Master research Internship

Bibliographic report

Machine learning approach for 3D surface reconstruction from misaligned 2D slices (with 3D printing applications)

Field: Imaging analysis - Machine Learning

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Abstract: This paper presents the state-of-the-art of 3D image reconstruction through data analysis and image processing algorithms, as well as a preview of our upcoming work. Our project aims to reconstruct 3D models from microtome data, given misaligned physical 2D slices which may contain various types of distortion. While most powerful algorithms for 3D surface reconstruction are based on point cloud theory, to our knowledge they have not yet been implemented in the context of a series of 2D sections. Our work will also apply machine learning by support vector machine to identify trends in misalignments by analyzing existing biological data, to facilitate the automation of 2D image stack correction and 3D reconstruction from microtome data to acquire a better approximation of the original object. In this review, the background and some of the tools that will help us implement this will be presented and compared. Ultimately, we aim to 3D print these models for educational and/or regenerative medicine purposes.

Contents

1 Introduction

1.1 Why 3D surface reconstruction?

3D surface reconstruction allows the visualization and study of 3D shapes. This technique is a fundamental tool used in fields such as medicine, fundamental biology, biomechanics, biomimetics, but also criminology, forensics, education, video gaming, and so on. [14]. Over the last few years, research has brought about many new techniques that improve the quality of 3D models acquired from real-world shapes. Indeed, visible objects may can now be obtained from 3D scanning the object itself, while the 3D structure of internal organs may be obtained by Magnetic Resonance Imaging (MRI) or Computerized Tomograpjy (CT) scans. The quality of equipment is ever increasing, and microscopic structures may now be captured in 3D by a number of methods such as microCT, Confocal Laser Scanning Microscopy (CLSM), Scanning Electron Microscopy (SEM), or even more traditionally by physical slicing using a microtome. However, 3D reconstruction still involves errors, both inherent to the quality of the collected data (distortion, rotation, translation, noise, etc.), or shortcuts taken for reconstruction processing due to limitations in computational power. The data often presents itself either as a cloud of points or coordinates in 3D space (3D scanners), or as a series of 2D slices separated by gaps (other methods, microtomes). Each presents their own challenges depending on the acquisition method employed. This study focuses on microtome data, and proposes a novel strategy to implement some of the existing powerful point cloud processing algorithms to the reconstruction of 3D micro-structures from microtome-produced physical 2D slices.

1.2 Microtome data acquisition

In this study, we focus on microtome data reconstruction, also known in the medical field as histological volume reconstruction. Microtomes are mechanical instruments that cut objects in very thin sections, and they can be classified depending on their features and uses (see [11]). Although sub-micrometer slices ($< 0.1\mu m$) may be achieved when using a diamond knife on more recent machines, microtomes in general have been around since as early as the late 17th century, and microtome data of varying quality is stored in museums around the globe. Figure 1 shows a rotary microtome, while Figure 2 gives an idea of what microtome data looks like compared to other types of data acquisition in the medical field. In our case, we aim to 3D print the obtained models, for educational purposes, or perhaps for future regenerative medicine applications using 3D bioprinters. More traditional applications of microtomes are detailed in Section 4.

Microtome slicing involves a major issue: image distortions. Previous studies [8] [16] have suggested methods to highlight and correct these distortions, which come from the cutting phase, especially because of sharpness of the blade and the pressure applied during cutting, but also introduce slight rotations when the slices are mounted on a glass slide for microscopy.

