Final Medical Image Registration and Applications (MIRA) Project

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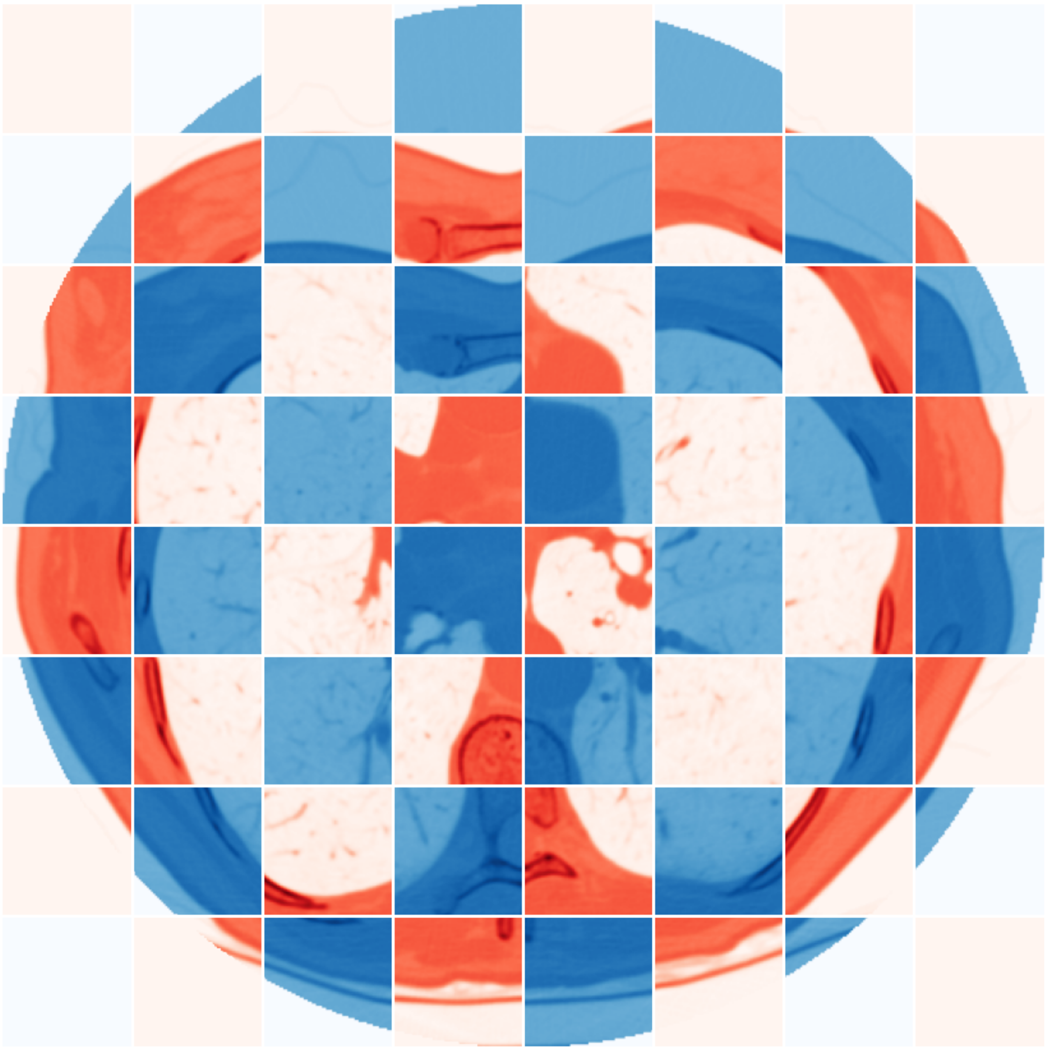

1 Introduction

Image registration is the process of aligning two or more sources of data to the same coordinate system. It is usually done by aligning two images, or more, conventionally named as fixed and moving. Although there are many registration methods used, the most common one is the Deformable Image Registration method where we transform one image into another by minimizing the difference between target and source image with a voxel-by-voxel deformation matrix. This has many applications in medical imaging and is widely used including during a breathing cycle (4D CT). The aim of this project is to minimize the difference between the given landmarks and the transformed landmarks produced after registration. The dataset provided is taken from dir-lab COPDgene (COPD1, COPD2, COPD3, COPD4). Each of these CT volumes has 300-feature pixel indices text files. Basically, we have to find transformed exhale landmarks given inhale points and both exhale and inhale volumes of lung CT scans. Performance evaluation is done by calculating the mean and standard deviation of 3-dimensional Euclidean distances referred to as Target Registration Error or TRE (error).

2 Materials and methods

In this Final Project, we wanted to explore two different Image Registration algorithms. On the one hand, a more innovative and recent apprach based on Deep Learning (DL), VoxelMorph. On the second hand, a classical approach using the well-known Image Registration software, Elastix.

The Deep Learning will be presented first. Even though our initial apprach was to make a reasonable comparison of both algorithms, due to bad results and high training times, this comparison is not established in the project. The DL approach is presented, with some results, and then the Elastix-based algorithm. The later, is the final algorithm used in the challenge, based on good results, execution time and robustness, as will be explained in the following sections. This remark was done at the beginning of the project to make the overall idea more understandable.

