An Automated Image-based Method for Multi-Leaf Collimator Positioning Verification in Intensity Modulated Radiation Therapy

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ABSTRACT

Intensity Modulated Radiation Therapy (IMRT) is an innovative, three-dimensional conformal radiation treatment that can deliver highly focused and precisely shaped radiation to a tumor site through the use of the Multi-Leaf Collimators (MLC). A crucial step in IMRT procedure is the verification of MLC positioning to assure the accuracy of radiation treatment delivery. In this paper, we have developed an automated image based method for MLC positioning verification using images acquired from an Electronic Portable Imaging Device. The method consists of three major steps: 1) non-linear geometric distortion correction, 2) isocenter estimation, and 3) MLC leaf boundary recovery. Preliminary experiment on real image data shows that the proposed method is both fast and robust to image artifacts such as intensity inhomogeneity and noise, making it a promising approach for replacing manual verification of MLC in the IMRT treatment.

Keywords: distortion correction, template matching, circle detection, IMRT, MLC verification.

1. Introduction

Intensity Modulated Radiation Therapy (IMRT) is an innovative, three-dimensional conformal radiation treatment that delivers highly focused radiation to a tumor site with minimal impact to surrounding healthy tissues. The delivery of radiation that precisely conforms to the tumor site is made possible by the use of the Multi-Leaf Collimators (MLC). Under computer control, MLC can be arranged dynamically to adjust the shape and intensity of the beam that passes through. A crucial step in IMRT procedure is the MLC positioning verification before the procedure to assure that the treatment is delivered to the target accurately. The current practice for MLC positioning verification, however, is time consuming and requires laborious manual inspection of MLC radiation field through trials and errors by service technicians. In recent years, there has been an increasing interest in automated geometric distortion correction [1] and MLC radiation field verification [2]. Both are important steps for MLC positioning verification. In [1], geometric distortion is corrected along the scan direction based on the physics of EPID imaging. In [2], a moment-based method is used to match two radiation fields.

In this paper, we have developed an automated image based method for MLC positioning verification using images acquired from an Electronic Portable Imaging Device (EPID). The method first corrects the non-linear geometric distortion that presents in the EPID images by analyzing the grid pattern reconstructed from the EPID image of a calibration phantom. The method then employs an active template matching algorithm to match

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precisely a template with the corresponding radiation field. The matching results can be used to estimate both the isocenter location and the MLC leaf positions. The detected leaf positions are then used to verify the accuracy of MLC positioning.

2. Method

2.1 EPID Image Distortion Correction

Because EPID image suffers from nonlinear geometric distortion due to its imaging process, we need to correct the distortion before detecting the MLC leaf positions. To estimate the distortion field, we use a phantom consisting of bearing balls placed on a regular rectangular grid. Fig. 1a shows the EPID image of the phantom. The image clearly shows the nonlinear distortion of the rectangular grid pattern. In addition, it is apparent to see that the image also suffers from imaging artifacts such as intensity inhomogeneity and spurious structures near the bottom of the image. To deal with the imaging artifacts, we propose using a circle-enhancement filter to preprocess the image before applying the algorithm to compute the distortion field.

Circle-enhancement filter: Given an image $I(i,j)$, $i \in [0, K\text{-}1]$, $j \in [0, L\text{-}1]$, a circle template T of radius R is given by

$$T(m,n) = \begin{cases} 1/Q & r \le R \\ -1/P & r > R \end{cases}$$

where $m \in [0, M\text{-}1]$, $n \in [0, N\text{-}1]$, $r = \sqrt{[m-(M-1)/2]^2 + [n-(N-1)/2)^2]}$, and M and N are both odd numbers. Q is the number of pixels in the template that has $r \le R$, and P is the number of pixels in the template that has $r > R$. Such defined template has the property of yielding zero response at regions with homogeneous intensity. A straightforward template matching method will filter an image with the given template for matching circles. However, due to intensity inhomogeneity, circles at different region of image can have very different intensity characteristics, which can significantly degrade the algorithm detection performance. Here, we implement the circle-enhancement filter using a normalized correlation filter that can handle intensity inhomogeneity and yield satisfactory detection results. The normalized correlation filter is defined as follows:

$$F(i,j) = \frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} I(i+m, j+n) T(m,n)}{\sqrt{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} I(i+m, j+n)^2}\sqrt{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} T(m,n)^2}}$$

where $i \in [\frac{M-1}{2}, K - \frac{M+1}{2}]$ and $j \in [\frac{N-1}{2}, L - \frac{N+1}{2}]$.

