Outline of research and development in ageing related area

Dr. James Cheung
Research Assistant Professor

Good quality of life is required good sleep, enjoying eating and going anywhere, and good safety at home. The smart home, osteoarthritis, dysphagia, and sleep quality are the targets to handle using latest computing and sensor technologies

Smart home

Osteoarthritis

Dysphagia

Quality of sleep

Invention Awards

Smart People (Smart Ageing)
Silver Award
智慧市民(智慧樂齡)銀獎

2020

Department of Biomedical Engineering,
The Hong Kong Polytechnic University
香港理工大學生物醫學工程學系

eNightLog
www.polyu.edu.hk/bme/

The smart multi-function monitoring system – eNightLog, is developed to track elderly's (especially those with dementia) activities in bed for preventing fall or wandering away. The safe and non-restraint eNightLog system is specially designed for coping with the typical environment of nursing homes in Hong Kong, thus, will help to improve the elderly's quality of life, while enhancing the efficiency and lessening the workload of healthcare personnel.

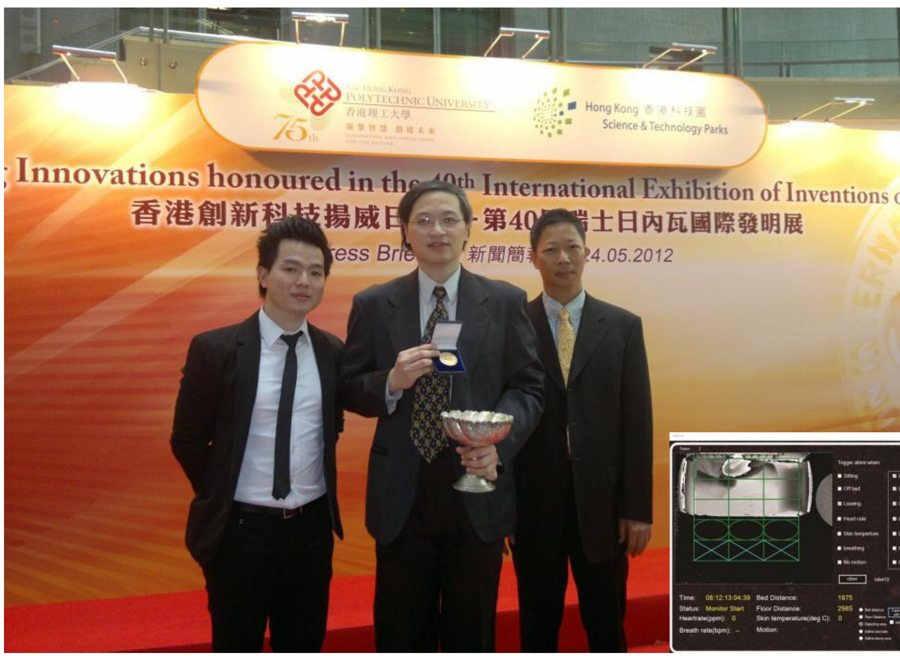
Installed above the bed, the non-contact and non-invasive eNightLog system can track the real-time activity status of multiple residents and display onto the caregivers' computer at the nurse stations or mobile devices. Signals detected beyond the pre-set normality range (e.g. sitting at bedside) will trigger alarms for caregivers to take immediate actions.

The development team is exploring to extend the functions of eNightLog (patent under examination) and connect the system with different kinds of smart devices such as electronic diaper and ultrasound bladder volume detector to provide more information for health care of elderly. By the end of the year 2021, it is expected that 112 sets of eNightLog systems will be equipped in four nursing homes for advancing the elderly care services in Hong Kong.

多功能智能監測系統eNightLog可檢測（尤其患有認知障礙症的）長者在睡床上的活動，以預防跌倒或走失。針對香港安老院舍的環境，eNightLog系統特別採用安全和非約束式的監察技術，以改善長者的生活質素，提高護理人員的工作效率並減輕他們的工作量。

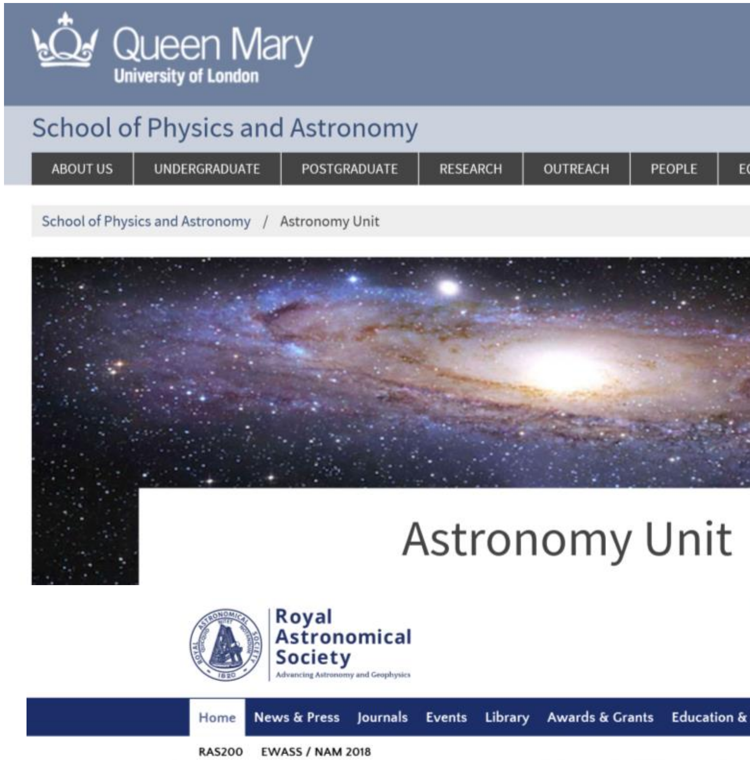
安裝於睡床上方的eNightLog智能監測系統，能以非接觸、非入侵的方式實時並同步地監察多名院友的最新狀態，若院友狀態異常（如：處於坐在床邊的狀態），護士站內的電腦及護理員的流動電話將會同時發出警報，以便提醒護理人員適時為院友提供支援。

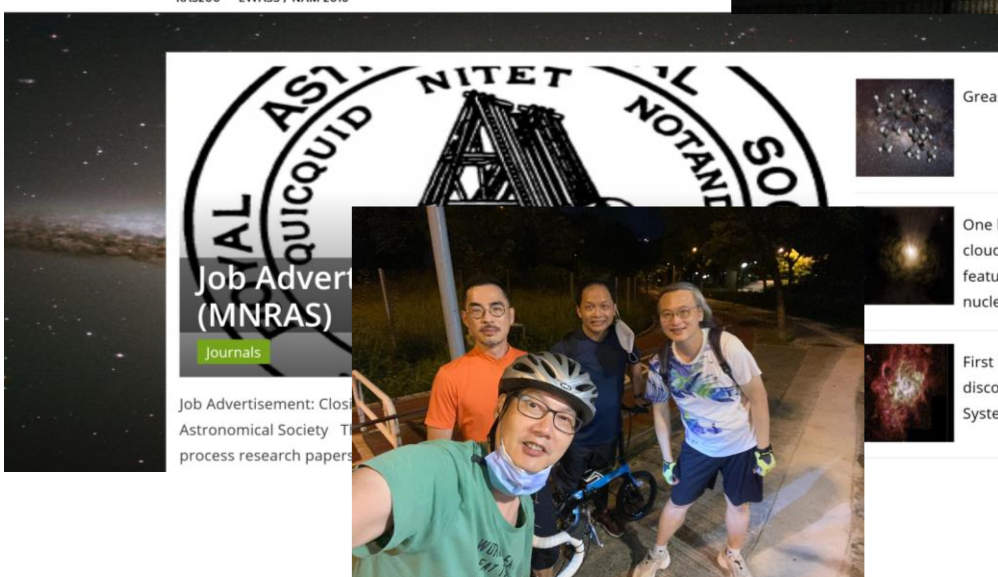
科研團隊已為eNightLog技術申請專利，並積極研究提升eNightLog系統的功能，如：接駁各種智能裝置，包括：電子尿片、超聲波量度膀胱尿量檢測儀等，以便為護理員提供更多資訊，改善長者護理服務。團隊將於2021年底前，為四間院舍設置共112套eNightLog系統，以提升本港的安老服務質素。



Geneva International Exhibition of Inventions: Gold Medallist (2012,2018)
Smart People (Smart Ageing) Silver Award (2020)

My interest





I am nocturnal?!

My team and fun

Research Team Members

Research students and assistants

- 9 PhD Students (Andy C, Andy T, Ana, Derek, James, Selina, Ethan, Patrick, Robbie)
- 6 MPhil Students (Bryan, Leah, Magic, Neil, Sonar, Tim)
- 3 PhD (Genbo, Ariel and Wangjiao coming cohort Sem1)
- 2 PhD in application
- Scholarship: 3 Competitive Scholarship, 1 PolyU Presidential PhD Fellowship Scheme, 1 Research Excellence Scholarship, 1 Dual PhD Scholarship
- Background BME, Computing, Electronic (Optics, Communication, Microelectronic stream), Electrical, Materials, Polymer Science, Nutrition Science, Clinical medicine
- 8 Capstone students
- 4 Research Associate Assistants, 3 Student Helpers

Collaborators

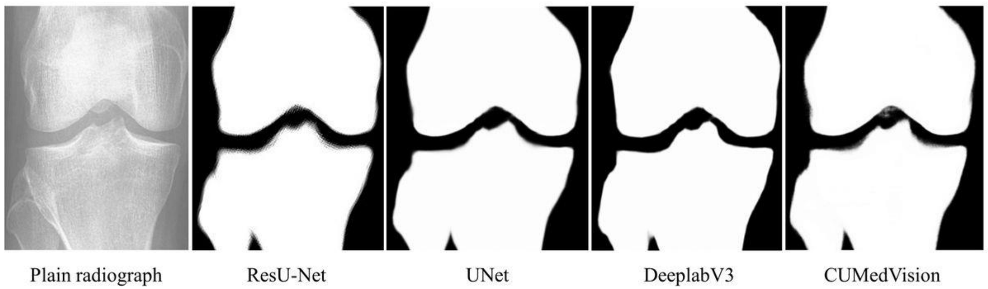
- Biostatistician (BME)
- Geriatrician (CUHK, PWH)
- Psychiatrists (CUHK, SH)
- Nephrologist and Cardiologist (HKHA)
- Gerontechnology specialist (US Florida State)
- Occupational Therapy (TWC)
- Nurse (PolyU)
- Speech Therapy (Monash University, Australia)
- Orthopedic surgery (Shanghai University of Medicine and Health Science)

Subgroup Teams

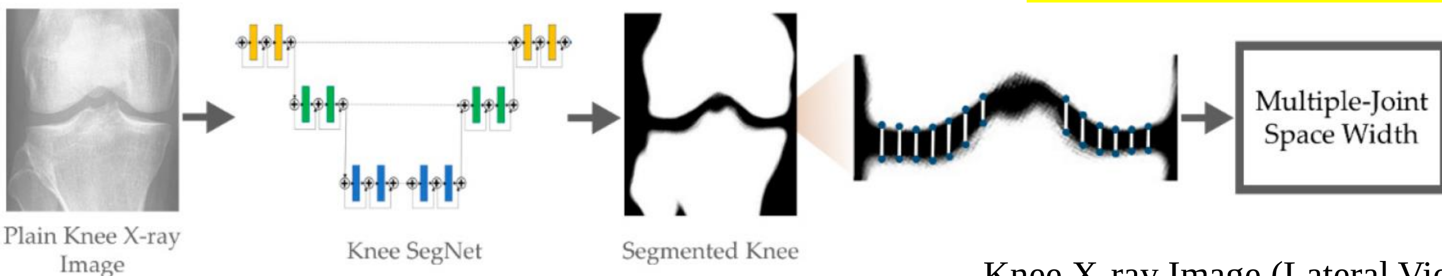
- Medical Imaging Team
- Radar Technology Team
- Robotic Team
- Soft Materials Team
- Soft Robotic Team

Osteoarthritis

Two joints are involved in the KOA development

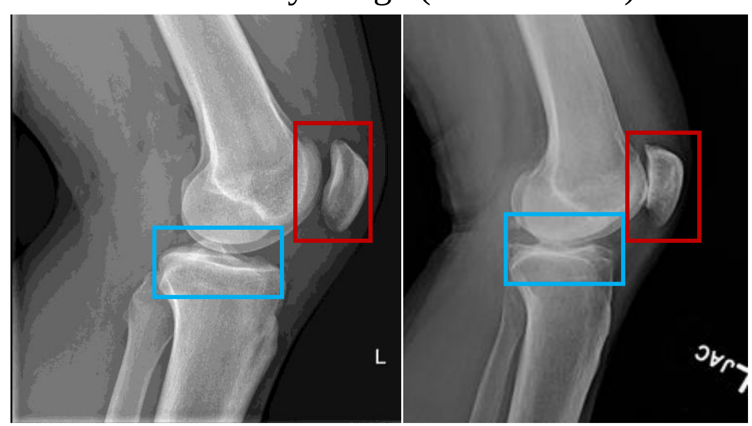


Segmentation technique will be improved and ultimately develop a better technique segmentation for knee join and provide base platform for diagnosis and analysis.



Knee X-ray Image PA view automatic segmentation and multiple JSW analysis, which demonstrated it superior in performance comparing with mJSW in classification KL grade and prediction in progression [1].

Knee X-ray Image (Lateral View)



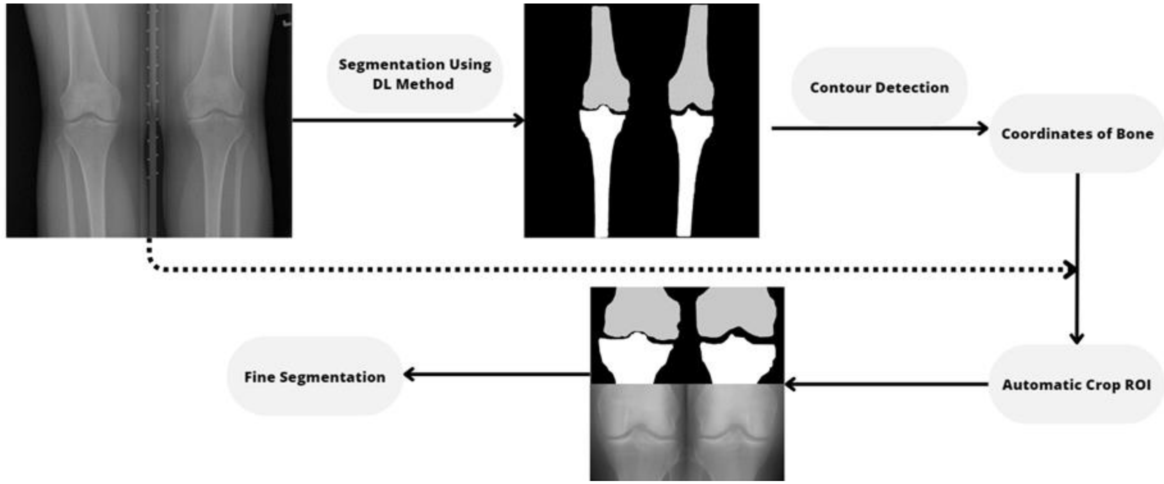
Healthy **Knee OA**

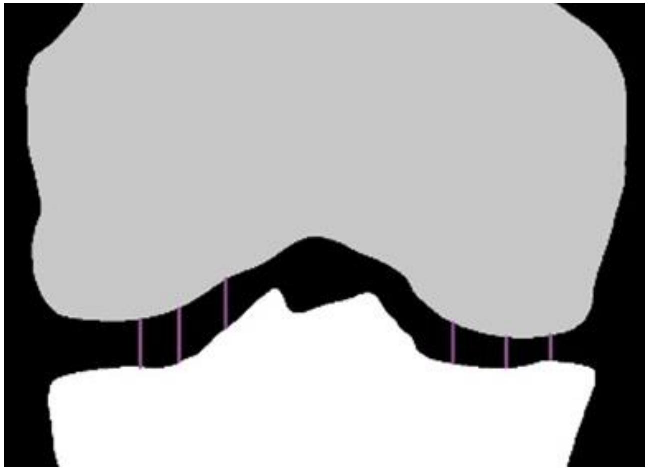
Patellofemoral (PF) joint

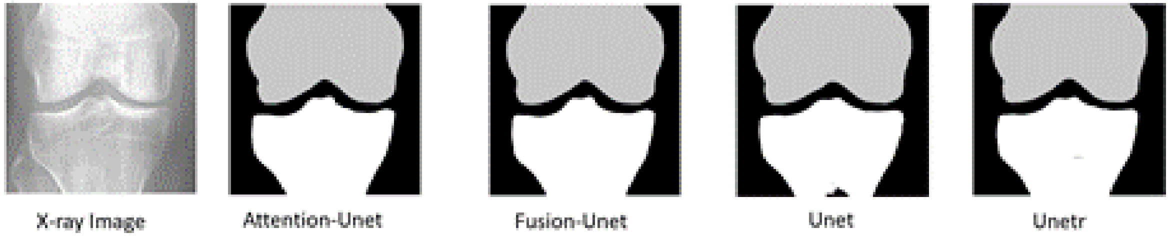
Tibiofemoral (TF) joint

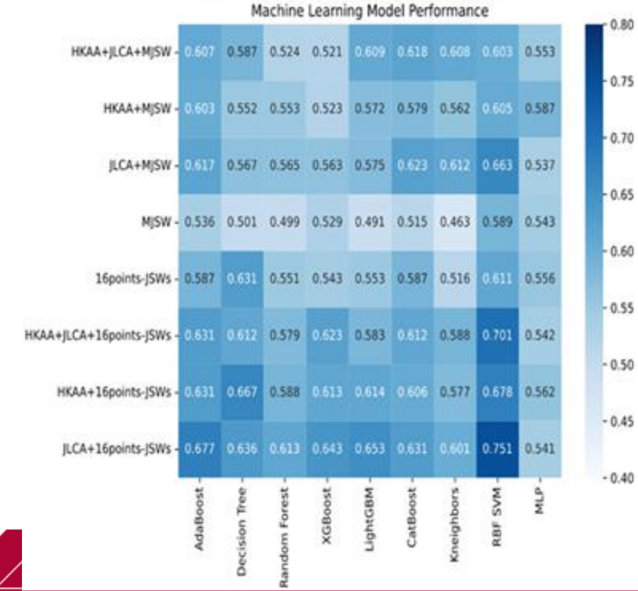
[1] Cheung, J.C.-W.; Tam, A.Y.-C.; Chan, L.-C.; Chan, P.-K.; Wen, C. Superiority of Multiple-Joint Space Width over Minimum-Joint Space Width Approach in the Machine Learning for Radiographic Severity and Knee Osteoarthritis Progression. Biology 2021, 10, 1107.