2.1 Voxelmorph based registration

Instead of the non-learning approaches, we also tried a learning-based approach using convolutional neural networks. VoxelMorph, a fast learning-based deep learning framework for deformable, pairwise medical image registration. VoxelMorph is an unsupervised learning algorithm to perform registration. It learns the transformation function and uses a spatial transform layer to reconstruct an image from the other while constraining large displacements in the registration field.

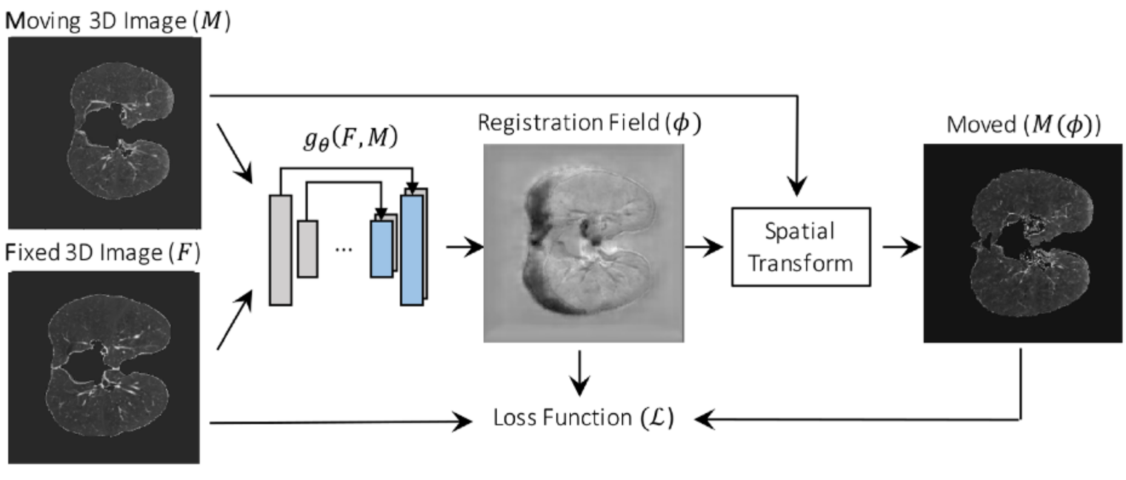

Figure 2.1: Basic pipeline of VoxelMorph.

VoxelMorph tries to learn the function G'(F,M) = phi. Here phi is the registration field and G' is the transformation function after learning the parameters.

2.1.1 Implementation Details

We build a custom datagenerator that takes two inputs (both inhale volume and exhale volume). It takes inhale as fixed and exhale as moving and outputs a registration field which is used to register the moving image with the fixed image by a spatial transformer network by interpolating and wrapping the moving image to the fixed image.

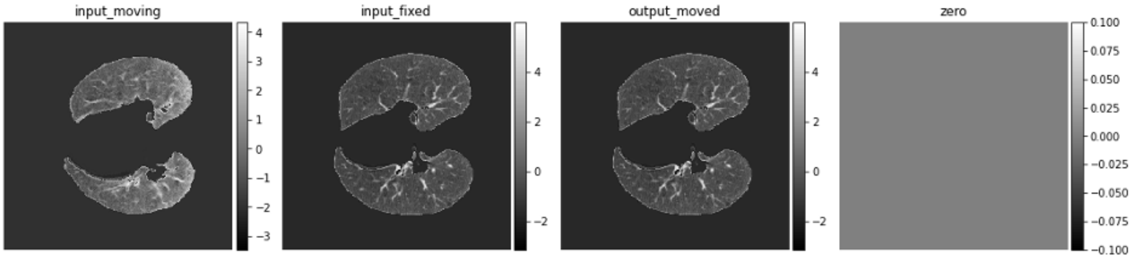

Figure 2.2: Inputs and Outputs for the model froum our datagenerator.

For the loss function, we tried Mean Squared Error (MSE) and Normalized Cross-Correlation (NCC) as a similarity metric. Basically, it calculates two losses, one for maximizing the similarity metric and another for regularizing the registration field to avoid the wrong displacement.

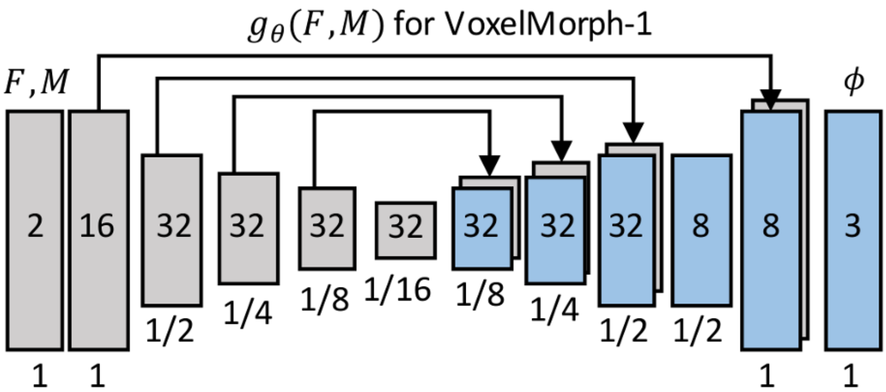

Figure 2.3: Basic architecture of VoxelMorph.

2.1.2 Experiments

We performed several experiments with VoxelMorph to study how it behaves under different circumstances. We divided all those experiments into two types of models. One that is trained on 4 sets of volumes of lungs and one which is trained on 8 sets of volumes of lungs.

