Recreating Pelvic Trauma Surgery in Virtual Reality for the Development of Novel C-arm Interfaces

Background Review

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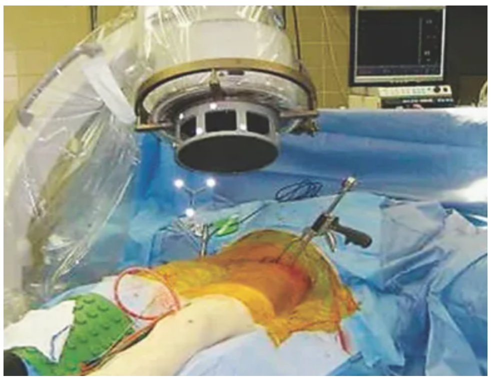
1. Project Summary

Although percutaneous pelvic fracture surgery provides better wound healing and less damage to major vessels and nerves, it has inadequate visualization and brings excessive radiation exposure for surgeons under intraoperative fluoroscopy(Figure 1). There is a need for clinicians to have a fluoroscopy-guided training environment, enabling the practice of the procedure without exposure to ionizing radiation. This project aims to build a virtual reality environment(Figure 2) with patient models and an interactable C-arm for recreating the internal fixation of pelvic fractures, using digital reconstructed radiographs(DRR) from CT scans.



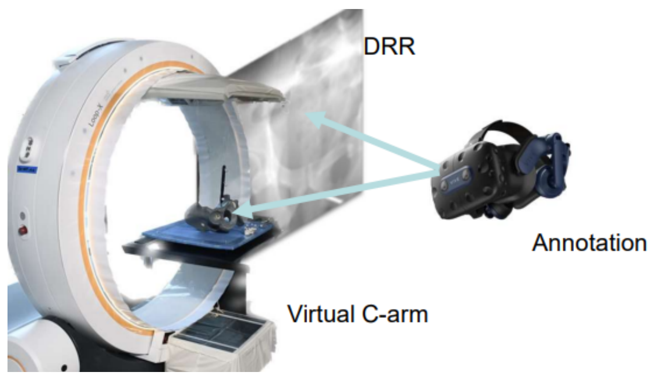


Figure 1. Percutaneous Pelvic Fracture Surgery(Rami Mosheiff, Chip Routt)   Figure 2. Training Environment with DRRs

2. Choice of Papers

1. D. R. Allen, C. Clarke, T. M. Peters, and E. C. S. Chen, “Development and evaluation of an open-source virtual reality C-Arm simulator,” *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, vol. 0, no. 0, pp. 1–6, Dec. 2022, doi: 10.1080/21681163.2022.2152374.
2. M. Unberath et al., “DeepDRR -- A Catalyst for Machine Learning in Fluoroscopy-guided Procedures,” *arXiv.org,* https://arxiv.org/abs/1803.08606v1 (accessed Mar. 13, 2023).
3. A. L. Brazil, A. Conci, E. Clua, L. K. Bittencourt, L. B. Baruque, and N. da Silva Conci, “Haptic forces and gamification on epidural anesthesia skill gain,” *Entertainment Computing*, vol. 25, pp. 1–13, Mar. 2018, doi: 10.1016/j.entcom.2017.10.002.
4. J. Moo-Young, T. M. Weber, B. Kapralos, A. Quevedo, and F. Alam, “Development of Unity Simulator for Epidural Insertion Training for Replacing Current Lumbar Puncture Simulators,” *Cureus*, vol. 13, no. 2, p. e13409, doi: 10.7759/cureus.13409.

The first paper we selected (Allen et al.) describes a virtual C-arm in a virtual reality environment to provide a training environment for surgeons. However, we identified several areas for improvement that we plan to add to our implementation. We want to generate more accurate and realistic simulated x-ray images than the naive tracing method used in this work. Therefore, we chose the second paper because Unberath et al. develop a better method to generate more realistic simulated X-ray images called DeepDRR, which is able to generate significantly more realistic DRR images than conventional DRR methods, utilized for recreating comprehensive intraoperative fluoroscopy for our project. Additionally, we wanted to improve upon the Allen et al. simulation by providing intuitive simulated interactions with surgical tools to actually simulate the process of inserting orthopedic hardware, as well as adding a simulation of needle-tissue interaction. Therefore, we chose the third and fourth papers, which describe tissue simulation models that involve the needle, skin, and bone. From their work, we can easily set up a realistic physics simulation of the K-wire insertion for rendering percutaneous pelvic surgery in VR. Altogether, these papers provide a foundation of prior work we will combine and develop to create our improved surgical simulation.

