Histogram-Based Image Registration for Digital Subtraction Angiography

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Abstract. A generalized framework for histogram-based similarity measures is presented and applied to the image-enhancement task in digital subtraction angiography (DSA). The class of differentiable, strictly convex weighting functions is identified as suitable weightings of histograms for measuring the degree of clustering that goes along with registration. With respect to computation time, the energy similarity-measure is the function of choice for the registration of mask and contrast image prior to subtraction. The registration success for the automated procedure is compared with a manually shift-corrected image pair of the head.

1 Introduction

DSA image enhancement is generally a registration task (see [1] and the papers cited therein). A sequence of X-ray images of the patient is taken during injection of opaque dye, which is used as X-ray contrast agent. Usually, the first image of such a sequence is taken before dye injection and is called *mask* image, and all other images of the sequence are consequently called *contrast* images. Mask and contrast image must be properly aligned prior to subtraction to reduce degradation (cloud-like artifacts) in the image caused by patient motion. In [2,3] an algorithm for that purpose has been proposed. The algorithm is initialized with a (manually chosen or automatically determined) rectangular region-of-interest that includes the interesting vascular structures, and consists of the following steps.

Firstly, the region-of-interest in the contrast image is divided into a number of non-overlapping templates (or blocks) with predefined size that cover the entire region. Secondly, for the templates defined in step one the corresponding templates in the mask image are identified. This is done by optimization of an appropriate similarity measure. The resulting shifts are used to establish a motion-vector field. It has been mentioned in [4] that angiographic images are usually of low contrast with no sharp edges. For that reason the matching criteria usually utilized by template-matching techniques can fail. This problem can be solved by a template-exclusion technique [2,3] that takes into account the amount of contrast variations inside a template. Therefore, as an additional step, those templates are excluded that are located in regions with insufficient contrast variation (evaluated by the entropy of the mask image inside a template).

The motion-vector field yields a set of homologous points for mask and contrast image. These points are essentially the centers of the respective templates, and serve, in a third step, as basis for fitting an affine transformation. The transformation is only valid for the

selected region-of-interest and is consequently applied only in that region. In a final step the contrast and corrected mask image are subtracted to yield a DSA image that is enhanced inside the region-of-interest. For application in clinical practice, the algorithm must be fast, robust, and reliable. These requirements raise several questions that must be answered. The quality of the corrected image depends heavily on the similarity measure used to estimate the motion-vector field. A comparison of similarity measures such as e.g. cross correlation [5,6], sum of absolute differences [7,8], deterministic sign change [9,10] and entropy [2] has been carried out in [11].

As a result the histogram-based entropy similarity measure turned out to be the most robust measure with respect to dissimilarities of the image pairs introduced by the contrast agent. In this paper a generalization of histogram-based measures to convex-weighted histograms is briefly described (section 2). From that larger class of functions the energy similarity-measure turns out to be the measure of choice, as, when implemented with integer values, it is the fastest function showing all the desired properties of the entropy (or information) measure. In section 3, the successful registration of an image pair of the head is demonstrated. A comparison is presented between a manual-shift motion correction and an automatic-affine motion correction.

2 Similarity measures based on convex-weighted histograms

In order to estimate the motion between images of a DSA sequence, the horizontal and vertical shift r and s of a $(K \times L)$ -pixel template in the contrast image $g_c(x,y)$ with respect to the mask image $g_m(x,y)$ is determined by optimizing an appropriate similarity measure.

Histogram-based measures have been introduced for DSA in [2]. These measures are computed by applying appropriate weighting functions onto the values of a difference-image gray-value histogram and integrating over all bins of the histogram. Such measures are therefore defined in a 3-step procedure:

- Firstly, subtraction of images:

$$d(x,y;r,s) = g_c(x,y) - g_m(x+r,y+s) . \quad (1)$$

- Secondly, calculation of gray-value histogram of the difference image $d(x,y;r,s)$ and normalization of the histogram according to

$$\sum_{k=1}^N p_k = 1, \quad (2)$$

where p_k is the fraction of pixels with gray-value g_k and $k=1$ can be identified with g_{min} and $k=N$ with g_{max} the minimum and maximum grey-value of the difference image, respectively. The histogram depends on the shift parameters r and s : $p_k = p_k(r,s)$.

- And thirdly, evaluation of the criterion:

$$M(r, s) = \sum_{k=1}^N f(p_k), \quad (3)$$

using an appropriately defined weighting function $f(p)$.

The histogram-based similarity measures are motivated by the observation that for optimal registration of mask and contrast image the difference image shows low contrast variation in the area of the template, whereas in the case of misregistration the contrast variation is larger. Therefore, the histogram is very peaky for the perfect registration and shows dispersion for misregistration. The exact shape of the histogram for the desired case of registration is not known a priori. But this is not considered to be a problem, because we know the most undesired shape of the histogram which is the equal distribution. An optimization procedure has to maximize the distance from that worst case. That distance is measured by a suitable similarity measure.

