MVA2002 IAPR Workshop on Machine Vision Applications, Dec. 11 - 13, 2002, Nara - ken New Public Hall, Nara, Japan

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Detection of Foreign Bodies in Food by Thermal Imagery

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Abstract

This paper deals with the problem of detection of foreign bodies in food. A new method for inspecting food samples is presented, using thermographic images to detect foreign bodies that are not detectable using conventional methods. The main part of the present paper introduces specific image processing methods that show a good recognition power of foreign bodies within food. Results are promising and the methods work even on some poorly contrasted images.

1 Introduction

Consumers have high expectations about food purity. The industry extensively invests in machinery, processing and inspection equipment to ensure a high product quality. Unfortunately, in spite of advanced technology, some contamination always occurs. To overcome this problem the food industry is investigating in all fields of purity control.

A foreign body is defined as a piece of solid matter present in a product that is undesirable [4]. It may be an intrinsic foreign body, e.g., hair or bone in an animal product, or extrinsic one, e.g. an insect, a stone, etc.

This work deals with the problem of using infrared thermography for locating foreign bodies in food products. For image acquisition the system shown in Figure 1 was used. We focused our attention on the development of appropriate image processing methods to make suitable information available from the acquired data

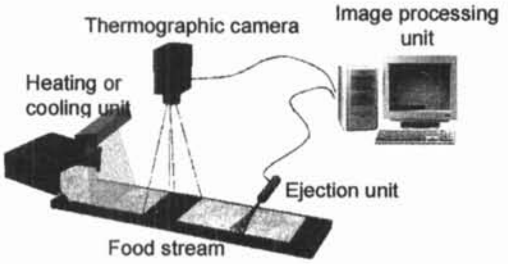

Figure 1: Example of an inspection system using thermography.

2 Foreign body recognition by thermography

The possibility of distinguishing between different materials and objects using thermal images depends on different factors. As no real object will behave like a black body, many different phenomena have to be considered to adapt the model accordingly. Some of them are related to mechanical characteristics of the objects, such as density, geometric shape and surface roughness, while others depend on environmental factors like temperature uniformity, lighting and humidity.

Principally there are two different ways to distinguish between food material and foreign bodies by means of thermography, i.e. either by differing emissivities or by using the different heat conductivities or capacities of the materials. If there is a relevant difference in the emissivity coefficient of the materials, as shown for magnesium oxide and human skin at 4 μm, the two materials can be distinguished by infrared radiation. The second method is to apply a heat pulse and to observe the penetration of the heat into the material. The two materials can be distinguished because of the differing heat conductivities.

To perform the recognition process, a well-contrasted image should be obtained. The emissivity of different food and foreign bodies is often not sufficient to get well-contrasted infrared images. To obtain a higher contrast, it is advisable to heat or cool the samples before grabbing the frames. In this case, the differing heating conductivities and capacities cause a different increasing or decreasing behavior of the surface temperature.

Good thermographic images can be achieved using pulse thermography [2]. The basic principle is to leave the object at rest below the infrared (IR) camera, to apply a heat pulse, e.g. produced by a flashlight, and to observe the decreasing surface temperature. Because of the different heating conductivities and capacities, the objects will cool down with different speeds. To measure the different heat conductivities a sequence of IR images has to be taken, i.e. shortly enough after the pulse to observe the decreasing temperature of material with high conductivity (e.g. metal) and long enough for materials with low conductivity (e.g. wood).

In our experiments, a long sequence (500 frames, 80 frames/sec) has been recorded to extract the data as described above. The acquired sample contains a collection of different materials used to simulate foreign body contamination in real experiments. The average gray level of a 10×10 pixel neighborhood has been computed for each object along the sequence.

By plotting the absolute differences between the previous curves, the temporal behavior of the contrast between different materials is computed (Figure 2), thus making it possible to distinguish between two materials.

When we take wooden sticks, cardboard pieces or metal chips as foreign bodies, the maximum contrast is reached near the beginning of the cooling process. Thus, it is advisable to acquire a frame as soon as possible in the process. On the other hand, stones show the best contrast near the end of the sequence. We can also note that the contrast coming from metal-chip or stone characteristics is much smaller than that of wooden sticks or cardboard pieces. For this reason, foreign body recognition in these cases is expected to be harder.

