The Journal of Open Source Software

zea: A Toolbox for Cognitive Ultrasound Imaging

Tristan S. W. Stevens [1¶], **Wessel L. van Nierop** [1], **Ben Luijten** [1], **Vincent van de Schaft** [1], **Oisín Nolan** [1], **Beatrice Federici** [1], **Louis D. van Harten** [1], **Simon W. Penninga** [1], **Noortje I. P. Schueler** [1], and **Ruud J. G. van Sloun** [1]

1 Eindhoven University of Technology, the Netherlands ¶ Corresponding author

DOI: 10.xxxxxx/draft

Software

- Review
- Repository
- Archive

Editor: Adam Tyson

Reviewers:

- @tomelse
- @benfrey
- @rafaelorozco

Submitted: 25 June 2025
Published: unpublished

Summary

Ultrasound imaging is a powerful medical imaging modality that is widely used in clinical settings for various applications, including obstetrics, cardiology, and abdominal imaging. While ultrasound imaging is non-invasive, real-time, and relatively low-cost compared to other imaging modalities such as MRI or CT, it still faces challenges in terms of image quality and interpretation. Many signal processing steps are required to extract useful information from the raw ultrasound data, such as filtering, beamforming, and image reconstruction. Traditional ultrasound imaging techniques often suffer from reduced image quality as naive assumptions are made in these processing steps, which do not account for the complex nature of ultrasound signals. Furthermore, acquisition (action) and reconstruction (perception) of ultrasound is often performed disjointly. Cognitive ultrasound imaging (Sloun, 2024), see Figure 1, is a novel approach that aims to address these challenges by leveraging more powerful generative models, enabled by advances in deep learning, to close the action-perception loop. This approach requires a redesign of current common ultrasound imaging pipeline, where parameters are expected to be changed dynamically based on past and current observations. Furthermore, the high-dimensional nature of ultrasound data requires powerful deep generative models to learn the structured distribution of ultrasound signals and to effectively solve inverse problems that capture the challenges of ultrasound imaging (Stevens, Overdevest, et al., 2025). This necessitates a flexible and efficient toolbox that can handle the complexities of cognitive ultrasound imaging, including a real-time ultrasound reconstruction pipeline, dynamic parameter adjustment, and advanced generative modeling.

We present zea (pronounced *ze-yah*), a Python package for cognitive ultrasound imaging that provides a flexible, modular and differentiable pipeline for ultrasound data processing, as well as a collection of pre-defined models for ultrasound image and signal processing. The toolbox is designed to be easy to use, with a high-level interface that allows users to define their own ultrasound reconstruction pipelines, and to integrate deep learning models into the pipeline. The toolbox is built on top of Keras 3 (Chollet & others, 2015), which provides a framework for building and training deep learning models with the three major deep learning frameworks as backend: TensorFlow (Abadi et al., 2016), PyTorch (Paszke et al., 2019) and JAX (Bradbury et al., 2018). This means that it is easy to integrate a custom ultrasound reconstruction pipeline in a machine learning workflow. In the past few years, several works have used and contributed to zea, including Luijten et al. (2020), Schaft et al. (2025), Stevens et al. (2024), Nolan et al. (2025), Federici et al. (2025), Stevens, Nolan, Robert, et al. (2025), Penninga et al. (2025) and Stevens, Nolan, Somphone, et al. (2025).

