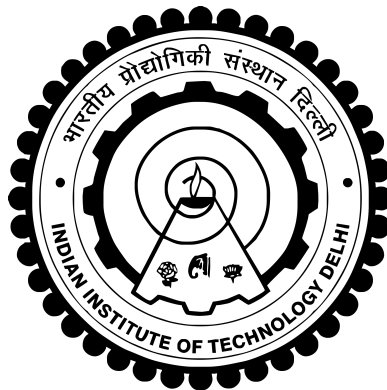


**ROBOTIC SONOGRAPHER: ROBOT LEARNING
ULTRASOUND PROCEDURE SKILLS FROM
DOMAIN EXPERTISE**

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Robotic Sonographer: Robot Learning Ultrasound Procedure Skills from Domain Expertise

by

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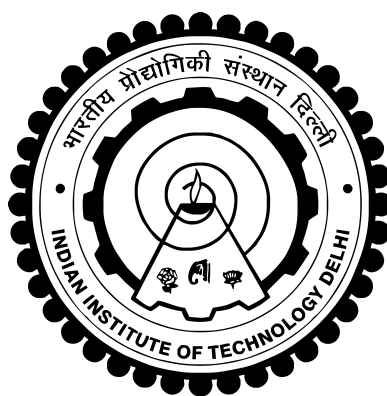
Department of Mechanical Engineering

Submitted

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Doctor of Philosophy

to the



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CERTIFICATE

This is to certify that the thesis titled **Robotic Sonographer: Robot Learning Ultrasound Procedure Skills from Domain Expertise**, submitted by **Deepak Raina (2019MEZ8497)**, to the Indian Institute of Technology, Delhi, for the award of the degree of **Doctor of Philosophy**, is a bona-fide record of the research work done by him under our supervision. The thesis has reached the standards fulfilling the requirements of the regulations related to the award of the degree. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

Ultrasound imaging is a widely used medical imaging modality to visualize several structures and tissues inside the human body. It has proven effective in several diagnostic and therapeutic procedures. It has several advantages over other imaging modalities, such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and X-rays. It is relatively inexpensive, radiation-free, and provides real-time feedback. However, the manual ultrasound imaging procedure has a few disadvantages. One significant drawback is its dependence on the experience and skill of the sonographers. But, expert availability is limited in rural and underserved regions. This limits the accessibility of ultrasound imaging for patients in these areas, leading to delayed diagnoses and potentially poorer health outcomes. The emergence of COrono VIRus Disease 2019 (COVID-19) pandemic further exposed the disadvantages of manual ultrasound procedure, which poses a risk of virus transmission to both sonographers and patients due to direct physical contact. Further, sonographers often end up having musculoskeletal disorders due to challenging postures and repetitive probe motions involved in ultrasound acquisitions. These issues emphasize the need for robotic automation of ultrasound procedures.

Robotic Ultrasound System (RUS) is an important alternative to manual ultrasound procedures. RUS can broaden the pool of skilled sonographers, enhance the safety of health-care workers during pandemics, and improve the accessibility of ultrasound in rural areas where experienced sonographers are scarce. However, the realization of RUS poses a critical challenge. It requires precise control of probe maneuvers in high-dimensional space over the patient's body while effectively interpreting complex ultrasound images, similar to the perception-to-action skill of an experienced sonographer. This thesis addressed this challenge by developing a RUS that incorporates the domain expertise of sonographers in multiple forms. First, an Expert-supervised RUS (E-RUS) is proposed that enables an expert sonographer to conduct the procedure from a remote station. This system also incorporates a novel robotic gripper that enables autonomous gel dispensing, making ultrasound scanning fully remote. Then, deep-learning-based models for UltraSound Image Quality

Assessment (US-IQA) are proposed, which are trained using a dataset of ultrasound images labeled fully or partially for quality by expert radiologists. Finally, an autonomous probe controller is developed using a Bayesian Optimization (BO) framework to efficiently search for high-quality images within the scanning region. This framework incorporates the expert's prior knowledge of probing techniques in the form of Gaussian Process (GP) model priors and kernels. The GP model is gleaned from experts' demonstrations of high-quality probing maneuvers by E-RUS and image quality feedback by the US-IQA model.

