

# Automatic detection of foreign objects in computed radiography

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**Abstract.** This paper presents an effective two-step scheme for automatic object detection in computed radiography (CR) images. First, various structure elements of the morphological filters, designed by incorporating available morphological features of the objects of interest including their sizes and rough shape descriptions, are used to effectively distinguish the foreign object candidates from the complex background structures. Second, since the boundaries of the objects are the key features in reflecting object characteristics, active contour models are employed to accurately outline the morphological shapes of the suspicious foreign objects to further reduce the rate of false alarms. The actual detection scheme is accomplished by jointly using these two steps. The proposed methods are tested with a database of 50 hand–wrist computed radiographic images containing various types of foreign objects. Our experimental results demonstrate that the combined use of morphological filters and active contour models can provide an effective automatic detection of foreign objects in CR images achieving good sensitivity and specificity, and the accurate descriptions of the object morphological characteristics. © 2000 Society of Photo-Optical Instrumentation Engineers. [S1083-3668(00)00704-8]

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## 1 Introduction

Object detection and characterization through medical imaging technologies are among the major clinically driven tasks towards the ultimate goal of diagnosis and treatment of diseases. In particular, newly introduced computed radiography (CR) has shown the potential to replace screen-film radiography (SFR) in routine clinical practice due to its numerous advantages including greater dynamic range and wider exposure latitude.<sup>10</sup> Some quantitative comparison of CR and SFR in detection of specific diseases such as pneumothorax has demonstrated their equal detectability at equivalent exposure factors of two imaging systems.<sup>5,9</sup> More importantly, due to its native digital storage form, image processing and analysis techniques can be seamlessly integrated into the CR system. The objective of this work is to develop an automatic foreign object detection algorithm which locates foreign objects in CR images and provides their accurate boundary descriptions for further diagnosis and treatment.

Object detection in CR images can be accomplished through an accurate representation of the object of interest in terms of its location, size, and shape description. In general, there are two general approaches: (1) data-directed (bottom-up) approach such as edge detection<sup>3</sup> and region growing;<sup>7</sup> and (2) goal-directed (top-down) approach as in knowledge-guided boundary detection.<sup>11</sup> The bottom-up approach operates on the image only based on individual gray level values to extract the object boundary or to obtain the object region, while the top-down approach relies entirely on *a priori* con-

straints regarding the location and shape of the object of interest. In this paper, we propose an automatic object detection technique which incorporates fundamental object characteristics such as the size and generic shape information to initially localize the object of interest from the scene image, and then to confirm the correct presence of suspicious targets through a boundary refining procedure.

The presentation is organized as follows. In Sec. 2, we present a brief review on the object detection problem and address the difficulties of object detection in CR images. The proposed new approach is described in detail in Sec. 3 where two major steps (i.e., morphological filters and active contour models) are explained. In Sec. 4, the application of approach to a set of hand–wrist CR images is reported with the experimental results presented. Discussion and conclusion are provided in Sec. 5.

## 2 Problem Statement

Automatic object detection is still a difficult task in medical image processing since many clinically acquired medical images may be noisy and low contrast. In addition, the presence of the objects in question is frequently self-occluded or partially transparent with uncertain position, size, orientation, shape, motion, etc. Therefore, the precise boundary characterization of these objects may be very difficult.

Most research on object detection falls into two categories: (1) edge detection and (2) region growing. Many edge detection algorithms have been proposed based on the assumption

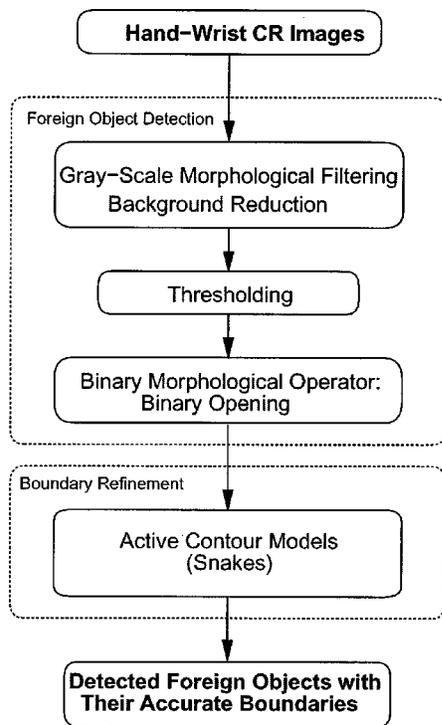


Fig. 1 Block diagram of automatic foreign object detection.

