FAST AND ROBUST MARKER DETECTION WITH ROENTGEN STEREOPHOTOGRAMMETRIC ANALYSIS

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INTRODUCTION

Roentgen stereophotogrammetric analysis is a highly accurate tool for the 3D kinematic analysis of bones and orthopaedic implants. The basis of this method is the analysis of x-ray image pairs. An important task in image analysis is the recognition of common shapes such as circles. Circles often identify landmarks of objects for the purpose of location and measurement. A necessary step in RSA is the identification and location of markers that appear near circular on each x-ray image. These circular patterns are formed by the x-ray projection of metallic spheres onto a plane. Spheres of different sizes are used both to define objects used to calibrate the photogrammetric arrangement, and to kinematically define bones and occasionally implants.

Modern RSA systems deal with digital images. The markers visible on these images can be identified by manual selection and processed to determine their locations [1]. This procedure has replaced the more tedious and subjective process of manual marker location via a digitizing table. To further reduce user input and analysis time requirements, the RSA marker identification process has also been performed automatically [2]. For this task, a number of possible routines are available. Most common are the variants of the Hough circle transform [3]. In general, these routines have fairly high computational expense and have a response that relates to the degree of fit between the marker outline and a circle of given radius. This presents a problem for RSA marker detection, since the generally elliptical outlines resulting from the projection of spherical markers will yield a reduced response. This reduced marker response is easily confused with noise or other artifacts, which complicates the process of thresholding the response to determine marker locations. The purpose of this study was to create a marker detection method that was both more robust to marker outline eccentricity than the standard Hough circle transform and more computationally efficient.

METHODS

Current methods

Automatic RSA marker detection has been previously implemented using the fuzzy Hough circle transform [2,4]. The fuzzy aspect of this algorithm provides the flexibility to deal with both marker eccentricity and, to a degree, fluctuation in marker size. This algorithm does however involve a fairly large computational burden and represents 95% of the total RSA processing time, currently representing several minutes per x-ray pair [2]. There are several variants of the Hough circle transform, such as the random and probabilistic formulations, that can reduce computational expense. However these do not provide the same flexibility toward marker eccentricity and size.

Circle detection by convolution

The process of circle detection can be formulated as the convolution of an edge image and a circular template [5]. In this paradigm, a convolution has to be performed for each marker radii. This is not generally a problem in RSA in terms of the computational expense associated with searches encompassing unknown radii, since the equipment arrangements are sufficiently consistent to limit the search to only a few discrete known radii. In this regard the convolution process is quite efficient and can address the issue of computational expense. The template used in the convolution must accommodate the remaining issue of robust response.

Creation of a marker detection template

The convolution template must deal with both elliptical outlines and small variations in marker size that result from slightly changing x-ray arrangements. It must also deal with image noise that causes irregularities in the outline. The proposed template is an annular ring with a Gaussian-like cross-sectional profile (Fig. 1).

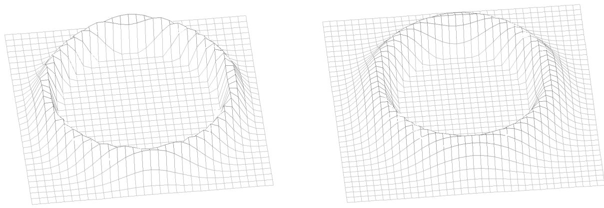

Figure 1: A sample pair of convolution templates for detection of RSA markers with radii of 12 pixels.

The template is created by applying the McClellan transformation [6] to a 2D profile constructed from two identical Gaussian functions set apart by the targeted diameter. The cross-sectional shape is controlled by σ of the input Gaussians. Wider cross-sections accommodate larger marker eccentricities and greater ranges of radii at the cost of center position specificity and reduced signal to noise ratio. As the marker detection results only regionalize marker locations, positional errors of several pixels are acceptable. Once a marker region is isolated, it can be processed to determine the sub-pixel location of the marker.

