Motion Detection for Adaptive Spatio-Temporal Filtering of Medical X-Ray Image Sequences

Marc Hensel[1], Gordon Wiesner[1], Bernd Kuhrmann[2],
Thomas Pralow[2] and Rolf-Rainer Grigat[1]

[1]Vision Systems, TU Hamburg-Harburg, D-21079 Hamburg
[2]General X-Ray, Philips Medical Systems, D-22335 Hamburg
Email: marc.hensel@tu-harburg.de

Abstract. Spatio-temporal filters are used to improve the quality of X-ray image sequences exhibiting severe noise in real-time. The spatial and temporal ratios have to be adapted locally in order to avoid artifacts. We propose a method processing the positive and negative pixel values of difference images independently in order to detect regions dominated by motion and single pixels dominated by noise. In the context of noise-adaptive binarization using Euler numbers, the influence of noise and motion on Euler curves is investigated.

1 Introduction

X-ray image sequences visualized in real-time play an important role in clinical applications as e.g. angiography, where medical instruments are navigated or the flow of contrast agents is observed. As patients and medical staff are exposed to radiation over a long period during examinations, the radiation doses used are very low resulting in low image quality possessing severe noise.

The use of digital sequences enables us to apply image processing algorithms like multiscale analysis [1] or spatio-temporal filtering for noise reduction in real-time. In our experience, temporal filtering, e.g. by averaging several images, has proven to be essential for a stable image impression when viewing a sequence. However, temporal filtering in the presence of object motion causes distractive artifacts. Therefore, moving structures must be detected in order to reduce the ratio of temporal filtering at these structures. The task is complicated significantly by severe signal-dependent noise, because fluctuations at a given pixel location over time might be mistaken for changes due to motion.

The objective of the presented work was local adaptive motion detection using binary difference images and the usage of motion detection to control the spatial and temporal ratios of an averaging noise reduction filter.

2 State-of-the-Art

Temporal recursive filters are common for noise reduction of X-ray image sequences possessing severe noise. Temporal filtering improves subjective image quality in regions without strong motion significantly. While the preservation of static structures is superior to spatial filters of comparable complexity, artifacts due to motion, e.g. motion shadows, are a challenge.

As motion generates large signal values in difference images, the method applied so far is based on gray value differences of the current image and the previous filtered image. For each pixel it is estimated to what extend the difference is due to noise or to motion. A signal-dependent noise estimation is used to take into account the high degree of signal-dependency of the noise. The estimated motion probability having a smooth transition between *motion* and *noise* is used to control the spatial and temporal ratios of the filter at a given pixel [2]. Although the method has low complexity and adopts to the signal-dependency of the noise, the estimation of the motion probability on a pixel basis not taking into account the local neighborhood produces artifacts as e.g. fringed edges and salt-and-pepper noise.

The method proposed in this paper works with binary images. The noise-adaptive determination of binarization thresholds is based on the topological term Euler number. Rosin and Ellis [3] introduced Euler corners to determine appropriate thresholds from Euler curves, i.e. the Euler number of a binary image as function of the threshold used in the binarization process.

3 Methods

A locally adaptive spatio-temporal recursive filter is given by

$$f_{st}(x,y,t) = [1-\alpha(x,y,t)] \cdot f_{st}(x,y,t-1) + \alpha(x,y,t) \cdot f_s(x,y,t) \qquad (1)$$