Table 2.1: Unregistered TRE values of four volumes of COPD

	COPD1	**COPD2**	**COPD3**	**COPD4**
Before Registration	26.4 (11.4)	21.8 (6.5)	12.6 (6.4)	29.6 (12.9)

Table 2.2: Results of using 4 COPD volumes showing the mean and standard deviations

	Regularization	**COPD1**	**COPD2**	**COPD3**	**COPD4**
Unnormalized + Unsegmented	0.5	2806.9 (517.2)	3521.9 (420.3)	3153-9 (437.1)	3412.1 (507.4)
Normalised + Unsegmented	0.5	25.9 (11.8)	21.8 (5.7)	8.9 (3.9)	27.3 (11.9)
Normalised + Segmented	0.5	26.2 (10.9)	21.5 (6.1)	10.1 (5.3)	25.0 (9.6)
Normalised + Affine + Unsegmented	0.05	21.9 (11.1)	20.5 (4.9)	7.7 (3.3)	21.4 (9.4)
Normalised + Affine + Segmented	0.05	22.8 (11.0)	20.7 (5.0)	7.3 (3.5)	20.2 (9.2)
Normalised + Affine + BSpline + Unsegmented	0.0001	7.3 (6.2)	12.0 (9.1)	8.6 (9.9)	9.6 (5.7)
Normalised + Affine + BSpline + Segmented	0.0001	6.5 (4.7)	11.1 (7.1)	5.8 (5.0)	8.4 (4.8)

All the experiments were run on Google Colab and our machine with Nvidia 1060 6 GB VRAM. The deep learning framework used was Keras.

Table 2.3: Results of using 8 COPD volumes showing the mean and standard deviations

	Regularization	COPD1	COPD2	COPD3	COPD4
Unnormalized + Unsegmented	0.5	3282.1 (749.9)	3933.1 (526.6)	3920.6 (437.1)	3325.0 (509.3)
Normalised + Unsegmented	0.5	20.0 (9.1)	19.9 (6.1)	11.3 (5.4)	24.2 (7.7)
Normalised + Segmented	0.5	21.7 (11.3)	21.2 (6.4)	11.7 (5.5)	24.0 (8.4)
Normalised + Affine + Unsegmented	0.05	19.7 (11.2)	20.4 (4.6)	8.4 (3.5)	20.5 (9.1)
Normalised + Affine + Segmented	0.05	20.8 (10.0)	21.3 (4.7)	7.2 (3.7)	20.1 (9.2)
Normalised + Affine + BSpline + Unsegmented	0.0001	6.7 (9.1)	11.2 (7.7)	6.6 (7.3)	9.4 (8.2)
Normalised + Affine + BSpline + Segmented	0.0001	6.1 (9.7)	10.3 (4.4)	5.3 (5.6)	8.7 (7.4)

Here we can draw many conclusions from our set of experiments. One thing is true that if given more data, VoxelMorph generally has better or equal results than with fewer data. Also, the regularization term when reduced gives better results as it gives more weightage to the similarity loss than the smoothing loss. But on going beyond .0001, it started to give wrong deformations. We can see that registration without using the segmentation masks results in the network learning to register more outside than lung area and therefore leading to sometimes higher TRE. While doing registration with the segmentation masks, the network sometimes fails to learn the registration of the fine details of the lungs that have the landmarks and resulting in a high TRE as well. This could have been better if we had more sets of volume data. Also, as we have fewer data so, if we do some registration before anything else and then feed the transformed images to the model, they work better. Similar trend can be seen while using Affine and Affine with Bspline and their output as the input for the model. Although much improvement cannot be seen.

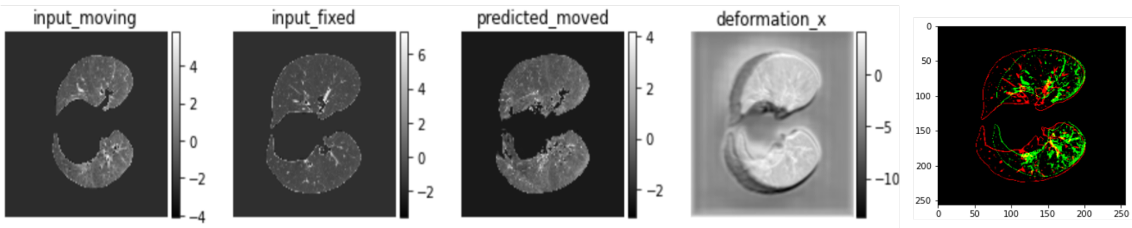

Figure 2.4: VoxelMorph Prediction along with the actual and deformation.

2.1.3 Conclusion

In this section, we applied different transformations using deep learning techniques. We tried VoxelMorph which is not an efficient solution because the data provided to us was very less and efficient training of VoxelMorph requires a lot more data. But training a deep learning model reduces the execution time for registration. The nodules and fissures were not properly registered due to a lack of data. However, encouraging results were obtained using VoxelMorph.

2.2 Elastix-based Registration

2.2.1 Registration Paradigm

In order to understand the different parameters and commands used by Elastix, a simple introduction to the Image Registration paradigm is made at the beginning of this section.

Image Registration was defined as a general concept in the introduction. However, Figure 2.5 introduces a more detailed idea of Image Registration.

The basic components shown in Figure 2.5 are:

- The metric computes the similarity between the fixed and transformed moving image.
- The optimizer tries to find the transformation parameters that maximize the similarity metric.
- The transform is the set of geometrical operations applied to the moving image in order to be aligned to the fixed image.

