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Data Article

IQ-UltraRecon: Demodulated IQ ultrasound dataset of human hand and arm tissue for deep learning-based reconstruction

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Dataset link: The dataset supporting this article is available on Mendeley Data at: https://data.mendeley.com/datasets/tm9tjpg542/1. The complete code for loading and visualizing the IQ data, along with a README file providing detailed usage instructions, is archived on Zenodo at: https://doi.org/10.5281/zenodo.16462892

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ABSTRACT

This dataset presents demodulated in-phase *(I)* and quadrature *(Q)* ultrasound data collected from the human hand and forearm using a Verasonics Vantage 64LE system with an L11–5v linear array transducer. A total of 48 .mat files have been acquired from healthy adult subjects, yielding 4800 data samples. The dataset comprises both single-angle and multi-angle acquisitions, indicated in the filenames, and includes raw IQ data prior to B-mode image formation. Multi-angle files capture sequences with shape (400, 2, 256, 256), representing two channels *(I and Q)* across multiple insonification angles. Single-angle files provide spatially consistent data for baseline comparison. This dataset supports research in ultrasound signal analysis, beamforming alternatives, and deep learning-based image reconstruction. All data are stored in MATLAB format, are anonymized, and are publicly available through Mendeley Data.

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Specifications Table

Subject	Medical AI, Deep Learning, Signal Processing
Specific subject area	Demodulated IQ ultrasound signal data from hand and arm tissue
Type of data	Raw signal data; MATLAB .mat files; demodulated *I* and *Q* components
Data collection	Data has been acquired using a Verasonics Vantage 64LE ultrasound system with an L11–5v linear array transducer. Each .mat file contains single- or multi-angle acquisitions with demodulated *I* and *Q* signal components
Data source location	Pusan National University, Busan, Republic of Korea
Data accessibility	Repository name: Mendeley data Data identification number: doi: 10.17632/tm9tjpg542.1 Direct URL to data: https://data.mendeley.com/datasets/tm9tjpg542/1
Related research article	None

1. Value of the Data

- This dataset provides demodulated in-phase *(I)* and quadrature *(Q)* ultrasound data before B-mode image formation, offering access to raw signal features for advanced analysis and algorithm development.
- Researchers working on deep learning–based ultrasound reconstruction, beamforming, or RF-signal modeling can use this dataset to develop and validate methods with both single- and multi-angle acquisitions.
- The dataset supports the development of models such as signal-to-image networks, adaptive beamformers, and phase-aware reconstructions by providing clean, directional IQ sequences.
- Its structured multi-angle data format ($400 \times 2 \times 256 \times 256$) allows for simulation of spatial compounding, coherence-based methods, and contrast enhancement using angle diversity.
- This dataset may serve as a foundation for comparative studies between traditional image formation pipelines and AI-driven direct signal-to-image approaches.

2. Background

This dataset has been collected to support the development of deep learning models that operate directly on demodulated in-phase *(I)* and quadrature *(Q)* ultrasound signals before traditional B-mode conversion. Raw IQ signals are often discarded in standard imaging pipelines, despite containing rich amplitude and phase information useful for beamforming, coherence analysis, and signal-level reconstructions. By acquiring both single-angle and multi-angle data from human hand and arm tissue, this dataset offers a diverse and realistic signal source suitable for machine learning tasks involving directional encoding, compounding, or signal-to-image translation. The dataset is motivated by the need for open-access, high-quality raw ultrasound datasets for AI research that go beyond post-processed B-mode images.

3. Data Description

This dataset comprises **4800 demodulated ultrasound signal samples**, stored across 48 MATLAB .mat files [1]. Each file contains either in-phase *(I)* or quadrature *(Q)* components of raw ultrasound signals, acquired from the hand and forearm regions of human subjects using a Verasonics ultrasound system. The dataset is intended to support signal-level analysis and deep learning-based ultrasound reconstruction.

All files are organized in a **flat directory** without subfolders. Each file is named using a structured format that encodes metadata, including acquisition date, subject ID, session number, number of frames, and signal type.

Table 1
Categorization of .mat files based on signal type, acquisition view, and array structure.