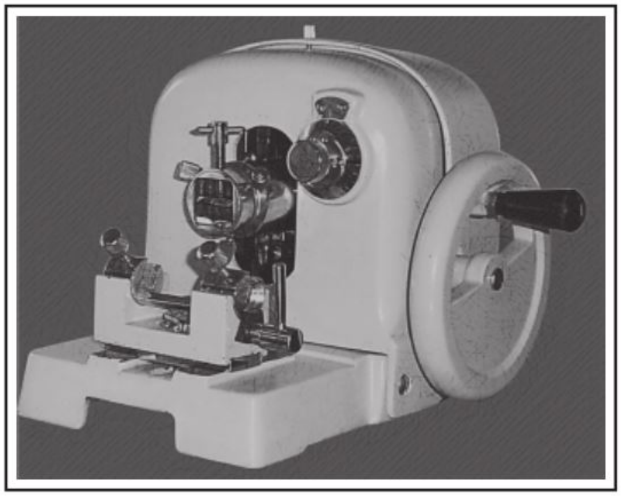

Figure 1: Example of histological slice (left), blockface image (center) and MRI (right) [1]

Figure 2: A rotary microtome from Mohammed et al. paper [11]

The global process for microtome data acquisition and 3D reconstruction thereof can be organized into the following steps, although this may vary slightly depending on the acquisition method:

- Collecting the original object (sampling, fixation, etc.)
- (Optional) Point cloud acquisition (laser range scanners, for objects of suitable size only)
- Paraffin embedding and setting of physical markers (optional: pre-registration)
- Slicing, mounting on glass slides, staining (microtome, etc.)
- Slice digitization (using a microscope)
- Image processing (alignment, segmentation, etc.)
- Image registration (following on from image processing)

Definition. "Registration is a fundamental task in image processing used to match two or more pictures taken, at different times, from different sensors or from different viewpoints" defined Lisa Gottesfeld Brown in her survey [5]

1.3 About point clouds

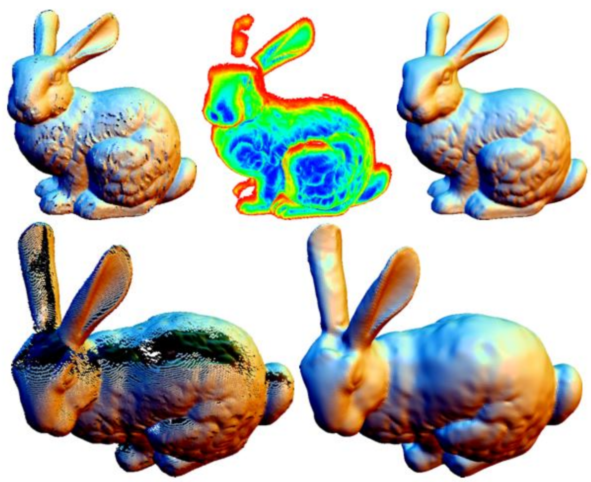

Figure 3: Noisy set of data example (Top left and bottom left). From[12]

A *point cloud* is a large set of points, with coordinates in three-dimensional space and is often used for surface reconstruction. While most technologies produce a series of 2D images or slices that can be digitized (CLSM, microtome, etc.), 3D scanners acquire a cloud of points, usually numbering in the millions or billions, representing the shape (edges, boundaries...) of an object.

One of the main main issues of this technique is the noise appearing during acquisition, which originates directly from the acquisition device. Even though technology has improved greatly over the years, physical limitations dependent on the type of sensor prevents us from getting a perfect data set. Noise can take the form of holes, as seen in Figure 3. Another critical issue is the sampling density, as 3D scanners are typically unable to acquire data in shaded areas that are masked by other features. The sampling density refers to the number of points recorded per unit distance. If the sample density is too low, the precision of the reconstructed model is limited by the lack of data, and the reconstructed shape can be dissimilar to the original one in problematic areas.

A novel approach that we are going to investigate would be to use the 2D data mentioned in the previous section to create a point cloud of uneven density representing the contour of the object of interest. After processing each 2D slice to correct for distortions and rotations, points will be sampled from each 2D slice around the contour of the object. The delicate part of this method is to choose the sampling method and resolution to use for the point cloud because there is a near infinite number of points on the contour of each slice. However, there will be a total absence of points in the micrometer-scale gap between each slice. Given the plethora of powerful algorithms available to deal with the 3D reconstruction of point clouds, we hope that this approach will complement existing methods for handling 2D image stacks and add more flexibility in handling transformations of the reconstructed surface, such as smoothing or averaging over multiple similar objects.