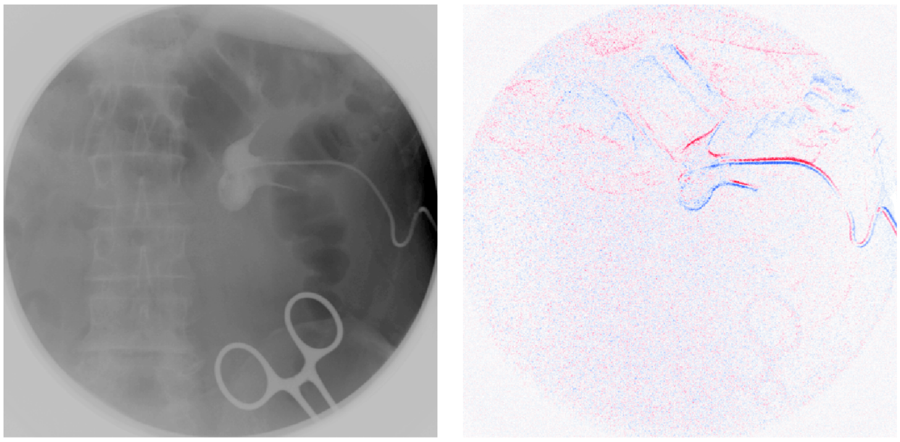
with spatial filtered images $f_s(x,y,t)$, spatio-temporal filtered images $f_{st}(x,y,t)$, and a weighting term $\alpha(x,y,t) \in [0,1]$ controlling the ratio of spatial and temporal filtering. $\alpha(x,y,t)=0$ and $\alpha(x,y,t)=1$ correspond to temporal or spatial filtering only, respectively. At a given pixel, $\alpha(x,y,t)$ is chosen depending on whether the pixel has been classified as motion, noise, or none of the previous.

3.1 Algorithm

The proposed method can be divided into four steps:

1. Independent binarization of the positive and negative ranges in a difference image. This yields *two* binary images representing positive and negative fluctuations from one image to the subsequent image.
2. Postprocessing of the binary images generating *four* binary images. Each of the two binary input images is split into an image representing significant motion and an image representing strong noise.
3. Combination of the two motion or noise images to one motion or noise image, respectively.
4. Assignment $\alpha(x,y,t) \in \{\alpha_{motion}, \alpha_{noise}, \alpha_{else}\}$ depending on the binary motion and noise masks.

Fig. 1. Example image taken from a sequence (left), continuous difference image with positive (blue) and negative (red) ranges (right).



3.2 Binarization

Figure 1 shows the positive and negative ranges of a difference image. The ranges are thresholded independently generating two binary images I^+ and I^-. Thresholds are determined adaptive to the signal-dependent noise using Euler numbers $E = N_{obj} - N_{hole}$, with N_{obj} the number of N8 objects and N_{hole} the number of N4 holes in the objects. To achieve local adaptive binarization, the image is segmented into blocks and thresholds are determined for each block. Measurements are taken to avoid blocking artifacts.

3.3 Postprocessing and Classification

The binary images I^+ and I^- contain pixels of high fluctuation, i.e. pixels representing significant motion as well as pixels representing strong noise. Postprocessing based on morphological operations splits each binary image into an image representing motion and noise, respectively (fig. 2). The resulting masks are combined to a motion image $I_{motion} = I^+_{motion} \vee I^-_{motion}$ and a noise image $I_{noise} = I^+_{noise} \vee I^-_{noise}$ with $I_{motion} \cap I_{noise} = \emptyset$. Finally, $\alpha(x, y, t)$ is mapped to one of the constant values α_{motion}, α_{noise}, and α_{else}, depending on $I_{motion}(x, y)$ and $I_{noise}(x, y)$, and the image is filtered using equation (1).

4 Results

For the evaluation of the proposed method, X-ray sequences showing a mechanical test object in motion and clinical examinations were available. The parameters were optimized using theoretical considerations, artificially created sequences containing noise, and the above mentioned X-ray image sequences.

Fig. 2. Positive binary image I^+ before postprocessing (left), pixels classified as significant motion I^+_{motion} (middle) and strong noise I^+_{noise} (right). Note that static structures and objects, e.g. the instrument in the lower right, are clearly visible in the noise image. This is not due to motion, but illustrates the signal-dependency of the noise.

It has shown that the independent processing of positive and negative difference image ranges significantly improves the detection and discrimination of pixel fluctuations due to motion and noise. Motion is observed as connected objects in the positive *or* the negative binary image I^+ or I^-. Noise generates a mixture of positive and negative values that, contrarily to thresholding absolute difference values and using one binary image, does not form objects of significant size in the positive or negative binary image (fig. 2).