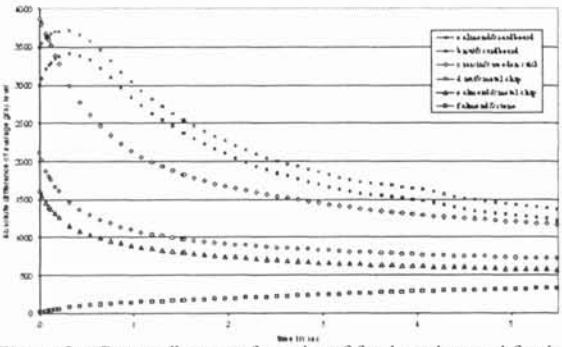

Figure 2: "Contrast" curves for pairs of food product and foreign bodies shown as absolute difference of gray levels vs. time.

3 Experimental setup

The thermographic apparatus used for the experiments is a Thermosensorik-System CMT 384 M [3]. The camera possesses a matrix of 384 x 288 HgCdTe (CMT) cooled infrared sensors, capable of detecting middle infrared radiation in the range of 3.4 to 5.2 μm. The temperature resolution is smaller than 15 mK (NETD) and each pixel has a 14-bit resolution. The pixel pitch is 24 × 24 μm and the maximum full frame rate is 80 to 90 Hz.

4 Thermographic image processing

As our experiments have shown, the thermographic images of food are very different for different materials. Only sometimes a simple gray value threshold can separate the foreign bodies. Usually the whole image is more or less noisy and the detection of the foreign bodies is not that simple.

To solve this problem we implemented a software tool for the interactive selection of the best sequence of image processing operations by testing it on some sample images.

Before analysis and recognition can be done, preprocessing has to be performed in order to enhance the image information content. The preprocessing consists of the following steps: (i) dead pixel correction, (ii) 1st enhancement filter application, (iii) 2nd enhancement filter application shading correction, (iv) histogram stretching.

The first preprocessing task is the correction of dead pixels, defined as those sensor elements in the thermal detecting matrix that behave in an unpredictable way. Such abnormalities, which affect new systems (i.e. at the time of delivery) with a percentage that may reach 1% of total pixels [3], are caused by the destruction of the pixels through cosmic rays, by heat deterioration of sensors and by a high incidence of static electricity. Consequently, a perturbation similar to salt and pepper noise is produced, thus heavily affecting the results of the following processing phase and the recognition output.

These dead pixels have a constant position on the detector surface and may only increase in number in the course of time. Thus, the easiest way to correct this instrumentation defect is to find all dead pixels and correct their intensity values. They can be easily found by acquiring two images, one related to a uniformly hot surface, and the other to a cold one; black and white points respectively detected create the array of dead pixels.

As the information for each dead pixel is missing, and as it is not possible to predict its correct value, we used a simple operator that substitutes each dead pixel value with a good one chosen in its 8-connected neighborhood.

Afterwards, images are enhanced by a filtering step. In many cases, best results can be obtained by applying a median filter, eventually followed by a 3 × 3 cross-shaped (morphological) opening operator.

Another undesirable effect comes from shading. In fact, due to non-homogenous illumination and differing sensitivities between the center and the borders of the sensors, the image can present an inhomogeneous lighting that can lead to severe errors in the following tasks. To avoid this drawback, a background image has to be acquired and subtracted from the original one; it should present slowly varying gray values and its subtraction should not reduce the contrast between background and foreground objects.

Finally, a histogram stretching may be performed for rendering only.

At this point, data are ready to be analyzed and recognized through the scheme that is outlined below. Shortly, three different approaches were designed and tested to solve the problem from different points of view and to fit the majority of occurrences. They rely on binarization, statistical and morphological analysis.

4.1 Adaptive binarization

The first approach was developed to classify images with a good contrast, according to real-time constraints. The basic idea is to select a set of starting regions of interest (ROI) and to perform a local analysis aimed at achieving a better recognition on each of them. The main advantage of this method lies in its simplicity and computational speed. This fits our primary objective, i.e. the real-time recognition of objects on a conveyor belt. Moreover, by reducing the observation window to a neighborhood of pixels around the candidate objects, we obtain more stable statistics and reduce noise (i.e. irregular object patterns). Consequently, the automatic determination of the threshold level is more precise and effective.

The main problem of binarization lies in the automatic threshold level determination; at first we tested and used two different methods from the state-of-the-art (discriminant analysis [5] and recursive binarization [8]). Results of both methods show good performance on bimodal histograms (Figure 3).

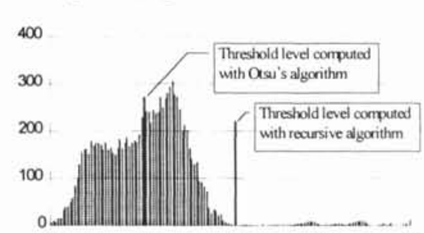

Figure 3: Otsu's vs. recursive algorithm for a threshold level determination.

