Utilization of Deep Learning to Advance Radiographic Positioning Simulation and Education

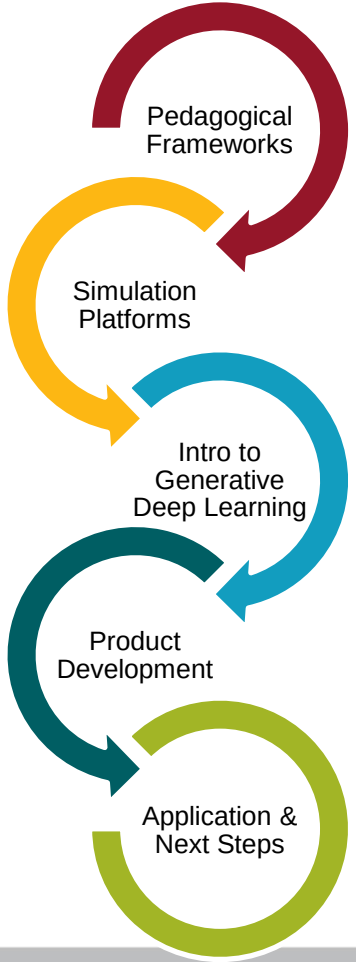
Ellie Miller, BS, RT(R)(CT), RDMS, RVT
University of Nebraska Medical Center
College of Allied Health Professions - Radiography

Eric Psota, PhD
University of Nebraska Lincoln
Department of Electrical & Computer Engineering

Qing Hui, PhD
University of Nebraska Lincoln
Department of Electrical & Computer Engineering

Hello!

University of Nebraska
Lincoln | Medical Center



Session Objectives

- Describe basic pedagogical principles of simulation instruction.
- Compare and contrast the types of simulation currently used in radiographic positioning instruction.
- Discuss the application of generative deep machine learning to radiographic positioning simulation.
- Apply pedagogical principles of simulation instruction.

Kolb's Experiential Theory

applied to radiographic positioning simulation

Concrete Experience

Practice radiographic positioning skills on a simulation model or phantom.

Reflective Observation

Observe outcome of applied radiographic positioning skills on a simulated resultant image.

Abstract Conceptualization

Predict the effect of variations on patient position on the anatomic alignment in resultant images.

Active Experimentation

Test conceptual understanding by creating resultant images from variations and predicted effects.

*Figure adapted from McLeod (2017). *Kolb- learning styles.* Simply Psychology. https://www.simplypsychology.org/learning-kolb.htm

Kirkpatrick's Four Levels of Training Evaluation

Level	Description	
1 – Reaction	Degree to which participants find the training favorable, engaging and relevant to their jobs	**Did the students like the training?*
2 – Learning	Degree to which participants acquire the intended knowledge, skills, attitude, confidence and commitment based on their participation in the training	**Did the students learn anything?*
3 – Behavior	Degree to which participants apply what they learned during training when they are back on the job	**Is the student learning transferred to clinical performance?*
4 – Results	Degree to which targeted outcomes occur as a result of the training	**Depends… What are your targeted student outcomes from simulation training? Self-efficacy? Increased competence? Faster clinical integration?*

*Table adapted from Kirkpatrick, J. D., & Kirkpatrick, W. K. (2016). *Kirkpatrick's four levels of training evaluation*. Association for Talent Development.