3. Paper Analysis

Allen et al. "Development and evaluation of an open-source virtual reality C-Arm simulator."

Paper Selection

This paper is highly relevant to our proposed project, discussing a virtual reality simulator designed for C-Arm positioning in interventional spine procedures. Allen el at. also provides a complete architecture for building the virtual training system using a head-mounted display(HMD).
Indeed, this paper evaluates the effectiveness of their simulator with medical residents and expert clinicians, showing a significant improvement in C-arm placement with angular accuracy.

Summary of Problem and Significance

The challenge addressed in the first paper is the need for safe and effective training for medical residents in the use of C-arm fluoroscopy machines for interventional spine procedures. The standard of training involves hands-on experience in the fluoroscopy suite, which exposes the trainee to ionizing radiation and limits the amount of training time and space availability. The paper introduces a virtual reality(VR) simulator as an alternative training tool that can be used outside the fluoroscopy suite without radiation and unlimited training time, which aims to provide medical residents with a safe and effective way to learn C-arm placement skills.

Authors' Methods/Experiments, Key Results

The system is built in the 3D Slicer software instead of the unity because of its built-in medical research modules, which could be used for further iteration. Due to the generation of DRR and drive of the HMD system, they use Windows 10 Pro computer with 3.2GHZ Intel Core i7-8700 CPU with 32GB of RAM. An HTC VIVE Pro HMD, hand controllers, and tracking device were used to provide the interaction. The overview of system architecture is shown in figure3.

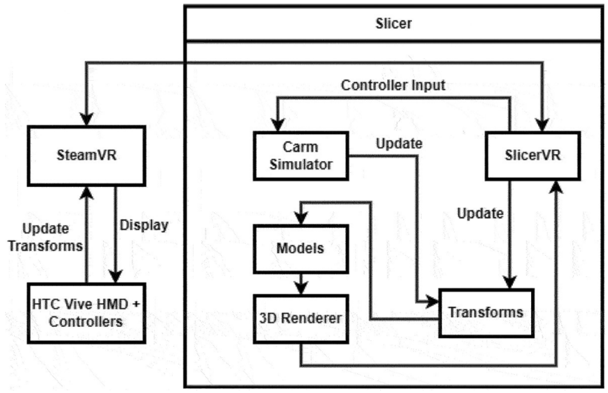


Figure 3 The high-level system architecture overview.(Allen et al. 2022)

They imported the CT model from TurboSquid, achieving the 3-DoF rotations including gantry, cranial/caudal support, and wag support parts, shown in figure 4. By using forward kinematics with homogeneous transformation, they calculated the pose of virtual X-ray sources, and focal points to import the DRR space.

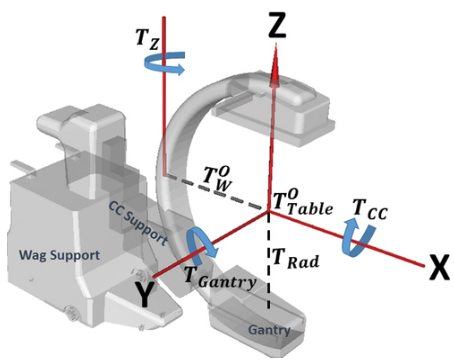


Figure 4 C-arm model(Allen et al. 2022)

User Study

To test the efficacy of the VR C-arm, they recruited 12 anesthesiologic and orthopedic residents and 2 expert users(1 anaesthesiologist and one interventional radiologist) to conduct a training and evaluation task. After training the residents with their simulator, all users are asked to manipulate the real C-arm to obtain 3 standard fluoroscopic views in interventional spine procedures: Full AP(Anterior-Posterior), Full Lateral, and Scotty Dog(around 20 laterals). The total procedural time, angular and translation accuracy were recorded as performance metrics to compare with the gold standard set by expert clinicians. Also, the number of virtual fluoroscopic shots as surrogates for the total x-ray exposure. After the evaluation, all users filled out a 5-point Likert scale questionnaire to evaluate the system

Result

The overall performance of each user improved after completing the training portion of the study, shown in figure 5. The performance of each user improvised after the training for all 3 standard views. The average number of virtual fluoroscopic shots decreased from 42.33 ± 22.29 to 26 ± 13.27($p > 0.05$). The average procedure time decreased from 20.71 ± 5.43 min to 9.72 ± 4.38 min ($p < 0.05$). Furthermore, the questionnaire shows positive feedback from users, shown in figure 6.