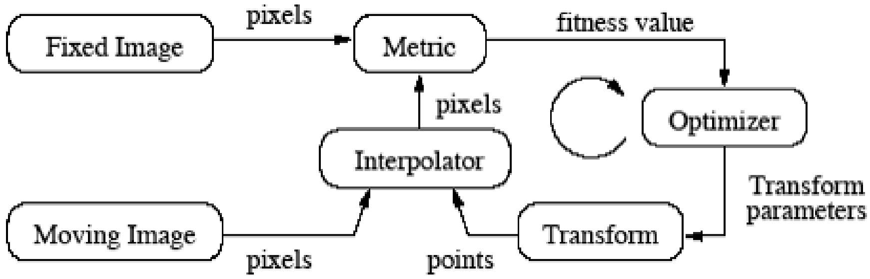

Figure 2.5: Detailed scheme of Image Registration paradigm.

– The interpolator samples the pixel values in the resulting transformed image given the moving image and the transformation.

This basic Registration algorithm can be developed in different resolutions (multi-resolution or pyramidal image Registration). A pyramid of 2 means that this algorithm will be run with the images downsampled by a factor of 2 to get a coarse transformation initialization and will be later fine tuned in the original resolution.

2.2.2 Data Preparation

After converting the raw volumes to Nifti files using ITK-Snap, the range of values were between 0 and 2500 on average. This range of values does not correspond to the values of CT scans (Hounsfield Units), therefore the volumes were subtracted 1000 to the values to match approximately with HU, checking that air was -1000, as it is supposed to be.

2.2.3 Elastix basic use

As commented, this part of the project is developed using elastix software. Elastix is composed of two different programs. Elastix is used to register images and Transformix is used to get the deformation field of the registration or to transform points.

This is the basic command of Elastix used in this project to register two images:

```
elastix -f dir/ImageFixed -m dir/ImageMoving -fMask dir/FixedMask -mMask
dir/MovingMask -out outdir -p params/NameParameter
```

where:

– dir is the path contining the volumes

– ImageFixed is the file of the fixed image

– ImageMoving is the file of the moving image

– Outdir is the output directory where the transformation parameters file and the transformed moving image will be stored

– NameParameter is a file containing all the parameters of the Image Registration to be perfomed

– FixedMask is an optional parameter of the file of the fixed mask

– MovingMask is an optional parameter of the file of the moving mask

This is the basic command of Transformix used in this project to transform points:

```
transformix -def dir/LandmarkMoving -out outdir -tp dir/TransformParameters.0(1).txt
```

where:

- dir is the path contining the landmarks and the transformation parameters file obtained using elastix
- LandmarkMoving is the file of the points to be transformed
- Outdir is the output directory where the transformed points will be stored
- TransformParameters.0(1).txt is a file containing all the transformation parameters obtained using elastix

This is the basic command of Transformix used in this project to get the deformation vector field:

```
transformix -def 'all' -out outdir -tp dir/TransformParameters.0(1).txt
```

where:

- dir is the path contining the transformation parameters file obtained using elastix
- Outdir is the output directory where the deformation vector field will be stored
- TransformParameters.0(1).txt is a file containing all the transformation parameters obtained using elastix

In the project, there are two volumes (inhale and exhale) and the objective is to perform registration between these two volumes and transform the inhale points to exhale points.

At the beginning, the intuitive idea will be to use the inhale volume as moving and exhale volume as fixed to find the transformation inhale-exhale. And then use this transformation to transform the inhale points. However, transformix does not use the direct transformation to transform points. Therefore, in this section we used the inhale volume as fixed and the exhale volume as moving to find the exhale-inhale transformation. Finally, inhale points will be transformed using the inverse transformation (inhale-exhale) using transformix.

2.2.4 1st optimization: elastix parameter files

As seen previously, all the Image Registration parameters are stored in the parameters file in elastix. In this section, we wanted to try two main transformations: affine and non-rigid (B-Splines) and a combination of both.

This optimization was done roughly, with many experiments trying to get a good registration result combining both transformations at the same time. These experiments were not included in this report since we didn't have time to properly design and report them. We found more interesting to do other experiments, later discussed.

The affine and non-rigid optimized parameter files used in this section contains the following parameters (main parameters, not all):

Number of resolutions: (can be also understood as the steps in the pyramid multi-resolution scheme). For values bigger than 1, the registration results improve as the number of resolution increases. However, computational time also increases considerably. For this reason, after 7 and 8 number of resolutions, the registration results does not improve noticeably, considering also the big increase in computational time. Therefore, the chosen number of resolutions is set to 6.

ImagePyramidSchedule: defines the downsampling factor used in each dimension at every resolution. The downsampling factor at a specific dimension for the z-dimension is set on average as 1/4th of the downsampling factor in x and y dimensions. This is due to the fact that volumes are 512x512x120 on average so the downsampling factor in z should be smaller also. Moreover, this downsampling factor should be decreased from the 1st resolution to the last and end up with 1, to go from coarse to fine-tuned registration. The chosen value is 14 14 3 10 10 2 8 8 2 4 4 1 2 2 1 1 1 1.

MaximumNumberOfIterations: defined at a specific resolution. Together with the number of resolutions, controls the execution time. After 2000 maximum iterations, no considerable improvement of the registration was observed, therefore this parameter was set to 2000.