Kirkpatrick's Four Levels of Training Evaluation

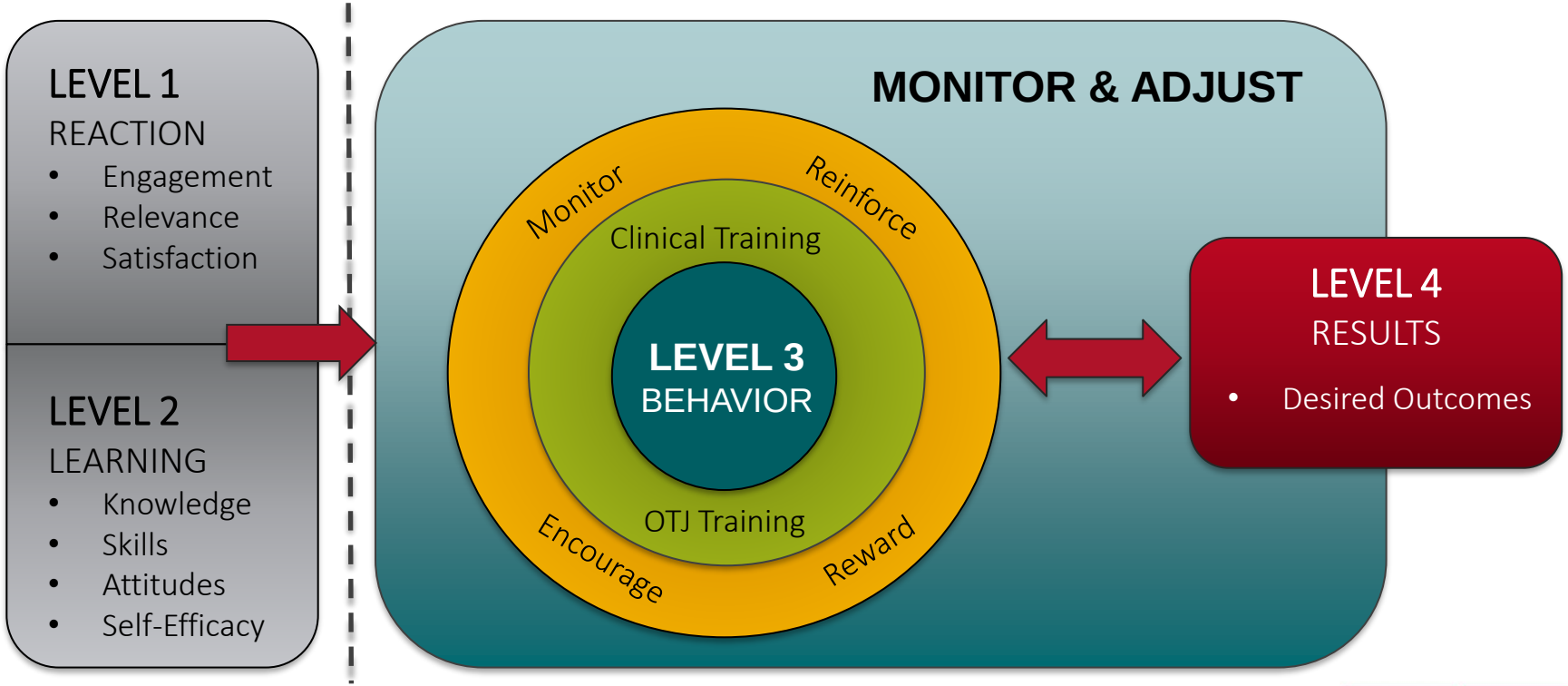


*Figure adapted from Kirkpatrick, J. D., & Kirkpatrick, W. K. (2016). *Kirkpatrick's four levels of training evaluation*. Association for Talent Development.

Simulation in Radiography

Role Playing

Physical Radiographic Phantoms

Whole Body Anthropomorphic

Regional

Digital Platforms

Non-immersive VR platforms

Fully immersive VR platforms

Role Playing

Role Playing

Benefits	Limitations
No cost	Feedback in the form of subjective critique by instructor
Low instructor preparation	Lack of objective feedback – No resultant image based off application of student's positioning skills
Promotes muscle memory from using real radiographic equipment	
Physical palpation of anatomic landmarks	
Allows for 'patient' interaction	
Readily available	
Student perceived knowledge and confidence gains (Kong, et al 2015)	

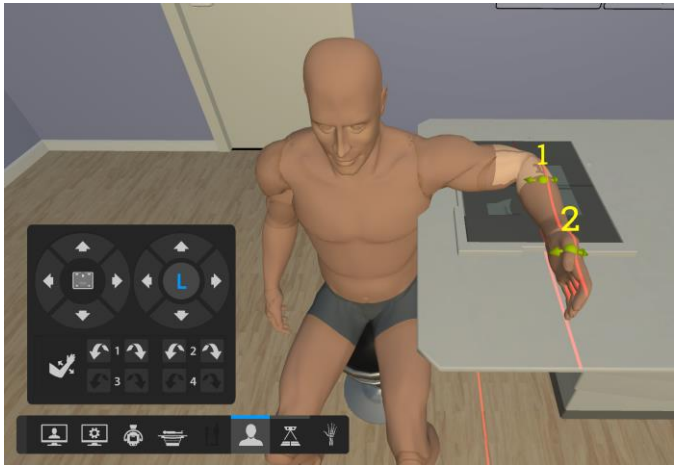
Anthropomorphic Whole Body Radiographic Phantoms

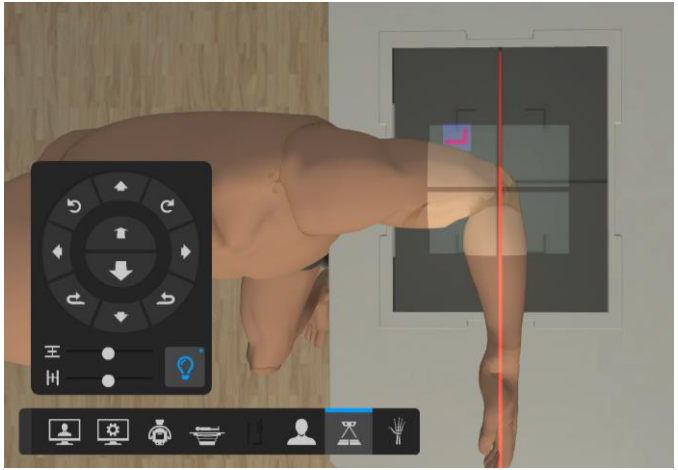
Regional Radiographic Phantoms

Radiographic Phantoms

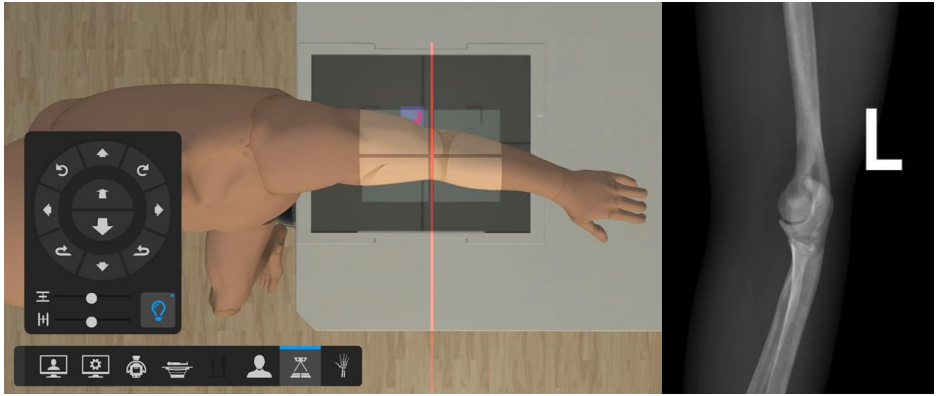
Benefits	Limitations
Produces a unique resultant image	Varying levels of realistic range of motion
Allows for objective student & instructor critique of application of positioning skills	May not stay in specific positions without being held or immobilized
Unlimited exposure opportunities	Variability of realistic anatomic landmarks
Promotes muscle memory from using real radiographic equipment	Registered radiographer must be present when exposures made
Physical palpation of anatomic landmarks	
Student perceived knowledge gains (Kong, et al 2015)	

Non-immersive VR / Desktop Sim Suites





*Images from Skilitics Health simulation software.