Other solutions for the correction of either microtome data or point clouds have been proposed, and current effective methods will be presented and discussed in Sections 2 and 3

1.4 Introduction to Machine Learning

Machine Learning (ML) is a sub-field of Artificial Intelligence. The objective of ML is to make the machine learn by its own by finding patterns or trends in the data. It is commonly used in computer science for pattern recognition, classification, image analysis... This field is particularly interesting for our study because it can be applied to detect patterns of distortions that occur when cutting with a microtome blade, as well as trends in the slight rotations of slices when they are mounted on glass slides for microscopy. Studies that applied standard ML algorithms such as *support vector machine* (SVM) and *k-nearest neighbors* (KNN) to the 3D point cloud problem will be introduced in Section 2.

In order to train the machine learner, it is necessary to provide it with a large enough quality data set. The data set is then iteratively divided into a *learning set* and a *test set*, and ML tries to predict the behavior of the test set from modeling the learning set. To learn about trends on rotation and translation of microtome data, a set of 100 plant seeds will be pre-registered and used for sectioning with a rotary microtome. As pre-registration is carried out by depositing physical markers into the paraffin block prior to slicing (cf. Section 1.2), the final range of rotation and distortion for each slice is known, and this will be our test set. Machine learning will be used to determine to what extent slice rotation and/or distortion may be predicted from the raw set of ordered 2D slices itself, even in the absence of pre-registration. Even if we do not know whether good results would be obtained, the stakes are high, because most microtome data currently available in hospitals or museums is not pre-registered. Being able to reconstruct accurate models from such data would mean that we can recycle old data for educational purposes.

2 Survey of existing algorithms

Over the last decades, a large range of algorithms and methods have been implemented to solve problems encountered during 3D surface reconstruction. In this section, we will present the most efficient ones.

2.1 Machine Learning algorithms

As a field of Artificial Intelligence, Machine Learning (ML) has known significant expansion over the last two decades. Nowadays, the panel of applications spans a large range of topics, such as object recognition, medicine (diagnostics), bioinformatics, cluster analysis, and so on. Many algorithms and methods already exist for image processing and pattern recognition, but here we describe the two most relevant to our case.

2.1.1 k-nearest neighbors

An interesting example is available in a study by Edward Tolson [15], showing application of the k-nearest neighbors (KNN) to both pattern recognition and image analysis in the medical field. In this study, KNN models are used to classify images depending on their relative *distance*. This method could be used to detect local discrepancies within ordered 2D image sequences, by comparing each slice with its n neighboring slices. This algorithm also presents many advantages such as training speed, and simplicity in determining optimal values for each parameter.

2.1.2 Support Vector Machine

Florian Steinke et al. [13] proposed a novel method for 3D shape processing that allows the reconstruction of a 3D model from point clouds, while eliminating noise and hole issues. This method is based on Support Vector Machine (SVM) regression algorithms. SVMs were first introduced by Vladimir Vapnik in 1992 [4]. They rely on kernel functions (similarity functions) and are non-parametric. As the method described by Steinke et al. [13] requires a solid mathematical background, we are not going to go into the details of the method in this report. Nevertheless, the results of experiments using this technique have shown an ability of SVM to adapt itself to structure of the data, automatically creating the necessary number of kernels. The computation time is satisfactory, partly due to the simplicity of the code. Besides, SVM-based solutions are able to manage noise and holes in a very robust way [13].

2.2 Algorithms for handling Point Clouds

2.2.1 The power crust algorithm

The *power crust* algorithm is probably the most famous algorithm used for 3D reconstruction from points cloud. Before understanding the power crust, we need to define what is a *Voronoï diagram*. It is the process of splitting a set a discrete points in regions, so that each region only contains one single point and all the space that is closest to that single point. (See Figure 4). The power crust algorithm is based on the Voronoï and has been improved over the course of several studies, of which we will only introduce the major ones. The first to propose a method for 3D surface reconstruction from an unorganized point cloud was Hugues Hoppe[7], providing the basis for the first version of power crust developed by Nina Amenta [3]. The power crust implements what is called the *Delaunay triangulation* on the Voronoïs, creating (1) triangles connecting the points of a point cloud, and (2) associated circles such that the points always fall on the circumference of the circle, but never inside it. The power crust algorithm turned out to be a very powerful way to reconstruct a model from point clouds with variations in local density. Indeed, density variations are unlikely to affect the outcome, owing to the fact that the algorithm adapts its local parameters to the local density of points. However, its performance is limited in case of high noise levels and sharp edges. These issues have been mostly corrected in subsequent work by the same author [2], which will be briefly introduced in the next paragraph.