Metric: is the similarity metric to compute between fixed and transformed moving image. The chosen metric was Mutual Information (called in elastix as AdvancedMattesMutualInformation). Normalized Correlation and Mean Squared Difference were also tried, however the registration performance did not improve.

NumberOfSpatialSamples: are the number of samples obtained in the images to compute the similarity metric. This value was set to 10000.

Transform: controls the type of transformation used in the registration. In our case, we used 2 different parameters file: one for affine transformation in which this value was set to "AffineTransform" and another for non-rigid transformation in which this value was set to "BSplineTransform".

2.2.5 2nd optimization: transformation type

In this section, the four volumes (COPD1, COPD2, COPD3 and COPD4) were used to evaluate the different experiments. In this part, the best transformation strategy was evaluated: just affine registration, just non-rigid registration, combined affine with later non-rigid registration or combined non-rigid with later affine registration.

Table 2.4 and Figure 2.6 show quantitative and qualitative results of the different transformations tested.

A remark has to be made for Figure 2.6: even though the registered images correspond to inhale volumes (as commented before inhale image was set to fixed and exhale as moving), the overlayed points correspond to transformed points in exhale. Therefore, the registered images should be compared to the inhale volume to asses the quality of the registration but overlayed points should be compared to exhale points (as transformix transforms using the inverse transform).

Table 2.4: TRE results (mean and standard deviation) for the different transformation strategies: affine registration, non-rigid registration, affine + non-rigid registration and non-rigid + affine registration

Scan ID	TRE no reg	TRE Affine	TRE NR	TRE Aff+NR	TRE NR+Aff
COPD1	26.3342 (11.4179)	25.9002 (11.2342)	5.9039 (5.1973)	5.8304 (5.2730)	5.8799 (5.2041)
COPD2	21.7860 (6.4605)	24.9766 (5.4522)	10.2683 (6.5943)	10.1746 (6.6216)	10.2779 (6.5941)
COPD3	12.6392 (6.3843)	7.3878 (3.4264)	3.5004 (3.3869)	3.3985 (3.2644)	3.5053 (3.3838)
COPD4	29.5836 (12.9242)	22.1712 (9.6226)	10.0803 (5.5946)	8.7096 (5.3032)	10.1106 (5.6120)
Average	22.5183 (9.2967)	20.1090 (7.4339)	7.4382 (5.1933)	7.0283 (5.1154)	7.4434 (5.1985)

Both quantitative and qualitative, NR, Aff+NR and NR+Affine are very similar, in terms of TRE values (approximately around 7mm) and in terms of visual results (registered images, transformed points and deformation vector field). However, the best results are obtained using first Affine and then NR registration. This is intuitive as affine registration produces a coarse first alignment, bringing the center of masses of the volumes together without distorting or degrading considerably the moving image. Then, a second non-rigid registration makes the smaller adjustments locally to register the images with a higher degree of freedom. Moreover, this type is the most robust one, as it produces the smallest standard deviation in the results (5.1154 mm). In terms of execution time, it takes around 5 minutes to perform a single registration, points deformation and vector deformation field estimation.

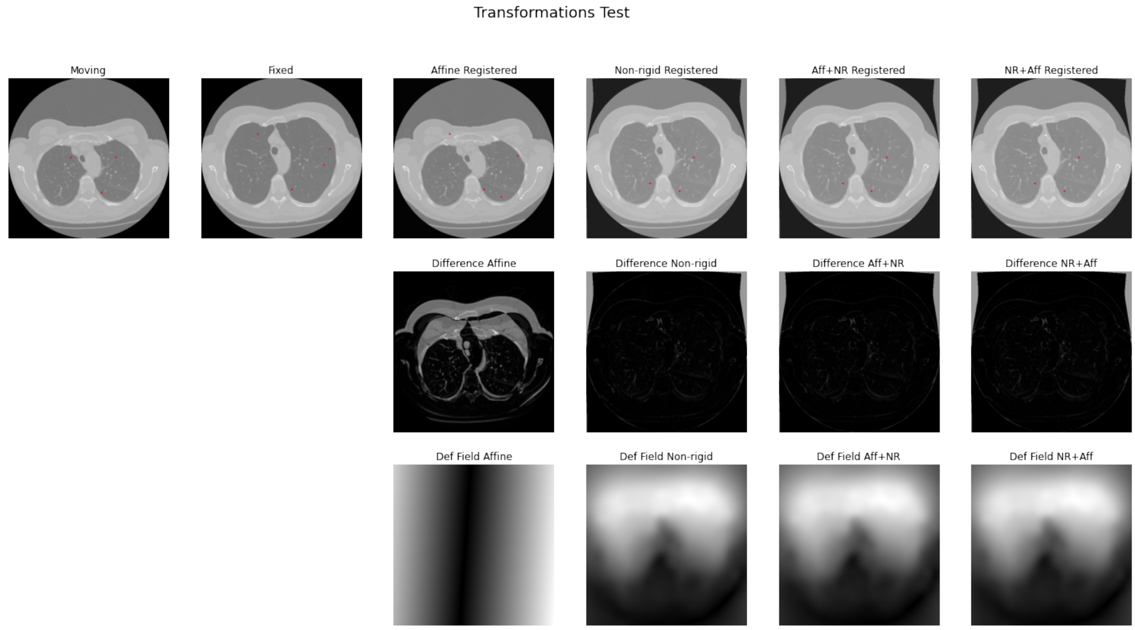

Figure 2.6: Qualitative results of the different transformation registrations. From top to bottom: registered images with transformed exhale points, absolute difference image between registered and fixed images and deformation vector field of the registration

Using only Affine produces the worst results as this type of transformation is not flexible enough (does not have enough degrees of freedom) for this specific task. Using non-rigid only, produces a high distortion to the different anatomical bodies, and is not as accurate as the combined Aff+NR approach. Using affine after non-rigid is not very smart as affine is losing all the flexibility and accuracy introduced by non-rigid registration, as it has less degrees of freedom.