Enhancing Knee Osteoarthritis Prognosis Prediction: Incorporation of JLCA by Two-Step Deep Learning-based Segmentation









Femoral Neck fracture mapping and visualziation

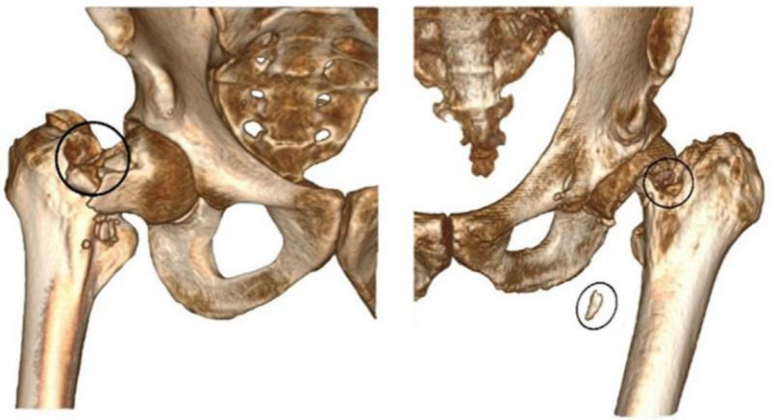


Fig. 3. Samples of fracture cases: (a) a comminuted fracture case feature with three fragments (as circled); two cases demonstrating the location of defect (as circled).

Table 3
Distribution of bone defects in various quadrants.

Quadrant	Qty	Proportion
Anterosuperior	20	43.48%
Posterosuperior	15	32.61%
Posteroinferior	22	47.83%
Anteroinferior	15	32.61%

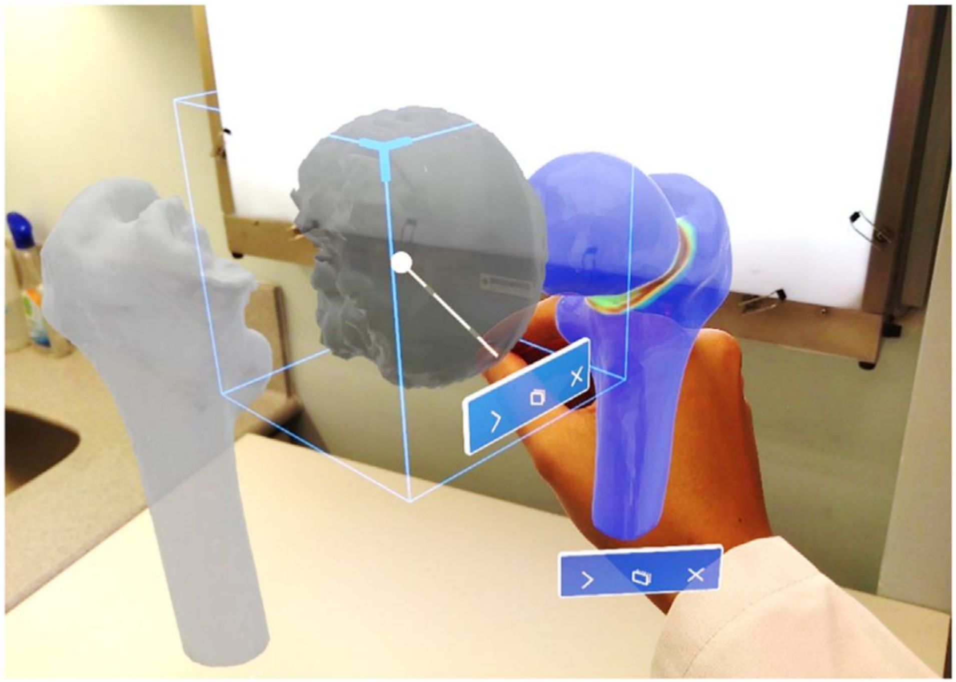
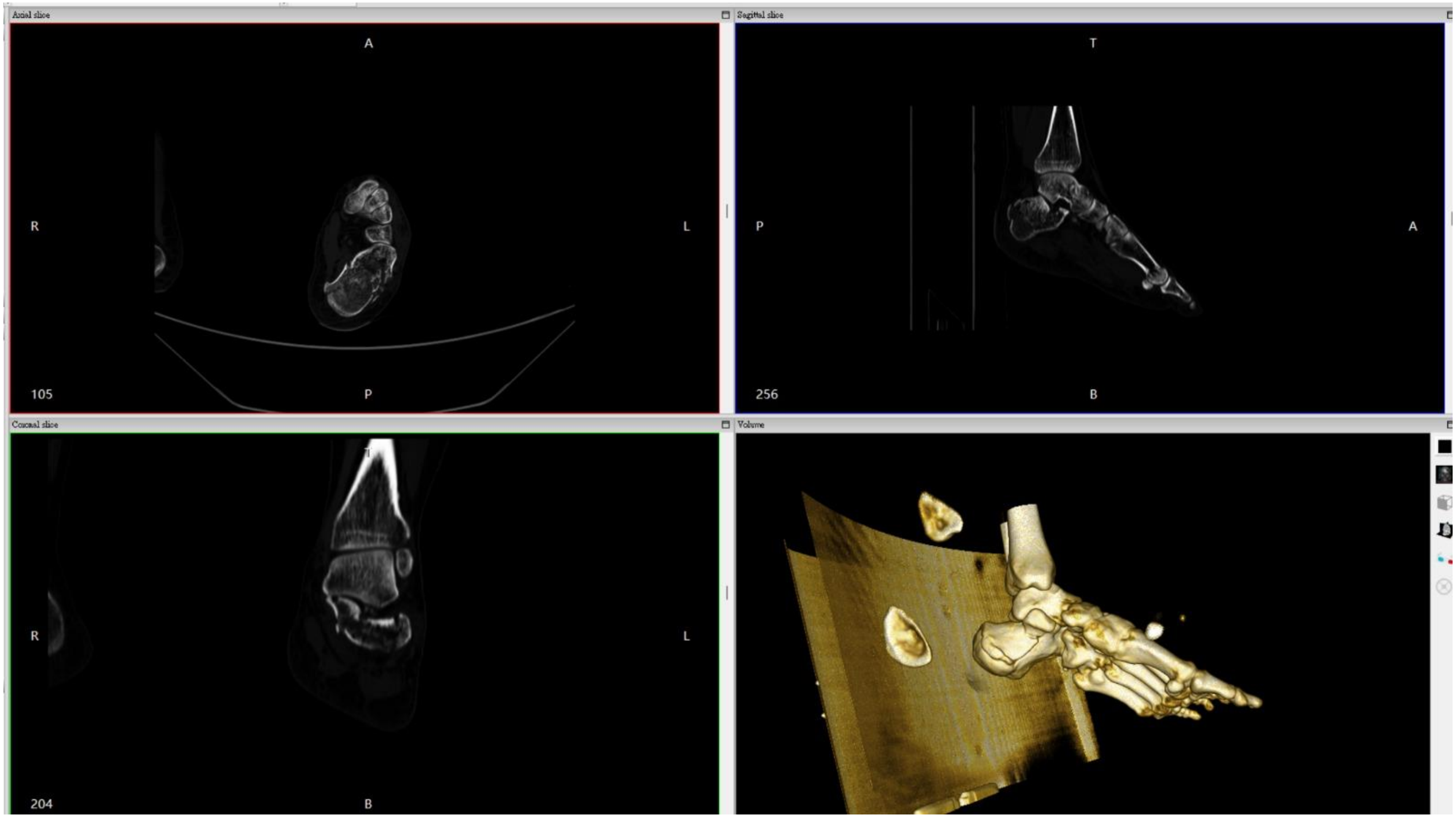


Fig. 5. An illustration of augmented reality technology to visualize and interact (drag) the fracture model fragment and fracture mapping model.

Yong-Qin Wang, Peng-Fei Li, Zi-Huan Xu, Ying-Qi Zhang, Qua-Na Lee, James Chung-Wai Cheung, Ming Ni, Duo Wai-Chi Wong,
Augmented reality (AR) and fracture mapping model on middle-aged femoral neck fracture: A proof-of-concept towards interactive visualization,
Medicine in Novel Technology and Devices, Volume 16, 2022, 100190,

CT Angle joint fracture type and grade classification us



eNightTrack

Multi-depth cameras system for bed exit and fall prevention of hospitalized elderly patients. The eNightLog is based

v

e

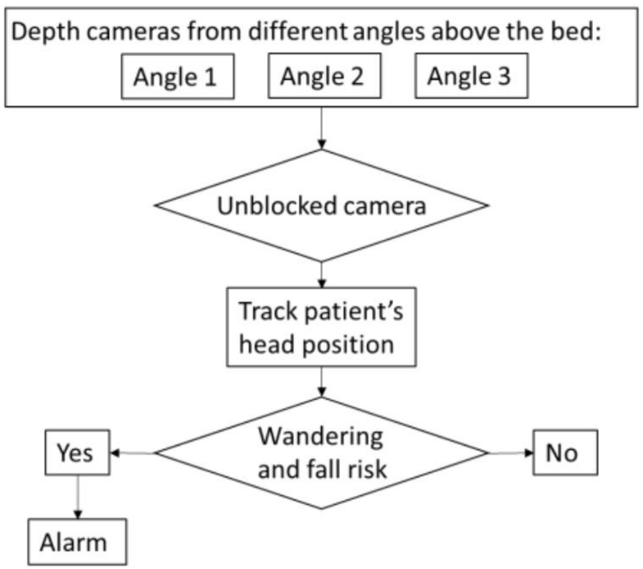


Figure 1. System designed for fall risk alarm

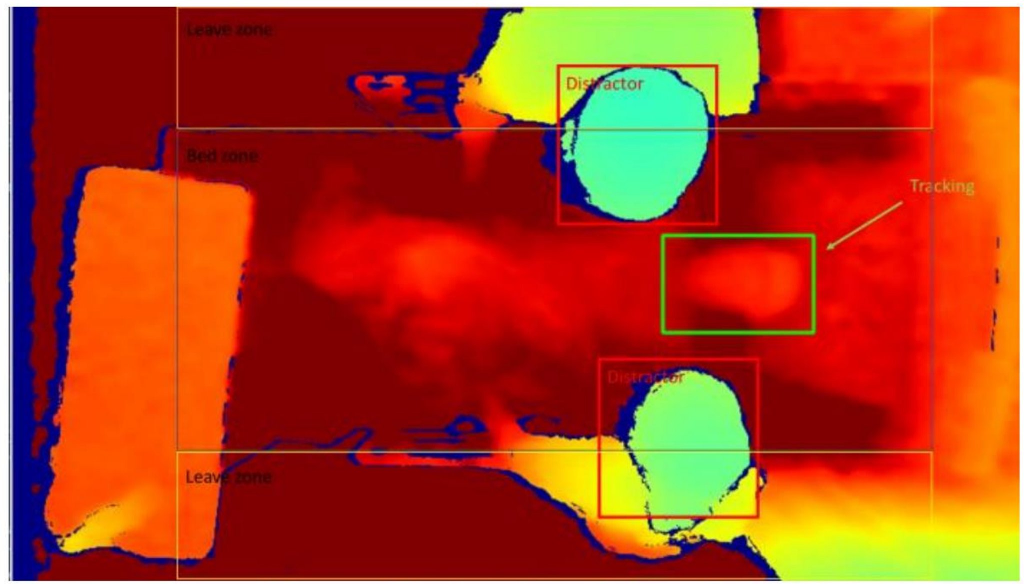


Figure 2. Depth image with virtual boundaries of bed and leave zone. The Head of the patient and distractor (nurse) were identified

Mao, Y.-J.; Tam, A.Y.-C.; Shea, Q.T.-K.; Zheng, Y.-P.; Cheung, J.C.-W. eNightTrack: Restraint-Free Depth-Camera-Based Surveillance and Alarm System for Fall Prevention Using Deep Learning Tracking. Algorithms 2023, 16, 477.

eNightTrack

Using latest Deep learning object recognition and tracking technique to detect subject status

Table 1. Simulated Bedtime Activity Scenario.

Scenario	Video Clips Count	Purpose of Simulation	State	Caregivers appear?
Sc01 [1]	15	Nurse helping dressing scenario—Nurse Putting on safety vest for patient.	Staying In Bed	Yes
Sc02	15	Exiting bedside scenario—Patient undress safety vest and slip away at the side of bed.	Bed Exiting	No
Sc03	15	Nurse changing sheets scenario—Nurse changing bed sheets when patient on bed.	Staying In Bed	Yes
Sc04	14	Exiting at bed end scenario—Patient exit bed at the rare end of the bed.	Bed Exiting	No
Sc05	14	Nurse helping adjust position scenario—Nurse pulling sheets up to help patient adjust sleeping position.	Staying In Bed	Yes
Sc06	15	Kneeling on rare edge of bed scenario—Patient kneeling on bed at the rare edge of bed.	Bed Exiting	No
Sc07	15	Adjusting bed level scenario—Nurse/ Patient adjusting level of bed from lying to sitting and rising the level of bed and return to original position.	Staying In Bed	Yes
Sc08	16	Picking belongings scenario—Patient leaning over the bed rail to look for personal belongings at the bottom of locker.	Bed Exiting	No
Sc09	15	Nurse helping turn scenario—Nurse helping patient turn and put pillow to support.	Staying In Bed	Yes
Sc10	15	Pillow mimicking scenario—Patient exiting bed when supporting pillow similar to human shape is still on bed.	Bed Exiting	No
Sc11	15	Changing position scenario—Patient changes from lying to sitting position.	Staying In Bed	No
Sc12	15	Climbing exiting scenario—Patient climb over bed rails, and leaves.	Bed Exiting	No
Sc13	15	Pushing table scenario—Patient pushing table towards the rare end of bed.	Staying In Bed	No
Sc14	16	Leaning scenario—Patient climbing over rail and leaning the upper body out to get items.	Bed Exiting	No
Sc15	16	Drinking scenario—Patient searching for personal belongings on top of the locker (only reaching hand out to get a cup of water)	Staying In Bed	No
Sc16	16	Sliding under the blanket scenario—Patient sliding under the blanket to the rare end of bed and leaves.	Bed Exiting	No
Sc17	16	Use of urinal scenario—Male patient sit near the edge of the bed and using urinal for voiding.	Staying In Bed	No
Sc18	16	Leaning forward scenario—Patient leaning forward when sitting at the edge of bed.	Bed Exiting	No
Sc19	17	Use of bedpan scenario—Patient using bedpan in bed.	Staying In Bed	Yes
Sc20	16	Sliding scenario—Patient sliding to the rare end of bed and leaves without blanket.	Bed Exiting	No

[1] Sc denotes scenario.