Skilitics

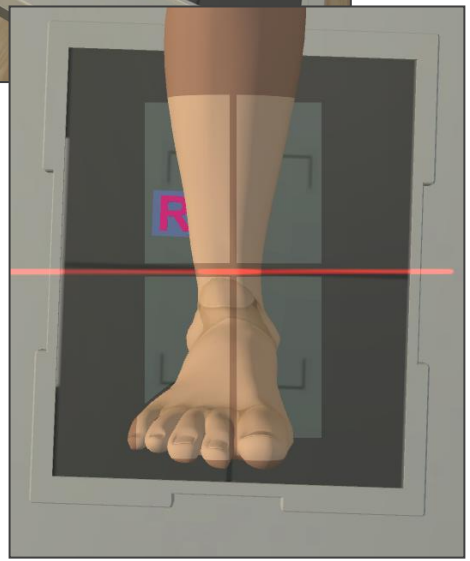
54 kVp @ 1.2 mAs
with visible mottle

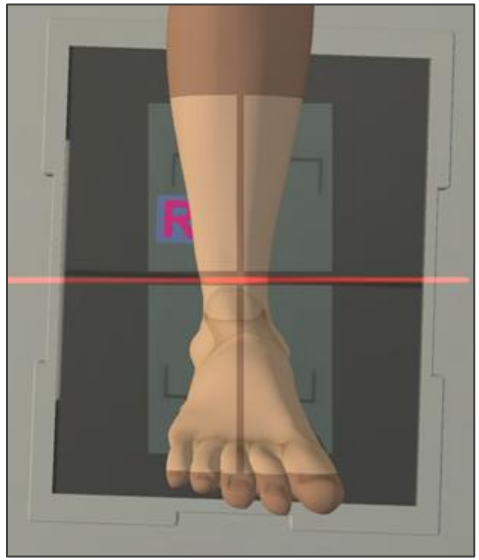
68 kVp @ 10 mAs
with visible darkening

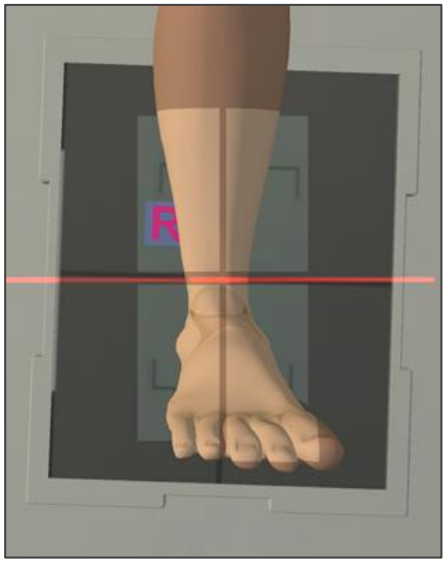
90 kVp @ 10 mAs
with excessive darkening, some areas of saturation

*Images from Skilitics Health simulation software.

Minor Positioning Adjustments without Palpable Landmarks







*Images from Skilitics Health simulation software.

Non-immersive VR / Desktop Sim Suites

Benefits	Limitations
Unlimited exposure opportunities; repetition	No physical manipulation of equipment or patient; no development of muscle memory
Not constrained by instructor availability, remote student access often possible	Time needed to learn software, software skills not transferrable to real world practice
Remote access experience *may* increase student satisfaction vs on-location (Shanahan, 2015)	No palpation of anatomic landmarks
Overall, general positive student perceptions (Shanahan, 2015)	Varying feedback about resultant image quality
Immediate Feedback // Unique Resultant Image	No patient interaction

