Literature Review

This report focuses on reviewing two pieces of literature relevant to the project. The study in the first paper (Kalinosky et al) is motivated by the same clinical goals as this project but takes on a different approach. The paper deals with assessing joint space narrowing in osteoarthritic (OA) joints via x-ray tomosynthesis images, and proposes the construction of joint space width (JSW) maps. The second paper (Yezzi et al) comes from a more mathematically-oriented perspective and describes a general framework compatible with the method used in our project, but with different implementation and applications.

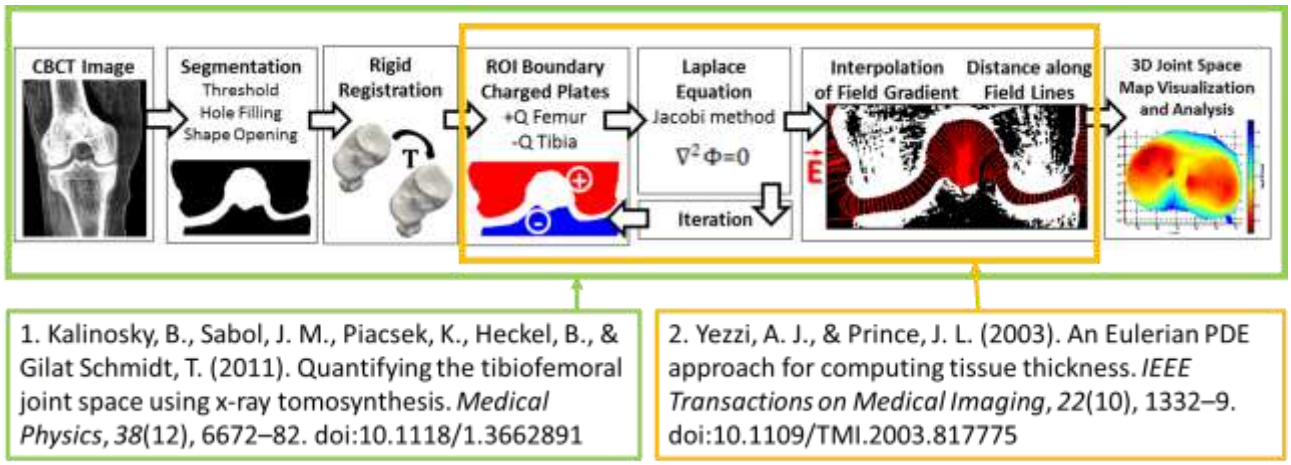

Fig. 1 Relation of selected papers to this project. Kalinosky et al presents an alternate method of generating joint space width maps using a different approach. Yezzi et al. proposes a PDE-based approach of measuring thickness in biological tissues, a method similar to ours.

Paper 1

Title: Quantifying the tibiofemoral joint space using x-ray tomosynthesis

Authors: Benjamin Kalinosky, John M. Sabol, Kelly Piacsek, Beth Heckel, and Taly Gilat Schmidt

Journal: Medical Physics

Summary

This paper is describes a semi-automatic method for quantifying 3D joint space with a 2D joint space width (JSW) map from x-ray tomosynthesis images of load-bearing osteoarthritic (OA) knees. In order to validate the results, the authors applied the method on a phantom of known width. The

authors conclude that x-ray tomosynthesis might be beneficial to improving diagnostic and assessment of treatment efficacy in OA with these quantitative images.

Overview of Methods and Results

The general structure of the method in the paper involves extensive pre-processing (in this regard, it is similar to ours), this includes selection of volume of interest (VOI) from the raw tomosynthesis image, segmentation, and the identification of the surfaces of femur and tibia. Selection of VOI is performed manually, by specifying boundary coordinates in a projection view. Segmentation involves first enhancing the edges along the vertical direction with 1D high-pass filters (recovering anisotropic gradient-like information). High-pass filters of multiple sizes were used and the convolution results (each representing edges of varying sizes) are combined to generate a final segmentation of the tibial and femoral surfaces. The authors then measure the distance between two surfaces vertically to generate distance maps.