Validation

The proposed marker detection template and convolution process was compared to the standard Hough circle transform in the categories of response, and processing time. The Canny edge detection results from an image comprised of 20 representative RSA markers (Fig. 2-A,B) was used to test response. Ten of the markers had completely un-obscured outlines, and the other ten, partially obscured or with marker sized artifacts in close proximity. The computational performance was evaluated with respect to increasing image size, using a single 361x361 pixel edge image placed on 15 blank backgrounds ranging from 361 to 1061 pixels square (constant number of edge pixels), and as a function of information quantity with ten 361x361 pixel image sections with differing quantities of edge pixels

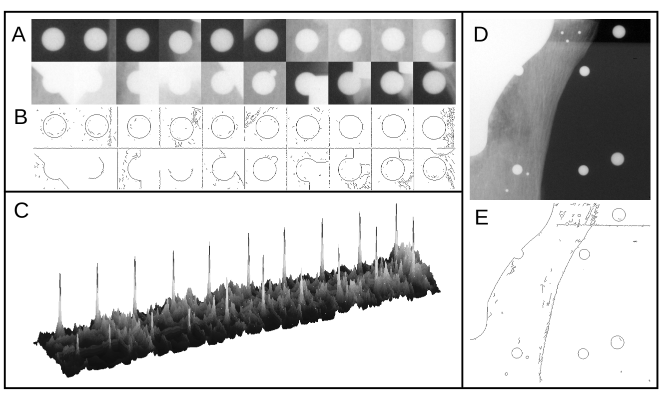

Figure 2: (A) A composite image of single markers; (B) The edge image for A; (C) The response for the convolution process; (D) A typical RSA image section; (E) The edge image for D

Results

A

	Mean Peak Response	Standard Deviation	Max Background Response	Minimum Normal Response (MPR-2SD)	Signal to Noise Ratio (MNR/MBR)
Convolution	164.62	2.86	88.37	158.9	1.798
Hough Transform	87.7	16.68	29	54.34	1.874

B

Marker	1	2	3	4	5	6	7	8	9	10
Convolution	39.6	42.8	49.9	45.4	72.9	92.5	65.3	86.2	97.9	100
Hough Transform	27.5	26.7	31.7	27.5	43.3	71.7	42.5	61.7	84.2	90.8

Figure 3: (A) The marker detection response for un-obscured markers; (B) The response for obscured markers (% of max).

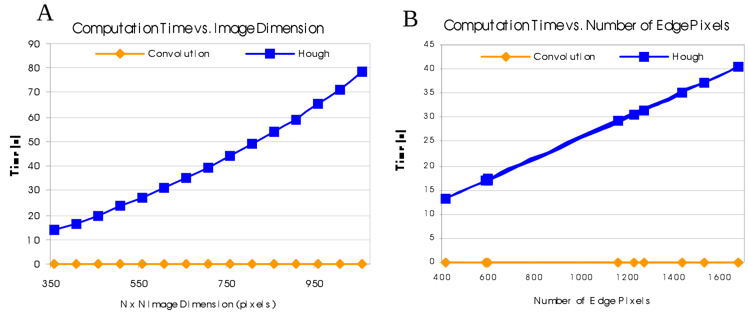

Figure 4: The performance of both marker detection methods with increasing image size (A) and information (B).

DISCUSSION

Response

The response of the convolution-based circle finding method compares very favorably with the Hough transform results. In general the convolution based method has a higher and less variable response (Fig 3-A). When combined with the signal to noise ratio, the ability to localize marker locations is as good if not better than the discrete Hough transform. The response to partially obscured markers (Fig. 3-B) is also a much higher percentage of the peak response with the convolution based method.

Computational Performance

The convolution based method holds a significant computational advantage over the Hough transform. This advantage is increased with increasing image size and content (Fig.4-A,B) and is compounded when multiple radii marker searches have to be performed.

CONCLUSION

The process of marker detection is responsible for the largest percentage of computational time in RSA process and has been previously implemented by use of the Hough transform. The new marker detection method has demonstrated considerable reductions in computational time and a more consistent response to RSA markers. Combined, these improvements provide a more efficient and robust approach to the process of RSA marker detection.

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