Failed Alarm" in Table 6 means an incorrect result that a clean dish is classified as dirty. Such results would reduce production in a real inspection process line because the clean dish will be sent back to be re-washed when this was not necessary. On the other hand, such a result is deemed superior to a dirty dish that is classified clean, which would be unacceptable for hygienic and other reasons.

For the results in Table 6, the average computation time for the inspection process was 1.28 second per dish (using Matlab® R14, Image Processing Toolbox V5.0, Window Vista, dual core 1.6GHz, 2GB RAM). If we add this to the average identification time reported earlier, the total average time required for both identification and inspection processes for the small area dish group is approximately 1.47 second, which is acceptable for our target of processing 30 dish pieces per minute (2 seconds per piece).

5 CONCLUSIONS

In this study we successfully implemented new and novel dishware identification and inspection algorithms. The experimental results show that these algorithms work well under variation of lighting conditions caused by variation of dish position under the camera axis. The algorithms implemented on a standardly available PC were sufficiently fast for real time processing at a minimum rate of 30 dish pieces per minute. We also experimented with other dish sets, including plain circular and oval shaped plates, and small bowls. With small changes in few parameters, the algorithms work equally well.

On the other hand, partitioning and adaptive thresholding combined with global thresholding as presented here will not work for dishes that have colored or molded patterns on the surface. However, because most dish sets used in large scale dinning operations are non-textured and mono-colored with uniform background, our procedure should be widely applicable.

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