that different objects have different intensity values.<sup>3</sup> However, since most medical images are low contrast and noisy, simple application of edge detection will most likely give broken boundaries of objects. On the other hand, region-based techniques often fail to yield the desired structure due to the difficulty of choosing a reasonable starting “seed” point, an appropriate growing rule or a suitable stopping rule. More recently, knowledge-guided boundary finding methods are proposed to extract geometric shapes based on site models which are best suited for objects poorly described by features or parts. Boundary descriptions using local information fails to give satisfactory results in practice because of poor-contrast boundary regions due to occluding and occluded objects, adverse viewing conditions, and noise. And further difficulty arises when we try to find a model to describe a relatively broad class of shapes such as that of deformable objects. Such difficulty in knowledge representation largely hinders the knowledge-guided boundary finding approach for the object detection problem.

To tackle the problems of aforementioned approaches, two important research areas attracted our attention: active contour models and morphological filters. In this paper, we propose to combine morphological filters with active contour models to automatically detect objects of interest in CR images. The diagram of our automatic foreign object detection algorithm is illustrated in Fig. 1. Morphological filters are first applied to locate the objects by concentrating on location and size information but with rough shape information. Then active contour models are used to modify the contours of the detected objects. Specifically, we model the initial contour extracted by morphological filters as a physical object, and the data as an external force to which the object is attracted, and an iterative procedure can then be initiated to cause the active

contour to move toward the data and ultimately conform to it.

The motivation of jointly using active contour models and mathematical morphological filters can be briefly explained as follows. Active contour models, also called snakes, have recently been developed for finding optimal contours which offer the advantage that the final form of a contour can be influenced by feedback from a higher-level process or an interactive user.<sup>8</sup> The initial contour is generally placed near the boundary of an object under consideration, then image forces draw the contour to the object boundary. Therefore, active contour models are usually used to *interactively* or *semiautomatically* extract object boundaries. On the other hand, mathematical morphology has been an important method for the analysis of geometric structures of objects.<sup>2,6</sup> It aims at analyzing the shape and form of objects by using mathematical set theory, topology, lattice algebra, and random functions. As nonlinear and shape-focused filters, morphological filters can suppress the background but still retain size and location information with a fair amount of accuracy. The geometric nature of the morphological filters is well suited to perform object detection tasks.

### 3 Methods

In order to achieve an automatic foreign object detection in CR images, the proposed approach consists of two major steps: the first step is to detect the foreign objects by using morphological filters: gray-scale *background reduction* and binary *opening* operation. Then the active contour models are followed to refine the boundaries of those detected foreign objects. In this section, we present detailed mathematical formulation of these two methods and describe our two-step algorithm in implementing their functions.

#### 3.1 Foreign Object Detection

Morphological filters are used to detect the foreign objects in CR images whose background is defined by complex bone structures, since morphological filters allow us to suppress the background while retaining size and location information.<sup>2,6</sup> Features brighter than the background, but smaller than the structuring element, can be removed from an image with the opening operation. Thus, if the features of interest are brighter than the background, opening the image by a structuring element bigger than the largest feature will remove the features from the image, leaving behind an estimate of the background. Subtracting the estimate of the background from the original image extracts the features of interest. The morphological filter, *background reduction*, is performed as follows:<sup>2</sup>

$$\text{Background reduction} = \mathbf{A} - (\mathbf{A} \circ \mathbf{B}), \quad (1)$$

where  $\mathbf{A}$  is the original image,  $\mathbf{B}$  is the structuring element whose size is larger than any of the brighter features of interest, and “ $\circ$ ” is the gray-scale *opening* operation, which is defined as:

$$\mathbf{A} \circ \mathbf{B} = (\mathbf{A} \ominus \mathbf{B}) \oplus \mathbf{B}. \quad (2)$$

