A novel marker enhancement filter (MEF) for fluoroscopic images

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Abstract. To enhance the measurements of radio-opaque cylindrical fiducial markers in low contrast x-ray and fluoroscopic images, a novel nonlinear marker enhancement filter (MEF) has been designed. It was primarily developed to assist in automatic initialization of a tracking procedure for intra-fraction organ motion analysis in fluoroscopic sequences. Conventional procedures were not able to provide sufficient improvement due to the complications of noise, small marker size, cylindrical shape and multiple orientations, intensity variations of the background, and the presence of overlaying anatomical measurements in this application. The proposed MEF design is based on the principles of linear scale space. It includes measures that assess the probability of each pixel to belong to a marker measurement, morphological operations, and a novel contrast enhancement function for standardization of the filter output. The MEF was tested on fluoroscopic images of two phantoms and three prostate patients, and was shown to perform better or comparable to the existing filters in terms of marker enhancement and background suppression, while performing significantly better in marker shape preservation.

1. Introduction

Image guidance with kilovoltage imaging units mounted on a linear accelerator has become a conventional clinical practice for radiation therapy [1]. One particular example is the monitoring of intra-fraction organ motion using fluoroscopic image sequences. Fluoroscopic tracking has the advantage of providing unassisted real-time organ motion information using existing equipment, but the desire to keep the imaging radiation dose as low as possible results in images that require significant postprocessing in order to extract the relevant content.

Often, radio-opaque fiducial markers are inserted prior to planning to improve the reliability of localizing organs with limited x-ray contrast, such as the prostate [2]. In order to measure the intra-fraction organ motion of prostate patients, we are designing a method for tracking the fiducial markers in lateral fluoroscopic image sequences [3][4]. Automatic tracking requires reliable initialization, i.e., finding markers in the first frame of a sequence. That is challenging due to the low contrast, noise, and the small marker size. In our case, the markers are gold cylinders 3 mm long and 0.8 mm in diameter that appear as about 12 × 3 pixel measurements. Automated tracking is initialized by preprocessing the fluoroscopic image to enhance the markers, and then registering it [5] to the 3D cone-beam computed tomography (CBCT) image.
Several approaches for marker enhancement and detection have been reported in the literature, such as morphological opening [6], template matching [7][8], and the marker extraction kernel (MEK) [9]. For cylindrical markers, these methods require the use of multiple templates, preliminary knowledge of marker orientations, and additional processing, such as noise reduction filters [6][9], edge enhancement [7], and intensity thresholding [7], for which the selection of parameters that will work well for different images can be challenging. In addition, these methods tend to distort the marker shape, e.g., by amplifying one side of the marker more strongly than the other. This distortion can degrade localization accuracy and compromise estimation of marker orientation.

In this paper, we propose a novel marker enhancement filter (MEF) that is tailored to the characteristics of the markers. The MEF amplifies the markers, suppresses the background and anatomical features, and preserves marker shapes. The proposed filter is designed within the linear scale-space framework [10] that has found wide utilization in the enhancement of vessels and other line-like and blob structures [11][12], and in feature detection and image matching applications for computer vision [13], due to its ability to achieve global contrast for the sought-for features. The MEF includes an adaptation of the vessel enhancement approach proposed by Frangi et al. [11], morphological operations [14], and a novel contrast enhancement function that is able to operate successfully on a variety of images with different intensity characteristics. While Frangi’s method was targeted at enhancement of the tubular structures, the markers we seek to amplify are quite different, which leads to a different filter design. The fluoroscopic images are subject to temporal filtering with a Dolph-Chebyshev filter [15] prior to the MEF application, which provided the best contrast-to-noise ratio among other methods that we tested on a phantom with moving markers [4].