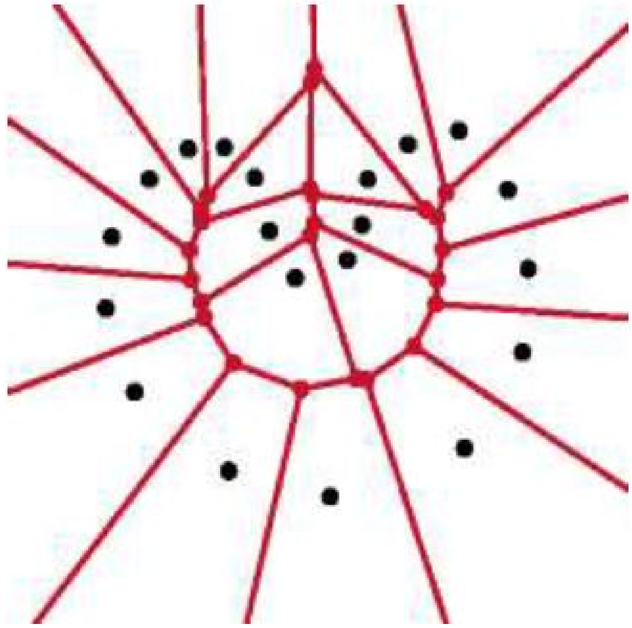

Figure 4: A Voronoï diagram in two-dimensional space. The vertices of the Voronoï (red dots) approximate the medial axis of the curve. From[3]

2.2.2 The improved power crust algorithm

Now that we have explained the basics of the power crust algorithm, we can focus on its latest implementation. This version proposes a more robust and reliable model that is able to deal reasonably well with sharp edges, which used to be the main issue.

The improved algorithm implements the following steps:

- A medial axis transform (MAT) computation, defined by Amenta et al.[2]

  Definition The medial axis transform of a surface F is the set of medial balls (See Figure 5a, in blue). The centers of all medial balls define the medial axis of F, including the radii (See Figure 5 a, in pink). The medial axis can also be defined as the closure of the set of all points with more than one closest point on F.

- a labeling phase for the cells of the power diagram to determine the inside and outside the surface (See Figure 5 b-e).

  Definition A power diagram is a kind of weighted Voronoï diagram. This phase is very significant to our project: knowing the inside and outside is essential for 3D printing.