Therefore, from now on, the specified transformation strategy is Affine + Non-rigid registration.

2.2.6 3rd optimization: use of masks

Since elastix offers the possibility to use masks in the registration, we wanted to make a first test to check whether including a mask containing the landmarks. To do so, a basic naive approach: a cube mask containing all the landmarks + 2 pixels of margin in each dimension (Figure 2.7)

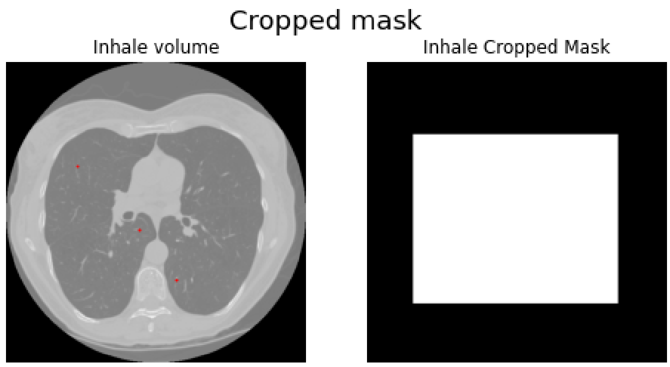

Figure 2.7: Inhale volume together with the cropped mask

Table 2.5 shows the TRE values of Affine + Non-rigid registration using no mask and cropped mask. As observed, the use of a mask restricting the registration space, improves considerably the TRE values by keeping the same execution time and improving considerably the robustness of the method (standard deviation is reduced by half). However, using this mask is not feasible in the challenge since we don't have the exhale landmarks and, therefore, no cropped mask can be generated.

Table 2.5: TRE results (mean and standard deviation) for the Aff+NR registration using no mask or cropped mask

Scan ID	TRE no reg	TRE Aff+NR	TRE Aff+NR (Crop Mask)
COPD1	26.3342 (11.4179)	5.8304 (5.2730)	1.7588 (2.0279)
COPD2	21.7860 (6.4605)	10.1746 (6.6216)	3.9797 (4.5883)
COPD3	12.6392 (6.3843)	3.3985 (3.2644)	1.6006 (1.4181)
COPD4	29.5836 (12.9242)	8.7096 (5.3032)	2.1726 (1.8587)
Average	22.5183 (9.2967)	7.0283 (5.1154)	2.3780 (2.4733)

After checking that a mask improves the registration, a general approach that is not dependent on the landmarks was developed. This strategy relies on the segmentation of the lungs.

Figure 2.8 shows the segmentation process of the lungs. First, using the properties of HU of CT scans, a thresholded image is obtained by clipping the range of values to those of the air (between -1000 and -300 HU). Second, contours are obtained from the thresholded image. Finally, a set of criteria are applied to the different component labels obtained by each contour (minimum area; ratio of two main axis, to remove elongated structures such as the bed; location of the center of gravity and maximum radius of enclosed circle, to remove the air surrounding the body).

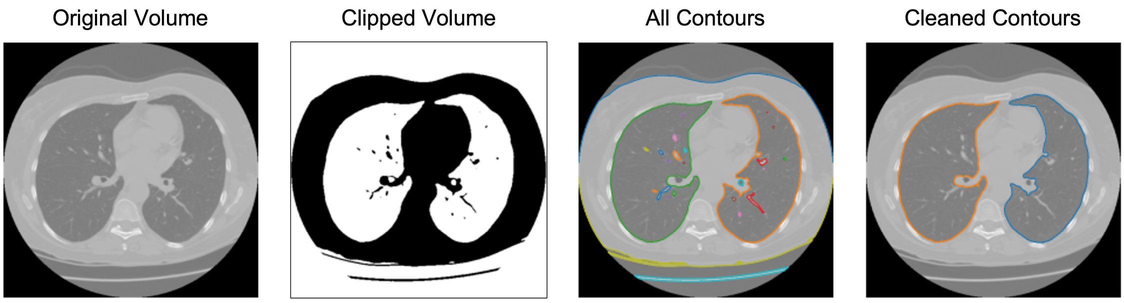

Figure 2.8: Segmentation process of the lungs

Figure 2.9 shows the segmentation results of the described algorithm for one volume. The processing time is 0.8 seconds on average for the whole volume.