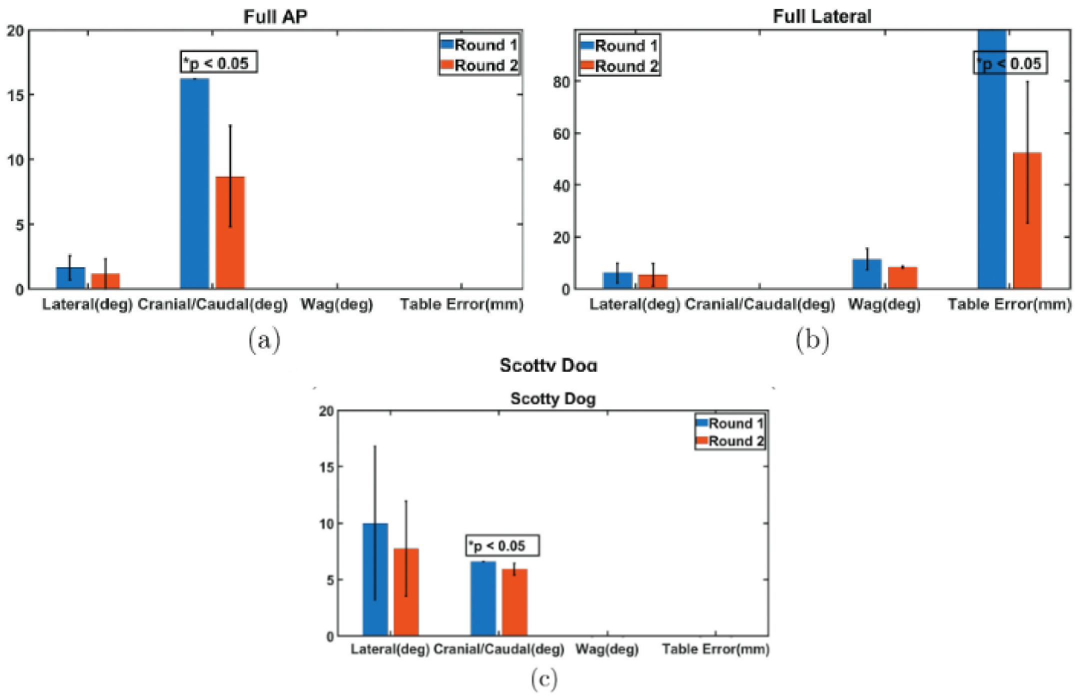


Figure 5 Novice User Study Result(Allen et al. 2022)

Table 1. Questionnaire results (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree).

Face Validity (*n* = 14 (12 novices, 2 experts))	Mean	Min	Max
The simulator realistically represents an X-ray image	4.6 ± 0.5	4	5
The X-ray image is representative of the virtual C-Arm and patient position	4.6 ± 0.6	3	5
Interaction with the C-Arm in the VR environment was user friendly	4.3 ± 0.9	2	5
Integration of simulator into medical education would be useful	4.7 ± 0.6	3	5
Your spatial understanding of the movement of the C-Arm in VR was more intuitive than on a 2D display	4.5 ± 0.6	3	5
Content Validity (*n* = 2 experts)			
The simulator is suitable for training novices	5.0 ± 0.0	5	5
The simulator is suitable for training experts	5.0 ± 0.0	5	5

Figure 6. Questionnaire Results(Allen et al. 2022)

Discussion

The VR C-arm simulator they made for interventional spine procedures shows proper effectiveness as a training tool and provides a great user interaction experience, which can reduce radiation exposure and constraint in a real OR room.

Our Assessment

Pros

Their system uses the 3D slicer as a VR platform, which can integrate the medical research modules. Also, their system verifies the feasibility of VR training with simulated digital reconstruct radiography. Third, they provide a great system architecture that is suitable for building other VR-related training environments.

Cons

First, the authors only involved 3 Dof rotations for the c-arm, while the real c-arm x-ray has 8 Dof, including the movement of the base, as shown in figure 7. The limited degree of freedom may not present the realistic c-arm simulation in OR. Indeed, their system can not provide direct interaction with c-arm for users, instead, they only use a mouse and keyboard. Second, their system did not involve any interaction with any surgical tools like drills and wires.