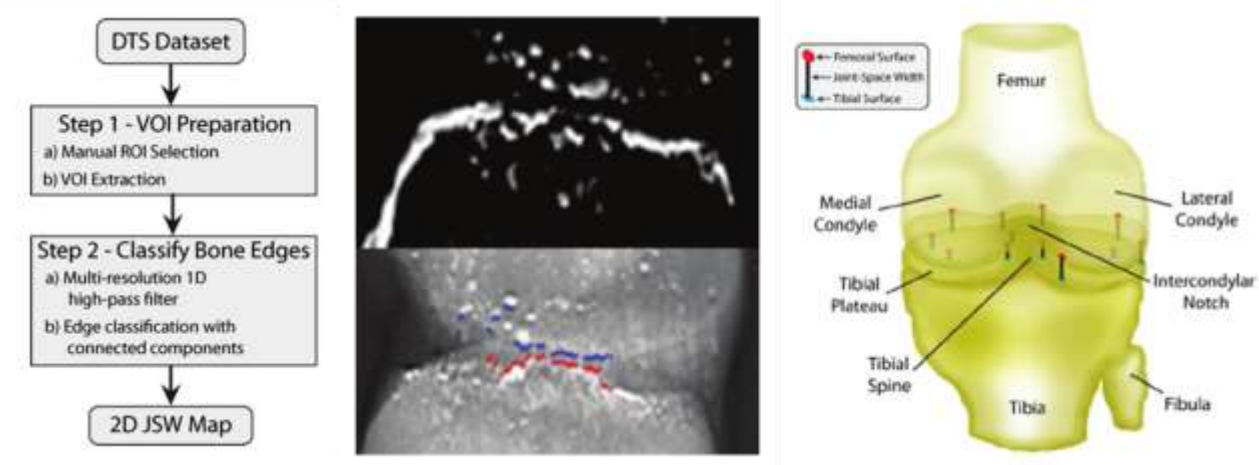

Figure 2 Overview of the tomosynthesis analysis method (left). Examples of automatic segmentation of the VOI (center). Definition of joint space widths as vertical distance between surfaces of the femur and tibia (right).

The resulting joint space width maps correlate with empirical knowledge of what the joint space looks like, this is confirmed via a phantom study with an artificial joint. The conventional marker, minimum JSW (minJSW) is also indicative of OA in clinically acquired images. The authors also explored two different acquisition geometries with the phantom, lateral and anterior-posterior (AP). They found that the AP geometry correlates well with known measurements (mean error of 0.34 mm) while the lateral does not (mean error of ~2.13 mm).

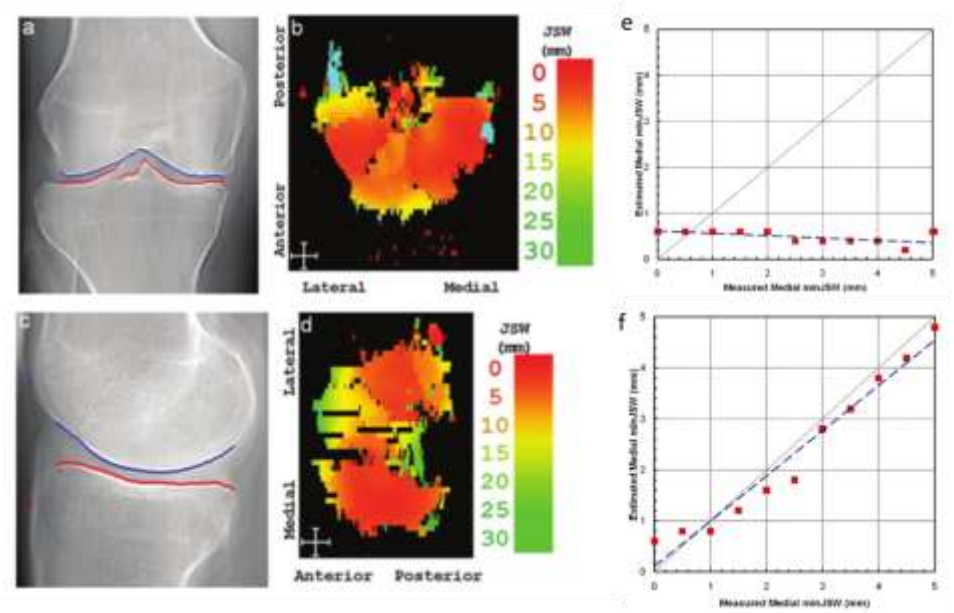

Figure 3 An example of a 2D JSW map computed by the authors' algorithm from (a-b) lateral scans and (c-d) anterior-posterior (AP) scans. The authors found that the AP scans yielded better correlation with known measurements in the phantom study (e-f).

Analysis and Relevance

This paper presents a study which is very similar to what our pipeline is trying to do: to characterize joint space morphology, particularly the separation between the femoral and tibial surfaces. Both projects start from data acquired with 3D volumes and ends with a mapping of joint space width. To this end, both frameworks have similar structures. They both depend on accurate preprocessing steps such as having good extraction of VOI and segmentation.

In the case of tomosynthesis (as is the case described in the paper), the segmentation is much more difficult, due to artifacts not found in CT volumes (this is due to sparse sampling during acquisition). And I think it is quite impressive that the authors were able to come up with a segmentation method that works as consistently as described in the paper. However, for severe-OA patients, with femoral and tibial surfaces impinging, this type of convolution-based edge-generation would fail. Unfortunately, the automatic algorithm that we have implemented fails too in this situation, and it is worth looking into more sophisticated methods that involve graph-cutting or classification techniques. Automatic segmentation of the knee joint has proven to be an extensive field and a difficult challenge [1].

Our method also demands better segmentation than the method presented in the paper. This is because the segmentation in our pipeline directly determines the boundary condition from which

our electric potential field (ϕ) can be calculated, thus if holes exist in the segmentation (as can be seen in figure 3a), the field lines for all nearby regions will be affected (this is because in our model, field lines are calculated from global spatial information, rather than local spatial information).