2. Marker enhancement filter design
2.1. Scale-space analysis

In computer vision, there is an accepted perspective that features in the images only meaningfully exist over limited ranges of scales [10]. To perform an automatic image interpretation, a multi-scale representation was proposed [10] (and references therein), in which the original image $A : \mathbb{R}^2 \rightarrow \mathbb{R}$ is embedded into a one-parameter family of derived images $L : \mathbb{R}^2 \times \mathbb{R}_+ \rightarrow \mathbb{R}$, where the additional non-negative scalar parameter is the scale. The scale-space representation is defined as the convolution of the image with the Gaussian functions of the appropriate scales:

$$L(x, \sigma) = A(x) * G(x, \sigma) \text{ for } \sigma > 0, \text{ and } L(x, 0) = A(x), \quad (1)$$

where the Gaussian is defined as $G(x, \sigma) = \exp \left( -\frac{\|x\|^2}{2\sigma^2} \right) / (2\pi\sigma^2)$, and $*$ denotes two-dimensional convolution. Due to the fact that the fiducial markers in our application are all of equal or very similar size to each other, we only compute $L$ for one fixed scale, $\sigma = \sigma_0$, that is selected to amplify the features close in size to the markers.

A common approach to analyze the local behaviour of an image intensity function is to consider its second order Taylor expansion in the neighborhood of a point $x_0$ [11][12]. Some methods directly utilize second order derivatives of $L$. For example, the Laplacian of Gaussian (LoG) [10] method was used in several studies for marker enhancement in portal images [16][17]. However, in addition to enhancing the markers, the LoG is prone to enhancing anatomical features that have a dimension that is of a similar scale to the markers. In the following sections we describe the proposed filter and show how it is able to overcome this issue.

2.2. MEF principles: Magnitude-and-ratio versus magnitude-only image

One way to characterize the contrast and shape of features in the image at a particular scale is to analyze the sign and magnitude of the eigenvalues of the Hessian matrix that is constructed from
Figure 1. The magnitude-and-ratio $Y_{mr}$ (left) and magnitude-only $Y_m$ (right) images. While both attain high response in marker pixels (encircled), $Y_m$ is characterized with better marker shape preservation, but also undesirably amplifies long anatomical features (e.g., in rectangle).

the second order derivatives of $\mathcal{L}$. For the bright markers on a dark background, the intensity function should: (i) be concave, which requires negative eigenvalues; (ii) possess a reasonable contrast that is reflected in the magnitude of the eigenvalues; and (iii) describe a feature whose dimensions are not very different, which can be assessed in terms of the ratio of the eigenvalues. More formally, if we let $\lambda_1$ and $\lambda_2$ denote the eigenvalues of the Hessian of $\mathcal{L}(x, \sigma_0)$ at a given point $x = x_0$, the magnitude measure at that point is defined as $X_m = \sqrt{\lambda_1^2 + \lambda_2^2}$, and the ratio as $X_r = \lambda_1 / \lambda_2$, where $|\lambda_1| \leq |\lambda_2|$ [11]. An effective marker enhancement filter should provide high response in the image pixels with $\lambda_1, \lambda_2 < 0$, and large $X_m$ and $X_r$.

Based on the insight from the work of Frangi et al. [11], we incorporate $X_m$ and $X_r$ into probability-like measures, based on which we define a magnitude-and-ratio image:

$$Y_{mr} = \begin{cases} 
1 - \exp \left( -\frac{X_m^2}{2\gamma^2} \right) \left( 1 - \exp \left( -\frac{X_r^2}{2\beta^2} \right) \right), & \text{if } \lambda_1 < 0 \text{ and } \lambda_2 < 0, \\
0, & \text{otherwise,}
\end{cases} \tag{2}$$