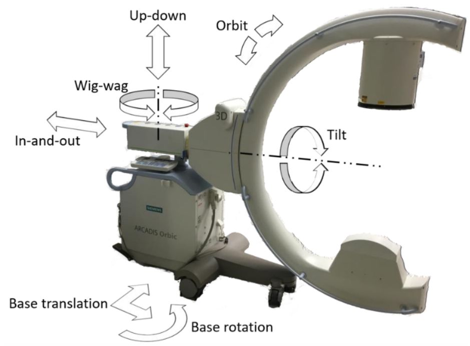


Figure 7 All available C-arm movements(Luke Haliburton 2017)

Conclusions

Based on this paper, we will integrate the architecture into our VR training environment by providing all degrees of freedom for the C-arm. Indeed, we will add not only the interaction between users and the environment but also the interaction with surgical tools in our system. On the other hand, multi-dimensional feedback will be provided to produce a more realistic tool-tissue interaction, such as audio, visual, and haptics.

Unberath et al. "DeepDRR – A Catalyst for Machine Learning in Fluoroscopy-guided Procedures"

Paper Selection

This paper is relevant to our project because one of the areas our virtual reality pelvic fracture surgery simulation aims to improve upon previous implementations is in the realism of the procedure. One of the ways we plan to achieve this is by tightly integrating our application with the open-source DeepDRR framework for realistic simulation of fluoroscopy from CT scans, which was presented for the first time in this paper. The success of our project is dependent on fully utilizing the features and benefits that DeepDRR offers to create the most realistic x-ray images possible so that the performance of surgeons in the simulation is as representative of their real surgical skills as possible. To do this, we must understand how to control all of the many parameters the DeepDRR API offers, and how the underlying computational methods of DeepDRR actually work.

Summary of Problem, Key Results, and Significance

Machine learning has been successful in diagnostic radiology but its impact in interventional radiology is limited, primarily due to the lack of annotated data. The large volumes of images taken during the procedures normally aren't saved and would be difficult to annotate. To address these challenges, computer-generated x-ray images projected from 3D CT scans (called Digitally Reconstructed Radiographs (DRRs)) can be used for training machine learning models, since annotations can be easily acquired by projecting segmentations or annotated points from 3D CT to the simulated x-ray images.

However, if the synthetic computer-generated fluoroscopy images are not realistic looking enough, models trained on the computer-generated images will not perform well on real fluoroscopy images.

To address this problem, the authors developed DeepDRR, a framework that emphasizes realistic and fast simulation of fluoroscopy and digital radiography. The approach involves combining machine learning techniques for material decomposition and scatter estimation with analytic forward projection and noise injection to produce synthetic images that accurately simulate real images.

They evaluated their approach by training a landmark detection model on DeepDRR-generated X-ray images of the pelvis and demonstrated that the trained model generalizes well to real X-ray images without requiring domain adaptation or retraining. This result suggests that the synthetic images generated by DeepDRR accurately capture the relevant information in real X-ray images.

Overall, DeepDRR has the potential to enable the use of machine learning in interventional radiology procedures by providing a source of labeled data for training models. This could ultimately lead to improved accuracy and safety in interventional procedures.

Background

A Digitally Reconstructed Radiograph (DRR) is a two-dimensional image created from three-dimensional medical imaging data, such as a CT (computed tomography) scan. The DRR image is generated by digitally simulating the path of an X-ray beam through the patient's body based on the CT scan, most commonly using a method called ray tracing. This simulated X-ray image is then projected onto a plane, resulting in an image that resembles a traditional radiograph or X-ray taken by an X-ray imaging device.

Hounsfield units are a scale that measures the attenuation of X-rays as they pass through different tissues in the body. The scale is based on the density of water, which is assigned a value of 0 Hounsfield units (HU), and the density of air, which is assigned a value of -1000 HU. Tissues that are denser than water, such as bone, have positive HU values, while less dense tissues, such as fat or air-containing structures, have negative HU values.

Authors' Methods/Experiments

DeepDRR consists of a pipeline of 4 stages to enable realistic and fast DRR generation.

1) CT volumes are segmented into materials with different Hounsfield units (HU) which describe the x-ray absorption properties of different types of tissue. Since simple thresholding of the CT volume is not sufficient to distinguish similar density tissues, a deep volumetric ConvNet with an encoder-decoder structure and skip-ahead connections, trained using a dataset of whole-body CT scans and multi-class Dice loss, are used to perform segmentation.