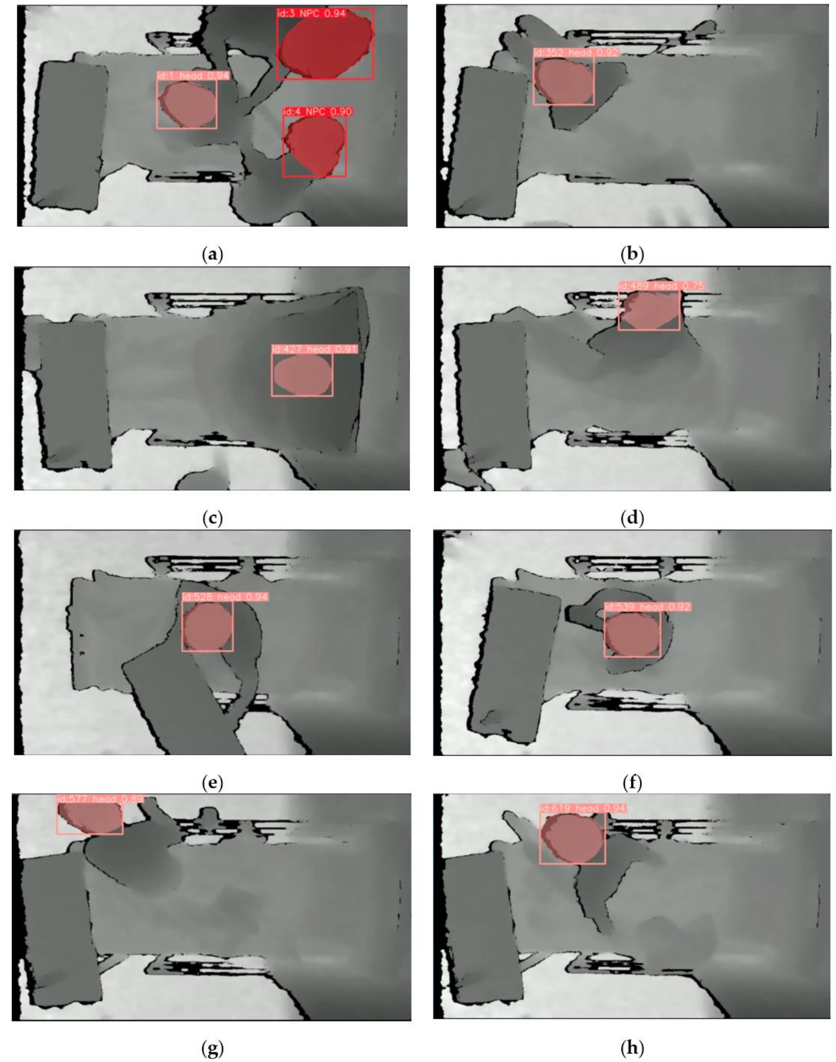
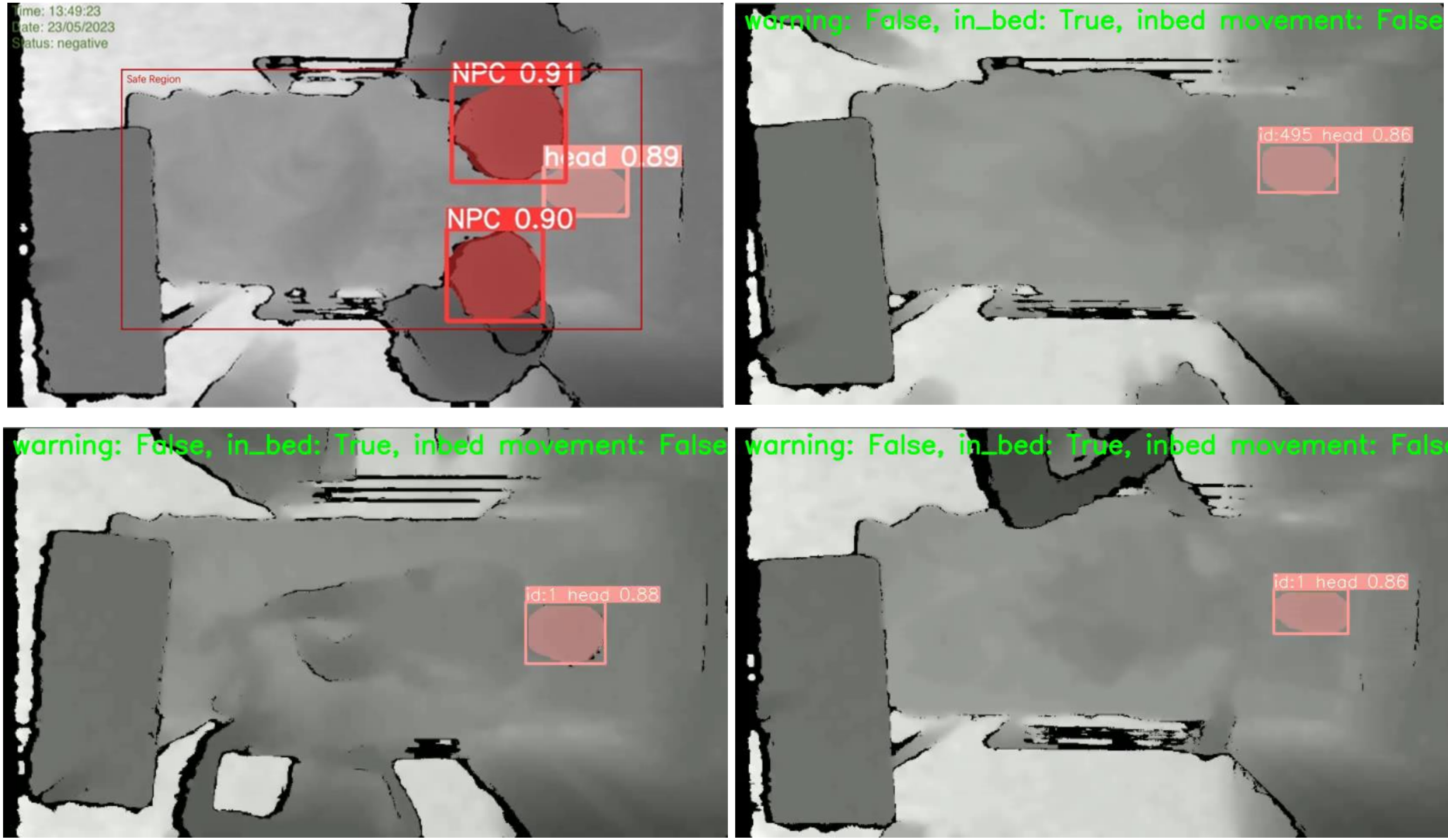
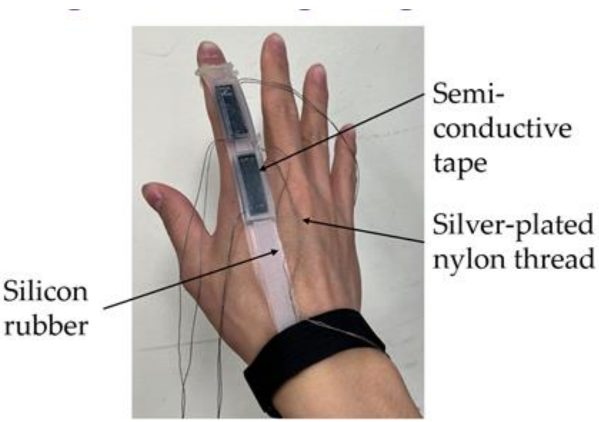


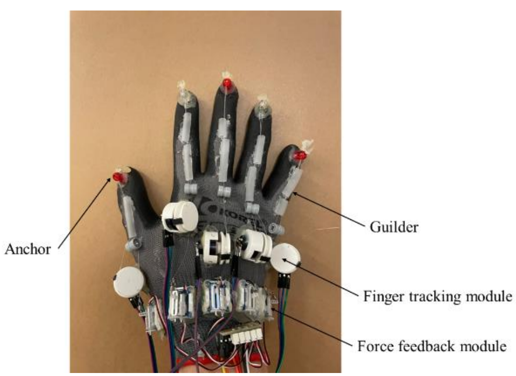
Figure 2. Illustrations of 8 Screenshots from Representative Scenarios: (**a**) Sc01; (**b**) Sc04; (**c**) Sc07; (**d**) Sc10; (**e**) Sc13; (**f**) Sc15; (**g**) Sc18; (**h**) Sc20.

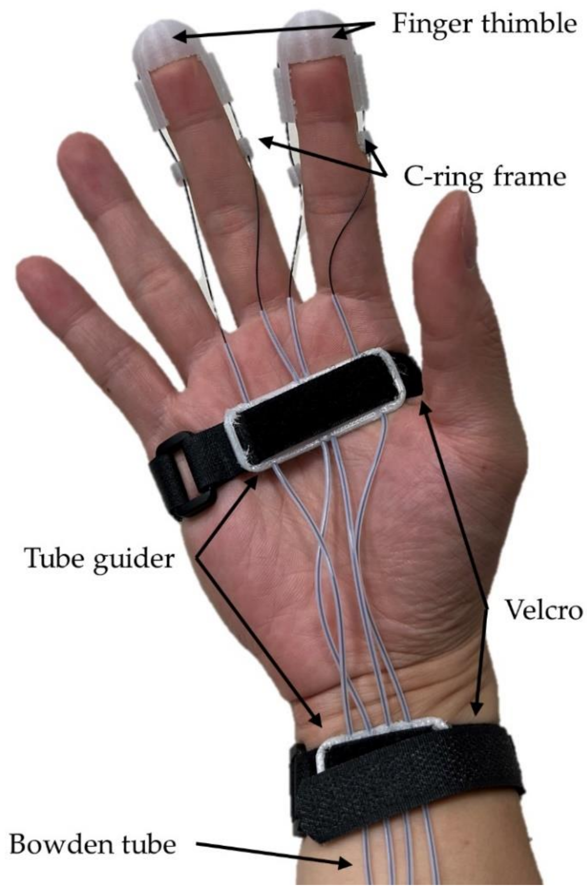


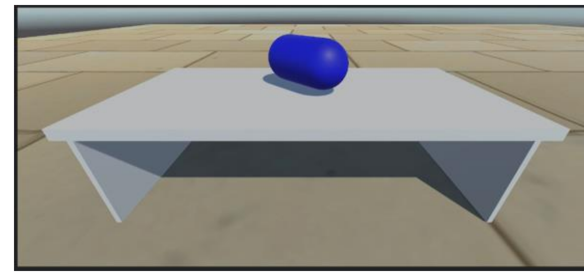
False positive: 57/307, False negative: 8/307 (in terms of video)

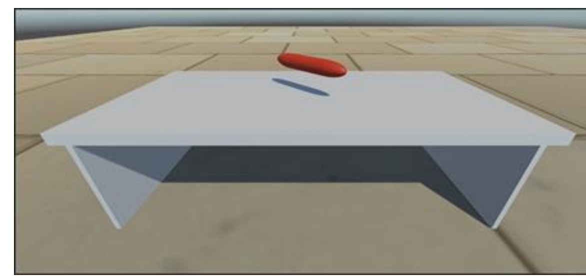
- **<u>Cheung CWJ</u>**, So PHB, Wong TCA, Tam YCA. Real-time Adjustable Kinesthetic and Haptic Glove for X-reality. **US patent filed US 63/368,372 (Jul 2022)**



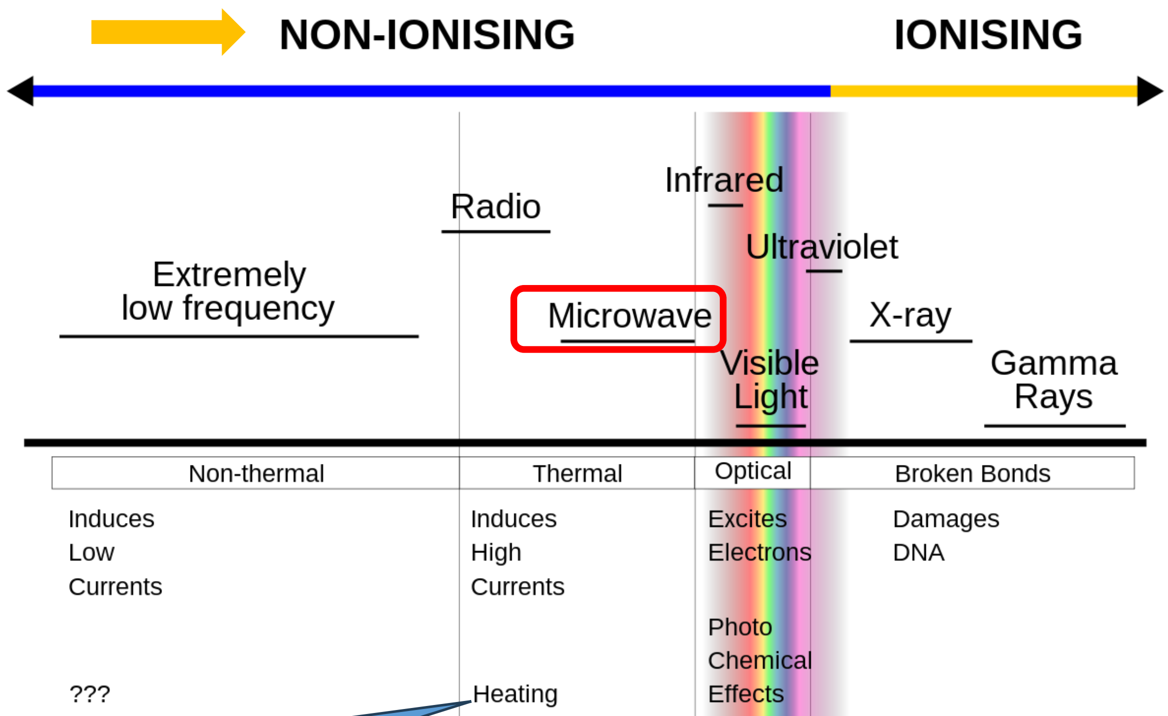








MRI
- High cost
- Not for some woman
    - Implant cases
    - Pregnant



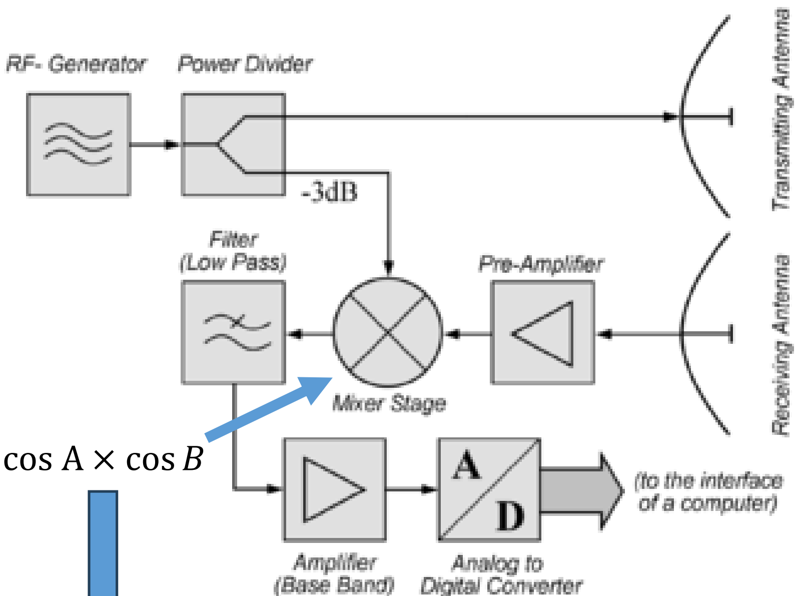
Not harmful at low power level

- Acceptable penetration depth
- Mature
- Can be a handheld/portable

[Wikimedia Commons]

X-ray
- Ionizing
- Uncomfortable in many cases

CW and FMCW



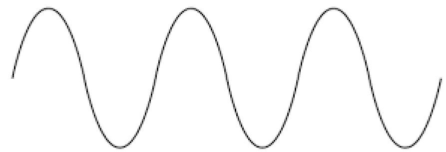
$\cos A \times \cos B$

Continuous-wave radar - Wikipedia

Phase sum --- $\cos\ (a+b)$

Phase diff --- $\cos\ (a-b)$ Our Target!!

- Continuous Transmitting

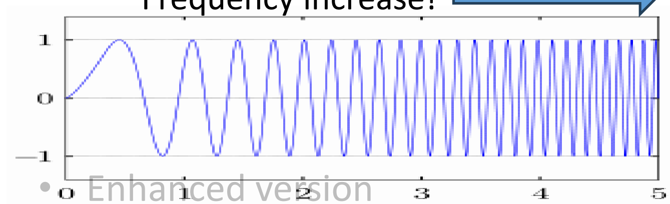


CW

- Can retrieve the velocity only!
- Not for distance.

By Doppler Effect

Frequency increase!

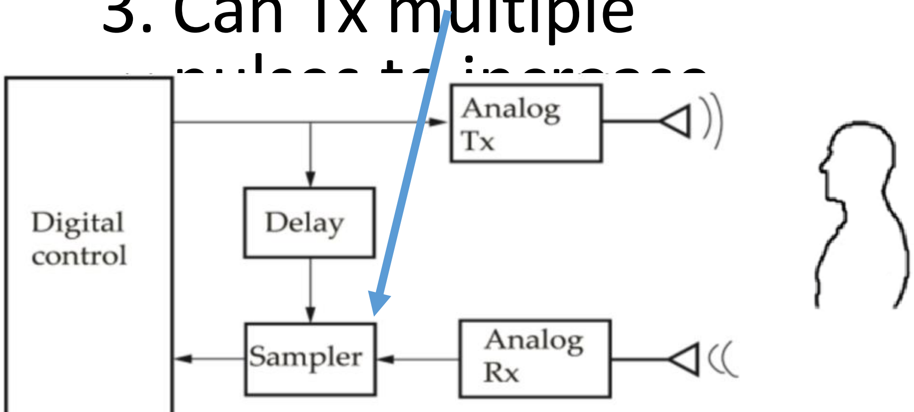


FMCW

- Enhanced version
- Can retrieve the distance and velocity!

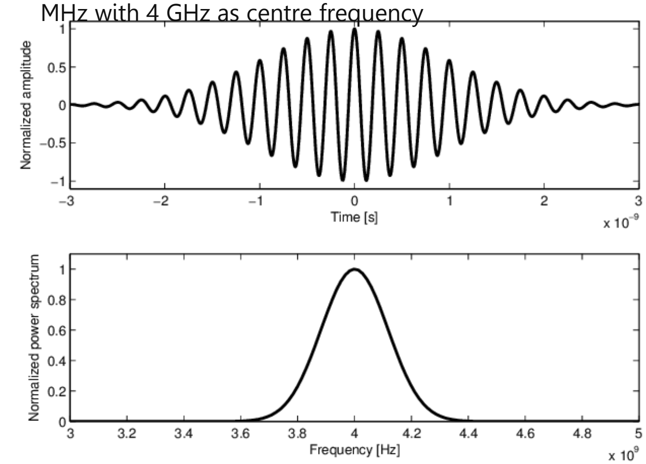
Impulse Radio Ultra-wideband (IR-UWB)

1. Tx a short Gaussian pulse
2. Power is limited
3. Can Tx multiple



M. Kebe, R. Gadhafi, B. Mohammad, M. Sanduleanu, H. Saleh, and M. Al-Qutayri, “Human Vital Signs Detection Methods and Potential Using Radars: A Review,” *Sensors*, vol. 20, no. 5, p. 1454, Mar. 2020, doi: 10.3390/s20051454.