where $\gamma$ and $\beta$ are used to normalize the values of $X_m$ and $X_r$. As suggested in [11], $\gamma$ is chosen to be half of the maximal $X_m$ value. For circularly shaped blobs, $\beta = 0.5$ would be used [11]. We reduce $\beta$ to 0.25 based on visual observations of the filtered images in order to produce high response for a range of shapes from circular to elliptical blobs. Although the marker dimensions are known, it is not practical to tune the filter to elliptical blobs exclusively, as the measurements are often corrupted by the noise and overlaying structures, and rarely possess exactly the same ratio as the markers. Observing that the markers may often have reasonably high contrast in fluoroscopic images, we have also considered a magnitude-only image:

$$Y_m = \begin{cases} 
1 - \exp \left( -\frac{X_m^2}{2\gamma^2} \right), & \text{if } \lambda_1 < 0 \text{ and } \lambda_2 < 0, \\
0, & \text{otherwise.}
\end{cases} \tag{3}$$

Comparing $Y_{mr}$ and $Y_m$ in application to our fluoroscopic images (see Figure 1), we notice that while the markers possess high intensities in both of them, $Y_m$ offers better marker shape preservation, but also undesirably amplifies long anatomical features similar in width to the marker size. To gain from the desirable properties of both images, we combine them by using $Y_{mr}$ as a mask for $Y_m$, i.e., the intensities in the filtered image are derived from $Y_m$, but only from the high-intensity regions of $Y_{mr}$.

2.3. Contrast enhancement function

Intensity thresholding is often used as a part of multi-stage procedures to improve the filtering outcome by further separating the sought-for markers from the background. It is typically
performed by setting all intensities in the image that fall below a preset value $\vartheta$ to the minimal background intensity, e.g., [7][17]. However, we prefer to use a smooth threshold function as it increases overall reliability of image registration that will be performed on the output of the MEF filter in the proposed application. In particular, given an image $Y$ with values in $[0, 1]$ we will construct the contrast enhanced image $C(Y) = Y Z(Y)$, where $Z(Y) = \frac{\vartheta \log_2(\tau)}{\vartheta - 1} (1 - \frac{1}{\vartheta})$. In this expression $\vartheta$ is the threshold, $\tau$ is the minimum intensity of all marker points after contrast enhancement, and $s$ is the sharpness of distinction between the marker and non-marker points. In our experiments we chose $\tau = 1/2$ and $s = 3$.

As in all thresholding methods, the choice of $\vartheta$ is critical. We have derived a marker-based model for choosing the threshold [4]: We seek to amplify as many bright pixels in the image, as there are expected to be occupied by the markers, and suppress everything else. For the cylindrical markers that are close to the isocentre and appear full-length in the lateral images, the number of pixels can be approximated by $m = n \lceil \frac{2rh}{\delta^2} \rceil$, where $n$ is the number of markers, $r$ and $h$ are their radius and length, respectively, and $\delta$ is the size of the pixel side. The intensity values in the image are sorted in a descending order, and the threshold $\vartheta$ for this image is chosen to be the $m$-th element in this sorted sequence.

### 2.4. MEF algorithm

The MEF consists of the following steps, which are depicted in Figure 2:

- The scale-space representation is computed for a (temporally filtered) fluoroscopic image.
  
  We found $\sigma_0 = 0.7$ mm to be the most appropriate for our marker size.
- Images $Y_m$ and $Y_{mr}$ are computed as described in Section 2.2, and $Y_{mr}$ is contrast enhanced by the function $C$ defined in Section 2.3.
- Computation of the mask $M$. As markers in $Y_{mr}$ often appear smaller than in $Y_m$ (see Figure 1), the high-intensity regions in $Y_{mr}$ are enlarged by morphological dilation [14] with the circle of radius $h/2$ as the structuring element. To have the same intensity for all points within one contiguous region, we group them and assign the largest intensity value to all.
- The grayscale mask $M$ is multiplied with $Y_m$, and the final MEF-image is produced after another contrast enhancement step with the function $C$.

Our experimental implementation of this algorithm in Matlab produced the MEF-image in Figure 2 in about 3 seconds on a modestly powered desktop (Intel Quad CPU Q6700 @ 2.66Hz, 4 GB RAM). This enables us to foresee a real-time implementation for clinical use.