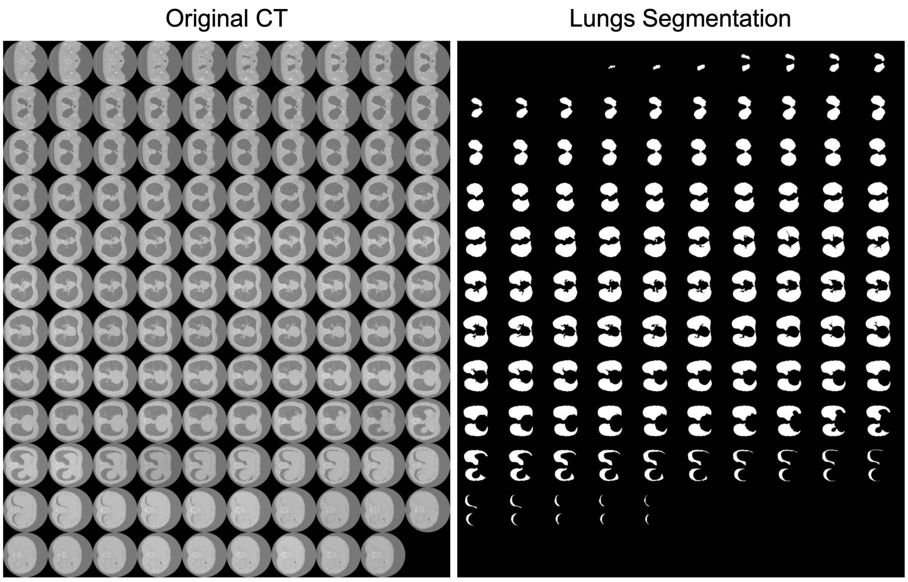

Figure 2.9: Overview of the segmentation of the lungs in one full volume

Table 2.6 shows the TRE results using no mask, crop mask or lung mask. The effect of using lung mask further improves the TRE values, decreasing as well the standard deviation and therefore increasing the robustness. Since the lung segmentation process takes less than a second, the overall computation time is still in the range of 7 minutes approximately. These results can be explained since all the landmarks are within the lungs, so using a mask in the lungs makes the registration process more accurate in this section.

The fact that lung segmentation is based on HU, makes the overall registration algorithm work only with CT images as it is. However, with some basic algorithm (K-Means clustering and basic Image Processing) the lungs can be segmented in MRI also, for instance. So, even though our algorithm as it is, is restricted to CT images, it can be extended to any modality very easily.

Table 2.6: TRE results (mean and standard deviation) for the Aff+NR registration using no mask, cropped mask or lung mask

Scan ID	**TRE no reg**	**TRE Aff+NR**	**TRE Aff+NR (Crop Mask)**	**TRE Aff+NR (Lung Mask)**
COPD1	26.3342 (11.4179)	5.8304 (5.2730)	1.7588 (2.0279)	1.1598 (1.0752)
COPD2	21.7860 (6.4605)	10.1746 (6.6216)	3.9797 (4.5883)	2.2016 (2.9853)
COPD3	12.6392 (6.3843)	3.3985 (3.2644)	1.6006 (1.4181)	1.1605 (0.9606)
COPD4	29.5836 (12.9242)	8.7096 (5.3032)	2.1726 (1.8587)	1.4798 (1.0230)
Average	22.5183 (9.2967)	7.0283 (5.1154)	2.3780 (2.4733)	1.5004 (1.5100)

Figure 2.10 shows qualitative results of the different registrations using either crop or lung mask. Even though overall the volume, crop mask achieves lower absolute difference image, lung mask achieves lower absolute difference within the lungs, with a lower TRE and closer transformed points to the exhale ones.

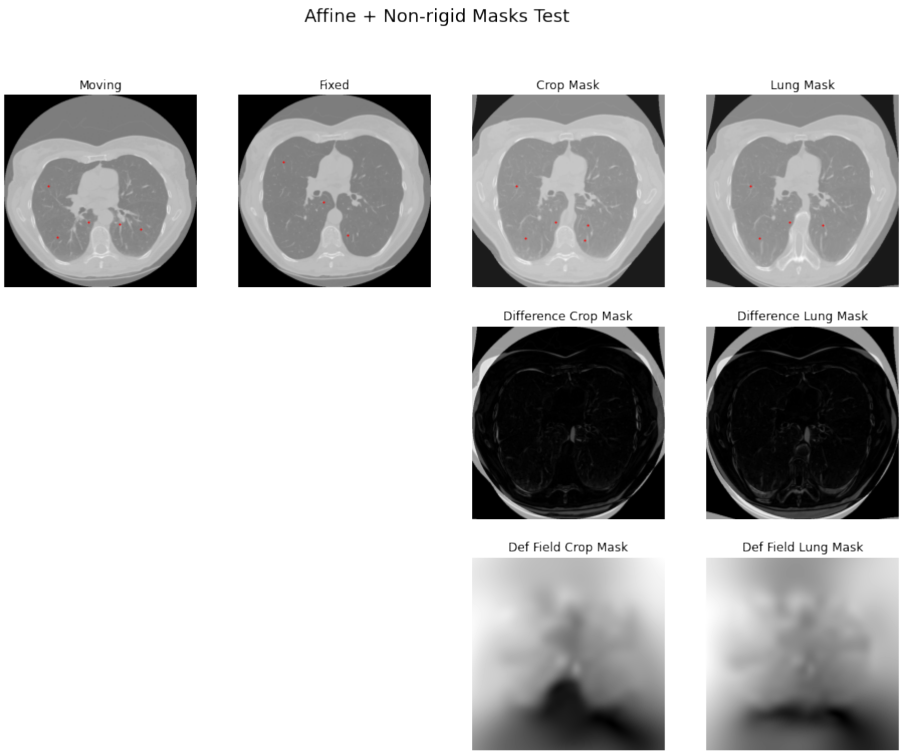

Figure 2.10: Qualitative results of the different registrations using different masks (crop and lung). From top to bottom: registered images with transformed exhale points, absolute difference image between registered and fixed images and deformation vector field of the registration

2.2.7 Other tests I: normalization, Sobel and Laplace

Three further improvements were tried. Al of them make use of the lung mask but instead of the original volumes, they use processed ones. In the normalized volume, the volume inside the lungs were normalized to a range [0,1]; in the Sobel approach, the gradient magnitude image (using horizontal and vertical Sobel filters, a first order edge detector) was used, and in the Laplacian, the gradient magnitude using the Laplacian filter, a second order edge detector, as shown in Figure 2.11.