Type	View	Shape (samples, channels, height, width)	Description
I data	Single-angle	(1, 1, 256, 256)	Single-frame I-channel data
I data	Multi-angle	(400, 1, 256, 256)	Sequence of I-channel frames from varying angles
Q data	Single-angle	(1, 1, 256, 256)	Single-frame Q-channel data
Q data	Multi-angle	(400, 1, 256, 256)	Sequence of Q-channel frames from varying angles

a) File Naming Format: [Date]_[SubjectID]_[Session]_[FrameCount]_[SignalType].mat
Where:
 - *im = In-phase, multi-angle*
 - *is = In-phase, single-angle*
 - *qm = Quadrature, multi-angle*
 - *qs = Quadrature, single-angle*

b) Examples of Files in Repository:
 - *240,819_EH_01_01_100_im.mat — In-phase, multi-angle*
 - *240,819_EH_01_01_100_is.mat — In-phase, single-angle*
 - *240,819_EH_01_01_100_qm.mat — Quadrature, multi-angle*
 - *240,819_EH_01_01_100_qs.mat — Quadrature, single-angle*

c) Data Structure:
Each .mat file contains a variable, *img_iq*, representing either the *I* or *Q* signals. The files organized into four categories are described in Table 1.

In cases where both *I* and *Q* components are stored together, the shape is: (400, 2, 256, 256), where the second-dimension indexes *[I, Q]* channels.

All data files are compatible with standard Python and MATLAB toolchains using functions such as scipy.io.loadmat, and are ready for use in preprocessing, reconstruction, and learning-based frameworks.

4. Experimental Design, Materials and Methods

4.1. Data collection

Ultrasound IQ data has been acquired using a Verasonics Vantage 64LE system equipped with an L11–5v linear array transducer (1D array). The acquisition is focused on the hand and forearm regions of healthy adult volunteers. Ultrasound gel has been deployed as a coupling agent to manually hold the probe on the skin. Insonification is performed under both single-angle and multi-angle plane wave transmission schemes.

The multi-angle acquisition protocol involved 400 frames captured at varying steering angles within $a \pm 15°$ sector. The acquisition parameters used are summarized in Table 2. The in-phase *(I)* and quadrature *(Q)* components are acquired directly from the system at the RF demodulated stage, before envelope detection or scan conversion. All subjects provided informed consent, and the data collection procedure is approved by the Institutional Review Board (IRB) of Pusan National University (Protocol No. PNU-2025–001). The acquisition parameters used are summarized in Table 2.

Each dataset file has been saved in .mat format and contains either single-view (1 frame) or multi-angle (400 frames) acquisitions.

Table 2
Ultrasound Transducer Specifications.

Parameter	Specification
Ultrasound system	Verasonics Vantage 64 LE
Transducer	L11–5v (1D array)
Element spacing	0.3 mm
Center frequency	7.6 MHz
Bandwidth	[4.68 MHz – 10.52 MHz]
Pulser voltage	11.3 V
Interpolation	4 pt
Transmit wave	Plane wave (zero-angle or steered)
Frame rate	60 fps

4.2. Data visualization

To illustrate the structural characteristics of the demodulated IQ ultrasound data, representative frames were visualized from each data category. A total of 16 images were plotted in a 4×4 grid where **rows** correspond to the four data types—***I* type (Single Angle), *I* type (Multi Angle), *Q* type (Single Angle)**, and ***Q* type (Multi Angle)**—and **columns** represent sequential frames (Frame 0 to Frame 3) extracted from each .mat file.

Two distinct visualization strategies are employed. First, **logarithmic compression** [8] is applied to the IQ signal amplitudes to improve contrast and enhance the visibility of subtle anatomical and signal features that are otherwise difficult to discern due to the high dynamic range of ultrasound data. These log-compressed images are plotted using the **'jet' colormap**, which offers a wide spectral gradient and is commonly used for visual interpretation of intensity variations, as shown in Fig. 1.

In contrast, the second set of visualizations presents the **raw (uncompressed)** IQ data, preserving its native intensity values. These are rendered using the **'gray' colormap**, which provides an unbiased representation of signal intensity without dynamic range manipulation, allowing for faithful inspection of raw signal structures as depicted in Fig. 2. This form of visualization is particularly valuable for assessing raw data characteristics before preprocessing or input into signal-based learning pipelines.