2) Ray tracing is performed to simulate the process of taking a fluoroscopy image using an x-ray source and detector at certain positions, taking into account the material segmentation and x-ray source spectrum.
3) Rayleigh scatter is simulated, which is the process by which x-rays are deflected at different angles instead of absorbed by matter. It is traditionally simulated using complex and slow Monte Carlo simulations. However, in this paper, a 10-layer ConvNet was trained to perform an estimate of Rayleigh scatter for the sake of generation speed.
4) Quantum and electronic readout noise are added. In real fluoroscopy images, there is quantum noise as a result of the statistical nature of x-ray photon interactions with matter. Quantum noise is simulated as a function of the number of photons detected and the mean photon energy for each pixel, followed by blurring the noise to simulate pixel crosstalk, which is the process by which the noise in one pixel is correlated to other pixels due to their proximity. Electronic noise due to imperfect circuits is simulated as adding Gaussian noise with correlation along rows due to the readout order of pixels in the detector.

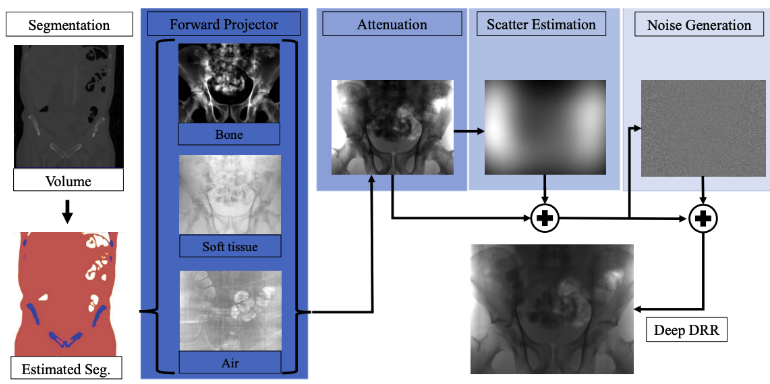


Fig. 1. Schematic overview of DeepDRR.

Figure 8 (Unberath et al. 2018)

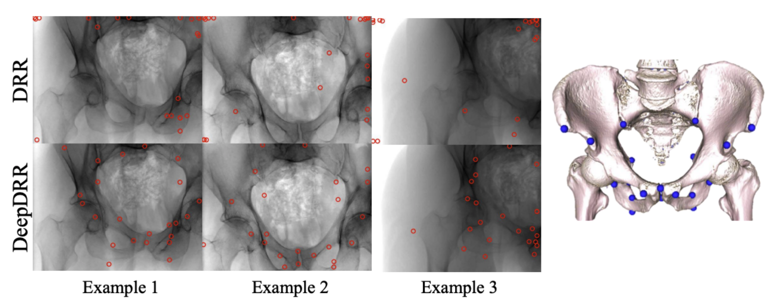


Fig. 3. Anatomical landmark detection on real data of cadaveric specimen using the method detailed in [9]. Top row: Detection results of a model trained on conventional DRRs. Bottom row: Detections of a model trained on the proposed DeepDRRs. No domain adaption or re-training was performed. Right-most image: Schematic illustration of desired landmark locations shown on a training set sample.

Figure 9 (Unberath et al. 2018)

The authors performed a framework evaluation of the ConvNets used in steps 1 and 3 of the pipeline and found a misclassification rate of 2.03+- 3.63% for the volumetric segmentation in step 1 and a mean squared error of 6.4% for the scatter estimation in step 3. The authors also performed a task-based evaluation by a machine learning model using sample data generated from a conventional DRR method and the proposed DeepDRR method, before comparing the results. The task for the model was a landmark detection task from x-ray images of the pelvis from arbitrary views. The authors present a qualitative evaluation comparing the two models in Fig. 3 and claim that the DeepDRR-trained model generalizes to real-world data much better than the conventional DRR-trained model.

Our Assessment

Pros

This paper goes into great detail on the high-level overview of the DRR generation pipeline that allows this new method to achieve much more accurate results compared to prior methods. The reasoning for each stage in the pipeline is clearly explained, and it contains a great block diagram figure of the outputs of each stage and how they are combined to achieve the final result (Fig. 1). The authors had a great approach to evaluating the new DeepDRR method against previous DRR methods by training a landmark detection model using each and then evaluating how well they generalized to real-world data.

Cons

However, we feel that the results of this evaluation could have been better described. From the qualitative results shown of the landmark detection output of each model on three representative examples in Fig. 3, the DeepDRR model-annotated landmarks appear to be better than the DRR landmarks, but still less than ideal, however, the authors write that "the model trained on DeepDRRs produces accurate predictions even on partial anatomy." It would have been helpful to include markers showing the desired locations for the annotations on the DRR images, perhaps annotated by experts in the field, in addition to the model-predicted locations shown. Quantitative statistics comparing the models also would have been helpful for evaluating the relative improvement of the DeepDRR model. It also would have been helpful to include a figure showing side-by-side images from a conventional DRR method vs. the DeepDRR method to allow readers to visually observe the differences.