### 3. Filter validation

In addition to visually verifying, on multiple images, that the MEF produces desirable results in terms of marker amplification, background suppression, and marker shape preservation, we have conducted quantitative validation experiments. The fluoroscopic images were acquired at 5.5 Hz at a technique of 120 kVp, 32 mA, 40 ms per frame for phantoms, and 120 kVp, 64 mA, 20 ms for prostate patients. MV irradiation was off.

### 3.1. MEF success rates

The true positive rate (TPR) is defined as the percentage of the points enhanced by the MEF (those with intensity greater than $\tau$) that belong to the markers. In the controlled environments we consider, the marker positions can be determined to high accuracy [4]. Table 1 shows median TPR for moving Quasar respiratory phantom (Modus Medical Devices Inc., London, ON; 23 frames, linear motion at 2.3 mm/sec), stationary pelvic RSVP phantom (The Phantom Laboratory, Salem, NY; 342 frames), and 3 prostate patients (200 frames each), for images obtained by combining $\ell$ frames with the Dolph-Chebyshev filter (i.e, temporal filtering). In
Figure 2. Steps of the MEF algorithm.

Table 1. TPR depending on the kernel size, $\ell$, of the Dolph-Chebyshev temporal filter.

| $\ell$ | Quasar | RSVP | Patient 1 | Patient 2 | Patient 3 |
|-------|--------|------|-----------|-----------|-----------|
| 1     | 100    | 78.17| 76.85     | 92.59     | 73.15     |
| 3     | 100    | 95.63| 97.22     | 100       | 88.89     |
| 7     | 100    | 99.6 | 100       | 100       | 90.74     |
| 11    | 100    | 100  | 100       | 100       | 93.52     |

In general, the TPR increases for larger $\ell$, and decreases as the region of interest (ROI) grows. Table 1 contains the results for ROIs that measure approximately 45 $\times$ 100 mm for the phantoms (include 7 markers) and 50 $\times$ 70 mm for the patients (include 3 markers). Note that substantial TPR improvement is observed from $\ell = 1$ (no temporal filtering) to $\ell = 3$, and that for the phantoms and the first two patients the TPR reaches 100% for $\ell = 11$.

3.2. Comparison to other filters
We have also compared the MEF to other filters reported in the literature, such as the MEK [9], LoG² [10], Sato’s blob filter [12], and Frangi’s line filter [11]. The data points in Figure 3 are obtained by computing the median true (TP) and false positives (FP) as a percentage of positives after applying a series of intensity thresholds to 342 images of the RSVP. As the results suggest, the MEF shows the least FP for high TPs.

4. Discussion
Although it was designed with a particular application in mind, the proposed filter can be used in a variety of marker localization and tracking applications. The main advantages of the MEF over other filters are its marker enhancement and shape preservation properties, and its successful background suppression. No preliminary information about the marker orientation is required. We also observe that the use of temporal filtering prior to the MEF application improves the filtering outcome and reduces the computational cost of constructing the mask $\mathcal{M}$.

The main limitation of the MEF comes from the assumption that among all features observed
Figure 3. TP and FP percentages for different filters for $\ell = 1$ (left) and $\ell = 7$ (centre). The figure on the right shows a zoom-in into the high TP and low FP region for $\ell = 7$.

at scale $\sigma_0$, the markers possess the highest contrast. While a couple of features similar to the markers in size and contrast typically do not jeopardize marker localization, the presence of a higher-contrast feature with one of the dimensions corresponding to $\sigma_0$ and the other much larger is not desirable. In scenarios in which one of the markers has extremely low contrast, the MEF tends to allocate more high-intensity points to the remaining markers rather than amplifying anatomical features. In our application [4], the missing markers are recovered by subsequent registration to the daily 3D CBCT image.

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