8DC00 Medische Beeldanalyse

Project 1 - Registration

Report

1-10-2021

Group 3

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# 1. Introduction

Image registration, the process of aligning two images, is a vital practice used throughout the field of medical imaging. It is used in the comparison of medical images of different moments in time, different modalities or different patients, necessary for clinical evaluation E.g., images from before and after treatment of a patient can be used to evaluate the effectiveness of the treatment, Computed tomography (CT) images can be aligned with Positron Emission Tomography (PET) images to further improve tumor detection and segmentation of structures in an image can be made easier when aligned with an atlas. For good and relevant comparisons between images, accurate alignment is needed (Kostelec & Periaswamy, 2003). The anatomy in the images must overlap in the area of interest, with as little error as possible to achieve this. Image registration can be done automatically to eliminate human the human factor and to make the registration objective. Various algorithms which optimize the alignment of the images can be used, each with its own characteristics and features.

In this report, different methods of registration are elaborated and applied on a provided dataset of MR brain scans. A transformation matrix is applied to the moving image to align it with a fixed image. The methods are evaluated with the use of different metrics to assess the quality of the registration. The goal of this project is to compare and evaluate the different inter-and intra-modal registration methods. Experiments will be performed to demonstrate the advantages and disadvantages of each.

# 2. Methods

## 2.1 Dataset

The dataset provided consists of transverse MR brain scan slices. For a total of three patients, three different slices are used, which are all scanned both T1-weighted and by T2-FLAIR (Mendrik, et al., 2015). For the T1-weighed scans, both the original and a randomly transformed image are used. Throughout this report, the following format is used: {Patient ID}\_{Slice ID}\_{Sequence}, where patient ID is one of the three patients, slice ID is one of the three slices and sequence is the modality used. For the randomly transformed image, a ‘d’ is appended after the sequence number.

For intra-modal registration the images 1\_1\_t1 versus 1\_1\_t1d and 3\_3\_t1 versus 3\_3\_t1\_d are used. For inter-modal registration the image 1\_1\_t1 versus 1\_1\_t2 and 3\_3\_t1 versus 3\_3\_t2 are used

## 2.2 Transformations

The geometrical transformations are the transformations applied to the moving image, . These include:

Translation: , with the original position vector and the translation.

Rotation: , with .

Scaling: , with

Shearing: , with .

## 2.3 Point-based and intensity-based registration

Point-based registration is performed semi-automatically based on user input in the form of reference points picked by the user. These points that are selected in the fixed image that are considered reliable, based on distinguishable features, are the fiducials (Fitzpatrick, J.M., et al.). The same points are selected in the moving image, after which a transformation matrix is calculated, using the difference in and coordinates, giving and . These values are then used in a rigid transformation on the moving image.

Intensity-based registration is performed automatically. The intensity values of the pixels in the images are used as the basis for the registration. The alignment of the fixed and moving images are iteratively improved. An optimal registration is reached when the values used to evaluate the alignment reach an optimum, as explained in the following paragraph.

## 2.4 Methods of registration evaluation

The different intensity-based similarity measures used in the evaluation of the alignment are:

**Sum of square differences (SSD)**

This is a simple and intuitive measure of similarity of and with pixel locations is the sum of squared differences :

. The SSD will be the lowest when the images are perfectly aligned. This measure is optimal when two images differ only by Gaussian noise, but hardly works for inter-modal registration and is very sensitive to outliers.

**Normalized cross-correlation (nCC)**

Normalized cross-correlation assumes there is a linear relationship between the pixel intensities in the two images. However, for inter-modality registration, there is a lack of linearity.

In which, and are the two images and is the pixel number. The nCC value is normalized, meaning it will have a value between . It is possible the value of is not reached when more transformations than translation are done because of inverse mapping.

**Mutual information**

The pixels of the images have a finite set of possible values; thus, the probability mass function (PMF) can be defined which maps each possible value to a probability. Mutual information uses this probability mass function (PMF) of the two discrete images, defined with normalized image histograms.

In which and are again the images, and . The logarithm can be base 2 in which case the MI is expressed in units of bits, or base e in which case it is expressed in nats.

TRE

[]

The folowing registration methods and evaluations are performed:

- intra-modal rigid intensity-based registration, evaluated through the method of normalized cross-correlation.

- intra-modal affine intensity-based registration, evaluated through the method of normalized cross-correlation.

- inter-modal affine intensity-based registration, evaluated through the method of normalized cross-correlation.