In the above equation,  $\oplus$  and  $\ominus$  are gray-scale *dilation* and *erosion* operations, respectively. If we denote the gray-scale dilation image of an image  $\mathbf{A}$  by a structuring element  $\mathbf{B}$  as  $\mathbf{C} = \mathbf{A} \oplus \mathbf{B}$ , we can define the element of  $\mathbf{C}$ ,  $c(x,y)$ , as

$$c(x,y) = \max\{a(x-i,y-j) + b(i,j) | (x-i,y-j) \in D_a; (i,j) \in D_b\}, \quad (3)$$

where  $a(x,y)$  is the element of  $\mathbf{A}$  and  $b(x,y)$  the element of  $\mathbf{B}$ ;  $D_a$  and  $D_b$  are the domains of  $\mathbf{A}$  and  $\mathbf{B}$ , respectively.

Similarly, an image  $\mathbf{C}$ , obtained by gray-scale eroding  $\mathbf{A}$  by  $\mathbf{B}$ , denoted by  $\mathbf{C} = \mathbf{A} \ominus \mathbf{B}$ , can be defined by

$$c(x,y) = \min\{a(x-i,y-j) - b(i,j) | (x-i,y-j) \in D_a; (i,j) \in D_b\}. \quad (4)$$

Note that the location of the extracted features by *background reduction* will be exactly the same as those in the original image. In gray-scale morphology, the structuring element can be any three-dimensional structure such as cylinder or hemisphere. In this application, we use an  $n \times n$  hemispherical mask whose individual element is given by

$$w(x,y) = \sqrt{g^2 - (gx/k)^2 - (gy/k)^2}, \quad (5)$$

where  $w(x,y)$  is the intensity at location  $(x,y)$  of the hemispherical structuring element,  $g$  is the peak intensity at the center of the mask,  $x$  and  $y$  lie in the range  $[-k,k]$  with  $k = (n-1)/2$ .

Some small bright bony structures are inevitably detected as foreign objects in hand-wrist CR images, but they can be easily delineated by using the size information as their size is usually much smaller than that of the foreign objects of interest. Therefore we convert the gray-level resulting image from the *background reduction* to a binary image by thresholding. A binary opening operation is then applied to specifically extract only the foreign objects. The binary *opening* of set  $\mathbf{A}$  by structuring element  $\mathbf{B}$ , denoted by  $\mathbf{A} \circ \mathbf{B}$ , can be defined as<sup>6</sup>

$$\mathbf{A} \circ \mathbf{B} = (\mathbf{A} \ominus \mathbf{B}) \oplus \mathbf{B}, \quad (6)$$

where  $\oplus$  and  $\ominus$  denote binary *dilation* and *erosion*, respectively. In other words, Eq. (6) says that the opening of  $\mathbf{A}$  by  $\mathbf{B}$  is simply the erosion of  $\mathbf{A}$  by  $\mathbf{B}$ , followed by a dilation of the result by  $\mathbf{B}$ . For completeness, we give the definitions of binary *dilation* and *erosion* as follows. Let  $\mathbf{A}$  and  $\mathbf{B}$  be sets in  $Z^2$ , the binary *dilation* of  $\mathbf{A}$  by  $\mathbf{B}$ , denoted by  $\mathbf{A} \oplus \mathbf{B}$ , is defined as

$$\mathbf{A} \oplus \mathbf{B} = \{(x,y) | (\hat{\mathbf{B}})_{(x,y)} \cap \mathbf{A} \neq \emptyset\}, \quad (7)$$

where  $\hat{\mathbf{B}} = \{(x,y) | x = -i, y = -j, \text{ for } (i,j) \in \mathbf{B}\}$  and  $(\mathbf{A})_{(x,y)} = \{(c,d) | c = i+x, d = j+y, \text{ for } (i,j) \in \mathbf{A}\}$ . The binary *erosion* of  $\mathbf{A}$  and  $\mathbf{B}$ , denoted by  $\mathbf{A} \ominus \mathbf{B}$ , is defined as

$$\mathbf{A} \ominus \mathbf{B} = \{(x,y) | (\hat{\mathbf{B}})_{(x,y)} \subseteq \mathbf{A}\}, \quad (8)$$

which, in words, says that the erosion of  $\mathbf{A}$  by  $\mathbf{B}$  is the set of all points  $(x,y)$  such that  $\mathbf{B}$ , translated by  $(x,y)$ , is contained in  $\mathbf{A}$ .