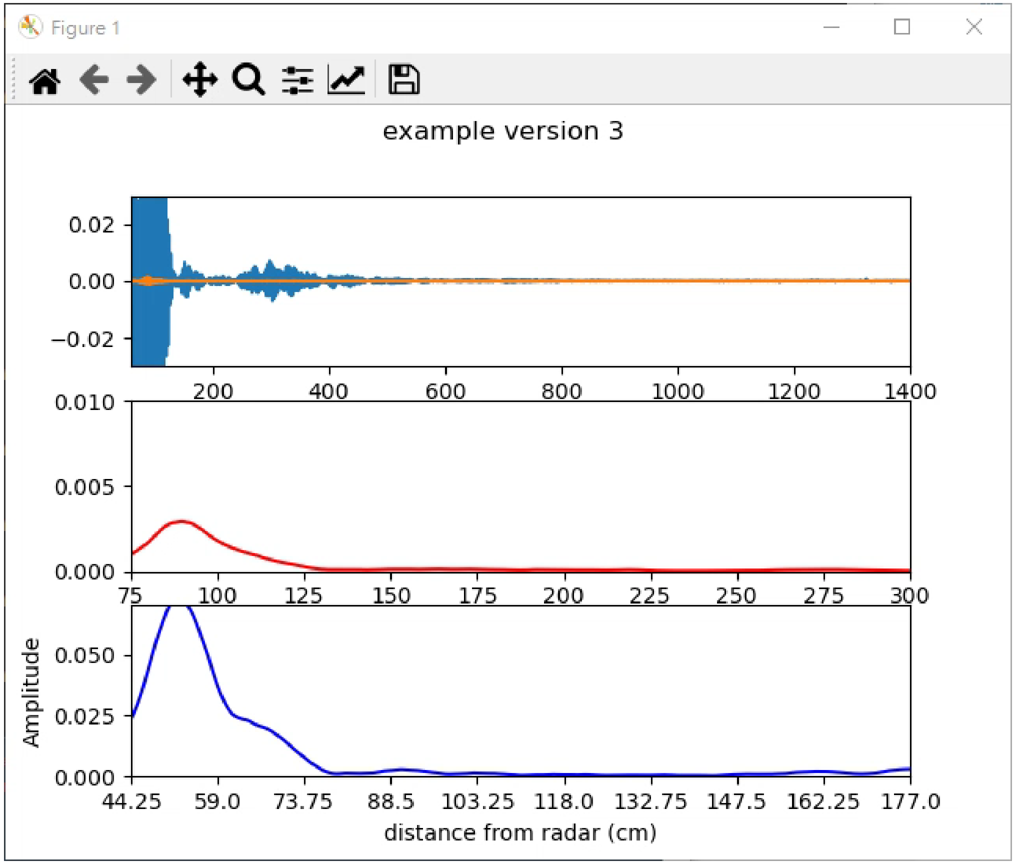
Gaussian pulse with 10-dB RF bandwidth of 500 MHz with 4 GHz as centre frequency



T. Krebesz, G. Kolumban, C. K. Tse and F. C. M. Lau, "Improving the noise performance of energy detector based UWB systems by optimizing the receiver parameters," *2009 9th International Symposium on Communications and Information Technology*, Icheon, Korea (South), 2009, pp. 1426-1431, doi: 10.1109/ISCIT.2009.5341039.

Microwave radar measurement

- A peak will be observed at the location of the target (reached maximum when the reflected side is perpendicular to the radar transmitter)
- Calculate and plot the data in terms of the distance from the radar
- The PCA processed signal will show peak in the same location when there is movement (Doppler shift - red curve)



Dual ultra-wideband (UWB) radar-based sleep posture recognition system: Towards ubiquitous sleep monitoring

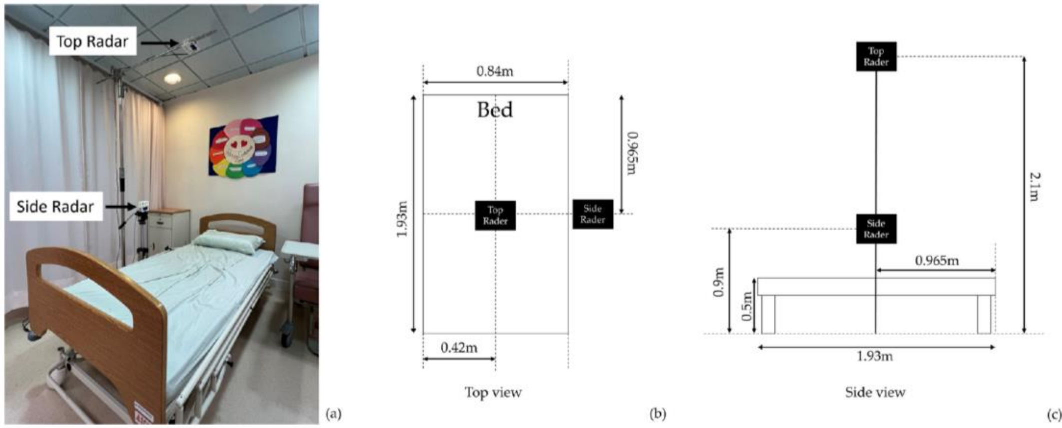


Fig. 1. System setup illustrating the top and side UWB radars positioned orthogonally over the bed.

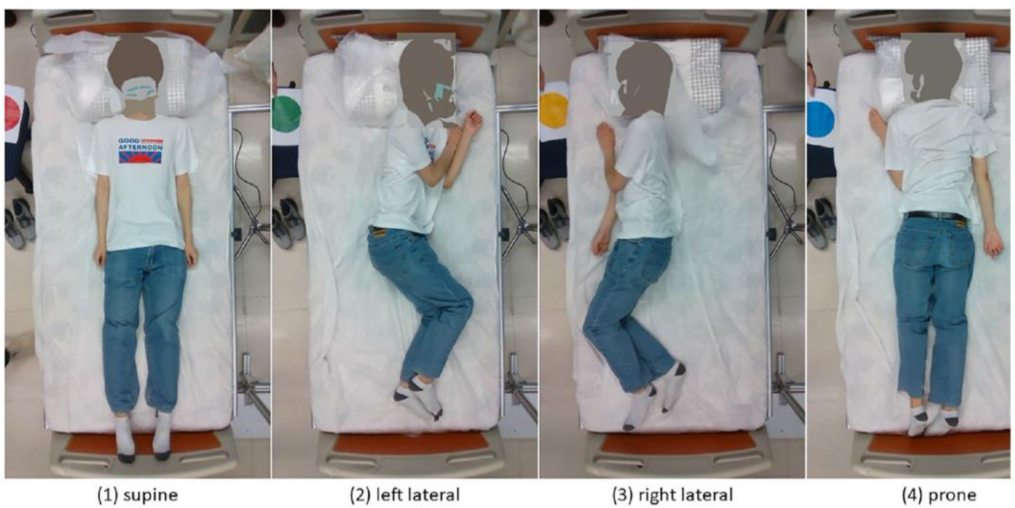
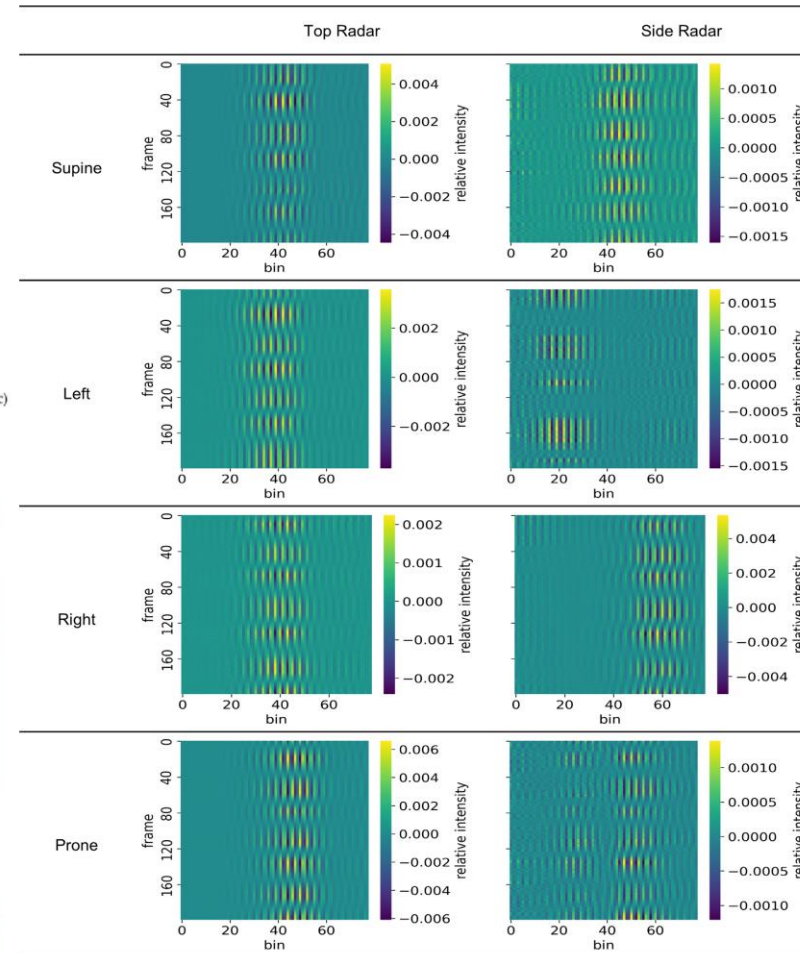
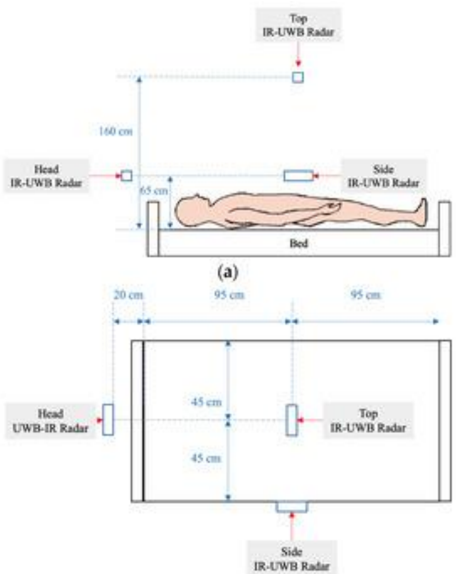


Fig. 2. Illustration of the four recumbent postures: supine, left lateral, right lateral, and prone.



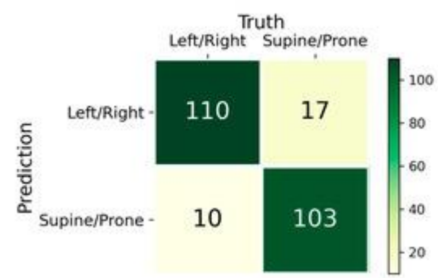
Vision Transformers (ViT) for Blanket-Penetrating Sleep Posture Recognition Using a Triple Ultra-Wideband (UWB) Radar System

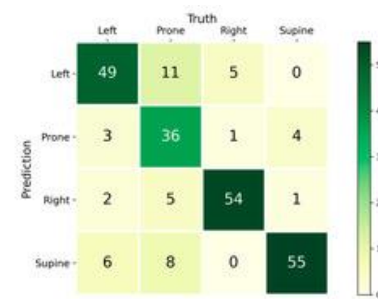


(b)

(c)

(a) (b) (c) (d)



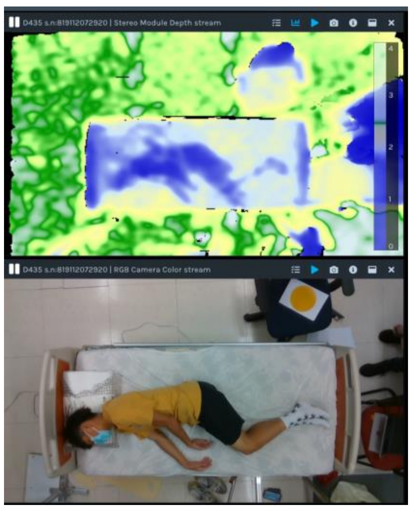


Lai, D.K.-H.; Yu, Z.-H.; Leung, T.Y.-N.; Lim, H.-J.; Tam, A.Y.-C.; So, B.P.-H.; Mao, Y.-J.; Cheung, D.S.K.; Wong, D.W.-C.; Cheung, J.C.-W. Vision Transformers (ViT) for Blanket-Penetrating Sleep Posture Recognition Using a Triple Ultra-Wideband (UWB) Radar System. Sensors 2023, 23, 2475. https://doi.org/10.3390/s23052475

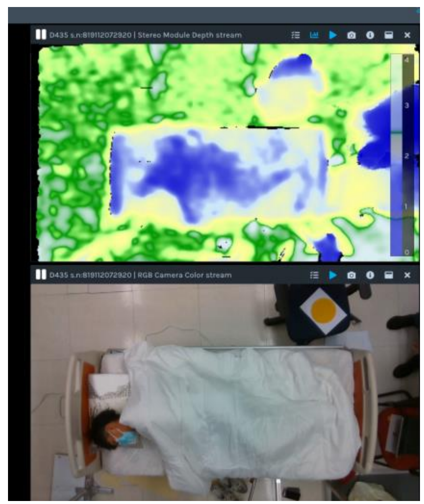
Sleep quality and posture analysis

Sleep quality is very important and related diseases require to undergo polysomnography study. It is not possible to fulfil the real need, especially for the elderlies. The imaging device and radar technology can provide information deriving sleep and related parameters for supporting diagnosis.

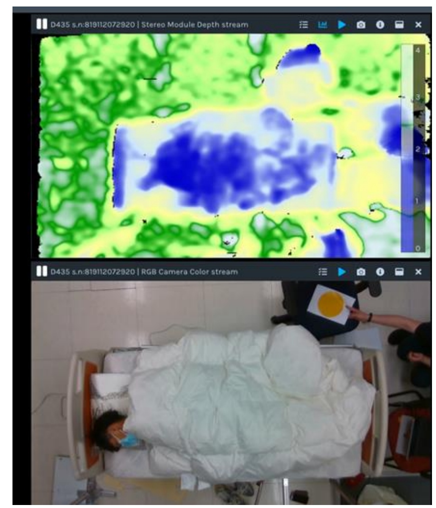
No Sheet



Thin quilt



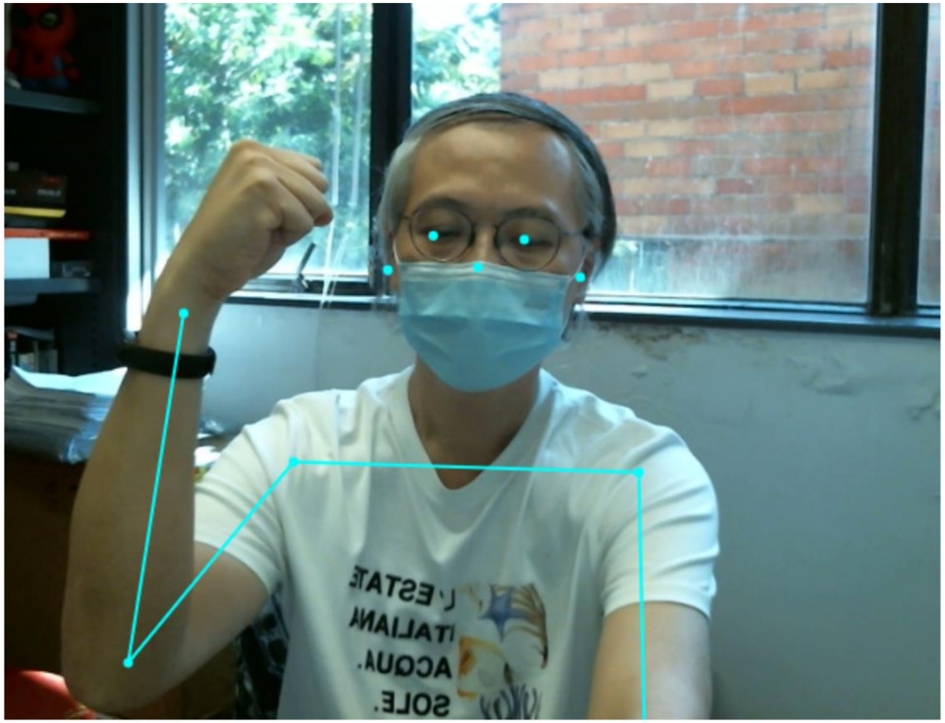
Thick quilt



Sleep posture is one of the factor affecting quality sleep. Deep learning technology with combining different modalities will possibly, accurately determine the posture and the vital sign including respiratory rate and heart rate, even in home setting.

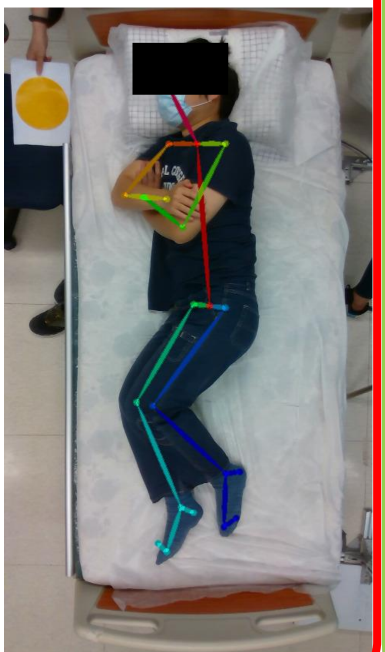
The system will help to monitor the elder sleep quality and provide information to support diagnosis.

