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Master Thesis

Brain Tractography Registration with Nonrigid ICP

Mohammed Abdelgadir Awadelkareem Hassan

Supervisor: Prof. Thomas Schultz

Bonn-Aachen International Center for Information Technology

University of Bonn

Supervisor: Dr. Martin Vogt

Bonn-Aachen International Center for Information Technology

University of Bonn

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ABSTRACT

The registration problem (also known as alignment, absolute orientation) is one of the outstanding and very basic problems in computer vision. In this problem, two or more datsets of points are given and the task is to optimally align them by estimating a best transformation (combination of translation, rotation and scaling). Due to its fundamental importance, it arises as a subtask in many different applications (e.g., object recognition, tracking, range data fusion, graphics, medical image alignment, robotics and structural bioinformatics etc [2].

In This thesis we show how to extend the ICP framework to nonrigid registration, while retaining the convergence properties of the original algorithm. The resulting optimal step nonrigid ICP framework allows the use of different regularisations, as long as they have an adjustable stiffness parameter. The registration loops over a series of decreasing stiffness weights, and incrementally deforms the template towards the target, recovering the whole range of global and local deformations. To find the optimal deformation for a given stiffness, optimal iterative closest point steps are used. Preliminary correspondences are estimated by a nearestpoint search. Then the optimal deformation of the template for these fixed correspondences and the active stiffness is calculated. Afterwards the process continues with new correspondences found by searching from the displaced template vertices. We present an algorithm using a locally affine regularisation which assigns an affine transformation to each vertex and minimises the difference in the transformation of neighbouring vertices. It is shown that for this regularisation the optimal deformation for fixed correspondences and fixed stiffness can be determined exactly and efficiently. The method succeeds for a wide range of initial conditions, and handles missing data robustly. It is compared qualitatively and quantitatively to other algorithms using synthetic examples and real world data[1].

INTRODUCTION

1 BRAIN STRUCTURE (FIBER PATHWAYS)

Human brain which is our focus in this thesis, is the central organ of the human nervous system, it is made up of two main components, gray matter and white matter. Scientists have learned a lot about gray and white matter and the two halves of the brain through autopsies and imaging techniques and by studying diseases or conditions associated with brain damage.

The thesis focused on **White Matter** which is refers to areas of the central nervous system that are mainly made up of myelinated axons, also called tracts or fiber pathways [3]. It is composed of bundles, which connect various gray matter areas of the brain to each other, and carry nerve impulses between neurons. Myelin acts as an insulator, which allows electrical signals to jump, rather than coursing through the axon, increasing the speed of transmission of all nerve signals [4].

Long thought to be passive tissue, white matter affects learning and brain functions, modulating the distribution of action potentials, acting as a relay and coordinating communication between different brain regions [5].

The Human Brain consits of these tracts in left and right side:

- Anterior Thalamic Radiation (ATR)

- Corpus Callosum (CC)

- Genu of the Corpus Callosum (genu)

- Splenium of the Corpus Callosum (splenium)

- Body of Corpus Callosum (truncus)

- Body of Corpus Callosum (truncus)

- Cingulum (Cing)

- Corticospinal Tract (CST)

- Inferior Fronto-occipital Fasciculus (IFO)

- Inferior Longitudinal Fasciculus (ILF)

- Superior Longitudinal Fasciculus (SLF)

- Ventral Tegmental Area (VTA)

2   REGISTRATION

The registration problem (also known as alignment, absolute orientation) is one of the outstanding and very basic problems in computer vision. In this problem, two or more datsets of points are given and the task is to optimally align them by estimating a best transformation (combination of translation, rotation and scaling). Due to its fundamental importance, it arises as a subtask in many different applications (e.g., object recognition, tracking, range data fusion, graphics, medical image alignment, robotics and structural bioinformatics ... etc) [2].