The feasibility study of E-RUS was conducted with 21 human trials at All India Institute of Medical Sciences (AIIMS), Delhi. The results demonstrated a P-value of less than 0.05 when comparing E-RUS and manually acquired ultrasound images. The system also achieved a gradual improvement of NASA-TLX test parameters and high acceptability on a questionnaire survey of doctors and volunteers. The US-IQA models were validated using ultrasound images of the human urinary bladder. The results showed that the prediction of image quality by these models closely aligned with the manual rating of expert radiologists. These models also surpassed the accuracy of the state-of-the-art models by 5-20%. The experiments on urinary bladder phantoms were conducted to validate the autonomous probe controller. The proposed framework acquired a high-quality image in relatively low 5-10 steps and sampled 50-60% more high-quality images than the standard BO. These results demonstrate the effectiveness of incorporating domain expertise for realizing an effective RUS.

Keywords: Robotic Ultrasound, Teleoperation, Gripper design, Image quality assessment, Probe controller, Deep learning, Machine learning

सार

अल्ट्रासाउंड छविमात्रा एक व्यापकता से प्रयुक्त चिकित्सा छविमात्रा विधी है जो मानव शरीर के अंदर कई संरचनाओं और ऊतकों को दृश्यमान बनाने के लिए होती है। इसने कई नैदानिक और चिकित्सात्मक प्रक्रियाओं में प्रभावी साबित होने का कारण किया है। इसमें अन्य छविमात्रा विधियों जैसे मैग्नेटिक रिज़ोनेंस इमेजिंग (MRI), कम्प्यूटेड टॉमोग्राफी (CT), और एक्स-रे की तुलना में कई लाभ हैं। यह सस्ता, विकिरण-मुक्त है, और वास्तविक समय प्रतिसाद प्रदान करता है। हालांकि, मैनुअल अल्ट्रासाउंड छविमात्रा प्रक्रिया में कुछ नकारात्मक पहलू हैं। एक महत्वपूर्ण कमी इसकी सोनोग्राफर्स की अनुभव और कौशल पर निर्भरता है। लेकिन, गाँवी और सेवा की जरूरतमंद क्षेत्रों में विशेषज्ञ उपलब्धता सीमित है। इससे इन क्षेत्रों के रोगियों के लिए अल्ट्रासाउंड छविमात्रा तक पहुँचने में सीमा आती है, जिससे देर से निदान और संभावित रूप से बीमारी के परिणाम में कमी हो सकती है। कोरोना वायरस रोग 2019 (COVID-19) महामारी के आगमन ने मैनुअल अल्ट्रासाउंड प्रक्रिया की नकारात्मक पहलूओं को और भी सामने लाया है, जो सोनोग्राफर्स और रोगियों के बीच सीधे शारीरिक संपर्क के कारण वायरस के प्रसार का खतरा पैदा करता है। इसके अलावा, सोनोग्राफर्स अक्सर अल्ट्रासाउंड अर्जनों में शारीरिक रूप से चुनौतीपूर्ण स्थितियों और पुनरावृत्ति की गतियों के कारण मांसपेशियों-संबंधित विकारों का सामना करते हैं। ये मुद्दे अल्ट्रासाउंड प्रक्रियाओं की रोबोटिक स्वचालन की आवश्यकता को जोरदार करते हैं।