The Journal of Open Source Software

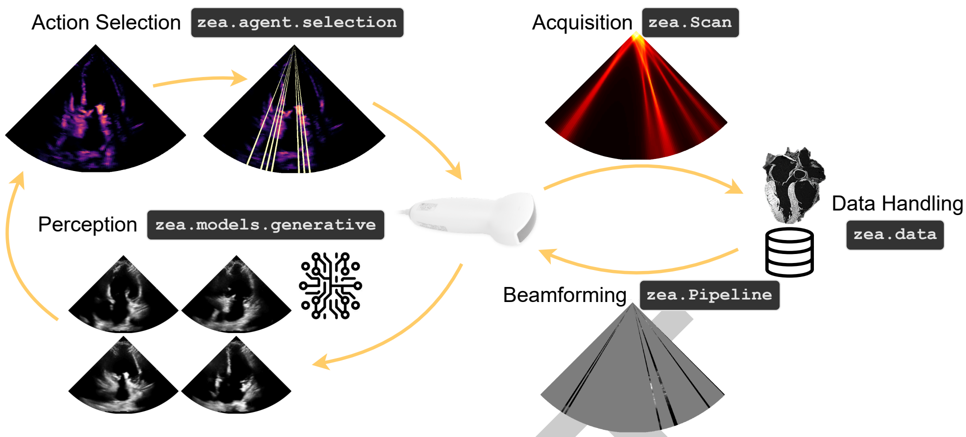

Figure 1: High-level overview of an ultrasound perception-action loop implemented in zea.

Statement of need

The ultrasound research community has advanced significantly due to publically available high-quality software, including simulation tools such as `Field II` (Jensen, 2004) and `k-wave` (Treeby & Cox, 2010), as well as reconstruction and real-time processing libraries like `USTB` (Rodriguez-Molares et al., 2017), `MUST` (Garcia, 2021), `ARRUS` (Jarosik & others, 2020), `FAST` (Smistad, 2021), `QUPS` (Brevett, 2024), and `vbeam` (Kvalevåg et al., 2023). However, existing solutions are not well-equipped for cognitive ultrasound imaging, where the integration of deep learning and dynamic, closed-loop ultrasound reconstruction pipelines is essential. Our aim with zea is to provide a complementary, highly flexible and differentiable pipeline written in a modern deep learning framework, as well as offer a convenient platform for pretrained models. This addresses the need for a modular and extensible library that supports cognitive ultrasound workflows and seamless integration with state-of-the-art machine learning models. While the full realization of cognitive ultrasound imaging remains an ongoing effort, we hope this toolbox will help spur further research and development in the field.

Overview of functionality

zea is an open-source Python package, available at http://github.com/tue-bmd/zea, that consists of the following core components:

- **Data**: A set of data handling classes such as `zea.data.File`, `zea.data.Dataset` and `make_dataloader()`, suited for machine learning workflows. zea works with HDF5 files, storing data and acquisition parameters together in a single file, which can be easily loaded and saved through the `zea.data` API. For more demanding workflows, such as training deep learning models, zea offers robust data loading utilities such as batching, shuffling, caching, and preprocessing. Additionally, we provide examples and conversion scripts for popular ultrasound datasets, such as CAMUS (Leclerc et al., 2019), PICMUS (Liebgott et al., 2016), and EchoNet (Ouyang et al., 2020).
- **Pipeline**: A modular and differentiable pipeline class that allows users to define a sequence of operations (`zea.Operation`) to process ultrasound data. The pipeline is stateless and supports *Just in Time* (JIT) compilation. Ultimately, this allows for dynamic parameter adjustment, as well as real-time integration of deep learning models inside the ultrasound reconstruction pipeline.
- **Models**: A collection of pre-defined models for ultrasound image and signal processing. Similar to the data, these models can be loaded locally or from the Hugging Face Hub.

The Journal of Open Source Software

Besides supervised models, zea also provides a set of (deep) generative models, with an interface to solve inverse problems in ultrasound imaging within a probabilistic machine learning framework.

- **Agents**: A set of tools to interact with the pipeline and models. These agents can be used to alter the pipeline parameters, or select a subset of acquired data. The agent module closes the action-perception loop (Sloun, 2024), tying together acquisition and reconstruction of ultrasound data.

For detailed examples and use cases, please refer to the example notebooks available on the documentation: https://zea.readthedocs.io/.

Availability, Development, and Documentation

zea is available through PyPI via `pip install zea`, and the development version is available via GitHub. GitHub Actions manage continuous integration through automated code testing (PyTest), code linting and formatting (Ruff), and documentation generation (Sphinx). The documentation is hosted on ReadTheDocs. At the time of writing, 20 example notebooks are available, covering the various discussed components of the toolbox. The package is licensed under the Apache License 2.0, which allows for both academic and commercial use.