2.1   *Iterative closest point (ICP)*

ICP, which is an algorithm employed to minimize the distance between two or more points clouds, is one of the widely used algorithms in aligning three dimensional models given an initial guess of the rigid body transformation required [6]. In ICP (in our case) one points cloud (vertex cloud), the reference, or target, is kept fixed, while the other one, the source, is transformed to best match the reference. The algorithm iteratively revises the transformation (combination of translation, rotation and scaling) needed to minimize a distance from the source to the reference points cloud.

3   PCA TRANSFORMATION

PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by some projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on[7]. PCA is used in the code as a preliminary step, so that the template and target are aligned as much as possible before the registration can begin.

4   LEAST SQUARES (LSQR)

LSQR uses an iterative method to approximate the solution. The number of iterations required to reach a certain accuracy depends strongly on the scaling of the problem ($||Ax - b||^2$). Poor scaling of the rows or columns of A should therefore be avoided where possible [8].

METHOD

1 THE FRAMEWORK

The main subject of this thesis is demonstrating how the ICP framework can be extended to nonrigid registration, whilst retaining the convergence properties of the original algorithm. The principle idea is the application of the work presented in [1]. The resulting optimal step nonrigid ICP framework allows for the use of different regularisations, as long as they have an adjustable stiffness parameter. The registration loops over a series of decreasing stiffness weights and incrementally deforms the template towards the target, recovering the whole range of global and local deformations. To find the optimal deformation for a given stiffness, optimal iterative closest point steps are used. Preliminary correspondences are estimated by a nearest point search. Subsequently, the optimal deformation of the template for these fixed correspondences and the active stiffness is calculated. Afterwards, the process continues with new correspondences found by searching from the displaced template vertices. We present an algorithm using a locally affine regularisation which assigns an affine transformation to each vertex and minimises the difference in the transformation of neighbouring vertices. It is shown that for this regularisation, the optimal deformation for fixed correspondences and fixed stiffness can be determined exactly and efficiently. The method is successful for a wide range of initial conditions, and handles missing data robustly. Furthermore, it is compared qualitatively and quantitatively to other algorithms using synthetic examples and real world data.

As has been defined in the introduction, vertex registration is a problem in which two or more datasets of points are given and the task is to optimally align them by estimating a best transformation. In our case, we use a dense registration method to find a mapping from each point in the template onto the target while sparse methods find correspondence only for selected feature points. This is done by deforming the template, locally moving it closer in each iteration to the target in order to wrap them together with respect to stiffness.

ICP moves the template S towards the target T step by step. In each iteration, it minimizes the difference between the template S and the target,

T as illustrated in figure (1), to reach the minimal value by solving the main equation (1):

$$||Ax - b||^2 \tag{1}$$

In equation (1) x is a list of X_i, each X_i is a 3×4 affine matrix which uses homogeneous coordinates $[x, y, z, 1]$ in 3D Euclidean space. By stacking X_i together we get $4n \times 3$ matrix x as shown in equation (2):

$$X = [X_1, X_2, ..., X_n]^T \tag{2}$$

If we were to simply solve the equation (1) by assigning A as the template and b as the target, we will get exactly $Ax = b$, which means the difference between them is zero. That leads to the deforming of A and a complete loss of its shape, therefore, we need to add the stiffness part to the equation that will prevent this deformation by keeping the vertices originally as close to each other as possible which we will later explain in this chapter.
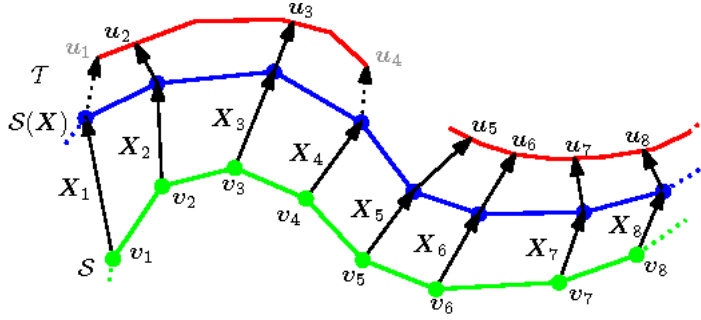