- intra-modal affine intensity-based registration, evaluated through the method of mutual information

- inter-modal affine intensity-based registration, evaluated through the method of mutual information

# 3. Results

Point based

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | Registration points [[ximage1][yimage1][ximage2][yimage2]] | Transformatie matrix | Target registration error points [[ximage1][yimage1][ximage2][yimage2]] | TRE |
| Intra-modal | 1\_1\_t1 1\_1\_t1\_d | [[126.81612903 162.58387097 140.01612903 150.66129032]  [107.69074194 108.54235484 129.83267742 129.40687097]] [[126.11935484 162.31290323 139.74516129 150.39032258]  [107.26493548 109.81977419 128.98106452 130.68429032]] | [[ 0.99978948 0.00330636 0. ]  [-0.03645333 1.04128303 0. ]  [ 0. 0. 1. ]] |  |  |
| Inter-modal | 1\_1\_t1 1\_1\_t2 | [[126.81612903 162.15806452 138.31290323 151.08709677]  [105.98751613 108.11654839 130.68429032 130.25848387]] [[123.13870968 158.48064516 134.20967742 146.55806452]  [121.31654839 124.723 145.16170968 145.58751613]] | [[ 1.00130403 0.02841567 0. ]  [-0.09203554 0.98189642 0. ]  [ 0. 0. 1. ]] |  |  |
| Intra-modal | 3\_3\_t1 3\_3\_t1\_d | [[123.83548387 156.62258065 115.74516129 170.2483871 ]  [122.59396774 120.89074194 173.69074194 173.26493548]] [[126.11935484 158.90645161 121.43548387 174.66129032]  [140.47783871 136.64558065 194.98106452 194.55525806]] | [[ 1.0247544 -0.0437922 0. ]  [-0.01360917 0.89816566 0. ]  [ 0. 0. 1. ]] |  |  |
| Inter-modal | 3\_3\_t1 3\_3\_t2 | [[123.40967742 155.34516129 115.31935484 172.37741935]  [122.59396774 120.03912903 173.69074194 171.98751613]] [[123.99032258 154.6483871 112.91935484 168.27419355]  [139.20041935 136.64558065 185.61332258 187.74235484]] | [[ 0.98857632 0.02105937 0. ]  [-0.1094837 1.00190368 0. ]  [ 0. 0. 1. ]] |  |  |

Intensity-based registration

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  | Mu | Best initial parameter vector | Result CNN  With x\_rigid = [0, 0, 0] and x\_affine = [0, 1, 1, 0, 0, 0, 0] | Result CNN  With x = best initial parameter vector |  |
| Rigid | NCC | Intra-modal | 1\_1\_t1 1\_1\_t1\_d | 0.0001 | [1.55e-06, 2.24e-06, -2.19e-06] | 1 | \* |  |
| Affine | NCC | Intra-modal | 1\_1\_t1 1\_1\_t1\_d | 0.0001 | [0, 1, 1, -9.31e-08, -8.34e-08, 3.19e-07, 5.03e-09] | 1 | \* |  |
| Affine | NCC | Inter-modal | 1\_1\_t1 1\_1\_t2 | 0.00001 | [0, 1, 1, 0.0024, -0.0025, 0.0019, -0.0019] | 0.53 | 0.54 |  |
| Affine | MI | Intra-modal | 1\_1\_t1 1\_1\_t1\_d | 0.00001 | [0, 1, 1, 2.32e-03, 8.89e-04, 1.16e-03, 1.22e-04] | 3.02 | 1.92  Raar dat deze juist lager is geworden |  |
| Affine | MI | Inter-modal | 1\_1\_t1 1\_1\_t2 | 0.001 | [0, 1, 1, 0.058, -0.050, -0.30, -0.078] | 0.72 | 0.85 |  |
|  |  |  |  |  |  |  |  |  |
| Rigid | NCC | Intra-modal | 3\_3\_t1 3\_3\_t1\_d | 0.0015 | [-0.031, -0.088, -0.015] | 0.60 | 0.63 |  |
| Affine | NCC | Intra-modal | 3\_3\_t1 3\_3\_t1\_d | 0.0015 | [0, 1, 1, 0.0033, -0.081, -0.021, -0.094] | 0.60 | 0.74 |  |
| Affine | NCC | Inter-modal | 3\_3\_t1 3\_3\_t2 | 0.001 | [0, 1, 1, 0.047, -0.044, -0.053, -0.079] | 0.56 | 0.60 |  |
| Affine | MI | Intra-modal | 3\_3\_t1 3\_3\_t1\_d | 0.001 | [0, 1, 1, 0.0030, -0.080, -0.042, -0.10] | 0.63 | 0.83 |  |
| Affine | MI | Inter-modal | 3\_3\_t1 3\_3\_t2 | 0.001 | [0, 1, 1, 0.051, -0.061, -0.069, -0.066] | 0.71 | 0.82 |  |

\* initial parameter vector is almost equal to the standard x\_rigid = [0, 0, 0] or x\_affine = [0, 1, 1, 0, 0, 0, 0].