रोबोटिक अल्ट्रासाउंड सिस्टम (RUS) मैनुअल अल्ट्रासाउंड प्रक्रियाओं का महत्वपूर्ण विकल्प है। RUS कई क्षमता धारित सोनोग्राफर्स के समृद्धि कर सकता है, महामारियों के दौरान स्वास्थ्य सेवा कर्मियों की सुरक्षा को बढ़ावा दे सकता है, और उन क्षेत्रों में अल्ट्रासाउंड की पहुँच को बढ़ा सकता है जहाँ अनुभवी सोनोग्राफर्स की कमी है। हालांकि, RUS की पूर्ण से सामना करना एक कठिन चुनौती है। इसमें मरीज के शरीर पर प्रोब के परिचालन की योजना की सटीक निगरानी और जटिल अल्ट्रासाउंड छवियों को सफलतापूर्वक व्याख्या करने की आवश्यकता है, जो एक अनुभवी सोनोग्राफर की अनुभूति-से-क्रिया कौशल के समान है। इस थीसिस ने इस चुनौती का सामना करने के लिए एक RUS का विकास किया है जो सोनोग्राफर्स के क्षेत्र ज्ञान को कई रूपों में शामिल करता है। पहले, एक विशेषज्ञ-निगरानीत RUS (E-RUS) की प्रस्तावित है जिससे एक विशेषज्ञ सोनोग्राफर को एक दूरस्थ स्थान से प्रक्रिया का संचालन करने की सुविधा होती है। इस सिस्टम में एक नई रोबोटिक ग्रिपर शामिल है जो स्वतंत्र रूप से जेल वितरण करने की क्षमता प्रदान करता है, जिससे अल्ट्रासाउंड स्कैनिंग पूरी तरह से दूरस्थ हो जाती है। तब, अल्ट्रासाउंड छवियों की गुणवत्ता का मूल्यांकन (US-IQA) के लिए गहरी सीख-शिक्षा आधारित मॉडल प्रस्तुत किए जाते हैं, जिन्हें एक विशेषज्ञ रेडिओलॉजिस्ट द्वारा पूरी या आंशिक गुणवत्ता के साथ चिह्नित अल्ट्रासाउंड छवियों के डेटासेट का उपयोग करके प्रशिक्षित किया गया है। अंत में, एक स्वतंत्र प्रोब नियंत्रक विकसित किया गया है जिसमें बेजियन ऑप्टिमाइज़ेशन (BO) ढांचा उच्च-विमीय स्थान पर प्रोब मुद्रण के लिए कुशल छवियों की

खोज के लिए किया जाता है। यह ढांचा समझदारी प्रकार के सोनोग्राफर्स के पूर्वज्ञान को गॉसियन प्रक्रिया (GP) मॉडल प्रायोरस और कर्नेल्स के रूप में शोधता है। GP मॉडल E-RUS द्वारा उच्च-गुणवत्ता के प्रोबिंग प्रवृत्तियों के एक्सपर्ट देखाव और US-IQA मॉडल द्वारा छवि गुणवत्ता प्रतिप्रतिक्रिया की देखरेख से हासिल किया गया है।

E-RUS के फैसिलिटी अध्ययन का परीक्षण ऑल इंडिया इंस्टीट्यूट ऑफ मेडिकल साइंसेज (AIIMS), दिल्ली में 21 मानव परीक्षकों के साथ किया गया। परिणाम ने दिखाया कि ई-आरयूएस और मैनुअल अल्ट्रासाउंड छवियों की तुलना में पी-मूल्य 0.05 से कम का परिणाम प्रदान करता है। सिस्टम ने नासा-टीएलएक्स परीक्षण पैरामीटर्स में धीरे-धीरे सुधार और डॉक्टर्स और स्वयंसेवकों के सर्वेक्षण से उच्च स्वीकृति प्राप्त की। US-IQA मॉडल्स की मान्यता मानव मूत्रशय की अल्ट्रासाउंड छवियों का उपयोग करके सत्यापित की गई। परिणामों ने दिखाया कि इन मॉडल्स द्वारा छवि गुणवत्ता का पूर्वानुमान मौजूदा रेडिओलॉजिस्ट्स की मैनुअल रेटिंग के साथ मिलता जुलता है। ये मॉडल्स अद्वितीय तकनीक के मॉडल्स की सटीकता को 5–20% से अधिक से पार करते हैं। मूत्रशय फैटम्स पर प्रयोग किए गए प्रयोग ने स्वतंत्र प्रोब नियंत्रक को मान्यता देने के लिए किए गए। प्रस्तुत ढांचा 5–10 कदमों में एक उच्च गुणवत्ता छवि हासिल करता है और मानक बीओ से 50–60% अधिक उच्च गुणवत्ता छवियों को सैंपल करता है। ये परिणाम इसे दिखाते हैं कि एक प्रभावी RUS की तय करने के लिए क्षेत्र ज्ञान को शामिल करने की क्षमता का प्रभावी उपयोग करना।