Figure 1: With one iteration of ICP, the template S moves closer to target T as it becomes $S(x)$, Reference [1]

2   SETUP

The method presented in [1] deals with graph representation of the data $S = (V, E)$ where S, V and E are signed to graph, vertices and edges respectively. As we describe in the introduction our data is human brain bundles (pathways) saved in **ply** data format as it shown in the simplified Figure 2. It consist of three parts, the upper part is the header of the file which has the description of the file (i.e. format, comment, etc), the important parts of the header elements parts, which describe how many elements each parts has. in the sample in figure 2, it has 69283 vertices in x,y,z and 603 fibers. The second part of the **ply** files, is vertices in 3D Eucledian coordinate and the last part of **ply** file represent the end index of each fiber.

As the method in [1] require the template to be in graph format, we develop a tool to read **ply** files and put them in a numpy array of array which can be later used as a graph. To be able to use **numpy ndarray** as graph, we put each

tract in a separet array with respect to the link, to do so, we put each points linked together next to each other, and then wrap all the tracts belong to the same bundle (i.e ATR, CC, genu, splenium, etc) in a new ***numpy ndarray***.

```
ply
format ascii 1.0
comment DTI Tractography, produced by fiber-track
element vertices 69283
property float x
property float y
property float z
element fiber 603
property int endindex
end_header
-4.71338558197 -19.9100589752 4.76097154617
-4.73113059998 -19.3581771851 4.68979740143
-4.72901630402 -18.8120174408 4.5764541626
-4.79067516327 -18.2503032684 4.52395439148
......
152
299
364
494
637
767
```

Figure 2: Simplified ply file sample

3 PREPARATION

After we read the data in suitable format, we need to align the template to the source as much as possible. For that we use *Principal Components Analysis*. To get the best aligning we scale the template to the source and use $[-1, 1]^3$ cube, we use the combination of the cube and mesure the distance each time to select the minimal distance as illustrated in table **??**.
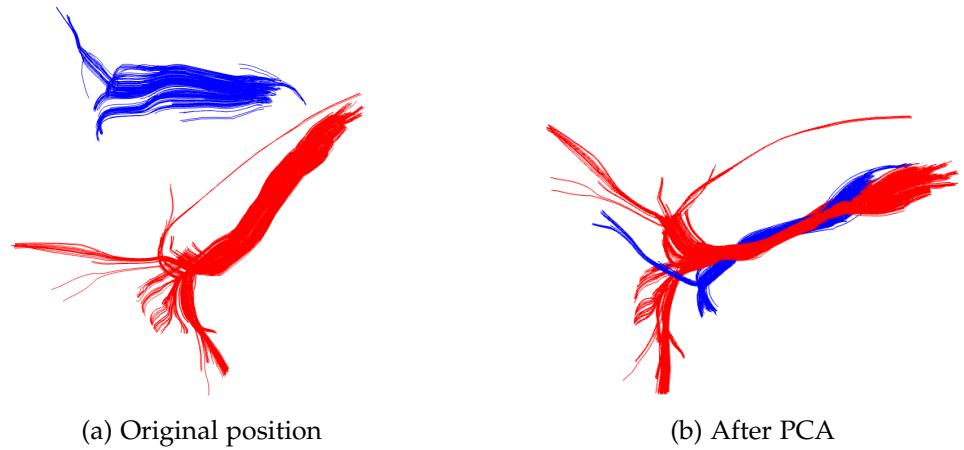

(a) Original position   (b) After PCA

Figure 3: PCA alignment

1	2	3	4	5	6	7	8
(x,y,z)	(x,y,-z)	(x,-y,z)	(x,-y,-z)	(-x,-y,z)	(-x,y,-z)	(-x,y,z)	(-x,-y,-z)

Table 1: PCA $[-1, 1]^3$ cube combination

3

RESULT

4

CONCLUSION

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