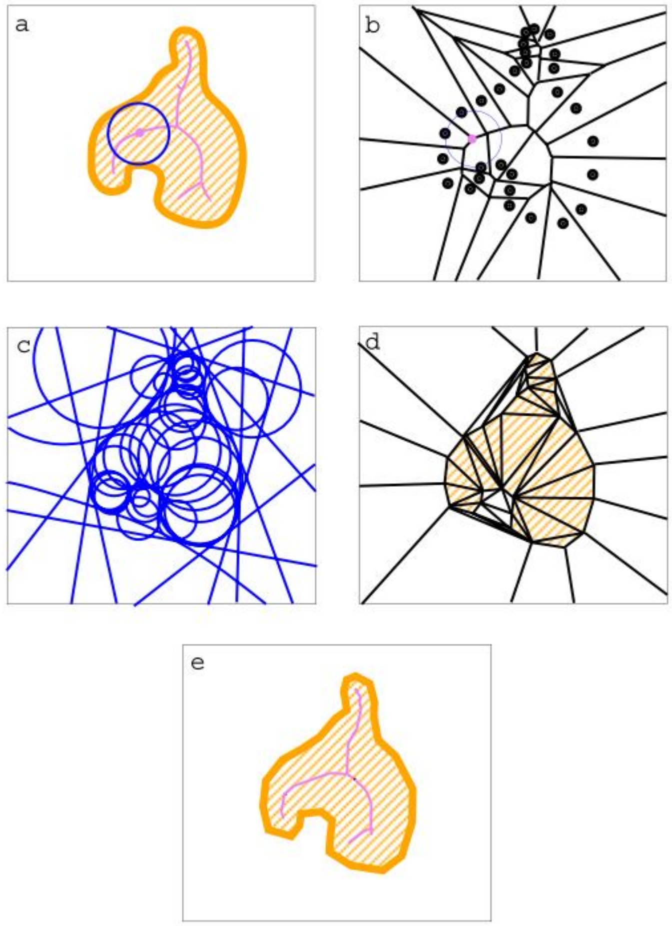

Figure 5: A two-dimensional example of the power crust algorithm. a) An object and its medial axis. b) The Voronoï diagram and its poles, the blue points corresponding to poles and the circles corresponding to polar balls. c) The set of inner and outer polar balls. d) The power diagram of the set of polar balls. The algorithms labels the cells of this power diagram inner or outer. e) The set of faces in the power diagram which separate inner from outer cells. From[10]

First, the medial axis transform (MAT) is approximated from the input data. Then, an inverse transformation is applied to obtain a piecewise linear surface approximation. These improvements of the power crust algorithm make the process easier, as post-processing is unnecessary to obtain the closest approximation model. See Figure 5. The power crust has been the subject of mathematical validation, highlighting its reliability.

A third Vornoi and power crust related method has been proposed by [10] defining an algorithm where "we discard any poles such that the radius of the associated polar ball is smaller than $\frac{lfs(S)}{c}$ where c>1 is a constant". The entire method rests on this modification of the power crust algorithm but further enables the reconstruction of accurate model noisy data sets.

2.2.3 Poisson surface reconstruction's approach

The Poisson surface reconstruction method rests on three major steps:

- Transforming the points cloud into a continuous 3D vector field
- Defining a scalar function closely approximating the vector field [9]
- Extracting the isosurface

2.2.4 Implicit shape representations

The implicit shape representation is a well known technique for 3D reconstruction that has been explored by many researchers in the past and like other techniques it has been improved over the years. One of those improvements has been proposed by Othake et al [12], including a multi-level partition of the data. This approach also implies local shape functions and the introduction of an octree hierarchy. An octree hierarchy is a tree hierarchy where each nodes can split in maximum eight children nodes. According to Othake et al [12], the benefits resulting of this method are :

- Fast surface reconstruction and rendering
- Representation of sharp features
- Reconstruction from incomplete data
- Choice of either approximation or interpolation of the data and the ability to adaptively vary the approximation accuracy

On the other hand, a correct representation of surfaces with boundaries is not guaranteed, and enhancement could be done to allow a better approximation of the distance function.

2.3 Image registration

The 3D reconstruction process may involve slices data. The pipeline for using this notion involve image processing, and thus algorithms to correct the misalignment between consecutive slices, to register images and correct distortions.

2.3.1 Image registration methods

This section takes its name from the work of B.Zitov and J.Flusser [17] who, in an article, proposed a review of the most popular and efficient methods for image registration. We are going to introduce the ones that fit our context at best.

2.3.2 Feature detection

Featured-based Method. This feature detecting method scan the image looking for "features" (i.e specificity, like corners, boundaries, etc.) in it. At first, it doesn't look like the best method for our use because of the difficulty of perceiving the details in our sample of images, however, pre-processing of the images (segmentation...) could make the features more definite, so that it will be the ideal method for 2D data.

Area-based method. This approach will be more detailed in the next section 2.3.3.

