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Procedia Computer Science 90 (2016) 194 – 199

Procedia
Computer Science

International Conference On Medical Imaging Understanding and Analysis 2016, MIUA 2016, 6-8 July 2016, Loughborough, UK

FASTR: Using Local Structure Tensors as a Similarity Metric

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Abstract

We describe a novel structural image descriptor for image registration called the Fractionally Anisotropic Structural Tensor Representation (FASTR), calculated from the local structural tensor (LST). The metric has several characteristics that are advantageous for multi-modality registration, such as not depending on absolute voxel intensities, and being insensitive to slowly varying intensity inhomogeneities across the image. This latter property is very useful, since many imaging modalities suffer from such artefacts. Registration accuracy is tested on both computed tomography (CT) to cone-beam CT (CBCT) rigid registration, and CT to magnetic resonance (MR) rigid registration. The performance is compared with Mutual Information (MI) metric and the Self Similarity Context (SSC) descriptor. The results show that, for images with significant intensity inhomogeneity, FASTR produced more accurate results than MI, and faster results than SSC. The results suggest FASTR gives similar benefits in images with intensity inhomogeneity, but at a fraction of the computation and memory demand.

Peer-review under responsibility of the Organizing Committee of MIUA 2016

Keywords: Medical; image; registration; FASTR; Structure; Tensors ; Similarity; Metric

1. Introduction

Medical image registration is concerned with the automatic alignment of multiple datasets to a common space. It is an essential component in a diverse array of applications, including diagnosis, treatment planning, atlas construction and augmented reality.

One categorisation of medical image registration concerns whether the datasets were acquired using the same imaging modality (i.e. *mono-modality*), or using different imaging modalities (i.e. *multi-modality*). In general, multi-modality registration is a harder problem, since different tissue types can have vastly different appearances (intensity, contrast, noise properties etc.) in each modality. Indeed, when aligning a functional and a non-functional imaging modality — such as Positron Emission Tomography (PET) and Computed Tomography (CT) — there may be no visible correlation between many parts of the images.

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Peer-review under responsibility of the Organizing Committee of MIUA 2016
doi:10.1016/j.procs.2016.07.015

A key component of any registration algorithm is some means for determining a figure of merit for how well aligned the images are. In general this is achieved using a similarity metric, which assesses the similarity between a reference image, R, and a test image, T. Typical similarity metrics include the sum of squared differences (SSD) between corresponding voxels, or the Mutual Information (MI) [1,2] between R and T. More recently, various multi-dimensional descriptors have been proposed to quantify the relationship between R and T. Examples of such descriptors include Normalised Gradient Fields (NGF) [3], Modality Independent Numerical Descriptors (MIND) [4], and Self Similarity Context (SSC) [5]. In this paper we propose a new descriptor named *Fractionally Anisotropic Structural Tensor Representations* (*FASTR*), and a similarity metric based upon it, which has a number of properties advantageous to multi-modality registration. Specifically:

- Similar to the NGF, since it is based on local gradient orientations the metric does not rely on absolute intensities.
- Furthermore, since it aligns parallel and anti-parallel gradients, it handles cases where the gradient is in the opposite direction in the two images (i.e. where a boundary goes from light to dark in one modality, but dark to light in the other).
- Since the vector field is estimated locally, the metric is robust to global illumination inhomogeneity, e.g. bias-field artefacts in magnetic resonance (MR) or cone-beam CT (CBCT) images.

2. Method

FASTR is based on *Local Structure Tensors* [6] (LST). These are positive semi-definite matrices which describe the distribution of gradients within a given image neighbourhood, $\mathcal{N}$. The LST is calculated at voxel $\mathbf{x}$, in an image I, within a neighbourhood $\mathcal{N}$ using

$$LST(I, \mathbf{x}, \sigma_{\mathrm{LST}}) = \sum_{i \in \mathcal{N}} w(i, \sigma_{\mathrm{LST}}) \begin{pmatrix} \frac{\partial I}{\partial x} \cdot \frac{\partial I}{\partial x} & \frac{\partial I}{\partial x} \cdot \frac{\partial I}{\partial y} & \frac{\partial I}{\partial x} \cdot \frac{\partial I}{\partial z} \\ \frac{\partial I}{\partial y} \cdot \frac{\partial I}{\partial x} & \frac{\partial I}{\partial y} \cdot \frac{\partial I}{\partial y} & \frac{\partial I}{\partial y} \cdot \frac{\partial I}{\partial z} \\ \frac{\partial I}{\partial z} \cdot \frac{\partial I}{\partial x} & \frac{\partial I}{\partial z} \cdot \frac{\partial I}{\partial y} & \frac{\partial I}{\partial z} \cdot \frac{\partial I}{\partial z} \end{pmatrix} \quad (1)$$

where $w(i, \sigma_{\mathrm{LST}})$ is a weighting function that decreases monotonically with distance from the centre of $\mathcal{N}$. In the following experiments $w(i, \sigma_{\mathrm{LST}})$ is a Gaussian function with standard deviation σ_{LST}. The size of the neighbourhood region, $\mathcal{N}$, is chosen such that $w(i, \sigma_{\mathrm{LST}}) \approx 0$ at the edge of $\mathcal{N}$.

2.1. Computing the FASTR descriptor

The fractional anisotropy (FA) may be calculated from the eigenvalues of the LST: $\lambda_1, \lambda_2, \lambda_3$ (where $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$). The principal eigenvector, $\mathbf{v}_1$, points in the dominant direction of the gradient vectors, ∇I, of the local patch $\mathcal{N}$. $\mathbf{v}_2$ and $\mathbf{v}_3$ are discarded as they are — by definition — perpendicular to the principal eigenvector.

The strength of the dominant direction (i.e. how dominant it is) may be calculated from the coherence for 2D images, and the FA for 3D volumes. Both coherence and FA share the following common set of properties [6]:

1. They are scalar, and are bounded between 0 and 1.
2. If they equal 0, there is no dominant direction within the local neighbourhood $\mathcal{N}$.
3. If they equal 1, there is an absolute dominant direction within the local neighbourhood $\mathcal{N}$, i.e. all non-zero second order gradient vectors are parallel.

The FA may be computed straightforwardly from the eigenvalues λ_1, λ_2 and λ_3 of the LST:

$$\mathrm{FA} = \sqrt{\frac{1}{2}} \frac{\sqrt{(\lambda_1 - \lambda_2)^2 + (\lambda_2 - \lambda_3)^2 + (\lambda_3 - \lambda_1)^2}}{\sqrt{\lambda_1{}^2 + \lambda_2{}^2 + \lambda_3{}^2}} \,. \quad (2)$$