OpenPose demonstration

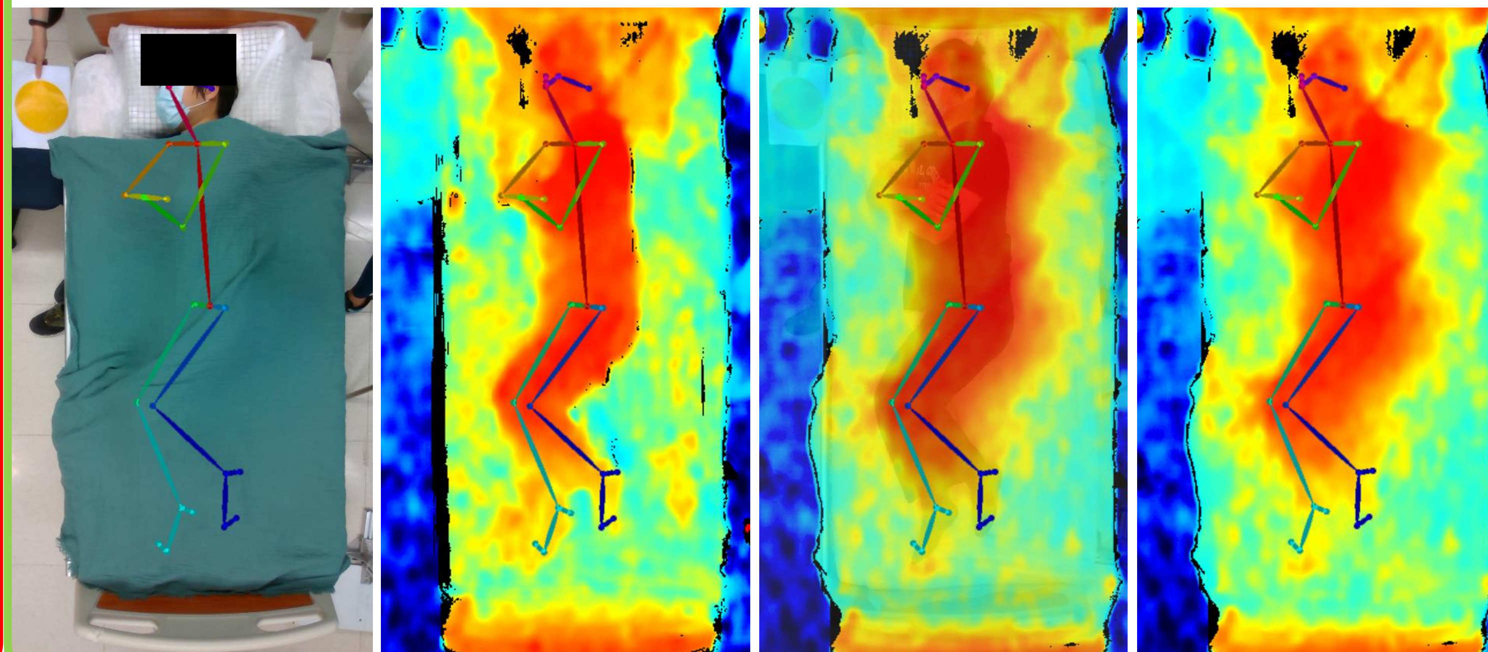


Preliminary work

Prior work



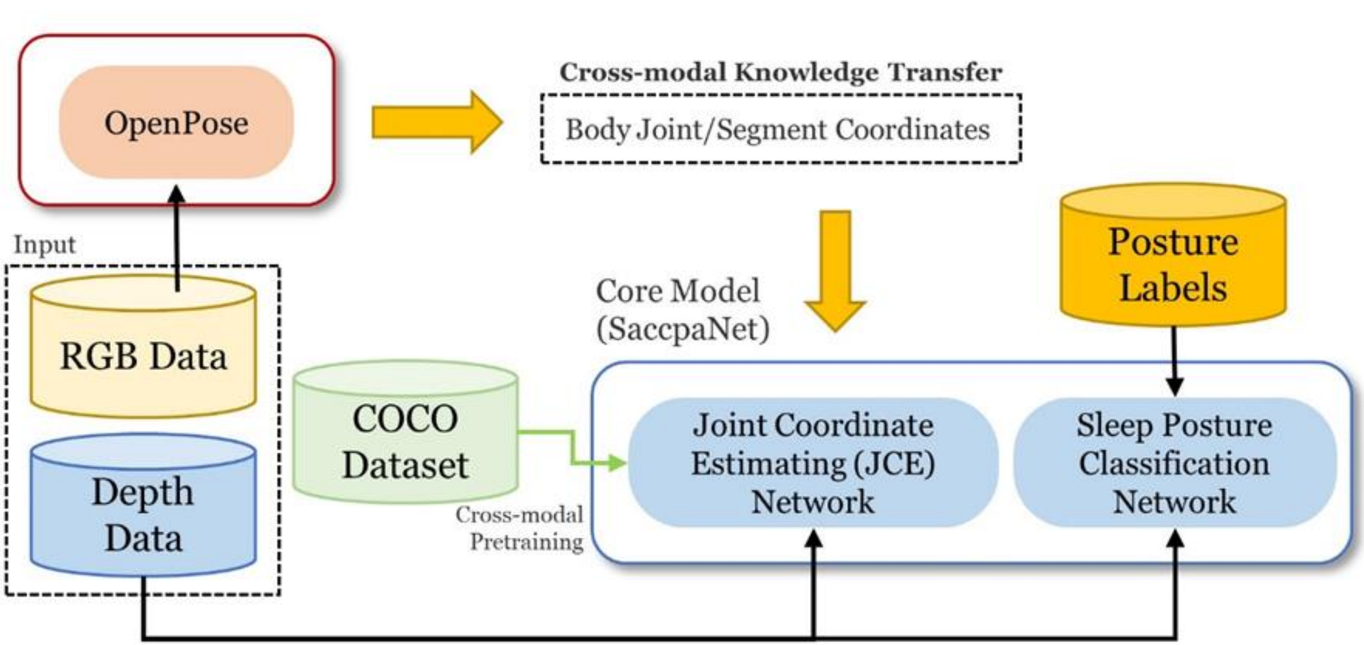
Expected result

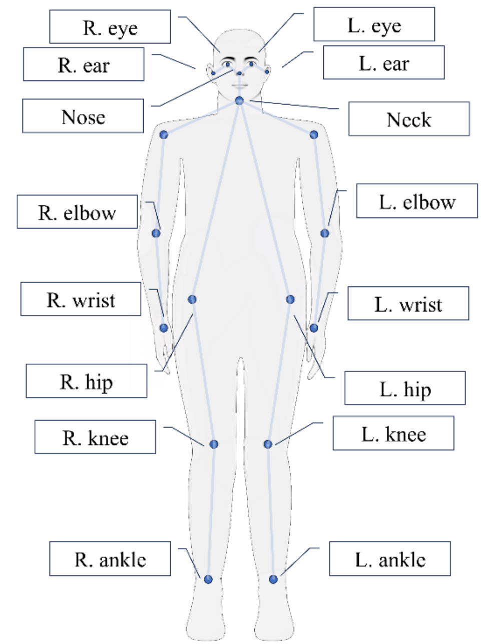


RGB channel

Depth channel

SaccpaNet: A Separable Atrous Convolution-based Cascade Pyramid Attention Network to Estimate Body Landmarks Using Cross-modal Knowledge Transfer for Under-blanket Sleep Posture Classification





Estimate Body Landmarks

For Joint coordinate estiamtion, the precision accuracy of joint coordinates on the testing set, in terms of PCK@0.1 value, was 0.6518. In other words, more than 65% of the (anatomical landmarks) joint coordinates were correctly predicted within 10% diagonal distance of the bounding box.

SaccpaNet: A Separable Atrous Convolution-based Cascade Pyramid Attention Network to Estimate Body Landmarks Using Cross-modal Knowledge Transfer for Under-blanket Sleep Posture Classification (**Recruited 150 subjects**)

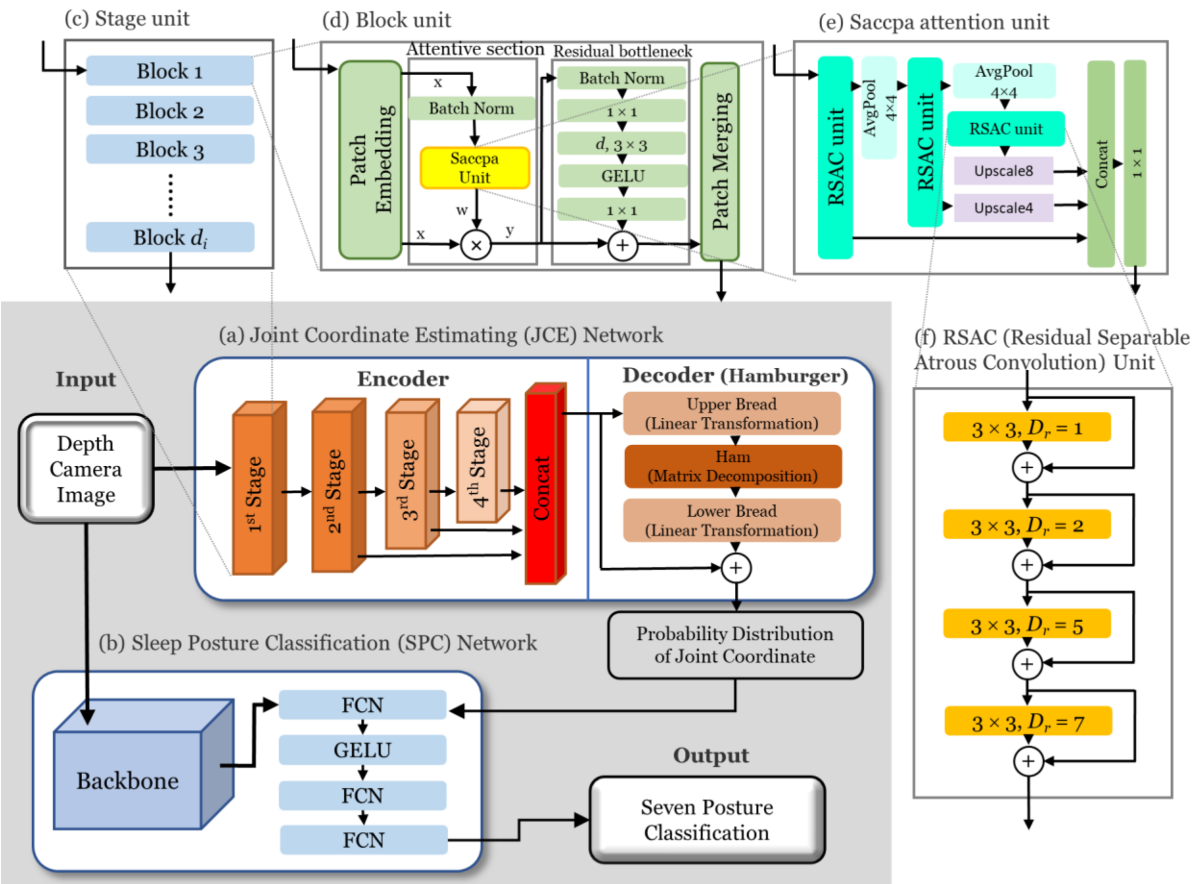
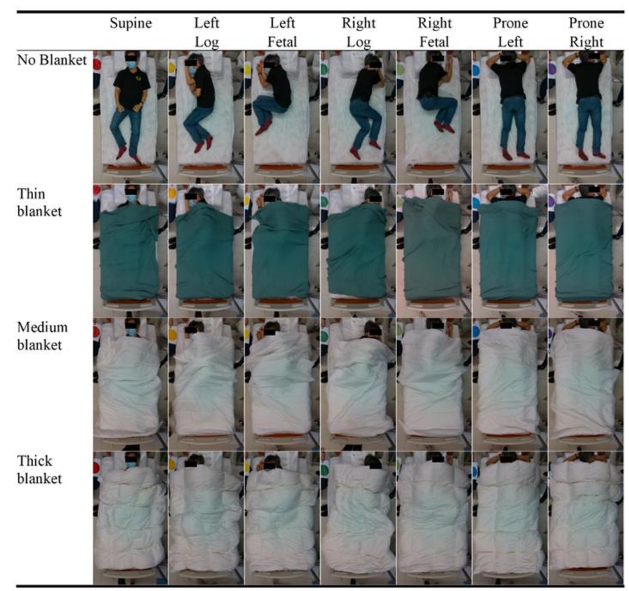


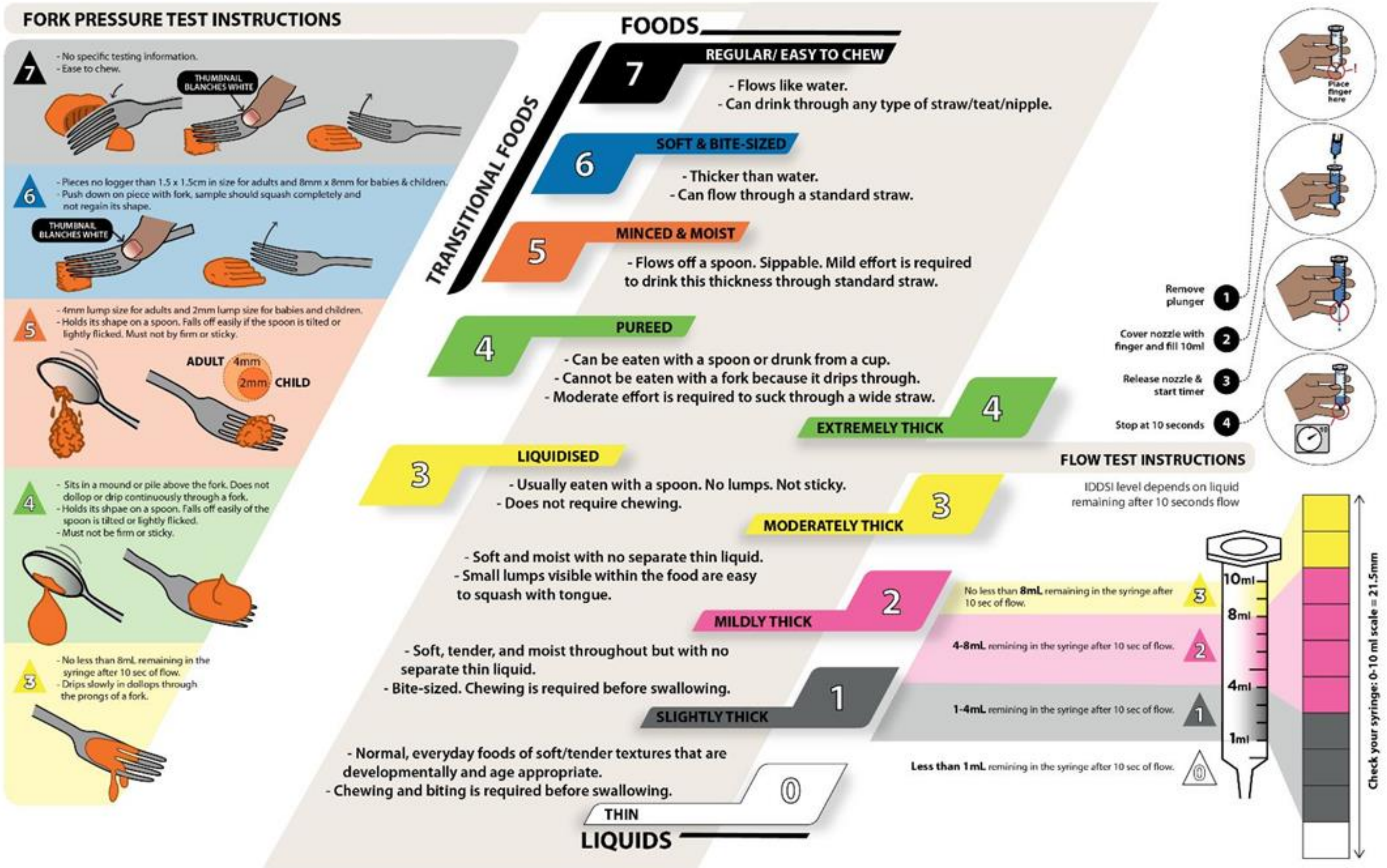
TABLE II
OVERALL CLASSIFICATION PERFORMANCE USING DIFFERENT DEEP LEARNING MODELS AS BACKBONE OF SPC.

Models	F1-score	AUC
EfficientNetB0	0.8561	0.9721
EfficientNetB2	0.8611	0.9752
EfficientNetB4	0.8602	0.9756
EfficientNetB7	0.8406	0.9737
ECANet34	0.8541	0.9734
ECANet50	0.8551	0.9722
ECANet101	0.8200	0.9637
ECANet152	0.8388	0.9655
ResNet34	0.8734	0.9760
ResNet50	0.8442	0.9728
ResNet101	0.8431	0.9722
ResNet152	0.8499	0.9755
CNN-Saccpa34	0.8221	0.9535
CNN-Saccpa50	0.8346	0.9590
CNN-Saccpa101	0.8718	0.9829
CNN-Saccpa152	**0.8849**	**0.9833**



Accuracy (F1-Score) at 88.49% (7 Classes), 0.9399 (6 Classes)

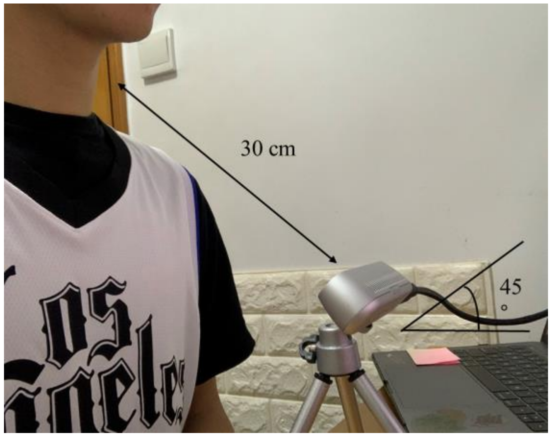
Supine, Left log/fetal, Right log/fetal, Prone (6 classes); Prone with head left and right (7 classes)



Lim, H.-J.; Lai, D.K.-H.; So, B.P.-H.; Yip, C.C.-K.; Cheung, D.S.K.; Cheung, J.C.-W.; Wong, D.W.-C. A Comprehensive Assessment Protocol for Swallowing (CAPS): Paving the Way towards Computer-Aided Dysphagia Screening. Int. J. Environ. Res. Public Health 2023, 20, 2998. https://doi.org/10.3390/ijerph20042998

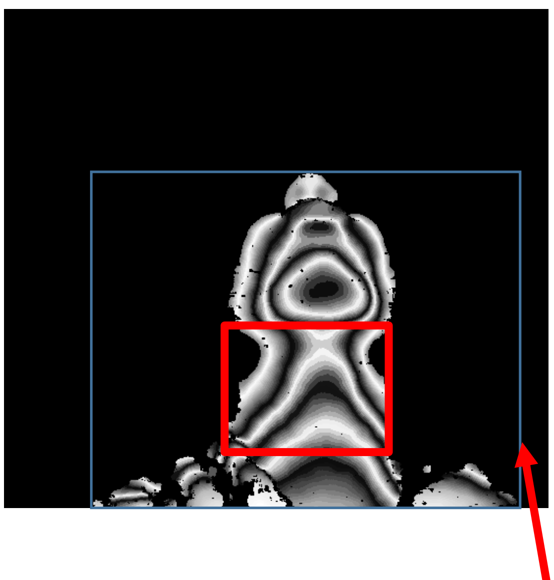
Dysphagia risk analysis and food intake

Dysphagia is caused by aging or other health conditions. People with dementia will mostly develop dysphagia at their late stage.

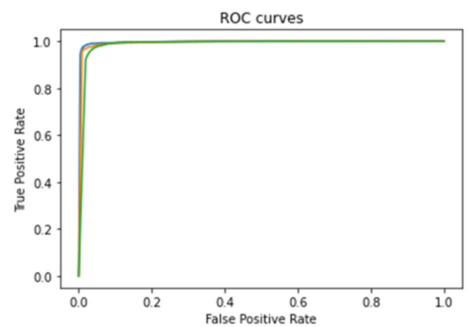


Currently, the segmentation and deep learning algorithm is being developed. This algorithm is intended to implement into IoT or wearable device to use anywhere.