2.3.3 Feature matching

Area-based Method. The objective here is to determine the more similar image to another one by computation. For this purpose, many mathematical implementations can be used, each one having its own advantages and shortcomings. There are limitations with this method, it correct only translation issues, therefore it might not be the best solution for us. Nevertheless, it could be interesting to compare the efficiency of the translation correction with other techniques, if the results are conclusive, we could use this method for pre-processing, before to use an other technique. Besides, some authors have proposed solution to extend the range of the algorithm to rotation correction, which is the other main criterion for alignment of the slices.

2.3.4 Transform Model Estimation

Once we have detect specific features useful for our study, we are able to decide how to transform our image to what kind of registration we want to apply. This step is crucial because it chooses the mapping function we will use to correct the distortions we observe on the image. A well known group of mapping functions example is the radial basis function group. One of the advantages of this kind of function is the possibility to overcome geometric distortions (e.g translation, rotation, etc.). It makes it well designed for our sample, knowing that we have to handle this type of distortions resulting from the use of the microtome.

2.3.5 Image re-sampling and transformation

The last step of our registration process is the registration itself. We apply the function chosen in the previous phase to transform our image. There are two ways of doing that, the first one processing pixel by pixel, and the other one "using the target pixel [...] and the inverse of the estimated mapping function" [17].

All this registration pipeline is explained in Zitov and Flusser survey, [17], in which you can find other methods, mathematical details and go deeper into the applications. Some accuracy verification are available as well.

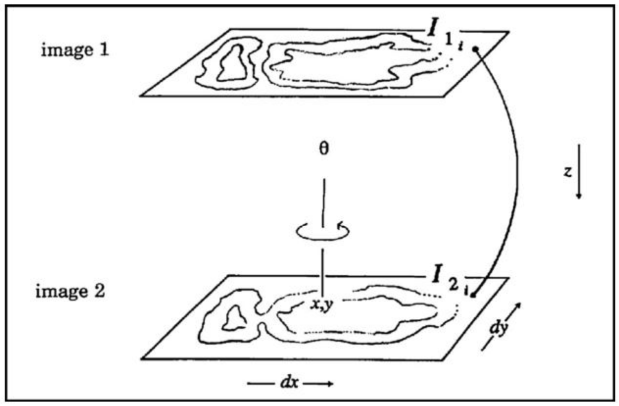

Figure 6: Classic alignment. The rigid registration program estimates the relative translation dx, then dy and the rotation θ in repeated cycles until convergence. [16]

In 2015, a study has been done by Y.-L. Zhang et al. [16] using a landmark-based large-scale image registration to reconstruct mouse and kidney organ part (nephrons). The registration phase of their work is particularly well explained and illustrated. It describes how the software used has handle translations and rotation. You can see the explanation illustration in Figure 6.

3 Discussion

Regarding to our objectives, it seems that all the algorithms evoked previously could be interesting to investigate. Nonetheless, the approach that we aim to take is to combine 2D data like microtome slice to build a could point in order to obtain the 3D reconstruction. Giving this, we need to concentrate our research on algorithms that will have a high efficiency on 2D data error correction, high potential for segmentation (the segmentation step will allow us to have a clear contour and make the choice of points easier), and, for the last step, an algorithm that have good properties in point cloud surface reconstruction. Besides, computation time and quantity of data tolerated will be parameters to consider seriously.

list the noise and distortion issues and attach the best solution for each, explain why, how we could combine some solutions...

3.1 2D data algorithms

As seen in Section 2, image registration is going to be a crucial part for correcting distortion and misalignment of the slices. In the course of the algorithms survey, we explored the different existing registration methods being able to satisfy our requirements.

Existing algorithms efficiency for image processing require specific tools. In this part we are going to introduce the most well-known and used of them.

3.2 VTK

VTK (for Visualization ToolKit) is an open-source software offering a wide range of algorithms for image processing, visualization and 3D application. "It consists of a C++ class library and several interpreted interface layers including Tcl/Tk, Java, and Python. VTK supports a wide variety of visualization algorithms including scalar, vector, tensor, texture, and volumetric methods, as well as advanced modeling techniques such as implicit modeling, polygon reduction, mesh smoothing, cutting, contouring, and Delaunay triangulation." [1] Delaunay triangulation is base of power crust and derived algorithms evoked in section 5, so VTK shows a real interest to us.