A convenient class of weighting functions is given by strictly convex, differentiable functions. Convex functions are defined by:

Definition: A function $f: \mathcal{R}_{\geq 0} \rightarrow \mathcal{R}$ is called strictly convex, if for all $x, y \in \mathcal{R}_{\geq 0}$ with $x \neq y$ and all $\alpha \in (0, 1)$

$$f(\alpha x + (1 - \alpha)y) < \alpha f(x) + (1 - \alpha)f(y). \quad (4)$$

As the entropy and the information similarity-measure, measures based of strictly convex weighted histograms reach their extremum, if all gray-value fractions in the histogram are equal. Additionally, they weight the amount of dispersion in the histogram. To show that strictly convex functions are suitable weighting functions, the following theorem for differentiable functions is necessary:

Theorem 1: Let $f: \mathcal{R} \rightarrow \mathcal{R}$ be a differentiable function. The function f is strictly convex, if for all $x \in \mathcal{R}$ the derivation $f'(x)$ of f is strictly monotonous and vice versa.

For the proof of theorem 1 see [12]. As important property of strictly convex functions that is needed for the registration task is given by the following theorem.

Theorem 2: Let $f: \mathcal{R}_{\geq 0} \rightarrow \mathcal{R}$ be a strictly convex, differentiable function. Further, let $p_k, k=1, \dots, N$, be the relative frequencies in a histogram with N bins satisfying

$$\sum_{k=1}^N p_k = 1. \text{ Then, the similarity measure } M = \sum_{k=1}^N f(p_k) \text{ is minimal, if}$$

$$p_k = \frac{1}{N}, \text{ for } k=1, \dots, N.$$

A second property of strictly convex functions that is needed for the registration task is different weighting of dispersion and clustering in the histogram. Generally, registration should lead to a clustering of the gray-value fractions as illustrated in fig. 1.

Fig. 1: Illustration of clustering in the difference-image histogram by registration of mask and contrast image. a , b and c denote relative frequencies p of gray-values g .

A histogram-weighting function suitable as similarity measure must, hence, fulfill the following inequality:

Theorem 3: Let $f: \mathcal{R}_{>0} \rightarrow \mathcal{R}$ a strictly convex weighting function, then for all $a, b, c \in \mathcal{R}_{>0}$ with $0 < c \leq a < b$ the inequality

$$f(a - c) + f(b + c) > f(a) + f(b) \quad (5)$$

holds.

For the mathematical proofs of theorems 2 and 3 see [11]. Examples of appropriate strictly convex weighting functions are plotted in fig. 2.

Under the point of view that computation speed is of great importance, f_2 is the function of choice. The corresponding similarity measure

$$M_{\text{energy}}(r, s) = \sum_{k=1}^N p_k^2 \quad (6)$$

is called *energy* [13]. Further speed improvement is expected, if integer arithmetic can be used for the evaluation of the similarity measure. This, in fact, is possible due to the following

Remark: If $f(p)$ is strictly convex, then $f(cp)$ with $c \in \mathcal{R}$ is also strictly convex.

This shows that the interpretation of the p_k 's as relative frequency as well as normalization of the histogram is not essential. For convenience the constant c is chosen to be LK , where L and K are the length and width of the template considered. In that case, the absolute frequencies of the gray-value histogram can be used as argument of

the weighting function. Nevertheless, integer arithmetic cannot be used for functions like the exponential function which vary over several orders of magnitude.

Fig. 2: Examples of convex functions that can be used as weighting functions for the histogram-based similarity measures.

3 Experimental result

In fig. 3a/b an X-ray image pair of the head is given. The interactively chosen region-of-interest is indicated as white rectangle in the images. A set of non-overlapping (64x64)-pixel templates are distributed with equal spacing inside the region-of-interest. In the presented case 20 percent of the less promising templates are discarded due to insufficient contrast, i.e. those with low entropy obtained from the mask image. The actual template positions are depicted by crosses in the region-of-interest. It can be seen that the discarded templates had been located in the less contrasted, homogeneous soft-tissue area of the head, and that all templates located at the bony structures are included.

Fig. 3c shows the result of the motion corrected DSA enhancement based on an affine transformation fitted to the motion-vector field. To demonstrate the quality improvement, fig. 3d displays the manually shift-corrected subtraction image. Here the motion artifacts from the bony structures are still visible. The patient motion is obviously more complex than a linear shift and, consequently, the interactively performed, pure shift operation is not sufficient to remove all motion artifacts from the subtraction image.

Fig. 3: Mask (a) and contrast (b) image of head fluoroscopies. A motion-vector field is estimated via template matching. As a result a set of homologous point landmarks are obtained and indicated as white and dark crosses in the mask and contrast image, respectively. The motion - visualized with white lines attached to the crosses in the contrast image - is compensated inside a user-defined region-of-interest indicated by white rectangles. Fig. 3d shows the manually shift-corrected subtraction result to demonstrate the improvement obtained by the algorithm.

4 Summary and Conclusions

The generalized framework of similarity measures obtained from convex-weighted histograms of difference images yields the energy similarity-measure as most suitable for the registration task in DSA. It turned out that one-dimensional histograms instead of two-dimensional feature space yields sufficient statistics which allows for the accurate estimation of motion-vector fields even for relatively small template sizes.

Additionally, the registration can be performed practically in real time which is a major requirement for automated DSA-algorithms to be acceptable in clinical routine applications. The affine transformation applied here is an appropriate correction for small motion artifacts that stem from the movement of rigid bodies like the head. If images from the abdomen are taken, the motion is usually more complex. Therefore, we are currently studying the use of elastic transformations for motion correction, to be reported on in future.

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