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ABBREVIATIONS

2D	Two-dimensional
3D	Three-dimensional
6D	Six-dimensional
AIIMS	All India Institute of Medical Sciences
AMI	Adjusted Mutual Information
A-RUS	Autonomous Robotic Ultrasound Systems
ARI	Adjusted Random Index
AUC	Area Under the Curve
BN	Batch Normalization
BO	Bayesian Optimization
CCE	Categorical Cross-Entropy
CDF	Cumulative Density Function
COVID-19	COrono VIRus Disease 2019
CT	Computed Tomography
CPU	Central Processing Unit
DEC	Deep Embedded Clustering
DH	Denavit–Hartenberg
DL	Deep Learning
DoF	Degrees-of-Freedom
D-CNN	Deep-Convolutional Neural Network
EI	Expected Improvement
EK	Expert Kernel
F-RCNN	Faster Region-based Convolutional Neural Network
FAST	Focused Assessment with Sonography in Trauma
GMM	Gaussian Mixture Model
GMR	Gaussian Mixture Regression
GP	Gaussian Process

Grad-CAM	Gradient-weighted Class Activation Mapping
GQR	Gaussian Quality Region
HDBSCAN	Hierarchical Density-Based Spatial Clustering of Applications with Noise
HMI	Human-Machine Interface
HQR	High Quality Region
ICC	Intra-Class Correlation
IoU	Intersection over Union
IQE	Image Quality Estimators
IRL	Inverse Reinforcement Learning
KG	Knowledge Gradient
KL	Kullback-Leibler
L-BFGS	Limited memory Broyden–Fletcher–Goldfarb–Shanno
LCB	Lower Confidence Bound
L2GSoP	Local-to-Global Second order Pooling
LSTM	Long Short-Term Memory
LUQV	Left Upper Quadrant View
MAP	Maximum A Posteriori
MSE	Mean Square Error
MS	Multi-Scale
MRI	Magnetic Resonance Imaging
M-US	Manual Ultrasound
NMI	Normalized Mutual Information
PCA	Principal Component Analysis
PDF	Probability Density Function
pHRI	physical Human-Robot Interaction
PI	Probability of Improvement
PP	Pre-Processing
PPE	Personal Protective Equipment
PT	Pre-Training
PV	Pelvic View
RAM	Random Access Memory
RBF	Radial Basis Function

ReLU	Rectified Linear Unit
ResNet	Residual Network
RGB-D	Red Green Blue-Depth
RFC	Random Forest Classifier
RoI	Region-of-Interest
ROC	Receiver Operating Characteristic
ROS	Robot Operating System
RL	Reinforcement Learning
RUS	Robotic Ultrasound Systems
RUQV	Right Upper Quadrant View
SC	Silhouette Coefficient
SOTA	State-of-the-art
SGD	Stochastic Gradient Descent
SSIM	Structural Similarity Index Measure
TEE	Transesophageal Echocardiog
TLX	Task Load Index
T-RUS	Tele-Robotic Ultrasound System
t-SNE	t-distributed Stochastic Neighbor Embedding
UMAP	Uniform Manifold Approximation and Projection
UB	Urinary Bladder
UCB	Upper Confidence Bound
US-IQA	UltraSound Image Quality Assessment
VAE	Variational AutoEncoder
ZNCC	Zero Normalized Cross Correlation

SYMBOLS

The important symbols are listed here in alphabetical order. Notational rules followed in this thesis are as follows:

- Matrices are in boldface upper-case letters.
- Column matrices, algebraic vectors and arrays are in boldface lower-case letters.
- Scalars are in light face letters.