3.3 ImageJ / Fiji

ImageJ is an open-source java-based software for image analysis and processing, extensible with plugins and macros.

3.3.1 StackReg Plug-in

StackReg is a Plug-in for ImageJ/Fiji that enables registration of images in order to proceed to 3D reconstruction. It's a propagation algorithm that takes one slide and then treat each slice one by one with the first slice for reference. It can take any kind of slice data except RGB-stack and HSB-stack.[2]

3.3.2 Application example

Fiji has already proved its interests for our domain in Hanslovski et al. work [6]. Indeed, the research team has proposed a method for continuous and discontinuous non-planar distortion correction in this study, using Fiji.

4 Perspectives

During the internship, we will give a particular interest to 3D reconstruction from physical slices of a biological sample (bone, teeth, prostate, plant or insect body parts, etc.) to investigate the distortions created, the best correction method we can apply, and the reconstruction algorithms that fit best with the solution. For this purpose we will experiment several cases and analyze the result. As we saw in the last part, some preferred techniques should be explored and combined to try to automate the 3D reconstruction with the best approximation of the original artifact. Our research is going to run through steps :

- Training phase
- Real conditions experiment
- Advanced application

[1] http://www.vtk.org/
[2] http://bigwww.epfl.ch/thevenaz/stackreg/

Training phase. To get the solution the more optimized as possible, we will have to choose carefully our work environment. Thanks to our previous survey, we will try the solutions that seem the more adapted to the object reconstruction and compare the results. Some of those methods include specific tools or software for implementation, thus it will also have to be compared. Therefore, the comparison test will take in account the efficiency of the methods (error rate between the original model and the reconstructed one), computation time, quality of the data, etc. The specificity of this phase is that the data will be artificial data to simplify the tests. For instance, classic structures like Stanford rabbit will be analyzed.

Real conditions experiment. Once the Training phase brings us satisfying results, experiments are going to be done on real data. This step is supposed to validate the theoretical choices we made during the first step, so many tests have to be performed, on various data set with various quality. The success of this research rests on the results of this step, because we will be able to check if our solution comes with improvements or if we need to take an other look at the solution found previously. Bad results would indeed mean that our hypothesis was wrong, or badly implemented. On the contrary, if the results show an enhancement, we could go on the last step.

Advanced Application. Depending on the previous results, we may have the possibility to test our technique on science data in order to recreate the model by 3D printing. This kind of application would the final validation phase for our work. It would show the interest of this work and the possible application.

Knowing that the first phase is the more important because it will lay the foundations of the validation process, we will give a particular interest in it. Consequently, the discussion part (Section 3) encourage us to explore VTK, Fiji and StackReg, MeVisLab. Other solutions are not excluded.

We also have to choose some algorithms (there are too many to run a test with all of them). Again, we are going to use the ones that gave us the best interest in the discussion part, in other words we will most likely implement machine learning algorithm for trends detection, power crust based algorithms, compare registration methods of different tools to select the best one. Of course, other algorithms are still considered, for instance we may find some already implemented with specific tools.

5 Conclusion

Our research focus on 3D reconstruction from microtome data and more generally 3D reconstruction from 2D slice data (MRI, CT-scanner, 3D scanner...). This technique involve collecting data that comes with the different steps of the process. The most restrictive ones are noise, rotation and translation of the slices (misalignment), distortions (shrinking of the slices...), computation time (common problem for all methods), sampling density (point cloud).

In order to correct those shortcomings, we are going to process to a battery of tests to compare the detection and correction methods for each issue. Those tests will also be used for determining the best tools and software to use for the final method. The first point of the tests will be to try to detect a pattern in the translations and rotations of the slices (and other distortion or shortcomings if possible). Once the pattern detected (we assume there is a non-random bias), we will find the best techniques for correction by comparing their efficiency on different models. Then, we will implement it in a way that allows us to automate the process.

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