These features provide vital information on determining risk of dysphagia. Besides, this technique could lead to develop a food counter for monitor.



Boundary box



Preliminary result from 22 subjects

Area under curve (AUC)

EfficientNetB0 = 0.996

ResNet50 = 0.993

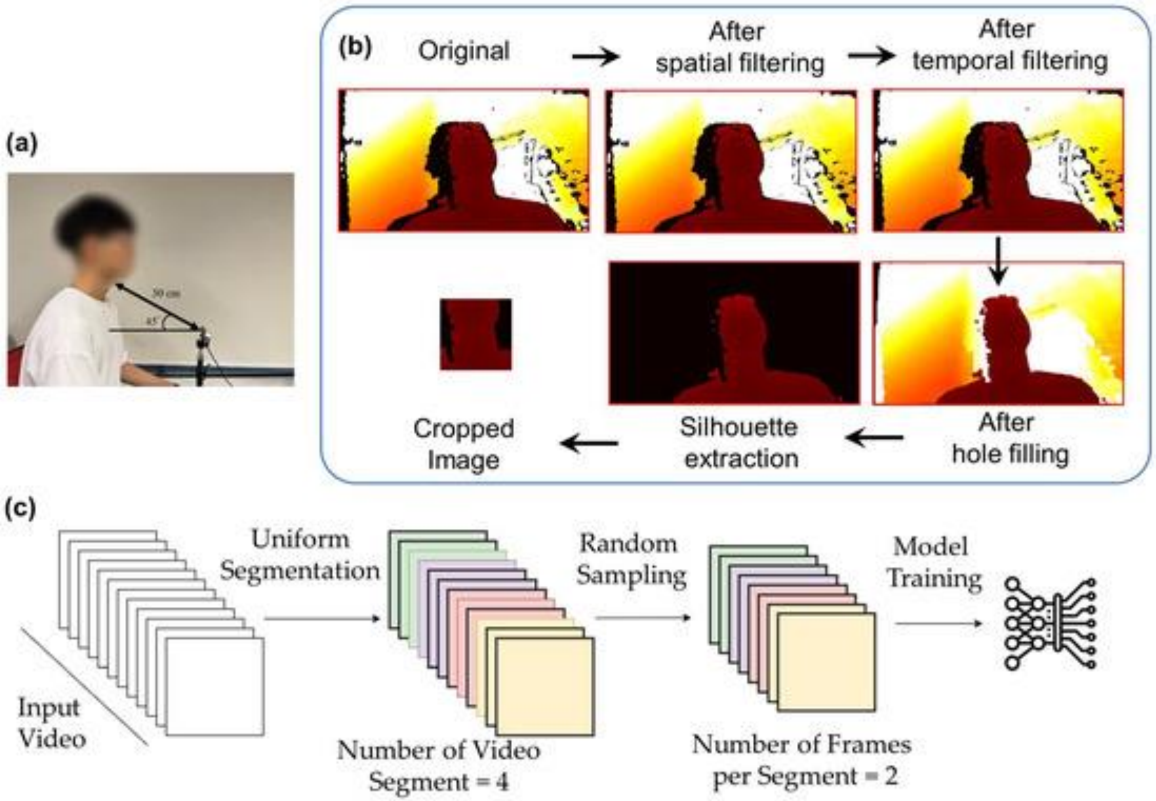
VGG16 = 0.987

The system will ultimately serve as a screening tool to assess risk of developing dysphagia and monitor food intake.

Current status

Undergo subject test with new 3D CNN algorithm

Transformer Models and Convolutional Networks with Different Activation Functions for Swallow Classification Using Depth Video Data



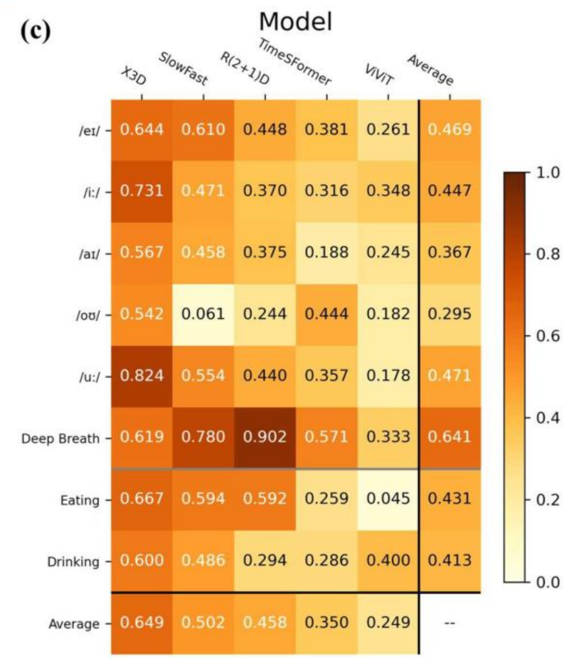


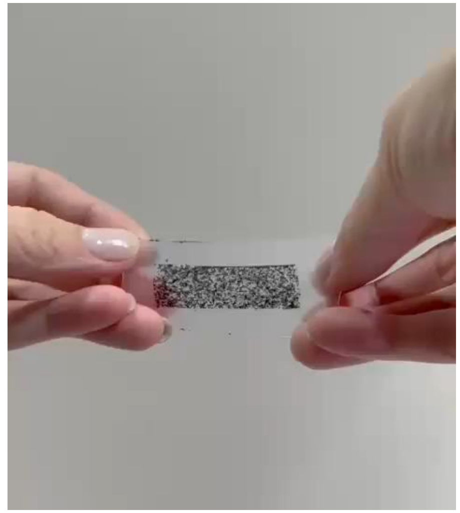
Table 3. F1-score of X3D on different activation functions.

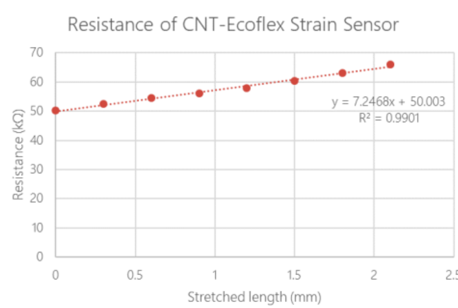
	ReLU (Default)	LeakyReLU	GELU	ELU	GLU	SiLU
Coarse Classification						
Swallowing	0.962	0.807	0.681	0.673	0.906	0.925
Non-swallowing	0.878	0.927	0.911	0.899	0.763	0.750
Coarse Average:	0.920	0.867	0.796	0.786	0.835	0.838
Fine-grained Classification						
Eating	0.667	0.551	0.418	0.407	0.488	0.593
Drinking	0.600	0.578	0.458	0.462	0.250	0.429
Deep Breathing	0.619	0.816	0.760	0.627	0.800	0.857
Vowel Pronunciation	0.959	0.925	0.895	0.839	0.895	0.924
Pronouncing "/eɪ/"	0.644	0.644	0.543	0.462	0.654	0.538
Pronouncing "/i:/"	0.731	0.596	0.519	0.545	0.596	0.378
Pronouncing "/aɪ/"	0.567	0.723	0.578	0.585	0.510	0.500
Pronouncing "/oʊ/"	0.542	0.591	0.474	0.500	0.511	0.341
Pronouncing "/u:/"	0.824	0.750	0.506	0.516	0.588	0.429
4-class Average:	0.711	0.718	0.633	0.584	0.608	0.701
8-class Average:	0.649	0.656	0.532	0.513	0.550	0.508

Accuracy F1 score at 71%; 4 classes include Eating, Drinking, Deep Breathing, Vowel Pronunciation

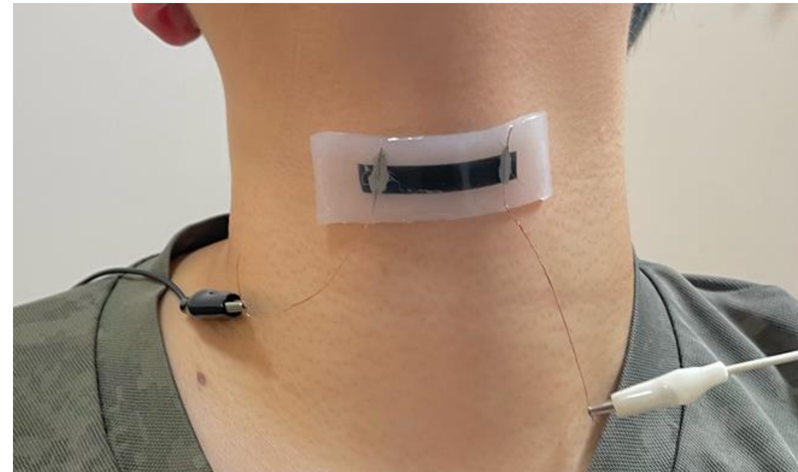
Lai, D.K.-H.; Cheng, E.S.-W.; So, B.P.-H.; Mao, Y.-J.; Cheung, S.M.-Y.; Cheung, D.S.K.; Wong, D.W.-C.; Cheung, J.C.-W. Transformer Models and Convolutional Networks with Different Activation Functions for Swallow Classification Using Depth Video Data. Mathematics 2023, 11, 3081.

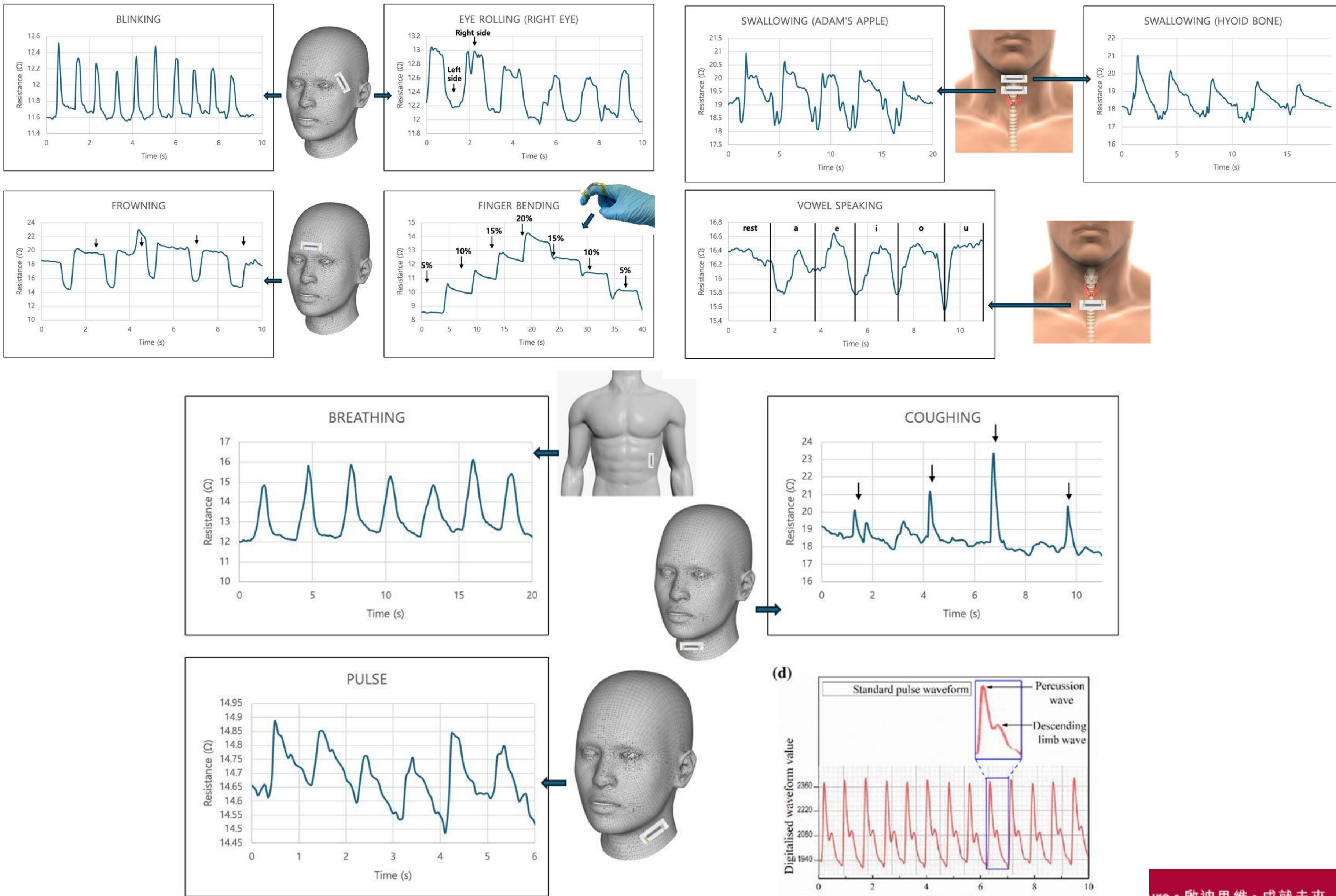
Nano materials based Stretchable Sensor and actuator





GF >> 100




BLINKING
Resistance (Ω)
Time (s)
EYE ROLLING (RIGHT EYE)
Right side
Left side
SWALLOWING (ADAM'S APPLE)
SWALLOWING (HYOID BONE)
FROWNING
FINGER BENDING
5%
10%
15%
20%
VOWEL SPEAKING
rest
a
e
i
o
u
BREATHING
COUGHING
PULSE
(d)
Standard pulse waveform
Percussion wave
Descending limb wave
Digitalised waveform value
Time (Sec)

A soft Nanomaterials based Sensing System for Realtime Detection of Swallowing and Identify Risk of Dysphagia in Nursing Homes

Nanomaterial SEM Results

The sprayed nanomaterials including MWCNTs and MoS_2 were prepared in 5 concentrations (0.01wt%, 0.05wt%, 0.1wt%, 0.15wt%, and 0.2wt%) and AgNWs prepared in 5 concentrations (0.25mg/ml, 0.625mg/ml, 1.25mg/ml, 1.875mg/ml, and 2.5mg/ml) were captured as an SEM image with a scale bar 20 µm as shown in Figure 6.

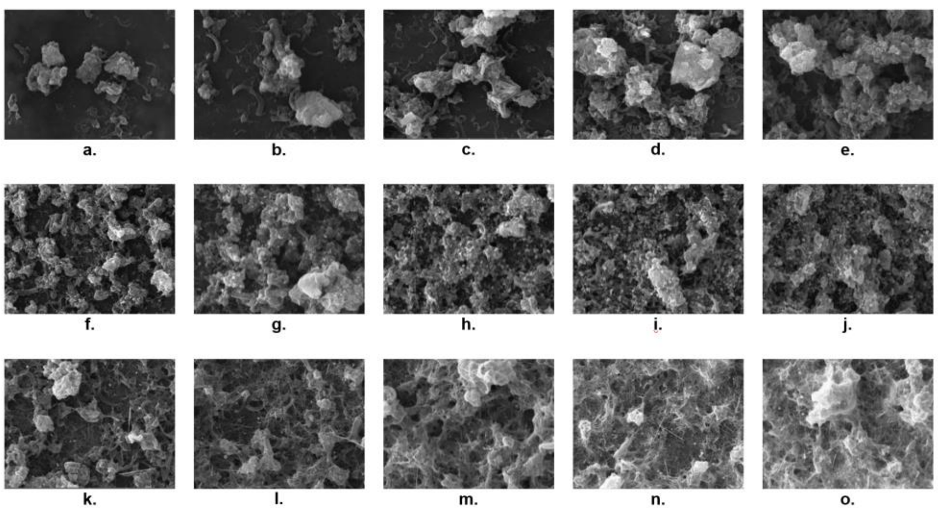
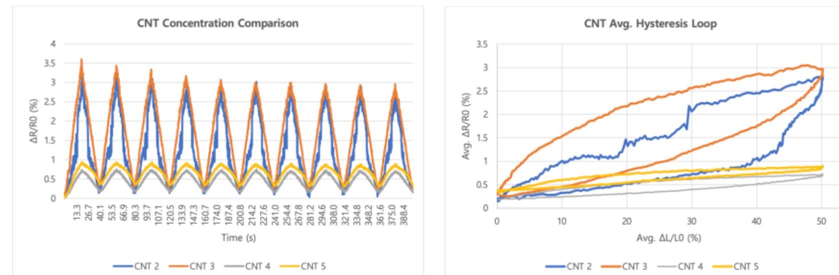
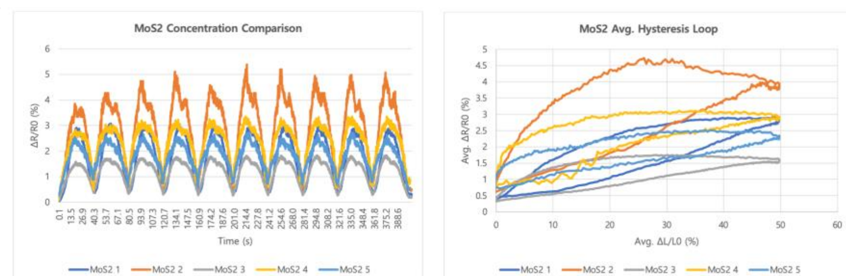


Figure 6. **a-e**, SEM image of MWCNT with concentration 0.01 wt%, 0.05 wt%, 0.1 wt%, 0.15 wt%, 0.2 wt%. Scale bar, 20 µm. **f-j**, SEM image of MWCNT-MoS_2 with concentration 0.01 wt%, 0.05 wt%, 0.1 wt%, 0.15 wt%, 0.2 wt%.



a. b.