Conclusions

The details included of how the DeepDRR pipeline works is very helpful for understanding the parameters in the DeepDRR API, which is necessary for our project. Given how well the DeepDRR model generalizes to real-world data, it seems reasonable to claim that DeepDRR-generated fluoroscopy images are significantly more realistic than previous DRR methods. However, since this paper mostly focused on evaluating the deep learning application of the generated DRRs, future work which involves human clinicians visually comparing DRRs vs. real fluoroscopy images could provide insight into the visual accuracy of the generated DRRs.

Moo-Young et al. “Development of unity simulator for epidural insertion training for replacing current lumbar puncture simulators.” / Brazil et al.“Haptic forces and gamification on epidural anesthesia skill gain.”

Paper Selection

The background of the third and fourth papers is mostly related to the K-wire simulation, a part of the maximum deliverable, in our project. The main difficulty with simulating K-wire insertion is determining how to realistically navigate the wire from outside the patient's body, through the tissue, and ultimately into the bones. Although the two papers focus on simulating epidural insertion, our K-wire simulation is essentially a simplified version of it. Since we do not have prior knowledge of insertion simulation in virtual reality, these two papers can provide us with a better understanding of tissue insertion simulation and enable a seamless integration of K-wire simulation with virtual reality.

Summary of Problem, Key Results, and Significance

Studies have shown that it takes many attempts for a novice to achieve the ability to insert an epidural, and such training is very difficult to achieve in a short period of time. Given the growing concern for patient safety, traditional apprenticeship methods are becoming less acceptable. Thus, a haptic device was developed to help trainees experience first-hand the sensation of simulated tissue resistance while practicing a medical procedure. Using haptic devices can also help practitioners identify transitions between tissue layers and organs or even bones, as well as their properties and properties.

Technical summary and discussion

Parallel Force Component

Even though we are using the K-wire that is going to be drilled into the patient's body, the needle insertion is similar to the K-wire, except it is inserted directly by applying the forward force. Therefore, let us consider the initial stage of inserting the K-wire, which involves inserting it into the skin first.
The paper “Development of Unity Simulator for Epidural Insertion Training” proposed a needle insertion simulation. This simulation can be likened to a spring model for the initial insertion of the needle into the skin. When the needle touches the skin but is not yet sufficient to puncture it, the skin exerts a reactive spring force on the needle, which increases continually until the skin is punctured. As the figure is shown below:

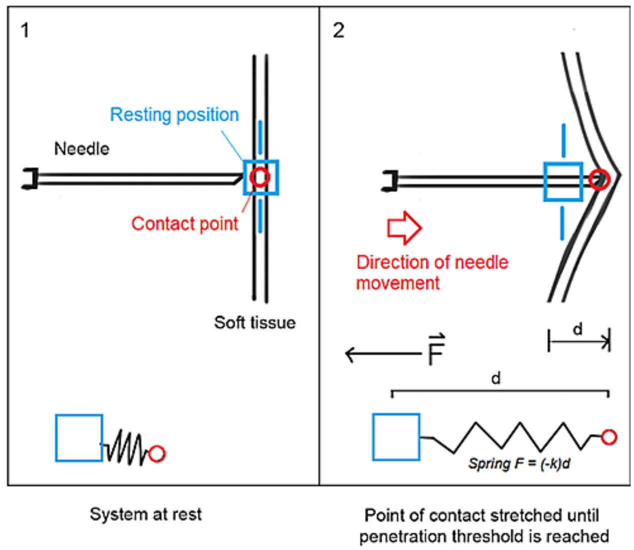


Figure 10(Moo-Young et al. 2021)

Applying this analogy to our project, when the operator brings the K-wire to the skin, the screw at the end will initially make contact with the skin. Prior to the start of drilling and insertion of the K-wire into the patient's body, the entire simulation process should be consistent with the diagram mentioned above.

The paper “Haptic forces and gamification on epidural anesthesia skill gain” investigated the force limitation of each kind of tissue in the human body. The table below summarizes their work.