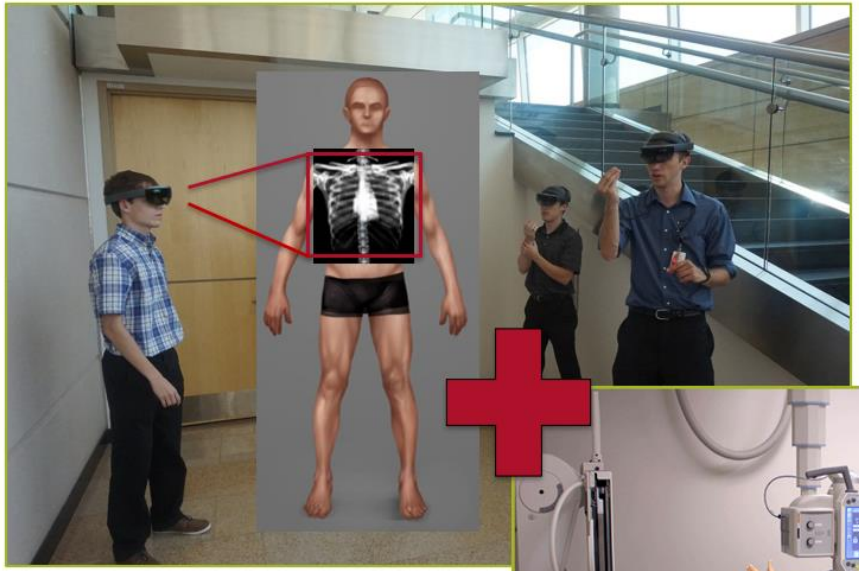
Fully Immersive VR

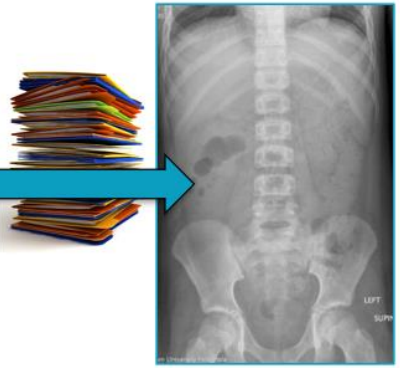
Fully Immersive VR

Benefits	Limitations
Unlimited exposure opportunities; repetition	Cost prohibitive
360° vantage points	Often limited suite availability to students
Some platforms include patient interactions	Possible vestibular disturbances*, fall risks
Overall, positive student perceptions that practical patient positioning skills developed (O'Connor et al, 2021) (Sapkaroski, 2021)	Considerable time needed to practice VR commands using paddles, goggles or eye trackers
Increased student confidence (O'Connor et al, 2021)	Not using realistic movements or equipment; not developing muscle memory
Immersive experience *may* be preferred by students over computer-based applications+ (O'Connor, et al, 2021) (Sapkaroski, 2018)	Not physically palpating anatomic landmarks
	Technical glitches
	Varying feedback about resultant image quality

	Unlimited Exposure, Resultant Image	Uses Real Equipment	Palpable Anatomic Landmarks	Realistic Range of Motion	Patient Interaction	Cost / Frequency	Increased Time to Learn Program	Instructor Needed
Role Playing	-	X	X	X	X	free	-	/
Phantoms	X	X	X	-	-	high, single	-	+
Computer Software	X	-	-	/	-	moderate - high, subscription	X	-
VR Immersive Caves	X	-	-	/	/	very high, single	X	-

Product Idea





Background on Generative Deep Learning

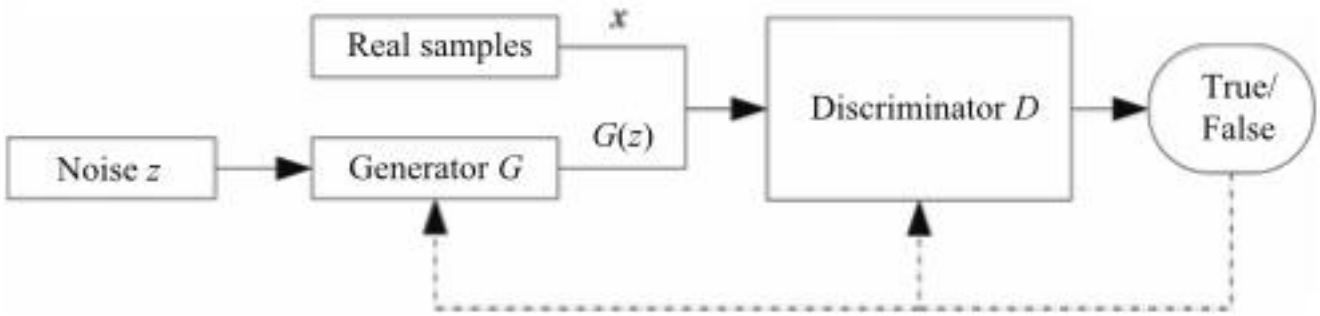
- **Background**
  - **Generative models: models obtained by learning with generative methods.**
  - **Deep neural networks: artificial neural networks with backpropagation training.**
  - **Adversarial learning: two-player zero-sum game.**

Introduction to Generative Adversarial Networks (GANs)

- **Introduction to Generative Adversarial Networks (GANs)**
  - **GANs often consist of a generator and a discriminator that are trained iteratively in an adversarial learning manner.**
  - **The generator tries to learn the potential distribution of real data.**
  - **The discriminator aims to correctly determine whether the input data is from the real data or from the generator.**

Implementation and Structure of GANs

- **Implementation of GANs**
  - **The generator and discriminator need to continuously optimize themselves to improve the generation ability and the discrimination ability, respectively.**
  - **The purpose of this optimization process is to find a compromise (a Nash equilibrium) between the generator and discriminator.**



Structure of GANs [1]

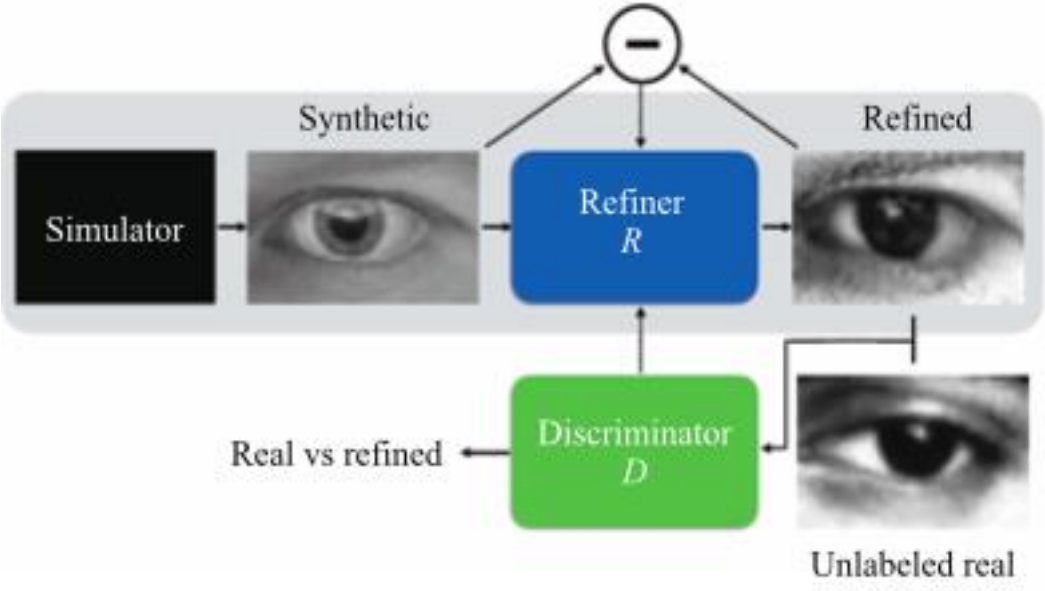
[1] K. Wang et al. Generative adversarial networks: Introduction and outlook. In IEEE/CAA Journal of Automatica Sinica, vol. 4. no. 4, 2017.