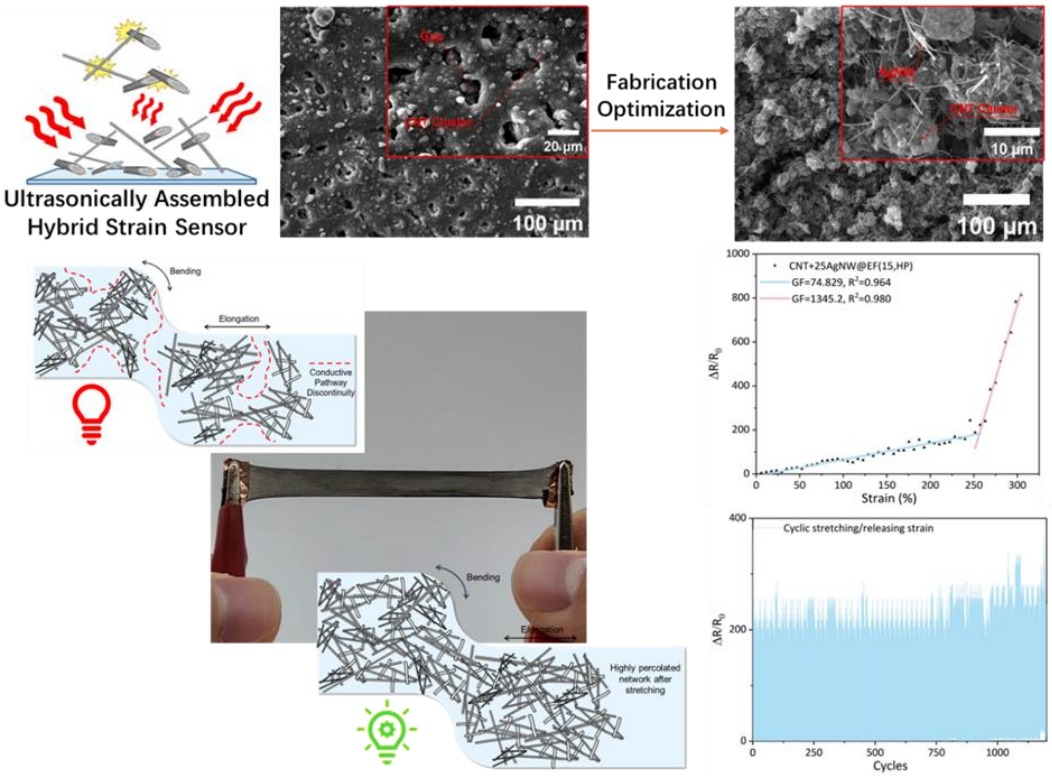
Figure 9. **a.** $\Delta R/R_0$ (%) vs. T (s) graph of CNT 2 (0.05wt%), CNT 3 (0.1wt%), CNT 4 (0.15wt%), and CNT 5 (0.2wt%). **b.** ΔR/R0 (%) vs. ΔL/L0 (%) graph of CNT 2 (0.05wt%), CNT 3 (0.1wt%), CNT 4 (0.15wt%), and CNT 5 (0.2wt%).

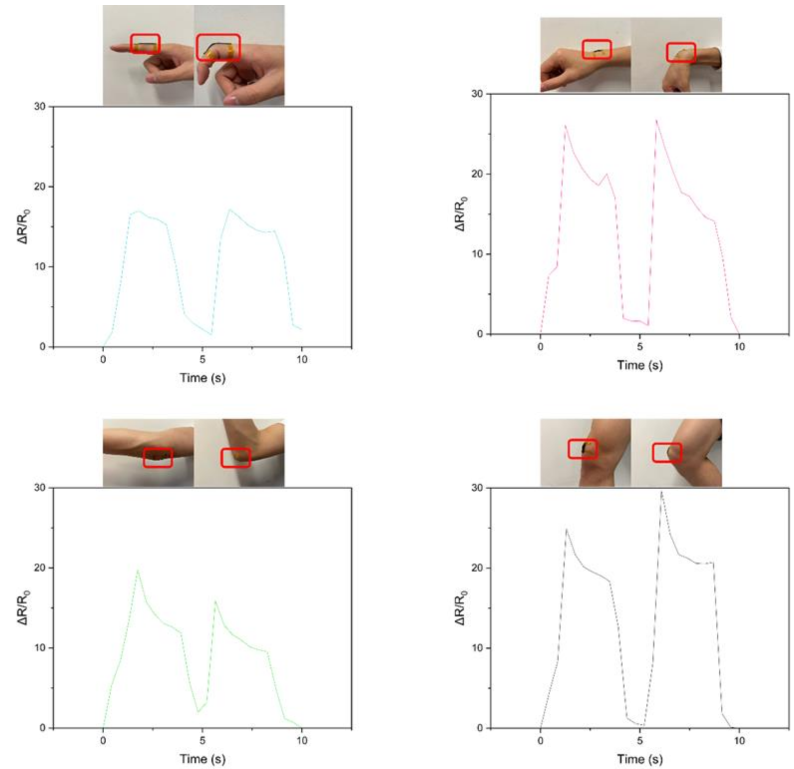


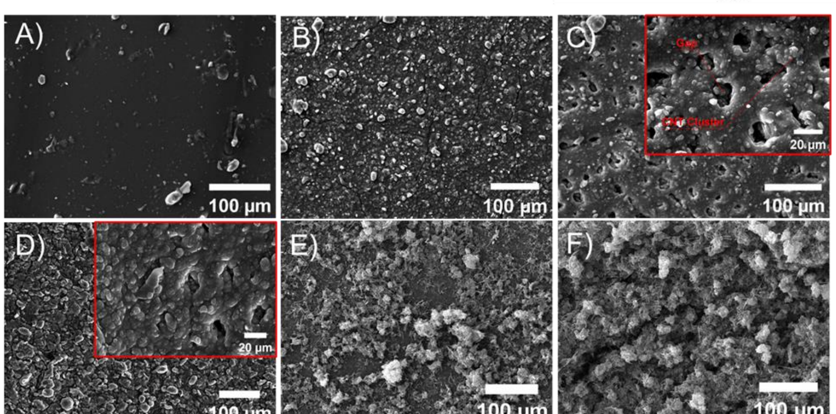
a. b.

Figure 10. **a.** $\Delta R/R_0$ (%) vs. T (s) graph of MoS_2 1 (0.01wt%), MoS_2 2 (0.05wt%), MoS_2 3 (0.1wt%), MoS_2 4 (0.15wt%), and MoS_2 5 (0.2wt%). **b.** ΔR/R0 (%) vs. ΔL/L0 (%) graph of MoS_2 1 (0.01wt%), MoS_2 2 (0.05wt%), MoS_2 3 (0.1wt%), MoS_2 4 (0.15wt%), and MoS_2 5 (0.2wt%).

A Facile Hybrid-Networked Strain Sensor Fabrication Using One-Pot Ultrasonic Treatment for High Linear and Sensitive Joint Motion Monitoring

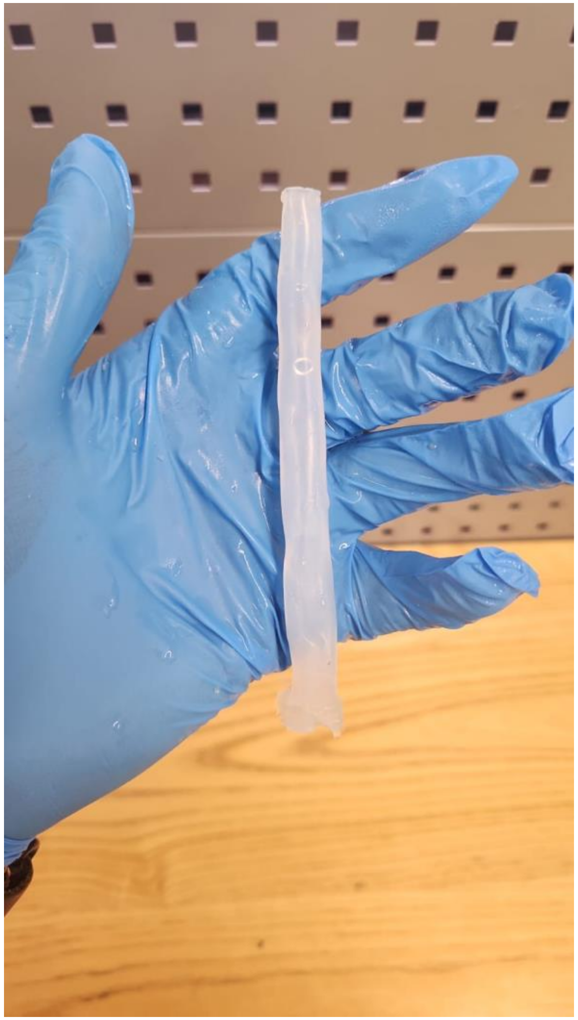


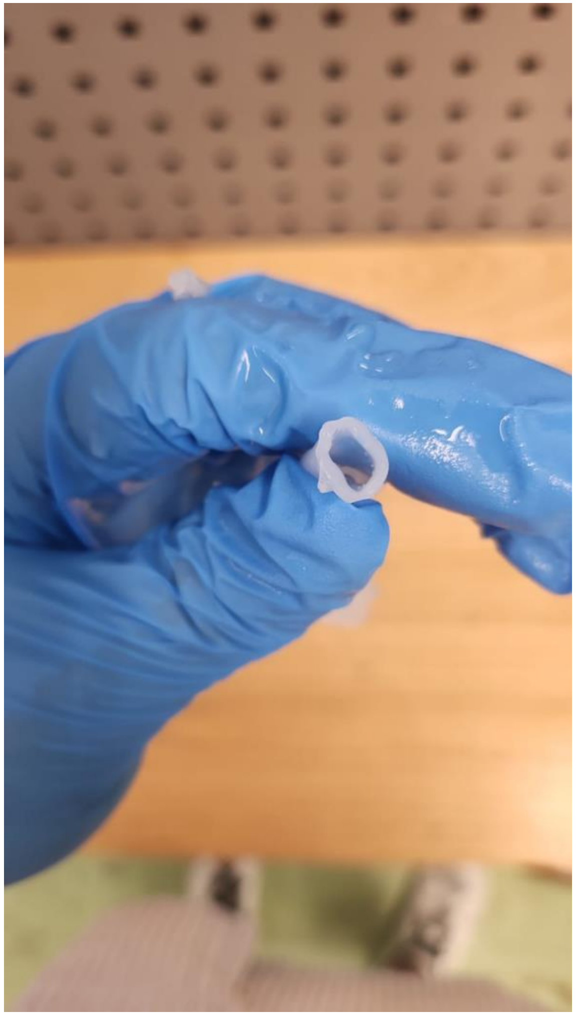




CNT with AgNW in different weight ratios

Development of phantom model for elastography





Research Introduction

Yao Keyu
Year 1 PhD

Academic background:

Material Science and Engineering, Imperial College London

Research on -Stimuli-responsive nanocomposite and hydrogel for soft millirobots

- Soft and flexible strain sensor for healthcare monitoring

-VAT 3D printing for soft and biocompatible materials

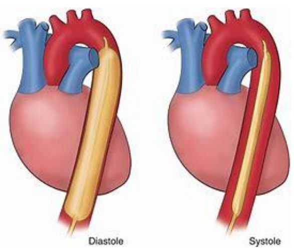
PhD research topics:

1. Transcutaneous Extra-aortic Counter-Pulsation Cardiac Assist Device using Magneto-active Hydrogel Nanocomposite (降主动脉外心脏反博柔性制动器)
2. Pneumatic-driven and Magneto-active Soft Robotics （气动和磁驱动柔性机器人）

Background:

1. High mortality rate amongst heart failure patients （高死亡率）
2. Lack of resolution strategy aside from medication intake and heart transplantation (缺乏长期有效的辅助手段)

Commercialized Aortic-assistive Device （商业化路图）:



1968

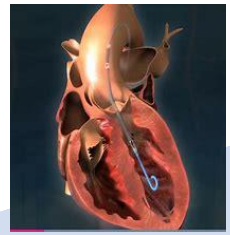
Intra-aortic balloon pump (IABP)

2006

Kantrowitz CardioVAD

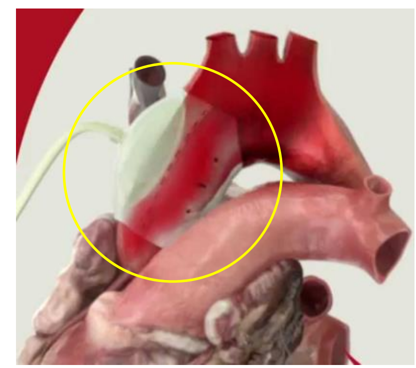
2008

Impella Device



2010

Extra-aortic balloon pump (C-pulse)



1. Counter-pulsation device (CP) or ventricular assist devices (VAD)

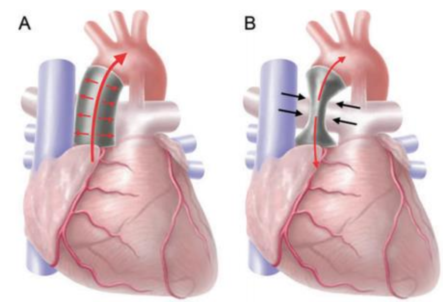
2. Current limitations for pneumatic-driven CP devices

-The pneumatic actuation require the large size of gas sources, surgery trauma;

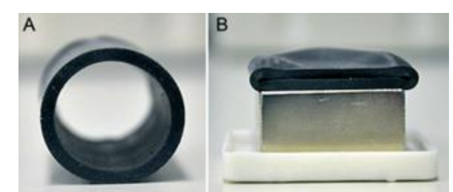
-Long inflation times that introduce uncontrolled delays in operation

Why extra-aortic （主动脉外） and why magnetic-driven （磁驱动）?

Two major drawbacks of existing assist devices:
(i) Contact of blood with the risk of thromboembolic complications （血栓栓塞并发）
(ii) The intra- to extracorporeal connection with the risk of infectious complications （高感染风险）

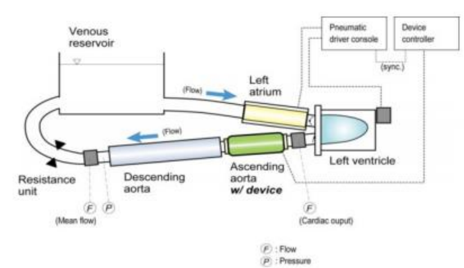


Ferromagnetic assist device (2013)
-Weak actuation with high requirements on the magnetic flux density(>1T) and actuation distance (<3cm) （驱动力弱）



-Simple geometry (cuff shape) results in high shear stress of the aortic tissue （设计局限性）

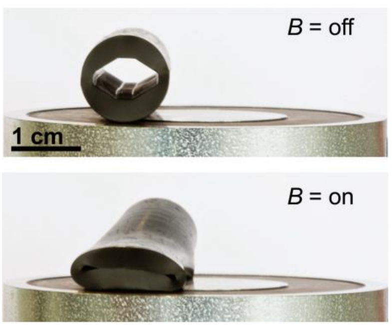
-Current designs have poor degree of freedom induces low actuation efficiency （驱动方式单一）

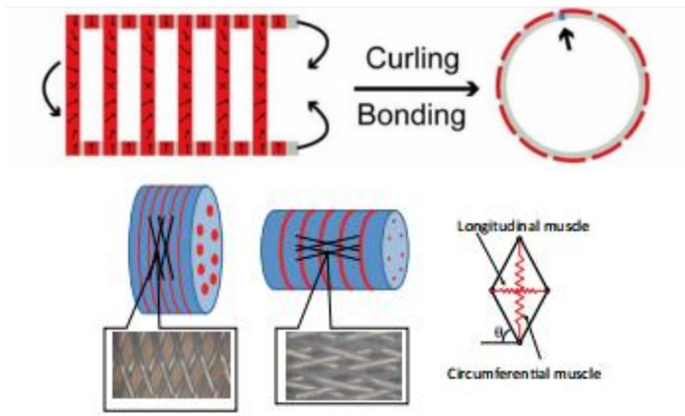


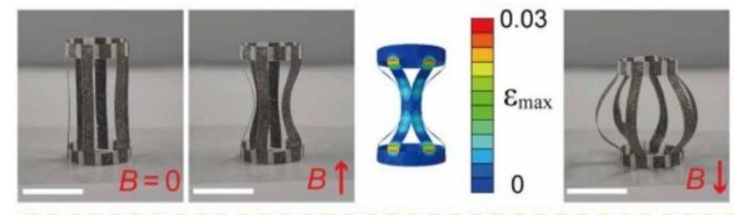
Research Protocol

1)**磁**驱材料 → **生物兼容性，机械特性和能量密度**

2)设计复杂度和功能性 → **内径形状，磁填料区域化，生物仿生**结构和日本折纸设计







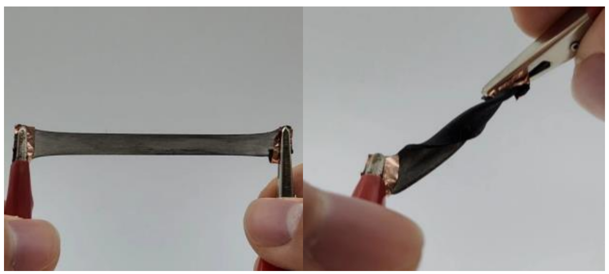
3) 驱动方式 → 电磁结构设计，驱动模式

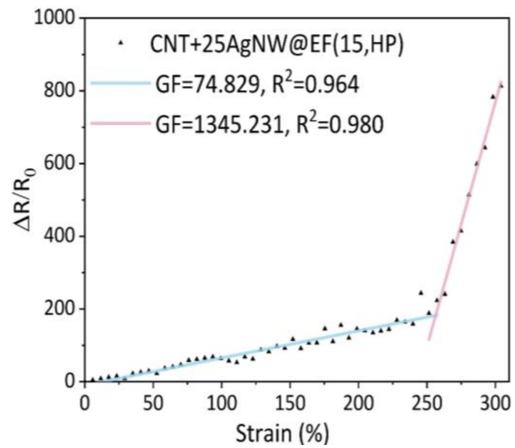
4) **自感知和反**馈回路 → **自主**设计拉伸传感器，**超声波**传感器监控