# Discussion

The discussion section should contain the analysis of the results

# Appendix

# References

<http://library.msri.org/books/Book46/files/07kostelec.pdf>

<https://link.springer.com/content/pdf/10.1007%2F978-1-4471-7320-5.pdf>

[*A.M. Mendrik, K.L. Vincken, H.J. Kuijf, M. Breeuwer, W.H. Bouvy, J. de Bresser, A. Alansary, M. de Bruijne, A. Carass, A. El-Baz, A. Jogh, R. Katyal, A.R. Khan, F. van der Lijn, Q. Mahmood, R. Mukherjee, A. van Opbroek, S. Paneri, S. Pereira, M. Persson, M. Rajchl, D. Sarikayan, O. Smedby, C.A. Silva, H.A. Vrooman, S. Vyas, C. Wang, L. Zhaon, G.J. Biessels, M.A. Viergever. “MRBrainS Challenge: Online Evaluation Framework for Brain Image Segmentation in 3T MRI Scans.” Computational Intelligence and Neuroscience, special issue on Simulation and Validation in Brain Image Analysis 2015. Article ID 813696.*](http://www.hindawi.com/journals/cin/aa/813696/)

Voorbeeld registration points aanklikkenA picture containing graphical user interface

Description automatically generated

Point error

Graphical user interface

Description automatically generated with medium confidence

Ls\_affine t1 en t1\_d van patient 1

Chart

Description automatically generated

Ls\_affine t1 en t2 van patient 1

Chart

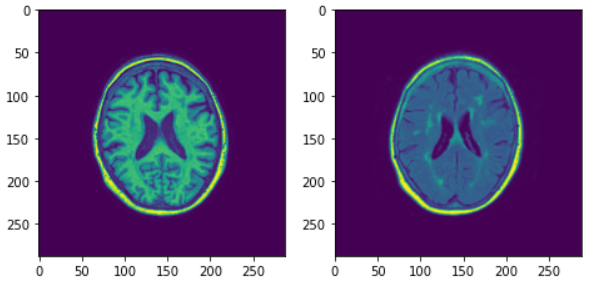
Description automatically generated

Ls\_affine t1 en t1\_d bij patient 3

Chart

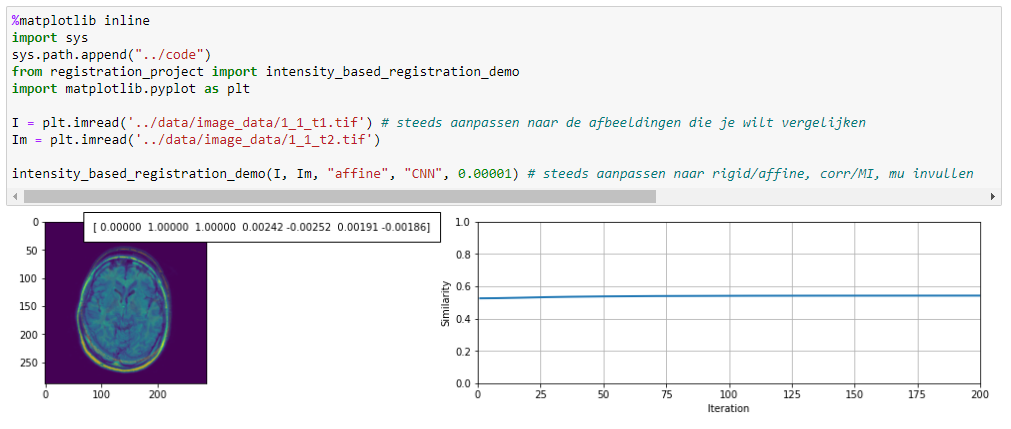
Description automatically generated with medium confidence

Ls\_affine t1 en t2 bij patient 3



Table

Description automatically generated with medium confidenceTable

Description automatically generatedTable

Description automatically generated with medium confidence

Graphical user interface

Description automatically generated

A picture containing chart

Description automatically generatedGraphical user interface

Description automatically generated with medium confidenceChart, line chart

Description automatically generatedA picture containing chart

Description automatically generatedGraphical user interface, table

Description automatically generated