These dual-mode visualizations offer insight into both the qualitative signal content and potential transformations that can be applied before downstream modeling, such as beamforming, B-mode reconstruction, or data augmentation in learning-based frameworks.

To support reproducibility, a Python code snippet is provided below, illustrating how to load a .mat file, access the img_iq variable, apply log compression, and visualize a single frame. Additional code examples and detailed usage instructions are included in the README file, which is available in the code repository (see Data Availability section).

```
import scipy.io
import numpy as np
import matplotlib.pyplot as plt

# Load the .mat file
mat = scipy.io.loadmat ('/content/240,819_EH_01_01_100_qs.mat')

# Show available keys
print("Available keys:", mat.keys())

# Load the actual variable
data = mat['img_qs']
print(f"\nLoaded variable: img_qs")
print("Original data shape:", data.shape)
```

```
# Remove singleton dimensions
data = np.squeeze(data)
print("Squeezed data shape:", data.shape)

# Handle non-finite values by replacing them with a small positive
  number
data[~np.isfinite(data)] = 1e-9

# Apply log compression

# Add a small constant to avoid log(0) - np.log1p already handles
  the +1
data_compressed = np.log1p(data)
print("Applied log compression.")

# Plot the last frame if 3D
if data_compressed.ndim == 3:
```

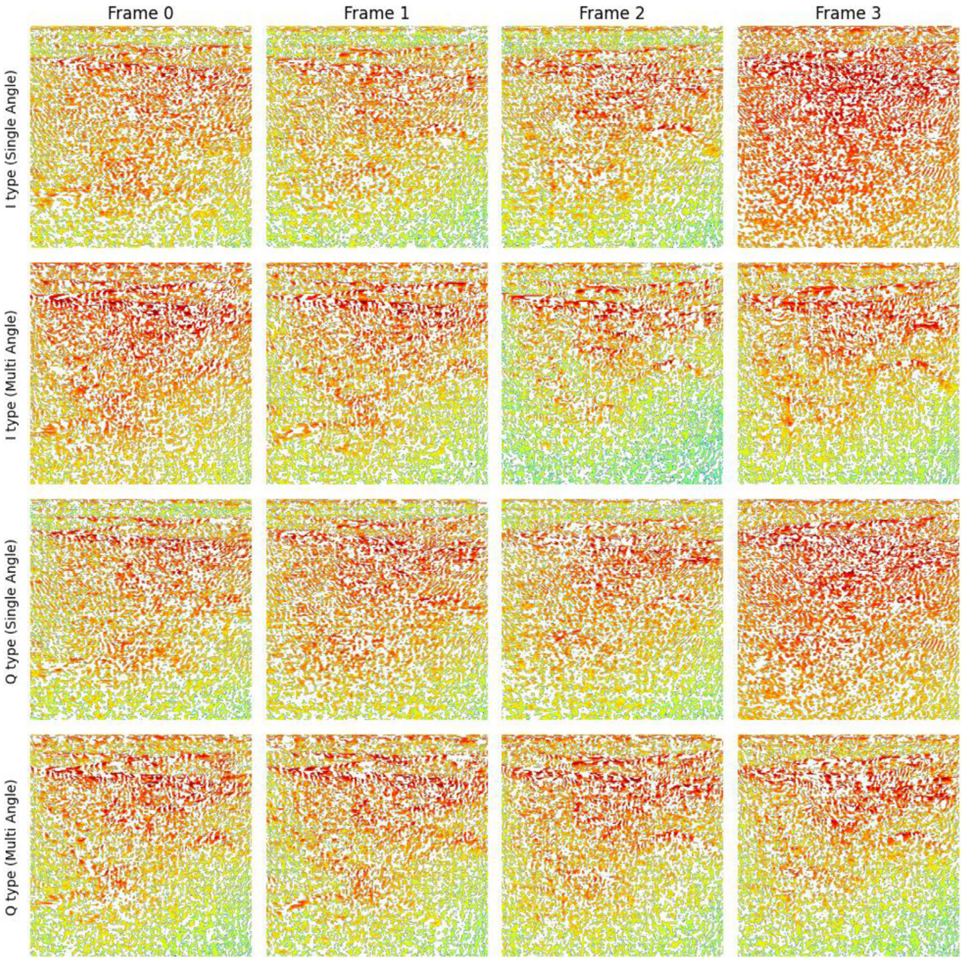

Fig. 1. Visualization of IQ ultrasound data after log compression with 'jet' colormap. (Rows: Data Types, Columns: Frame Index.