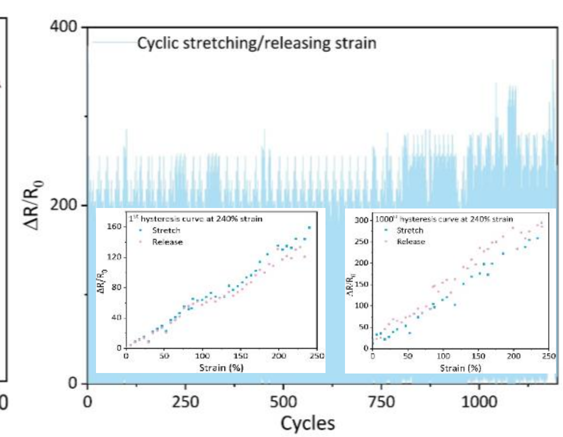
自研发拉伸传感器

1) 高拉伸度和高线性监测

首次使用超声波技术制备双材料（AgNW和MWCNT）拉伸传感器

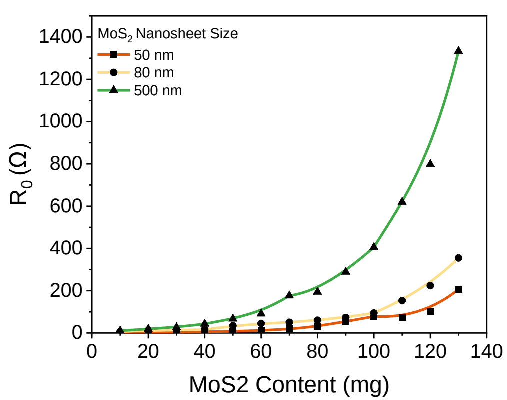


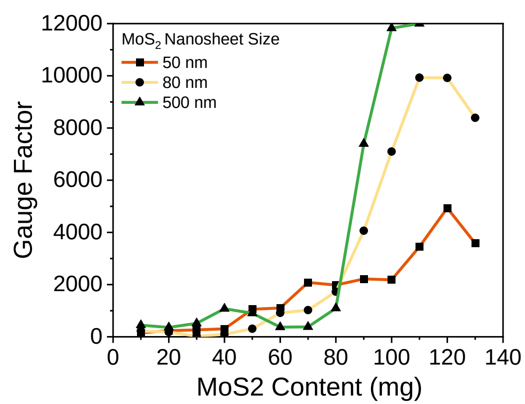




2) 超高灵敏度和低电阻监测

真空过滤法制备双材料（MWCNT和MoS_2）拉伸传感器, 利用MoS_2 润滑特性，极大的增强了CNT单材料传感器灵敏度不足的缺点



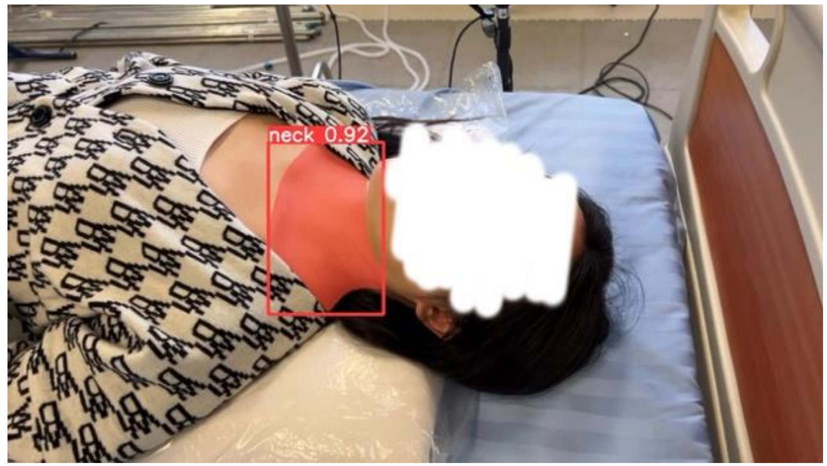


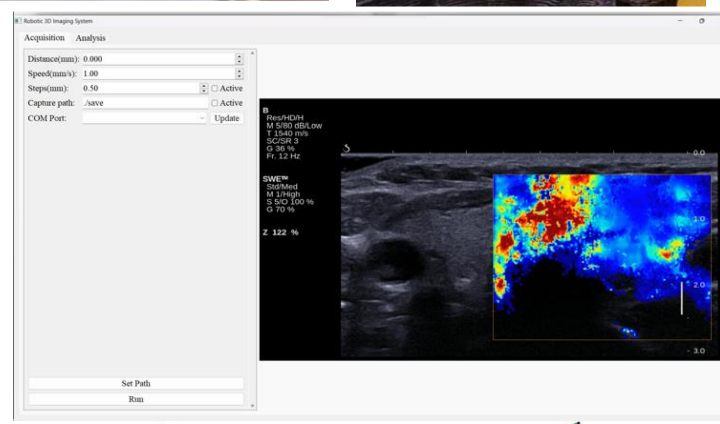
战略方向和合作意向

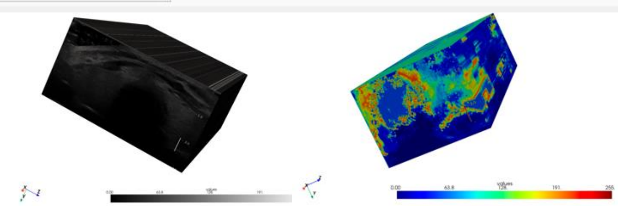
1. 结合拉伸和压力传感器制造双模式传感手段提升临床设备自感知能力，如心脏辅助设备，内窥镜，体内热疗/药物投递柔性机器人等

2. 通过超声技术作为监测辅助手段，传输实时升/降主动脉泵血以及柔性制动器制动模式数据，通过AI算法分析数据并根据数据调整磁驱控源完成反馈回路

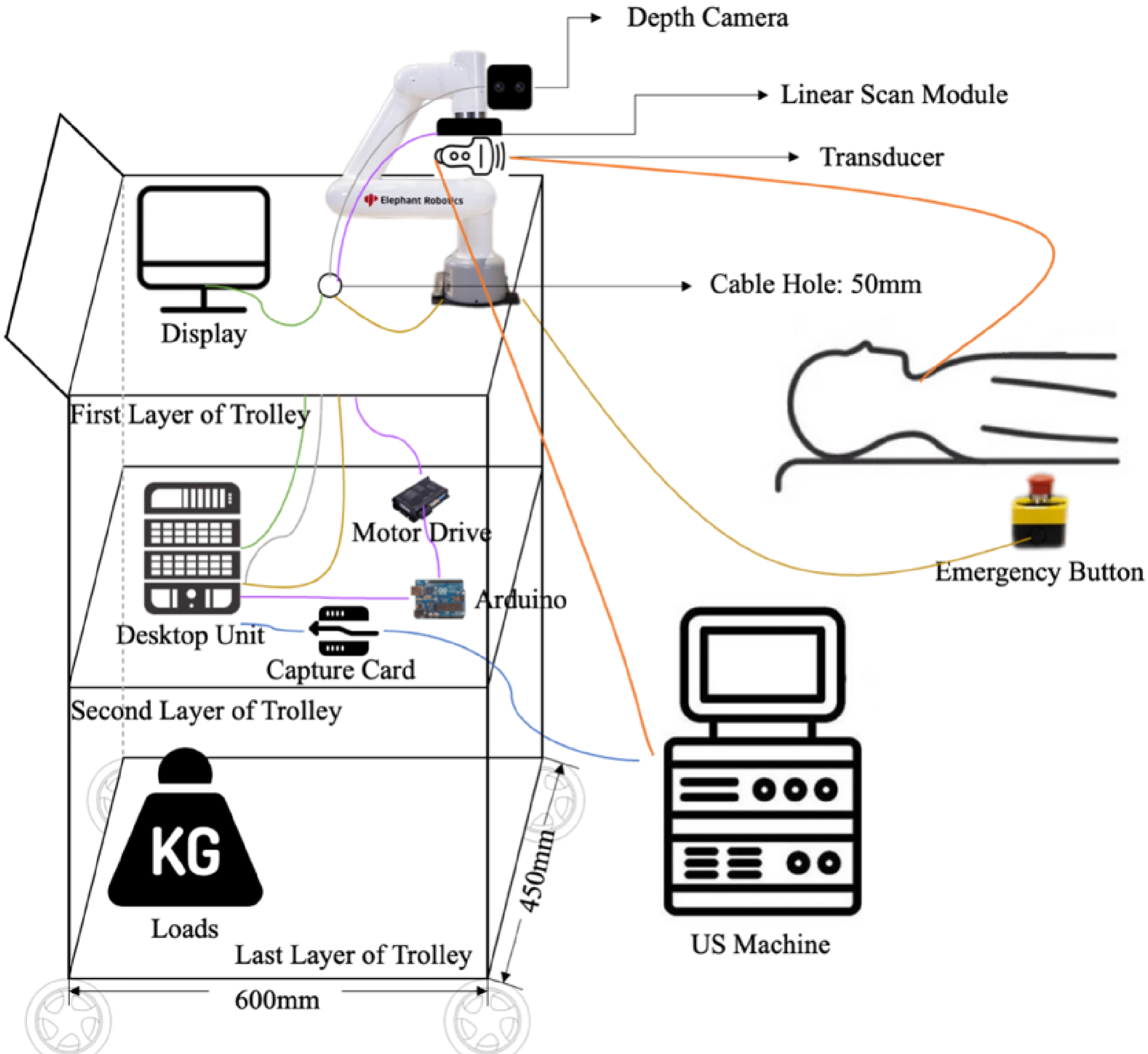
Development of a Robotic System for 3D Ultrasound Elastography Examination of the Thyroid





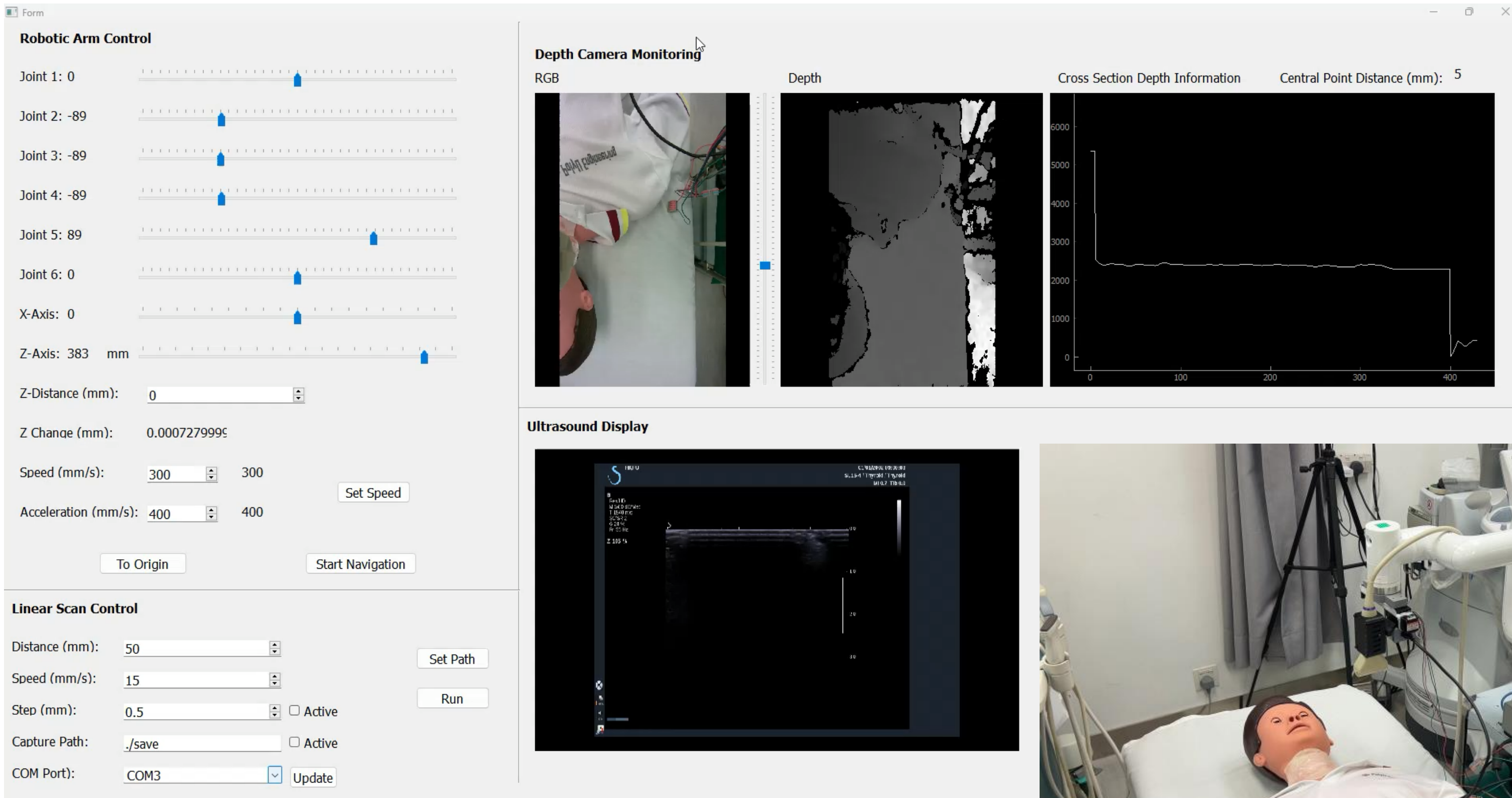


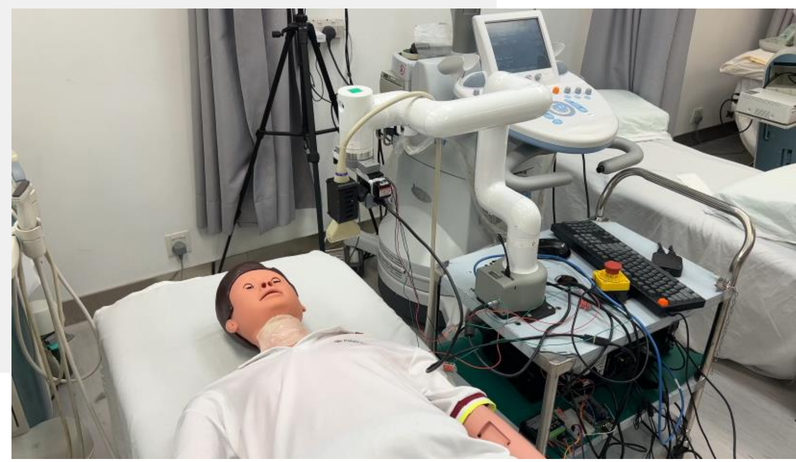
Robotic System Setup



Robotic System Setup

Demonstration





THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

Track: Work-in-Progress

Residual Generative Adversarial Network (GAN) Denoising for Elastography Ultrasound of Thyroid

Ye-Jiao Mao[1], Duo Wai-Chi Wong[1], James Chung-Wai Cheung[1,2]

[1]Department of Biomedical Engineering, Faculty of Engineering, The Hong Kong Polytechnic University

[2]Research Institute for Smart Ageing, The Hong Kong Polytechnic University

Proposed Methods

1. The GAN model can be divided into the generator and discriminator network.
2. The generator network contains convolutional layers, residual blocks, and deconvolutional layers (Fig. 2a).
3. The discriminator network contains convolutional layers (Fig. 2b).
4. Large dataset of thyroid elastographic images will be sourced from public repository.
5. All images will be resized to 256 × 256 ×3.
6. Different noises (distribution) will be added and assessed by the generator network.
7. The generator network produces noise to generate noisy images.
8. The discriminator will be trained based on the images before and after adding noise (Fig. 3).

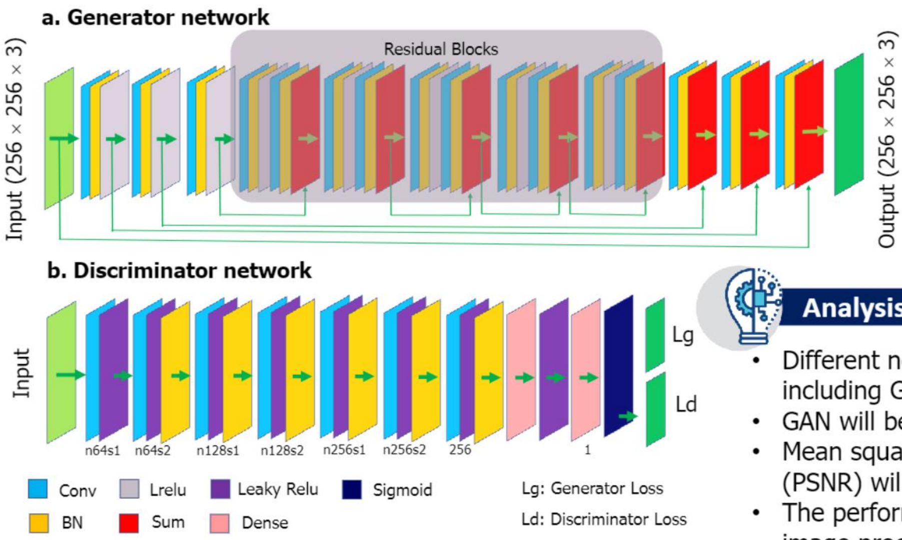


Fig. 2. Architecture of GAN Model

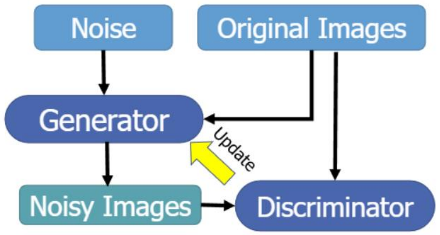


Fig. 3. Process of GAN Model Training

Analysis Strategy & Anticipated Outcomes

- Different noise distributions will be used for training, including Gaussian, Poisson, Salt & Pepper.
- GAN will be optimized for different noise distribution
- Mean squared error and peak signal to noise ratio (PSNR) will be evaluated.
- The performance will be compared to traditional image processing techniques, coherent and wavelet-based denoising.

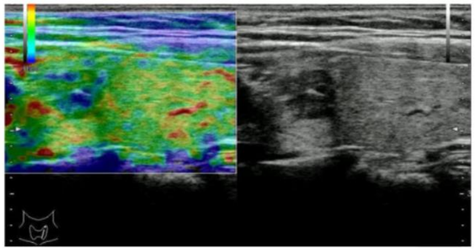


Fig. 1. An illustration of ultrasound elastography in identifying tiny thyroid microcarcinoma (Source: [4])

UAV & Landrover Rescue Support Project (Joining project with Hong Kong Police Force)