Figure 2.11: Alternative moving images used for the registration

Table 2.7 shows the TRE results of using the different images commented. Normalized and Laplacian images highly degrade the results. In the case of normalized image, even though the contrast inside the lungs is increased, the HU correspondence between moving and fixed images that highly benefits the registration, is lost and this physical information as well. In the case of Laplacian edges, the information content is so low (edges are very thin) that is more complex for the registration to align this information.

In the case of Sobel image, the edges help to localize better the landmarks, since they are based mainly on corners or edges keypoints. And since it is a 1st order derivative, the edges are thick enough to have enough content information and help the registration process, giving for cases COPD3 and COPD4 better TRE values. However, overall, the lung mask on the original volume produces on average better TRE results and is slightly more robust.

Table 2.7: TRE results (mean and standard deviation) for the Aff+NR registration using lung mask, normalised, Sobel or Laplacian moving images

Scan ID	TRE no reg	TRE Aff+NR (Lung Mask)	TRE Aff+NR (Normalised)	TRE Aff+NR (Sobel)	TRE Aff+NR (Laplacian)
COPD1	26.3342 (11.4179)	1.1598 (1.0752)	1.4200 (1.5131)	1.1682 (0.9940)	1.6341 (1.5563)
COPD2	21.7860 (6.4605)	2.2016 (2.9853)	13.6804 (15.7934)	2.3240 (3.4816)	6.7582 (6.2368)
COPD3	12.6392 (6.3843)	1.1605 (0.9606)	1.1827 (0.9841)	1.1420 (0.9475)	2.1693 (1.8489)
COPD4	29.5836 (12.9242)	1.4798 (1.0230)	6.5921 (11.4770)	1.4767 (1.1943)	2.2920 (1.8122)
Average	22.5183 (9.2967)	1.5004 (1.5100)	5.7188 (7.4419)	1.5278 (1.6543)	3.2134 (2.8633)

2.2.8 Other tests II: less Affine resolutions

The final test performed in this section was to decrease the number of resolutions in the first affine registration. Since the purpose of this first registration is to bring a coarse initial registration, decreasing the number of resolutions from 6 to 2 can both decrease the computation time and give a coarser initial registration which can help the subsequent non-rigid registration.

Table 2.8 shows the TRE results for this alternative test. Even though for COPD3 and COPD4 the TREs are better, on average using the lung mask on the original volume is better and slightly more robust.

To select the best algorithm, both TRE accuracy and computation time should be considered. The effect of using 2 resolutions instead of 6 in the Affine registration decreases the computational time from 5 to 4 minutes approximately. Since our objective was to obtain the best TRE possible for the challenge, we decided to use 6+6 resolutions. However, if computational time is a big issue, the alternative 2+6 approach gives the best TRE accuracy/computational time balance.

3 Final Comparison with challenge algorithms

Having chosen our final method as the elastix-based using Aff+NR registration, with lung mask and 6+6 resolutions, Table 3.1 shows the TRE results for four volumes of our method together

Table 2.8: TRE results (mean and standard deviation) for the Aff+NR registration using lung mask, using 2 and 6 resolutions in the Affine part

Scan ID	TRE no reg	TRE Aff (6)+NR (6) (Lung Mask)	TRE Aff (2)+NR (6) (Lung Mask)
COPD1	26.3342 (11.4179)	1.1598 (1.0752)	1.1409 (1.0676)
COPD2	21.7860 (6.4605)	2.2016 (2.9853)	2.2858 (3.2304)
COPD3	12.6392 (6.3843)	1.1605 (0.9606)	1.1558 (0.9680)
COPD4	29.5836 (12.9242)	1.4798 (1.0230)	1.4479 (1.0641)
Average	22.5183 (9.2967)	1.5004 (1.5100)	1.5076 (1.5825)

with some algorithms present in the DIR-LAB challenge results table. Even though, we don't get the best result for any volume, out TREs are quite close to the best ones an din many cases being the 2nd or 3rd best result for individual volumes.

Table 3.1: TRE results (mean and standard deviation) of some algorithms competing in the challenge together with our method

Algorithm	COPD1	COPD2	COPD3	COPD4
NLR	1.33 (1.55)	2.34 (2.88)	1.12 (1.07)	1.54 (1.61)
LMP	1.21 (1.46)	1.97 (2.38)	1.06 (0.96)	1.64 (1.75)
MILO	0.93 (0.92)	1.77 (1.92)	0.99 (0.91)	1.14 (1.04)
SGM3D	1.22 (2.73)	2.48 (3.79)	1.01 (0.93)	2.42 (3.56)
isoPTV	0.77 (0.75)	2.22 (2.94)	0.82 (0.80)	0.85 (0.86)
Ours	1.16 (1.07)	2.20 (2.98)	1.16 (0.96)	1.48 (1.02)