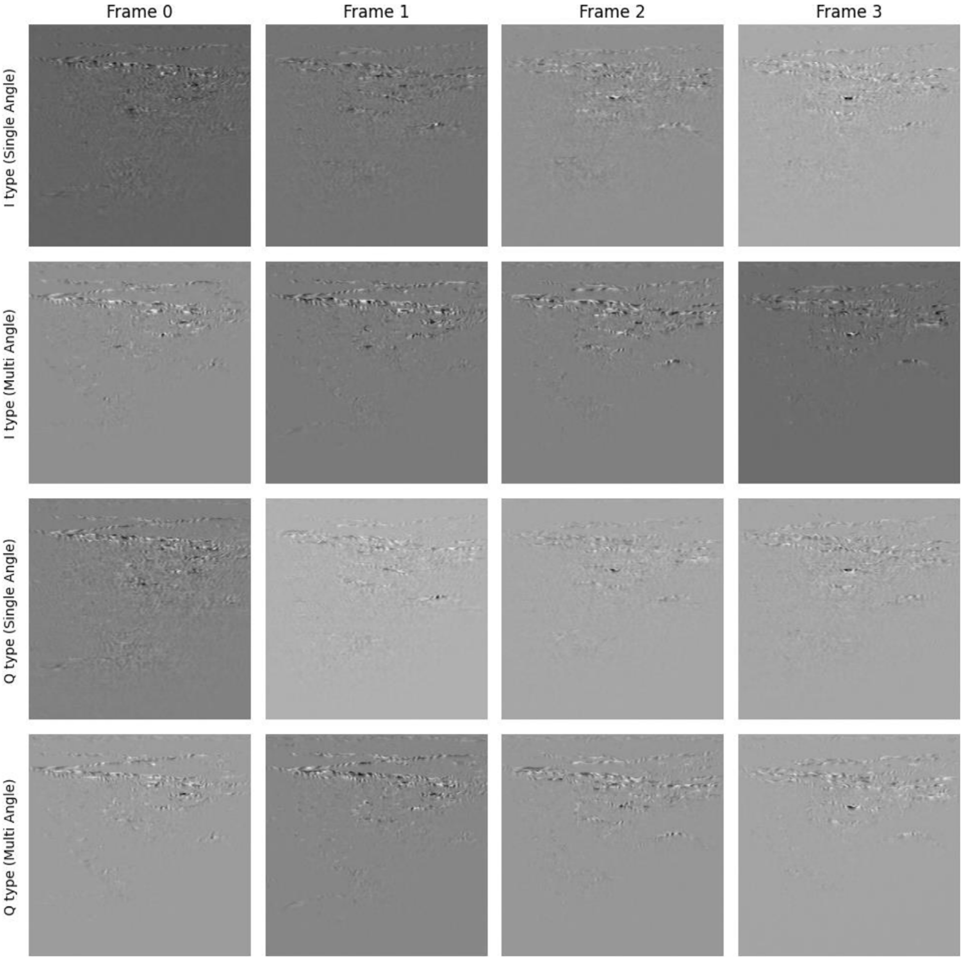

Fig. 2. Visualization of raw IQ ultrasound data without compression using 'gray' colormap. (Rows: Data Types, Columns: Frame Index).

```
    plt.imshow(data_compressed[:,:, -1], cmap='jet')
    plt.show()
else:
    print("Data is not 3D after squeezing.")
```

4.3. Data preprocessing

All ultrasound data are exported in MATLAB .mat format as raw demodulated in-phase (I) and quadrature (Q) components. These files contain a single variable *img_iq*, which encodes either one or both channels depending on the signal type.

No signal conditioning, scan conversion, or envelope detection was applied during acquisition, preserving the raw signal fidelity. Before using the dataset in machine learning pipelines, standard preprocessing steps are recommended. These include:

- **Axis standardization**: Ensuring consistent axis order (e.g., channels-first or channels-last) based on deep learning framework requirements (PyTorch, TensorFlow).
- **Data normalization**: Scaling pixel values to a uniform range (e.g., [0, 1]) or applying Z-score normalization to stabilize learning dynamics.
- **Logarithmic compression**: Applied to magnitude signals to reduce dynamic range and improve perceptual contrast for image-based processing.
- **Frame selection**: For multi-angle data, specific angular frames can be extracted to simulate specific clinical acquisition settings or to train angle-resilient models.
- **Channel merging**: In models requiring both *I* and *Q* channels, tensors of shape (n_frames, 2, 256, 256) can be merged or treated as two-channel input for CNN-based architectures.