Tissue	Human puncture force (N)	Thickness (mm)	Swine puncture force (N)	Swine steady-state force (N)
Skin	6.0372[b]	10.8	12.9[c]	–
Fat	1.974	2.8	6.027	–
Muscle	4.354[a]	1.9	8.407	3.675
Interspinous Ligament	7.467	18	–	4.053
Ligamentum Flavum	12.1330[a]	7.4[d]	6.1330	–
Epidural Space/Subdural Tissue/Dura-mater	2.437	8.6[e]	–	–
Bone	8.0265[f]	–	–	–

[a] Estimated values based on swine measurements, with a correction factor calculated from swine/human tissues puncture forces.
[b] 6.0 ± 0.7.
[c] With a standard deviation of 2.6.
[d] 5.4 after puncture.
[e] 10.6 after puncture.
[f] The bone is impassable in this case, this is the starting force, that keeps increasing after contact.

Table 1(Moo-Young et al. 2021)

As the K-wire simulation is our maximum deliverable, we will not consider a very complex model of this. However, from the table above, we can learn that the skin can withstand greater force than the underlying fat and muscle tissues without being punctured. Making an initial insertion into the bone is not difficult. However, when the needle goes through deep, it will become very hard.

Therefore, based on the above process, we can incorporate haptic feedback in the following manner: When the operator touches the skin with the K-wire without drilling it, the skin will always act like a spring, and the magnitude of the force will be reflected by the haptic feedback of the VR controller. However, once the operator starts drilling the K-wire, we will make a judgment. If the forward force applied by the operator exceeds the skin's limit, the K-wire will penetrate the skin, and we will remove the haptic feedback to indicate to the operator that the K-wire has been successfully inserted.

Force Model

The paper “Haptic forces and gamification on epidural anesthesia skill gain” also investigated the insertion model of the needle after it has been inserted into the skin. The model is summarized in a figure below:

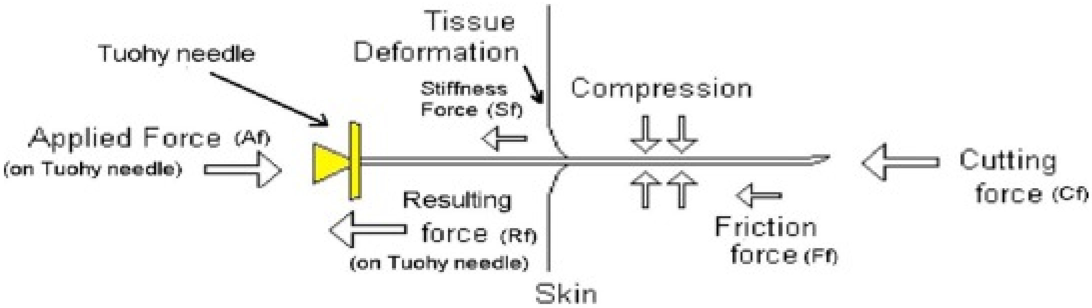


Figure 11(Moo-Young et al. 2021)

This model mainly emphasizes that the applied force must be greater than the resulting force. The resulting force is the combination of three forces: the stiffness force, which represents the elastic force of the skin tissue surface; the cutting force, which is the resistance produced by the tissue as the K-wire tip rotates and advances; and the friction force, which represents the frictional force exerted on the surface of the K-wire by the body tissues as it advances.

Based on the above model, the changes in the entire puncture process would be as follows: when the needle makes contact with the skin and continues to apply forward force, the stiffness force (Sr) will gradually increase. At this point, the friction force (Fr) and cutting force (Cf) are both zero. However, after the needle successfully pierces the skin, the stiffness force (Sr) will become zero, and the friction force (Fr) and cutting force (Cf) will be produced.

The below figure shows a simulation of needle insertion they have done by using a haptic feedback device.