Distortion Correction: Since the EPID image is usually quite large, to speed up the algorithm, we first apply the circle filter at a coarse image subsampled from the original one. Circle centers can be easily detected by finding the local maximums from the filtered image. An initial grid position and orientation can then be estimated based on the detected circle centers. For each circle center detected at the coarse image, we apply a circle filter to its local neighborhood at the original image to refine the detection of the circle center and the grid reconstruction. Finally a distortion field is computed by interpolating displacement vectors with bilinear interpolation between each grid point and the corresponding circle center. Applying its inverse transform to the subsequent EPID images corrects the geometric distortion.

2.2 Active Template Matching Algorithm

For both isocenter estimation and MLC leaf position estimation, we would like to recover the radiation field boundary shaped by the MLC leaves (see Figs. 2a and 3a). Due to the blurring caused by the EPID imaging, sharp corners are rounded out in the image and make it problematic to apply non-model based method that fails to incorporate the constraint that the radiation field is formed by rectangular MLC leaves. In this paper, we propose to use the active template matching method, a model based method that iteratively fits the model to the radiation field, and a local leaf position refinement to solve the boundary recovery problem. The matching algorithm used here can be regarded as a rigid matching version of the well-known active shape models [3]. The local refinement, described in 2.4, is only performed in MLC leaf position estimation. For isocenter estimation, this step is unnecessary since the radiation field has the shape of a square.

Detecting edge pixels of MLC field: Given the MLC field image, we apply a sequence of mathematical morphological filters to process the image and extract the edge pixels. First a binary image is computed by thresholding the original image with the mean image intensity. The binary image is then filtered through an area-closing algorithm that closes all the holes in the image. Then the largest object in the image is selected through a size filter implemented through region growing to remove the isolated small objects. Finally, the edge pixels are detected by finding all the boundary pixels of the extracted object.

Template construction: Since shapes of the radiation fields used for the verification of MLC leaf positions are known *a priori*, for each radiation field image, we can construct a template $\mathbf{T}$ which can be represented by $\mathbf{T} = [(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)]$. The shape of the template is given by connecting each node (x_i, y_i) with the next node (x_{i+1}, y_{i+1}). Note that even though the shape is specified by a list of discrete points, the shape they represent is really a continuous shape.

Finding the closest points on the template: Since the template consists of a list of line segments, the closest point of an edge pixel to the template can be computed straightforwardly by finding the closest point to each line segment and then choose the one that gives the minimum distance among all line segments. Here, because the template for MLC radiation field consists of a small number of line segments, finding the closest point directly is actually faster than using the general closest point finding algorithm such as either k-d tree or geometric bucketing technique.

Aligning two shapes: The set of closest points and the set of edge pixels represent two shapes with unique one-to-one correspondence. Matching two similar shapes represented by point sets is a well-studied problem and in our work we use the aligning algorithm described in [3]. Given two similar shapes, $\mathbf{x}_1 = (x_{11}, y_{11}, \ldots, x_{1n}, y_{1n})^T$ and $\mathbf{x}_2 = (x_{21}, y_{21}, \ldots, x_{2n}, y_{2n})^T$, we would like to choose a rotation, q, a scale s, and a translation, (t_x, t_y), mapping $\mathbf{x}_2$ onto $M(\mathbf{x}_2) + \mathbf{t}$ so as to minimize the weighted sum

$$E = (\mathbf{x}_1 - M(s,q)[\mathbf{x}_2] - \mathbf{t})^T \mathbf{W} (\mathbf{x}_1 - M(s,q)[\mathbf{x}_2] - \mathbf{t}), \quad (1)$$

where

$$M(s,q)\begin{bmatrix} x_{jk} \\ y_{jk} \end{bmatrix} = \begin{pmatrix} (s\cos q)x_{jk} - (s\sin q)y_{jk} \\ (s\sin q)x_{jk} + (s\cos q)y_{jk} \end{pmatrix}, \quad \mathbf{t} = (t_x, t_y, \ldots, t_x, t_y)^T,$$

and **W** is a diagonal matrix of weights for each point. In this application, the weight for each pair of points is chosen to be $w_i = (D+e)^{-1}$, i = 1, … , n, where D is the distance of each closest point to the nearby corner node point on the template, and e is an arbitrary small constant. The idea is to give points that are close to corners higher weights, resulting in a more robust aligning algorithm. If we write $a_x = s \cos q$, $a_y = s \sin q$, the optimal aligning parameters (a_x, a_y, t_x, t_y) to Equation (1) can be solved uniquely by a least-square minimization approach. The actual aligning algorithm is outlined below:

1. Construct a template based on the shape of the MLC radiation field.
2. Detect edge pixels of the radiation field
3. Find closest points on the template
4. Align the closest points with the edge pixels
5. Transform the template using the computed aligning parameters
6. Go to step *3*, until the change to the transformation falls below a given threshold.