GANs: Application in Image Generation

Face samples generated by BEGAN [1]

[1] D. Berthelot, et al. BEGAN: Boundary equilibrium generative adversarial networks. Available [Online]: arXiv: 1703.10717, 2017.

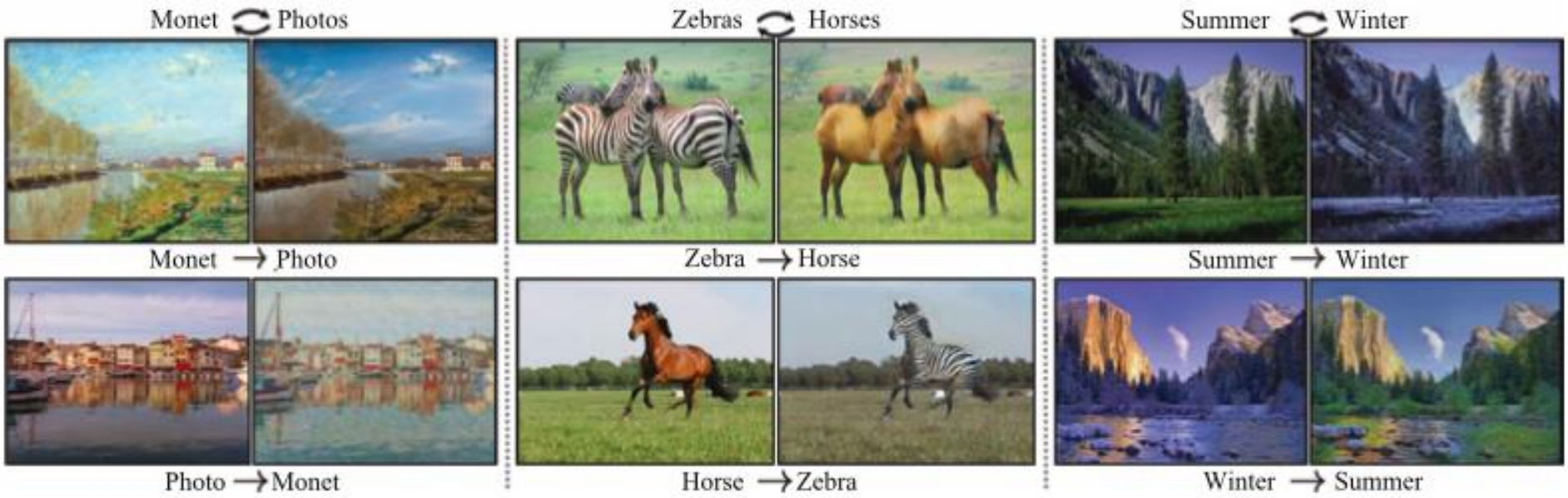
GANs: Application in Image Refinement



Learning from synthetic and real images to refine the picture by SimGAN [1]

[1] A. Shrivastava, et al. Learning from simulated and unsupervised images through adversarial training. Available [Online]: arXiv: 1612.07828, 2016.

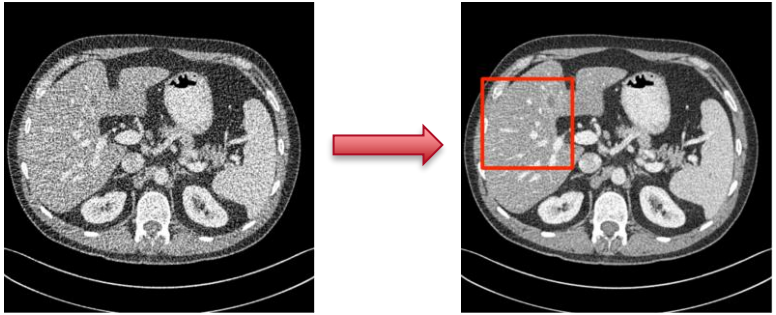
GANs: Application in Image Translation



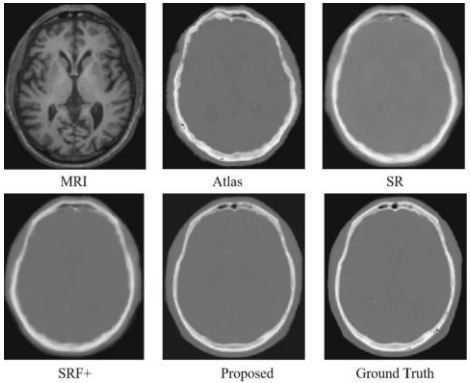
Unpaired image-to-image translation by CycleGAN [1]

[1] J. Y. Zhu, et al. Unpaired image-to-image translation using cycle-consistent adversarial networks. Available [Online]: arXiv: 1703.10593, 2017.