However, as in several cases data do not show a bimodal behavior, a third method was developed to select a histogram "tail". This method works well on a unimodal histogram for the food material and some outlier from the foreign bodies.

To identify the starting ROI we developed an adaptive thresholding algorithm. After region labeling and the center of mass computation, we have an array of points identifying the positions of candidate foreign bodies. Starting from these points, we perform local object recognition using a local threshold. We select a square

window centered on each center of mass, and iterate the thresholding for each window.
It is important to notice that if an array point does not belong to a foreign body, the local thresholding on the corresponding window will give a false recognition, while if any point of a foreign body is not included in the array, that corresponding body cannot be recognized. Thus the most important task is to determine a first threshold that provides a set of candidates including all the foreign bodies. Figure 4 shows an example of this method for raisins contaminated with wooden sticks.

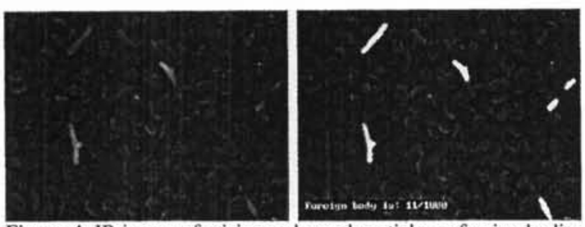

Figure 4: IR image of raisins and wooden sticks as foreign bodies (left) and the recognized contaminants (right).

4.2 Statistical analysis

In the case of images with poor contrast and with foreign bodies having the same gray values as the food objects, adaptive binarization cannot realize an efficient segmentation and identification of foreign bodies. To overcome this drawback, we implemented a method based on the interpretation of food product images as textures with spatially irregular repetitions of structural patterns and foreign bodies being the defects within this texture. Thus, we identified and measured some textural features able to enhance anomalies in a homogeneous behavior. Consequently, image portions containing foreign bodies can be identified.
Texture analysis can be performed in different ways; however, as our data clearly show random textures, the best approach is the statistical one.
The algorithm we implemented starts by dividing images into blocks of fixed size. For each block, a texture feature is measured and compared with that of a prototype. After this, the blocks are classified by thresholding their distance values.
The first problem to be solved relates to the size of blocks. It should not be too large, because it would be useless to segment images in wide regions containing not only foreign bodies but also a big part of the food product. On the other hand, each block has to be large enough to characterize the texture.
Another problem comes from image partitioning into blocks that may result in spreading foreign bodies among adjacent blocks, and a consequent erroneous classification of those blocks as homogeneous. A simple way to solve this could be to use overlapping blocks, even if this results in a considerably higher computational load (at least four times).
Finally, a prototype texel has to be defined for comparison with each block. A simple and effective method is to use the whole image if the foreign bodies constitute a small percentage of it. Otherwise, the block with minimum square distance from all the other blocks can be used.
By taking into account real-time constraints, we devised a method based on histogram analysis (first order statistics).
We define three different metrics: mean value distance $\bar{d}$, mean and standard deviation distance: $d_{\mu\sigma}$, Patrick-Fisher distance, d_{PF}.
A good metric should weight point-to-point differences according to their distance from the mean value. Unfortunately, this condition is not satisfied by any of the proposed metrics; however, this will not affect the estimation unless two histograms to be compared present very similar shapes, with a slight displacement of a group of pixels only.
To define a metric that meets all the previous requirements, we used the rank-order statistics [6, 7]. For a block of N pixels, quantized to M levels, the rank function $R_H(Z)$ of the corresponding histogram $H(gl)$ is defined as the ordered ascending sequence of gray levels:

$$R_H : [x] \rightarrow [y] \qquad (1)$$

where $x \in [1,\dots,N]$ is the position of a pixel in the ordered sequence, and $y \in [1,\dots,M]$ is the corresponding gray level.
It can be proven that there is a one-to-one equivalence between a rank function and its related histogram. Furthermore, to compare two rank functions with different cardinalities, functions must be normalized.
By using these rank functions, three simple histogram distances can be defined: integral square error distance, d_{ISE}, integral absolute error distance, d_{IAE}, deviation from RGV distance, d_{RGV}.
We selected the following distance between a textured block and a prototype:

$$d = \max\left(d_{\mu\sigma}, d_{IAE}\right) \qquad (2)$$

4.3 Morphological analysis

The third approach we implemented is a method using mathematical morphology. This approach was especially designed to meet the problem with small parts of food with the same gray level as foreign bodies, where binarization and statistical approaches may fail. This approach does not only use gray level information but also the difference in the shape to segment food objects from the foreign bodies.
In this case, the processing starts with a gray level skeletonization (thinning), followed by a gray level opening, so that region segmentation is obtained. Finally, small objects are deleted in order to obtain a binary food/foreign-body representation (Figure 5).