### 3.2 Foreign Object Contour Modification

The active contour models, snakes, are used to modify the contours of the foreign objects detected by morphological filters as explained in Sec. 3.1. Starting from the initial boundary of the detected foreign object, the active contour model

uses data, gradient image, as an external force to cause the initial contour to move toward the data and ultimately conform to it. The active contour model, snake, is defined as the following mapping:<sup>4</sup>

$$\Omega = [0,1] \rightarrow \mathcal{R}^2$$

$$s \mapsto v(s) = (x(s), y(s)). \quad (9)$$

We define an active contour model (snake) as a space of admissible deformations  $Ad$  and a functional  $E$  to minimize. This functional represents the energy of the model and has the form

$$E: Ad \rightarrow \mathcal{R},$$

$$v \mapsto E(v) = \int_{\Omega} w_1 |v'(s)|^2 + w_2 |v''(s)|^2 + P(v(s)) ds. \quad (10)$$

where the primes denote differentiation and  $P$  the potential associated with the external forces. The mechanical properties of the model are controlled by the functions  $w_j$ . Their choice determines the elasticity and rigidity of the model. If  $v$  is a local minimum for  $E$ , it satisfies the associated Euler-Lagrange equation<sup>4</sup>

$$-(w_1 v')' + (w_2 v'')'' + \nabla P(v) = 0. \quad (11)$$

To obtain the final solution of  $v$ , a variational calculus method was originally proposed by Kass,<sup>8</sup> while the dynamic programming method developed by Amini et al. allows addition of hard constraints to obtain a more desirable behavior of the snakes.<sup>1</sup> Recently a fast algorithm has been developed by Williams and Shah using a greedy algorithm and can be found in Ref. 12. In this paper, we use this greedy algorithm to modify the boundaries of foreign objects where the external forces are the gradient image data.

## 4 Experimental Results and Discussions

In order to validate the effectiveness of the proposed method in automatic foreign object detection in CR images, intensive computer experiments with both simulated and real cases have been conducted. In this study, we have acquired three different sets of CR images taken from both phantom and cadaver hand specimens. In all these cases, the images are embedded with some small foreign objects with different sizes, shapes, and materials (like plastic, glass, graphite, and wood). The CR images are digitally acquired with a size of  $1700 \times 2000$  and a gray-level resolution of 10 bits/pixel. An example is shown in Figure 2. Since in real-world clinical practice, CR images may be taken with varying radiation dosage depending upon the parameter settings, and it is desirable to obtain CR images with low radiation dosage while maintaining good detectability, our testing database has been designed to cover a broad range of cases by various radiation dosage.<sup>9</sup>

The gray-scale morphological filter, *background reduction*, is applied to the original image to detect the foreign objects with different location, size, shape, and materials. The structuring element is chosen as  $n \times n$  hemispherical mask where  $n$



Fig. 2 Original hand-wrist CR image.



Fig. 4 Binary image after thresholding.

(43 in this experiment) corresponds to the largest size among those foreign objects of interest. The initial detected foreign objects are shown in Figure 3 after application of the gray-scale morphological filter for *background reduction*. As we can see from Figure 3 all the foreign objects of interest are detected without any missing. This result demonstrates that the morphological filter can effectively capture the location and size information of the objects of interest. However, some redundant tiny spots are produced by very bright bony structures. To delineate those small redundant spots, we convert the gray-level outcome from the above step into a binary image simply by thresholding (see Figure 4). Then, we apply a binary *opening* operator to explicitly extract only the foreign objects as demonstrated in Figure 5.