All preprocessing operations are compatible with Python-based toolchains such as NumPy, SciPy, and PyTorch. The dataset structure supports seamless batching, slicing, and on-the-fly transformations during model training.

4.4. Possible deep learning algorithms

The demodulated IQ dataset enables several advanced deep learning tasks in ultrasound imaging research. Below are recommended algorithmic directions, organized by application category:

a) IQ-to-B-mode Image Reconstruction
   - U-Net, ResU-Net, or Dense U-Net architectures can be trained to convert raw IQ inputs into high-quality B-mode images using paired data or supervised learning objectives [4].
   - Pix2Pix and CycleGAN frameworks may also be applied for paired or unpaired IQ-to-B-mode transformations with adversarial training [3].

b) Super-Resolution and Image Enhancement
   - TransCycleGAN is particularly suited for learning mappings between low-quality and high-quality images across domains (e.g., narrow-angle to wide-angle reconstructions) [2].
   - ESRGAN (Enhanced SRGAN) and SwinIR (Transformer-based SR) may be used to improve structural detail in B-mode images synthesized from IQ inputs [5,6].
   - 3D convolutional models (e.g., 3D U-Net) can exploit spatio-angular context from multi-angle IQ volumes.

c) Denoising and Signal Restoration
   - DnCNN and FFDNet architectures can be trained using noisy-clean frame pairs extracted from the dataset [7].
   - Autoencoder-based models can be used for unsupervised IQ noise suppression and latent space compression.

d) Angular Feature Learning
   - Recurrent Neural Networks (RNNs) and Temporal Convolutional Networks (TCNs) can model dependencies across angular views.
   - Attention-based models (e.g., Vision Transformers, Temporal Transformers) can be employed to learn spatial and directional patterns in multi-angle datasets.

e) Cross-Domain Applications
   - Multitask Learning architectures can use the dataset for joint tasks such as B-mode reconstruction and tissue classification.
   - Contrastive Learning can be applied to learn angle-invariant feature embeddings using augmentations of multi-angle IQ frames.

These architectures require minimal modifications to ingest IQ data in 2D or 3D tensor formats, making this dataset highly adaptable for experimental algorithm design and benchmarking.

Limitations

The primary limitation of this dataset lies in its sample diversity. All IQ ultrasound data are acquired from a limited number of healthy adult volunteers under controlled laboratory conditions, which limits their use in disease-related or pathological studies. Future dataset extensions will aim to include pathological cases and clinically diverse samples to improve applicability in diagnostic contexts.

Additionally, although both single-angle and multi-angle acquisitions are included, the insonification angles are confined within $\pm 15^{\circ}$, which may not represent the full range of probe steering used in some clinical scenarios. The data are acquired using a single transducer model (L11–5v) and a fixed center frequency, limiting variability in probe characteristics and frequency-dependent behavior.

No phantoms or tissue-mimicking models are included in this dataset, which may reduce its applicability for calibration or material characterization studies. Finally, while the dataset size (4800 frames) is sufficient for exploratory and supervised training tasks, it may require augmentation or transfer learning strategies for deep learning models with large parameter counts.

Ethics Statement

This dataset has been acquired as part of a study approved by the IRB of Pusan National University (Protocol No. PNU-2025–001) and conducted under ethical approval from the Pusan National University IRB (2023–74-HR), ensuring compliance with human research guidelines. All volunteers provided written informed consent, and the data have been fully anonymized before processing and sharing.

Data Availability

The dataset supporting this article is available on Mendeley Data at: https://data.mendeley.com/datasets/tm9tjpg542/1. The complete code for loading and visualizing the IQ data, along with a README file providing detailed usage instructions, is archived on Zenodo at: https://doi.org/10.5281/zenodo.16462892 (Demodulated IQ Ultrasound Data of Human Hand and Arm Tissue (Original data)).

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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