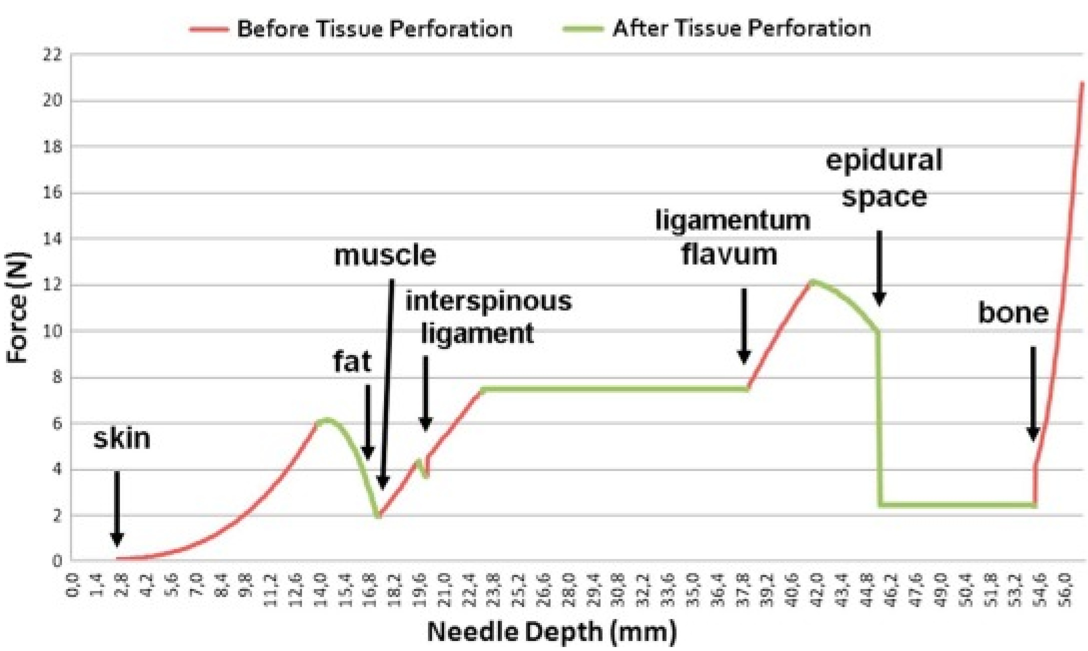


Figure 12(Moo-Young et al. 2021)

However, as our project only considers the skin and the bone in this stage, the would process would be like this: When the K-wire first touches the skin, the skin will apply a reactive force to the K-wire. When the operator starts to rotate the K-wire using the drill, the K-wire will pierce the skin and enter the skin tissue. This is the point where the stiffness force (Sr) disappears, and the friction force (Fr) and cutting force (Cf) appear, as shown in Figure 2. Since the drill will continue to rotate the K-wire, the friction force (Fr) will always be kinetic friction. Once the K-wire penetrates the skin tissue and touches the bone, the bone will exert a greater resistance force on the K-wire. As the bone is a hard object and its elasticity can be neglected in the current situation, we can assume that the bone will continuously apply a constant resistance force to the K-wire once the K-wire starts to drill the bone.

Our Assessment

Pros

Both authors use the haptic device to simulate the needle insertion process. It can achieve very realistic physical simulation, for example, it can truly reproduce the rigidity, damping, friction, etc. of the tissue. Both authors also measured the penetration limit strength of various tissues through experiments, thus providing a strong guarantee for the scientific nature of the entire simulation process.

Cons

The precise rendering haptic device is not very portable and is also very expensive, which is not conducive to the adoption of the entire training paradigm around the world. And the use of haptic devices can only simulate the needle insertion process, but in fact, before implementing the insertion operation, the operator also needs to locate the insertion point and then perform the insertion operation. During this period, the operator's body posture may also change, and if only using haptic devices, the operator will always sit in the same place. In our VR environment, the operator will be able to experience the whole process of the K-wire insertion.

Conclusion

Even though they are using the needle for the epidural insertion, which is different from us using the K-wire for the pelvic trauma surgery, the essential ideas are the same and the whole process is just a few changes for our project. Their work not only provides us with the experimental quantitative data of the skin and bone but also the skin-spring model to make the interaction more realistic.

4. References

[1] D. R. Allen, C. Clarke, T. M. Peters, and E. C. S. Chen, “Development and evaluation of an open-source virtual reality C-Arm simulator,” *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, vol. 0, no. 0, pp. 1–6, Dec. 2022, doi: 10.1080/21681163.2022.2152374.

[2] M. Unberath et al., “DeepDRR -- A Catalyst for Machine Learning in Fluoroscopy-guided Procedures,” *arXiv.org,* https://arxiv.org/abs/1803.08606v1 (accessed Mar. 13, 2023).

[3] A. L. Brazil, A. Conci, E. Clua, L. K. Bittencourt, L. B. Baruque, and N. da Silva Conci, “Haptic forces and gamification on epidural anesthesia skill gain,” *Entertainment Computing*, vol. 25, pp. 1–13, Mar. 2018, doi: 10.1016/j.entcom.2017.10.002.

[4] J. Moo-Young, T. M. Weber, B. Kapralos, A. Quevedo, and F. Alam, “Development of Unity Simulator for Epidural Insertion Training for Replacing Current Lumbar Puncture Simulators,” *Cureus*, vol. 13, no. 2, p. e13409, doi: 10.7759/cureus.13409.