The next step is to refine the boundaries of those detected foreign objects by active contour models. Taking the result from morphological filters as initial contour (Figure 6) and the gradient image as the external forces, we use the fast greedy algorithm to gradually move the initial contour to the final boundary by finding the minimum energy of the active contour model. The final boundaries of detected foreign objects are shown in Figure 7. As we can see, the detected boundaries conform very well to those of the foreign objects regardless of their different locations, sizes, shapes, and materials.

A more complex case is shown in Figures 8–11, where the background is the wrist part and the foreign objects are of various material properties. We can clearly see that the morphological filter separates the foreign objects from the complex background effectively. The active contour model then refines the foreign object contours to conform to the actual object boundaries.

A statistical analysis has been conducted to evaluate the performance of the proposed method. The two-step algorithm is applied to 30 hand-wrist CR images (image sets I and II where image set II includes more complex cases where the background is the wrist part) with a total number of 187 foreign objects embedded. The result is summarized in Table 1 where the foreign objects are categorized by their material properties: (1) metal, (2) plastic, (3) glass, and (4) wood. The performance of the algorithm can be measured by true positive fraction (TPF) (detection rate) defined as:

$$TPF = \frac{\text{number of detected foreign objects}}{\text{total number of foreign objects}}. \quad (12)$$

The bar chart of TPF for four different materials is given in Figure 12 for image sets I and II. The analysis based on TPF shows that the metal objects are the easiest to detect because of their relatively high contrast in CR images, while the wood



Fig. 3 Detected foreign objects by gray-scale morphological filter-background reduction.

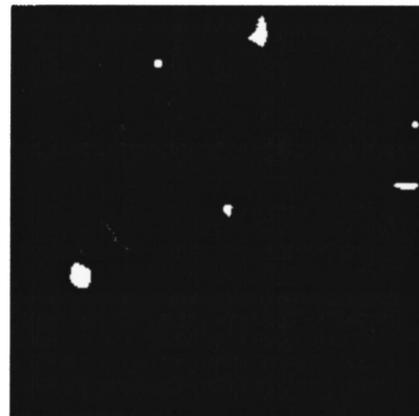


Fig. 5 Detected foreign objects after binary opening operation.



Fig. 6 Initial boundaries of detected foreign objects.

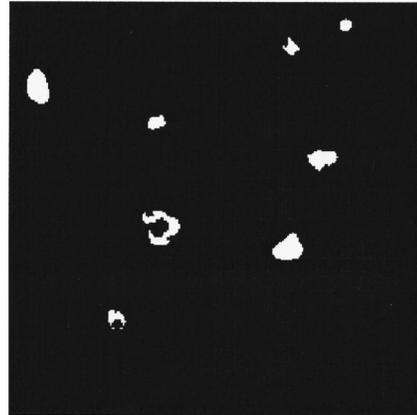


Fig. 9 A complex case: Detected foreign objects after *binary opening* operation.



Fig. 7 Final boundaries of detected foreign objects after active contour models.

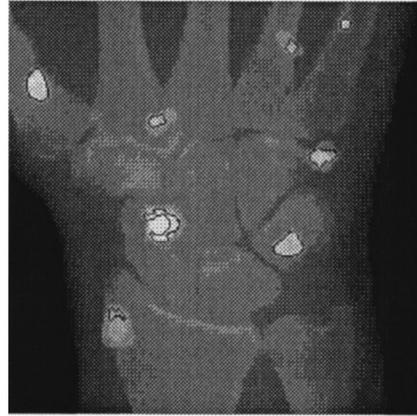


Fig. 10 A complex case: Initial boundaries of detected foreign objects.



Fig. 8 A complex case: original hand-wrist CR image.