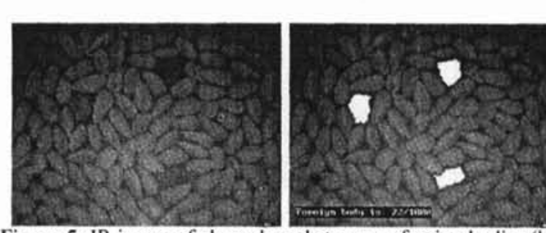

Figure 5: IR image of almonds and stones as foreign bodies (left) and the recognized contaminants (right).

The requirements for a skeletonization procedure of binary objects can be defined very clearly. In the case of gray level instead of binary images, the skeletonization rules have to be interpreted in a weak sense, as e.g. the curve thickness and the topology-preserving properties cannot be defined exactly for gray level images. We realized the gray level skeletonization through morphological operators where the skeletonization rules are used as qualitative principles.
Two cases must be considered, i.e. when foreign bodies are brighter or darker than the background (i.e. the

homogeneous food product). In the former case, skeletonization can be achieved by thinning the white to idempotence, while in the latter by thinning the black to idempotence (Figure 6); this is equivalent to thickening the white to idempotence.

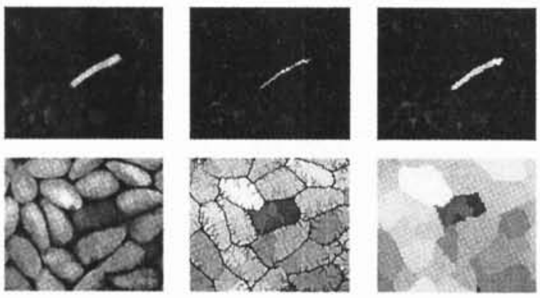

Figure 6: IR images of raisins and wooden sticks (upper row) and almonds and stones as foreign bodies (lower row). The original IR images are shown left, the thinned or thickened white to idempotence images are shown in the center and the dilated images are shown in the right column.

5 Experimental results

For the evaluation of our methods we used ten different test images. Eight of these images present bright foreign bodies on a more or less structured dark background created by the food objects. In two cases the foreign bodies are darker than most of the surrounding food objects. The results we achieved are of course not representative but they give a first impression of the usefulness of the proposed method. Of course experiments with images coming from the real production process have to follow.

The foreign body recognition results are evaluated using three features:

- the ratio between *recognized* and *misrecognized* foreign bodies, where *recognized* means foreign bodies present in the original data, and *misrecognized* means food objects recognized as foreign bodies;
- the ratio between foreign body area in original (interactively measured) and processed data; in this latter case, area relates to the number of pixels in recognized and misrecognized foreign bodies;
- the recognized object connectivity; this can be regarded as a quality index for processing, even if shape information is not essential for foreign body recognition at this stage.

A quality index (QI) that takes into account the previous factors, weighted appropriately, was defined:

$$QI = q_{objects} + q_{area} + q_{connectivity} \tag{3}$$

The results in Figure 7 show good quality QI values. It must be noted that QI values are not representative by themselves, but as comparison between different approaches.

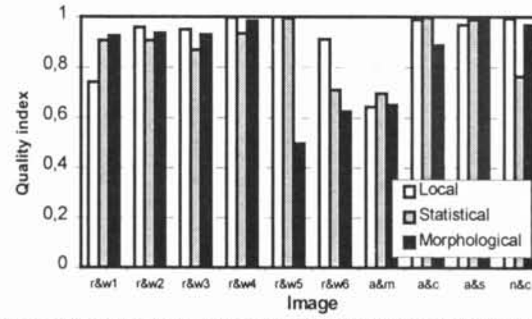

Figure 7: Quality index histograms for each image and recognition method (legend: r&w = raisins + wooden sticks; a&m = almonds + metal chips; a&c = almonds + cardboard pieces; a&s = almonds + stones; n&c = nuts + cardboard pieces).

For most of the 10 test images the three recognition methods give more or less the same performance. Even though the local method provides the best results in six cases, only in one case there is a noticeable difference to the QI of the second best method. On the other hand the local method is the worst method in one case. The statistical and the morphological method are the best of all in one case.

These first results show that the proposed recognition methods are well adapted to the problem of detecting foreign bodies in food using IR thermography.

Acknowledgments

The European Union and the University of Cagliari are gratefully acknowledged (Socrates-Erasmus program). The project was supported by FEI, AiF and the German Ministry of Economics and Technology (Ref: AiF-FV53 ZN).

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