GANs: Applications in Medical Imaging



Denoising a low-dose CT scan [1]



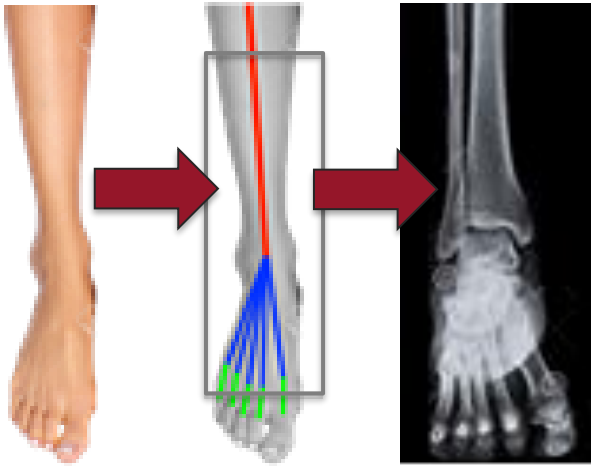
Converting from MR to CT scan [2]

Point clouds to x-rays for hands [3]

[1] H. Shan, et al. 3-D convolutional encoder-decoder network for low-dose CT via transfer learning from a 2-D trained network. In IEEE Transactions on Medical Imaging, vol. 37. no. 6, 2018.
[2] D. Nie, et al. Medical image synthesis with context-aware generative adversarial networks. In Lectures Notes in Computer Science, Springer, 2017.
[3] M. Haiderbhai. Generating synthetic x-rays using generative adversarial networks, Ph.D. dissertation, University of Ottawa, Canada, 2020.