2.3 Isocenter estimation

In order to report the MLC leaf positions in the IEC (International Engineering Consortium) coordinate system, the isocenter of the IMRT system has to be located. Given two square-shaped MLC radiation field images with rotation angle 0 and 180 (Fig. 2a shows one of the distortion corrected images), respectively, we apply the active template matching algorithm to find the best-fitting rectangle to match the radiation field boundary in each image. By matching the same corners from both images, we obtain 4 pairs of corner points. The position of the isocenter can then be estimated as the average of the midpoints between each pair of corner points.

2.4 MLC leaf position estimation

In the last phase, the MLC shape, i.e., MLC leaf positions will be detected using a diamond-shaped radiation field EPID image (Fig. 3a). Apply the same active template matching algorithm but a diamond-shaped template, we can find the best-fitting diamond shape to the radiation field image. Since the thickness of visible leaves is identical, the leaves given by the fitted template have the correct y coordinates. However, because of the possible leaf positioning error, the x coordinates of the leaves are only near to the actual leaf boundary. By using the x coordinate of each leaf from the fitted template as an initial starting point, we search horizontally for the local 50% intensity drop off near the maximum gradient to obtain the final x coordinate of the leaf. Using the physical value of the phantom grid spacing and the estimated isocenter as the origin, we can report the final MLC leaf positions in IEC coordinates for MLC positioning verification.

3. Results

The proposed method has been tested successfully to verify the MLC leaf positions of Siemens Mevatron IMRT system. The software is written in Microsoft Visual C++ and the entire process takes 1.4 seconds on a 1.5 GHz Pentium 4 PC. Fig. 1 shows the result of correcting the nonlinear geometric distortion. In particular, note that in Fig. 1b, the circle filter not only completely removes the intensity inhomogeneity apparent in the original image but also has the desired property of producing peaks at the circle centers. Figs. 2 and 3 show the active template matching results for radiation field boundary recovery. Fig. 4 shows the final detected and labeled MLC leaf positions. The coordinates are reported in millimeters.

4. Conclusion

In summary, we have developed a fast and robust method for MLC positioning verification based on EPID images and demonstrated its effectiveness through experiment on real images. This method can be used as a tool for the service technicians to perform the MLC calibration with less time. Moreover, the method can provide a basis for automatic MLC calibration and on-line MLC positioning verification.

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REFERENCE

1. S. S. Samant, et. al., "A new calibration technique for KCD-based megavoltage imaging," *Proc SPIE* 3659:779-792, 1999.
2. L. Dong and A. L. Boyer, "A portal image alignment and patient setup verification procedure using moments and correlation techniques," *Phys. Med. Biol.*, 41:697-723, 1996.
3. T. F. Cootes, C. J. Taylor, D. H. Cooper, and J. Graham, "Active shape models --- their training and application," *Computer Vision and Image Understanding*, 61(1): 38-59, 1995.