I do believe that, in terms of measurement methodology, we have the upper hand. As presented previously, our method does not depend on a rather arbitrary predefined direction (e.g. what is "vertical"?), and the map that we obtain is 3D, which is important because the tibial plateau is not a flat surface, but with protrusion and cavities. In OA patients, the structures are even more complex, in this case, a 2D map won't necessarily capture this intricacy.

Paper 2

Title: An Eularian PDE approach for computing tissue thickness

Authors: Anthony Yezzi and Jerry Prince

Journal: IEEE Transactions on Medical Imaging

Summary

The paper presents a general framework of measuring thickness of biological tissues using smooth vector fields corresponding to solutions of PDEs. Trajectories are formed based on the vector fields and the thickness is measured in terms of the length of the trajectories. This method is applied to the analysis of cardiac ventricular wall to measure the wall thickness and subsequently the gray matter of the brain cortex, with good results.

Overview of Methods and Results

The method proposed by the authors start by defining a domain R whose thickness needs to be measured and well defined boundaries $\partial_1 R$ and $\partial_0 R$. This is shown to be an annular-like region as in figure 4. Next a PDE is selected and its solution u is calculated in R using a relaxation method. Finally, the tangent field corresponding to u, $\vec{T}$ is calculated. Finally, trajectories L_0 and L_1 are calculated from the same point in upwind and downwind conditions based on the tangent field. Their sum W is then considered as the thickness along all points of trajectory L_0 and L_1.

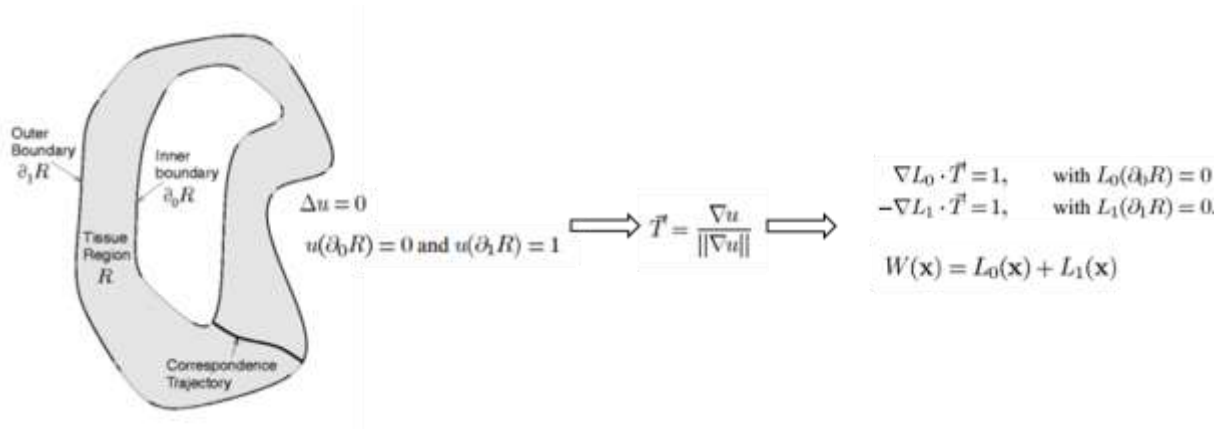

Figure 4 Mathematical description of the thickness-finding algorithm. The Laplace equation is solved in the annular region to arrive at the scalar field u. L_0 and L_1 are the upwind and downwind trajectories along the gradient of u starting from the same point. W is the thickness of the annular region along the trajectories. The authors used the Laplace equation in this study but notes that other PDEs can also be used.

This method is applied to the analysis of several biological tissues, notably the ventricular walls of the heart and the cortical tissues of the brain. The authors were able to obtain smooth maps of thickness in both cases.

Figure 5 Examples of the PDE method applied to cortical tissues of the brain. (Red denotes where the gray matter is thin; blue denotes where the gray matter is thick).

Analysis and Review

This methods paper is closely tied to our project because our electrostatic model involves calculation of the potential at every point in the joint space, which is effectively solving the Laplace equation in the region. This paper sets for us a precedence of applying PDEs to thickness measurement of biological tissues. The authors were very brief on how the solution to the PDE was solved, but

developed in detail the numerical methods involved in tracing the trajectory in upwind and downwind directions. The authors needed to describe this because they calculated a thickness for every point in the region, along all trajectories. This is not required for our application, which is focused just on one of the boundaries (e.g. the tibial surface).

However, we do need to take a closer look at the boundary conditions. In Yezzi's paper, the applications all had finite regions in which the PDE needs to be solved. They were bounded annular regions where the Dirac conditions could easily be applied. In contrast, the only real boundaries defined for us are the tibial and femoral surfaces, which leaves us with an open volume. In theory, the region in which we need to solve the PDE is infinite. But we are limited by the number of voxels that we can introduce into the field calculation without slowing it down too much. Hence, we need to introduce artificial boundary conditions, either by padding or by replicating boundary voxels. The details of this needs to be further fleshed out.

References

[1] Heimann, T., & Meinzer, H.-P. (2009). Statistical shape models for 3D medical image segmentation: a review. *Medical Image Analysis*, *13*(4), 543–63. doi:10.1016/j.media.2009.05.004