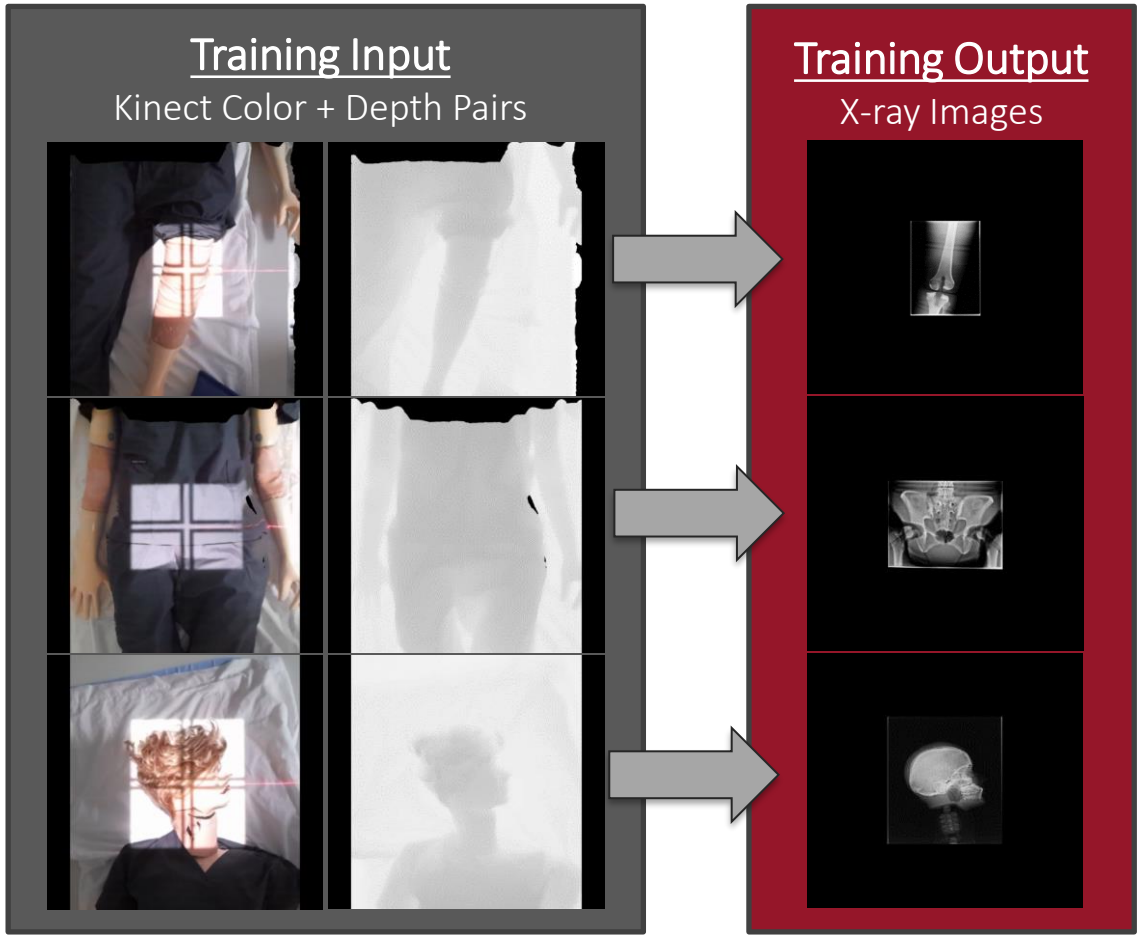
Aim

- Image Capture
- Feature Extraction
- Generative Processing
- Image Output



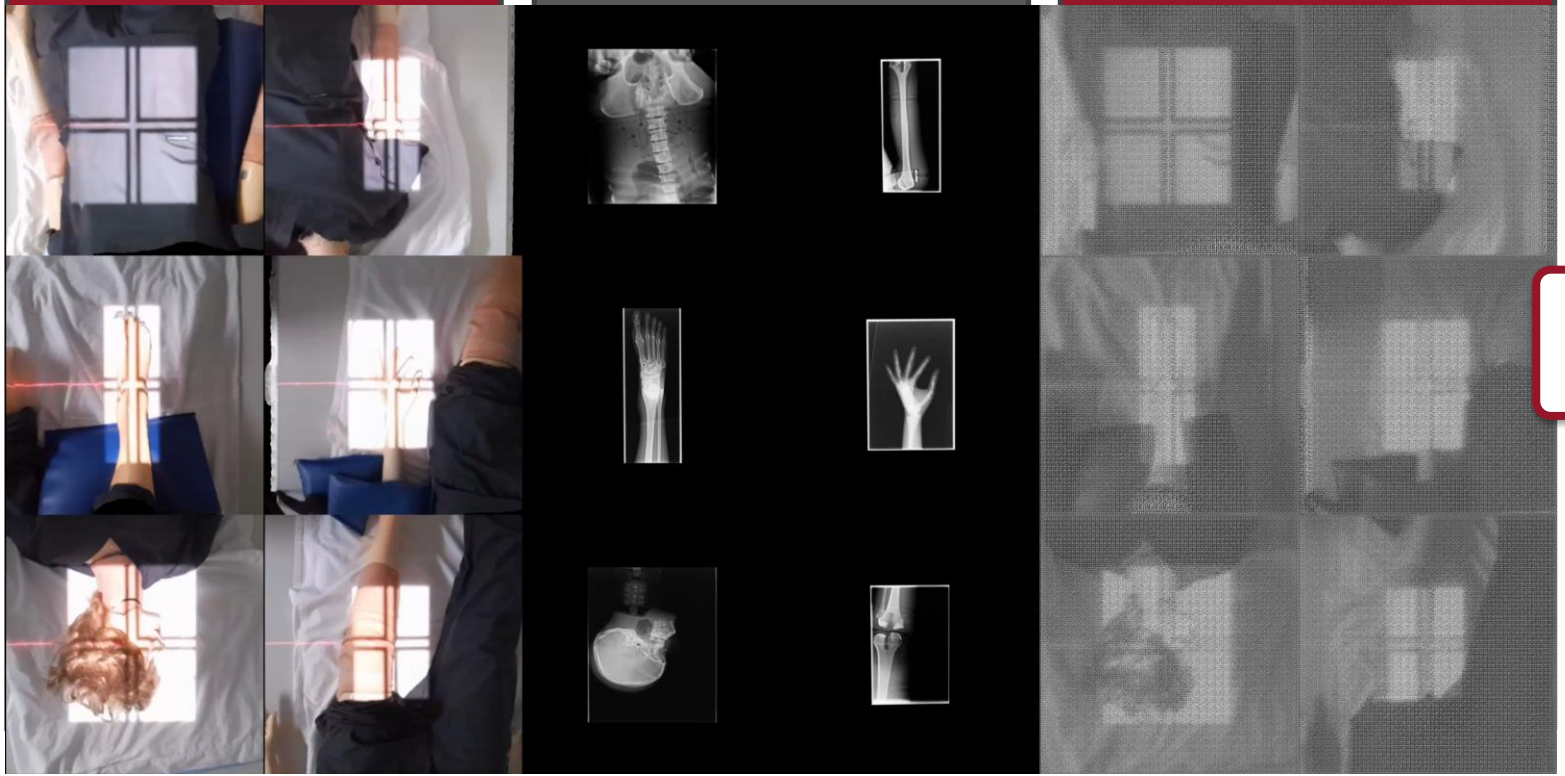
Methods

Microsoft Azure Kinect


Training Input
Kinect Color + Depth Pairs
Training Output
X-ray Images

Training

Input Image		Ground Truth		Output
Test	Train	Test	Train	Test



Results

Input Image		Ground Truth		Output	
Test	Train	Test	Train	Test	Train

Results

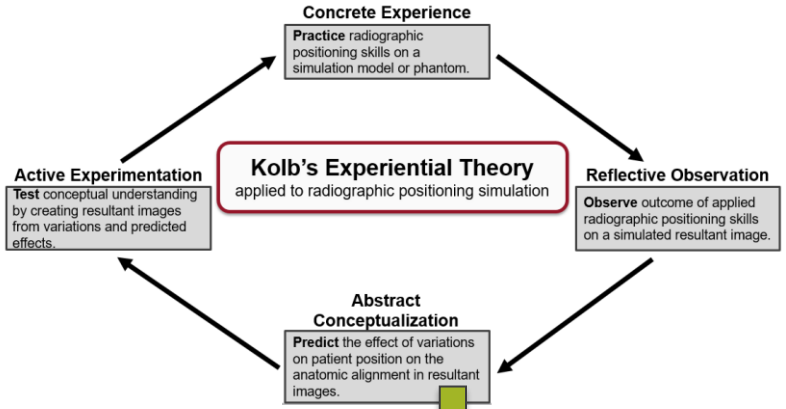
Progress of Product Development

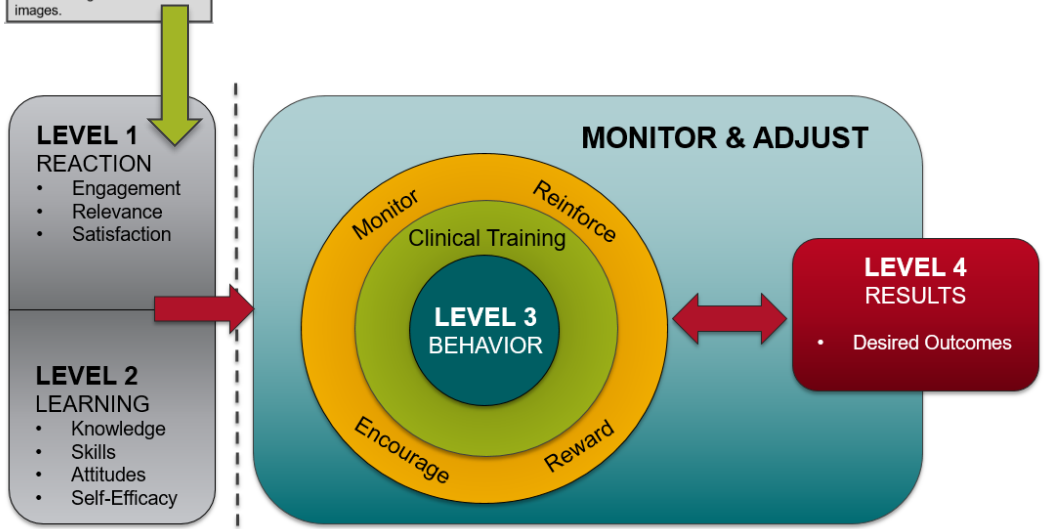
- Next steps include…
  - Expanding funding to continue development and refine algorithms
  - Capturing patient images from clinical sites
  - Exploring commercialization and marketing opportunities

	Unlimited Exposure, Resultant Image	Uses Real Equipment	Palpable Anatomic Landmarks	Realistic Range of Motion	Patient Interaction	Cost / Frequency	Increased Time to Learn Program	Instructor Needed
Role Playing	-	X	X	X	X	free	-	/
Phantoms	X	X	X	-	-	high, single	-	+
Computer Software	X	-	-	/	-	moderate - high, subscription	X	-
VR Immersive Caves	X	-	-	/	/	very high, single	X	-
Our Product	**X**	**X**	**X**	**X**	**X**	**low – moderate, single**	**-**	**-**

Putting it all together…

Application of pedagogical frameworks to instructional use of generative deep learning radiographic positioning simulation platform





Conclusion

Thank you!

All images are institutional photos except those noted below.

anthropomorphic whole body radiographic phantom images pulled from: here, here, and here
regional radiographic phantom images pulled from gt simulators website
skilitics images pulled from screenshots of trial version software access
vr immersive caves image pulled from here and video pulled from skilitics website
kinect camera image retrieved from microsoft' website
technologist image capture image retrieved from here
kinect camera image retrieved from microsoft' website
technologist image capture image retrieved from here

- gans image pulled from: D. Berthelot, et al. BEGAN: Boundary equilibrium generative adversarial networks. available [Online]: arXiv: 1703.10717, 2017.
- gans image refinement image pulled from: A. Shrivastava, et al. Learning from simulated and unsupervised images through adversarial training. Available [Online]: arXiv: 1612.07828, 2016
- gans application in image translation image pulled from: J. Y. Zhu, et al. Unpaired image-to-image translation using cycle-consistent adversarial networks. Available [Online]: arXiv: 1703.10593, 2017.