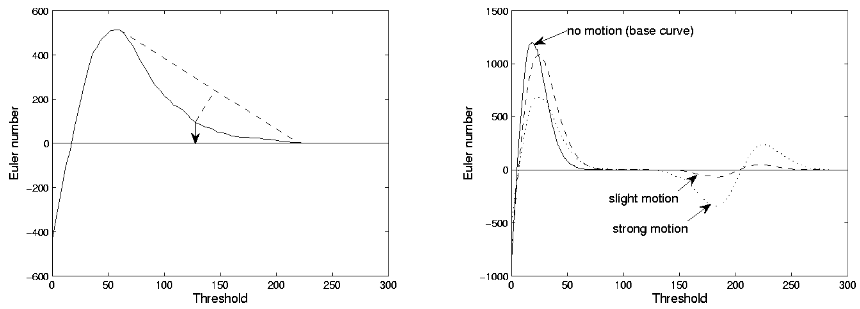
Euler numbers proved suitable for threshold determination and can be calculated efficiently with numerical complexity $O(n)$. Our experiments confirmed our expected interrelation of the Euler curve and the remaining noise in a binary image. The general form of the Euler curve is shown in figure 3. Noise basically affects the position of the maximum and the width of the curve, but not the maximum value. Image block size mainly affects the maximum Euler number linearly. Therefore, the block size should be chosen to contain preferably homogeneous regions, i.e. regions disturbed by comparable signal-dependent noise.

Our experiments indicate that motion inside a block leads to an Euler curve composed approximately of the superposition of the basic Euler curve and curves shifted by the absolute of the motion vector (fig. 3). As a result, the basic curve is broadened and disturbed by additional peaks. Therefore, Euler corners [3] are not suited for the given task. Instead, the threshold is determined by the Euler number $E_t = p \cdot \max\{E(t)\}$ with a fixed percentage $p \in [0,1]$. Evaluating artificial sequences with added Poisson-distributed noise, we found the optimum threshold at $p \approx 0.25$ without and $p \approx 0.7$ with postprocessing. In the latter, about 98% of the pixels representing motion were classified correctly.

5 Discussion

The presented binarization method has proven to be suited for motion detection in X-ray image sequences exhibiting severe signal-dependent noise. Postprocessing further improves motion detection and additionally produces a binary mask of pixels representing strong noise. In particular the independent processing of

Fig. 3. Euler corner method (left): The threshold is determined by the point of maximum distance to the line through the maximum and the first drop to zero. Influence of motion (right): Motion creates additional peaks disturbing the results of the Euler corner method. Peak sizes depend on the ratio of motion in the image block.



positive and negative instead of absolute difference values and combination of the results was of significance for the achieved quality of the binary motion and noise masks. Regarding neighborhoods instead of isolated pixels enables us to recognize motion as structure and noise as isolated small objects in the difference images, both removing significant artifacts of the method used so far.

An interrelation of noise-adaptive binarization and Euler numbers was established. In sequences containing motion and severe noise, the Euler number as function of the threshold can be used to determine a threshold suited to separate noise from significant motion. Noise estimation is not required as adaptation to noise levels takes place by the impact of the thresholds on the resulting images.

Subjective image quality of processed clinical sequences has improved significantly over large image areas and sequences seem more stable compared to motion detection on a pixel basis. Problems remain in image blocks dominated by motion. Introducing further classes in classification might solve the problem.

The presented method uses computational efficient binary algorithms suited for real-time applications. The improvements in noise reduction hold the potential to reduce radiation doses, and therefore exposure of medical staff and patients, while keeping the image quality constant.

References

1. Hensel M, Brummund U, Pralow T, Grigat RR. Noise Reduction with Edge Preservation by Multiscale Analysis of Medical X-Ray Image Sequences. In: Procs BVM; 2005.
2. Aufrichtig R, Wilson DL. X-Ray Fluoroscopy Spatio-Temporal Filtering with Object Detection. IEEE Trans Med Imaging 1995;14(4):733–746.
3. Rosin PL, Ellis T. Image Difference Threshold Strategies and Shadow Detection. In: Proc British Machine Vision Conference; 1995. p. 347–356.