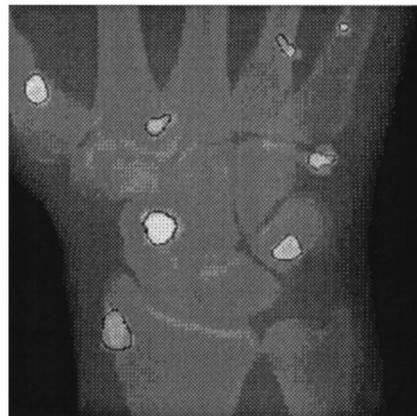


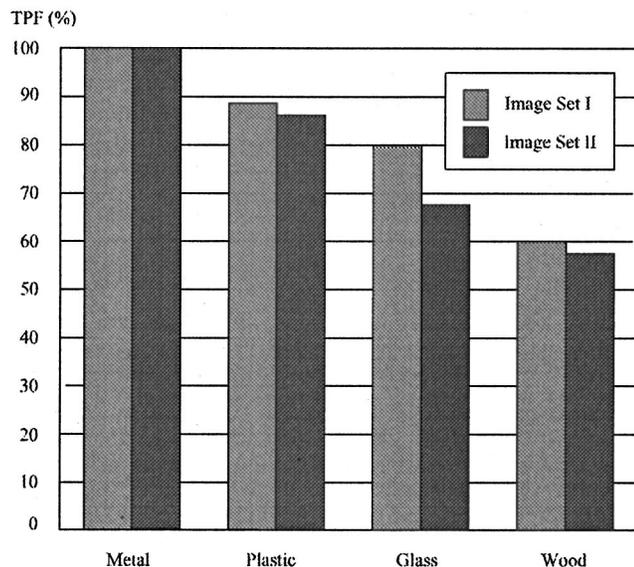
Fig. 11 A complex case: Final boundaries of detected foreign objects after active contour models.

**Table 1** Detection results categorized by various material properties where the number in ( ) is the total number of foreign objects.

Image set	Metal	Plastic	Glass	Wood
I (15 images)	30 (30)	25 (28)	16 (20)	6 (10)
II (15 images)	32 (32)	26 (30)	17 (25)	7 (12)

objects are the most difficult to detect. The statistical analysis further demonstrates that the performance of the proposed algorithm is very good in detecting a variety of foreign objects varying in shape, size, and material.

However, our experience also suggests that foreign object detection can be a very difficult problem. For example, when the acquired set of hand-wrist CR images are embedded with some tiny invading objects, it is very difficult to define the true boundaries of the objects by performing either edge detection or region growing, and direct application of morphological filtering might be problematic. In other cases, when the CR images are taken with low dosage the contrast will be degraded, which further complicates the detection task especially for complex bone structures that exist as the background in CR images. In this study, morphological filters are used to tackle the object detection problem by focusing on location and size of the objects but providing only rough shape information. Then, active contour models, which are capable of capturing accurate shape information, are used to refine the initially obtained rough boundaries. Notice that although the morphological filter implemented in this paper is a simple hemispherical element, it is possible to incorporate any other complex element such as the harmonic shape representation into the proposed algorithm. It is expected that such an extension to modeling complex shapes can enhance the proposed detection scheme dramatically.



**Fig. 12** The statistical analysis result: true positive fraction (TPF).

## 5 Conclusion

In this paper we have presented an automatic foreign object detection algorithm by using morphological filters and active contour models. The morphological filters are used to detect the objects of interest, focusing on the location and size information but only on a rough shape information, to provide the initial contours to active contour models. The active contour models are subsequently employed to refine the boundaries of the detected foreign objects since they can successfully capture the shape information. The algorithm has been applied to hand-wrist CR images to detect foreign objects with different locations, sizes, shapes, and materials. The experimental results demonstrate that the new automatic foreign object detection algorithm provides the location of the objects of interest with their accurate boundary descriptions.<sup>13</sup>

The automatic foreign object detection algorithm has been further integrated into our task-oriented image quality evaluation method which fully takes into account the clinical purpose of the medical images.<sup>14</sup> The task-oriented image quality evaluation method has been shown to be very promising in assessment of CR image quality for radiation dose optimization.<sup>15</sup> In this particular CR study, we can quantify the quality of those images acquired with different radiation doses by comparing the detected boundaries of the foreign objects and their segmented bone structures in addition to the wavelet analysis. The experimental results are consistent with the radiologists' subjective evaluation as reported in Ref. 9. In conclusion, the foreign object detection algorithm developed in this paper can play a significant role in the task-oriented CR image quality evaluation technique to optimize radiation dosage and hence reduce the amount of unnecessary radiation administered to patients during diagnostic procedures.

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