- gans application in medical imaging pulled from:
  - [1] H. Shan, et al. 3-D convolutional encoder-decoder network for low-dose CT via transfer learning from a 2-D trained network. In IEEE Transactions on Medical Imaging, vol. 37. no. 6, 2018.
  - [2] D. Nie, et al. Medical image synthesis with context-aware generative adversarial networks. In Lectures Notes in Computer Science, Springer, 2017.
  - [3] M. Haiderbhai. Generating synthetic x-rays using generative adversarial networks, Ph.D. dissertation, University of Ottawa, Canada, 2020.

University of Nebraska
Lincoln | Medical Center

References

1. About SSH. The Society for Simulation in Healthcare. https://www.ssih.org/About-SSH/About-Simulation. Accessed January 28, 2020.
2. Kirkpatrick, J. D., & Kirkpatrick, W. K. (2016). Kirkpatrick's four levels of training evaluation. Association for Talent Development.
3. Kolb DA. Experiential Learning: Experience as the Source of Learning and Development. Englewood Cliffs, NJ: Prentice-Hall Inc; 1984.
4. Kong, A., Hodgson, Y., & Druva, R. (2015). The role of simulation in developing clinical knowledge and increasing clinical confidence in first-year radiography students. *Focus on health professional education: a multi-disciplinary journal*, *16*(3), 29-44.
5. Little, J. (2021). Using Virtual Simulation To Increase Deep Learning in Radiography Students. *Radiologic Technology*, *92*(4), 324-330.
6. McLeod, S. A. (2017, Oct 24). Kolb - learning styles. Simply Psychology. https://www.simplypsychology.org/learning-kolb.htm
7. Motola I, Devine LA, Chung HS, Sullivan JE, Issenberg SB. Simulation in healthcare education: A best evidence practical guide. AMEE Guide No. 82. *Medical Teacher*. 2013;35(10). doi:10.3109/0142159x.2013.818632
8. O'Connor, M., Stowe, J., Potocnik, J., Giannotti, N., Murphy, S., & Rainford, L. (2021). 3D virtual reality simulation in radiography education: The students' experience. *Radiography*, *27*(1), 208-214.
9. Sapkaroski, D., Mundy, M., & Dimmock, M. R. (2020). Virtual reality versus conventional clinical role-play for radiographic positioning training: a students' perception study. *Radiography*, *26*(1), 57-62.
10. Shanahan, M. (2016). Student perspective on using a virtual radiography simulation. *Radiography*, *22*(3), 217-222.

University of Nebraska
Lincoln | Medical Center