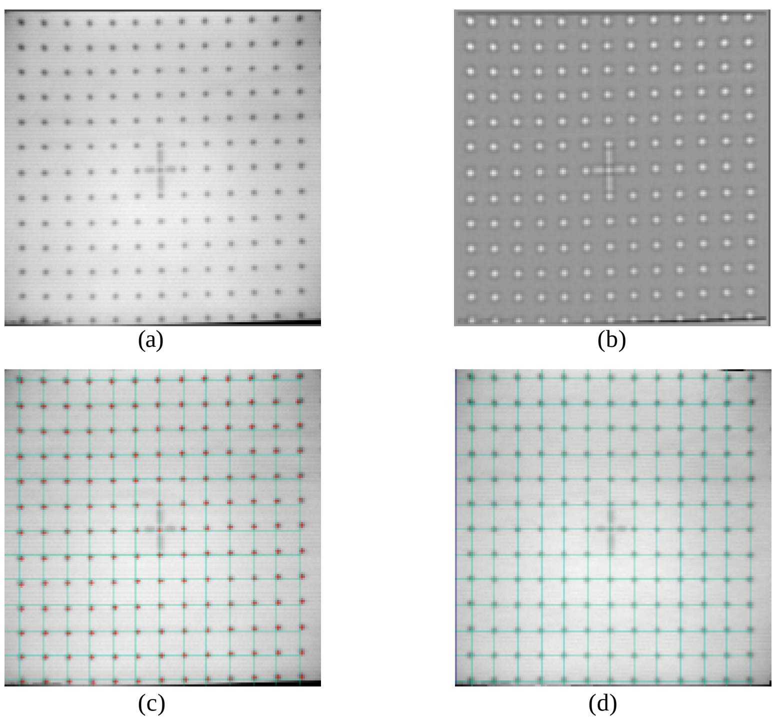
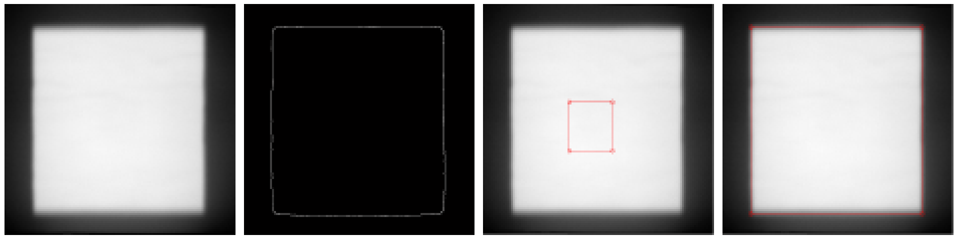
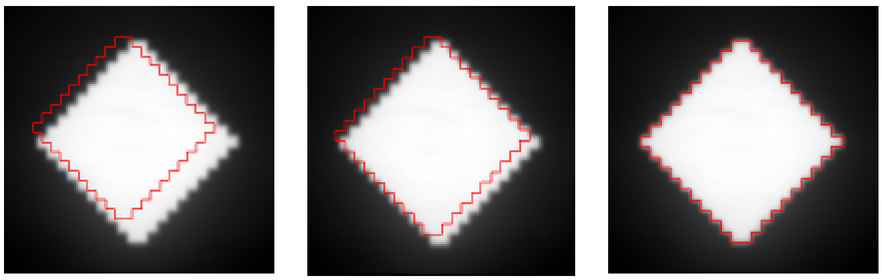


Figure 1: Distortion correction: (a) EPID image of the calibration phantom, (b) result after circle filtering, (c) detected circle center and reconstructed grid, and (d) distortion corrected image.



(a) (b) (c) (d)

Figure 2. Matching a template to a rectangle radiation field: (a) distortion corrected EPID image, (b) edge map, (c) initial template position, and (d) final template position.



(a) (b) (c)

Figure 3. Matching a template to a diamond-shaped MLC field: (a) initial template position, (b) intermediate template position, and (c) final template position.

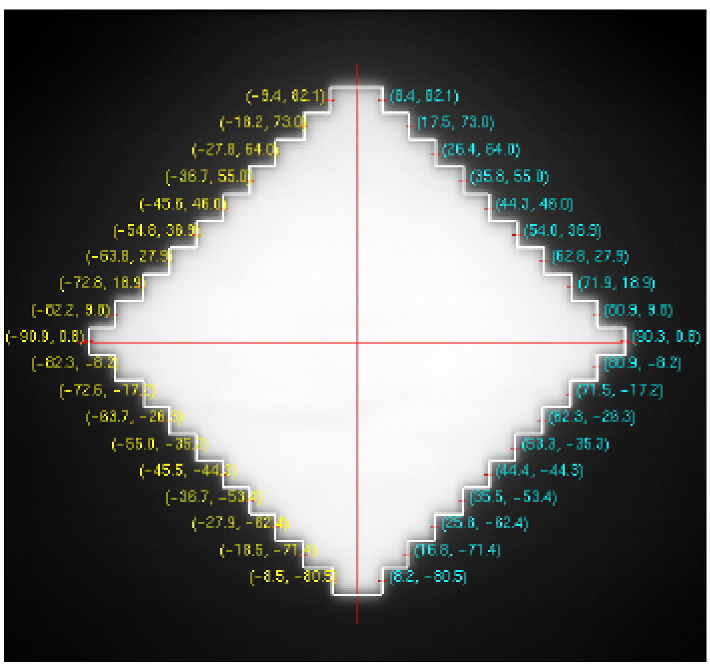


Figure 4. Labeling and detected MLC leaf positions