Latin letters

a_i	Link length (DH Parameter) associated with link i
b_i	Joint offset (DH Parameter) associated with joint i
A	Scanning region
$\mathbf{B}_d$	6×6 Desired Damping matrix
$\mathbf{B}_r^i$	i^{th} Residual Block of ResNet network
$\bar{\mathbf{C}}$	Covariance matrix
$\mathbf{e}$	6-dimensional pose error vector of robot
$\mathbf{f}^e$	3-dimensional force error vector of robot
$\mathbf{f}_d$	3-dimensional desired force vector of robot
$\mathbf{f}^g$	3-dimensional force vector of geomagic haptic device
$\mathbf{f}^r$	3-dimensional force vector of robot
f_r	Residual function
$\mathbf{I}_n$	Identity matrix of dimension $n \times n$
$\mathcal{I}$	Ultrasound Image
$\mathbf{K}_d$	6×6 Desired Stiffness matrix
L_{BCE}	Binary cross-entropy loss for segmentation network
L_{DC}	Dice coefficient loss for segmentation network
L_{JI}	Jaccard index loss for segmentation network
$\mathbf{M}_d$	6×6 Desired Inertia matrix

$\mathbf{o}^g$	3-dimensional orientation vector of geomagic haptic device
$\mathbf{o}$	3-dimensional orientation vector of robot
$\mathbf{x}^g$	3-dimensional position vector of geomagic haptic device
$\mathbf{x}$	3-dimensional position vector of robot
$\mathbf{p}$	6-dimensional pose vector of robot or robotic probe consisting of 3-dimensional position vector $\mathbf{x}$ and 3-dimensional orientation vector $\mathbf{o}$
$\mathbf{p}^*$	Predicted probe pose
$\bar{\mathbf{p}}$	Probe poses vector of dimension n
$\mathbf{P}(\Lambda)$	Diagonal matrix where each diagonal term is the power of Eigenvalue represented by $p(\lambda)$
$\mathbf{Q}_o$	Image quality feature map
$\mathbf{q}_o$	Image quality feature vector
q	Image quality value
$\bar{\mathbf{q}}$	Quality values vector of dimension n
$\mathbf{q}^+$	Best observed image quality so far during optimization
q_e	Expert-defined ultrasound image quality score
q_s	Segmentation-based ultrasound image quality score
s	Smoothness coefficient
t_s	Sampling time period
$\mathbf{u}_i$	i^{th} Eigenvector
$\mathbf{U}$	Orthogonal matrix whose i^{th} column is eigenvector $\mathbf{u}_i$ corresponding to eigenvalue λ_i
$\mathbf{v}^g$	3-dimensional linear velocity vector of geomagic haptic device
$\mathbf{V}_i$	i^{th} channel weighted dimension feature volume
$\mathbf{w}_i$	i^{th} channel weight vector
$\mathbf{X}$	3-dimensional image feature volume
$\mathbf{y}_p$	Predicted mask of ultrasound image
$\mathbf{y}_t$	Ground-truth mask of ultrasound image
$\mathbf{z}$	Latent variable of latent space in VAE
$\mathbf{1}$	Identity vector

Greek letters

$\alpha_\phi, \alpha_\theta, \alpha_\psi$	Scaling factors for roll (ϕ), pitch (θ), and yaw (ψ), respectively
α_i	Twist angle (DH Parameter) associated with link i
α_v	Velocity scaling factor
$\delta_\phi, \delta_\theta, \delta_\psi$	Offset factors for roll (ϕ), pitch (θ), and yaw (ψ), respectively
ϵ	Exploration-exploitation trade-off parameter
$\mathcal{E}(\theta)$	Expert's prior
$\mathbf{k}(\mathbf{p}_i, \mathbf{p}_j)$	Kernel matrix of GP
$\mathbf{k}_E(\mathbf{p}_i, \mathbf{p}_j)$	Expert's Kernel matrix of GP
λ	Eigenvalue
Λ	Diagonal matrix of eigenvalues λ
$\mathcal{L}(\theta \bar{\mathbf{p}}, \bar{\mathbf{q}})$	Log-marginal likelihood function
μ	Mean function
$\mathcal{N}(\mu, \sigma)$	Normal distribution with mean μ and variation σ
Φ	Probability density function
ϕ	Cumulative density function
θ_i	Joint angle (DH Parameter) associated with joint i
θ	BO hyperparameters consisting of overall variance σ_r , noise variance σ_w , and length scale l
$\Theta(\mathbf{p}_i)$	Output of the neural network for modeling expert's kernel
σ_r	ReLU activation