References

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, S., Murray, D. G., Steiner, B., Tucker, P. A., Vasudevan, V., Warden, P., … Zheng, X. (2016). TensorFlow: A System for Large-scale Machine Learning. In K. Keeton & T. Roscoe (Eds.), *12th USENIX symposium on operating systems design and implementation, OSDI 2016, savannah, GA, USA, november 2-4, 2016* (pp. 265–283). USENIX Association. https://www.usenix.org/conference/osdi16/technical-sessions/presentation/abadi

Bradbury, J., Frostig, R., Hawkins, P., Johnson, M. J., Leary, C., Maclaurin, D., Necula, G., Paszke, A., VanderPlas, J., Wanderman-Milne, S., & Zhang, Q. (2018). *JAX: Composable transformations of Python+NumPy programs* (Version 0.3.13). http://github.com/jax-ml/jax

Brevett, T. (2024). QUPS: A MATLAB Toolbox for Rapid Prototyping of Ultrasound Beamforming and Imaging Techniques. *J. Open Source Softw.*, *9*(101), 6772. https://doi.org/10.21105/JOSS.06772

Chollet, F., & others. (2015). *Keras*. https://keras.io.

Federici, B., Sloun, R. J. G. van, & Mischi, M. (2025). Active Inference for Closed-loop Transmit Beamsteering in Fetal Doppler Ultrasound. *IEEE Open Journal of Ultrasonics, Ferroelectrics, and Frequency Control*, 1–1. https://doi.org/10.1109/OJUFFC.2025.3636108

Garcia, D. (2021). Make the most of MUST, an open-source Matlab UltraSound Toolbox. *2021 IEEE International Ultrasonics Symposium (IUS)*, 1–4. https://doi.org/10.1109/IUS52206.2021.9593605

Jarosik, P., & others. (2020). *ARRUS: Research/remote ultrasound platform*. https://github.com/us4useu/arrus

Jensen, J. A. (2004). Simulation of advanced ultrasound systems using Field II. *2004 2nd IEEE International Symposium on Biomedical Imaging: Nano to Macro (IEEE Cat No. 04EX821)*, *1*, 636–639. https://doi.org/10.1109/ISBI.2004.1398618

Kvalevåg, M. D., Vrålstad, A. E., Rindal, O. M. H., Bjåstad, T. G., Denarie, B., Kristoffersen, K., Måsøy, S.-E., & Løvstakken, L. (2023). Vbeam: A Fast and Differentiable Beamformer for Optimizing Ultrasound Imaging. *2023 IEEE International Ultrasonics Symposium (IUS)*, 1–4. https://doi.org/10.1109/IUS51837.2023.10307255

Leclerc, S., Smistad, E., Pedrosa, J., Østvik, A., Cervenansky, F., Espinosa, F., Espeland, T., Berg, E. A. R., Jodoin, P.-M., Grenier, T., Lartizien, C., D'hooge, J., Løvstakken, L., & Bernard, O. (2019). Deep Learning for Segmentation Using an Open Large-scale Dataset in 2D Echocardiography. *IEEE Trans. Medical Imaging*, *38*(9), 2198–2210. https://doi.org/10.1109/TMI.2019.2900516

Liebgott, H., Rodriguez-Molares, A., Cervenansky, F., Jensen, J. A., & Bernard, O. (2016). Plane-wave Imaging Challenge in Medical Ultrasound. *2016 IEEE International Ultrasonics Symposium (IUS)*, 1–4. https://doi.org/10.1109/ULTSYM.2016.7728908

Luijten, B., Cohen, R., Bruijn, F. J. de, Schmeitz, H. A. W., Mischi, M., Eldar, Y. C., & Sloun, R. J. G. van. (2020). Adaptive Ultrasound Beamforming Using Deep Learning. *IEEE Trans. Medical Imaging*, *39*(12), 3967–3978. https://doi.org/10.1109/TMI.2020.3008537

Nolan, O., Stevens, T. S. W., Nierop, W. L. van, & Sloun, R. van. (2025). Active Diffusion Subsampling. *Trans. Mach. Learn. Res.*, *2025*. https://openreview.net/forum?id=OGifiton47

Ouyang, D., He, B., Ghorbani, A., Yuan, N., Ebinger, J., Langlotz, C. P., Heidenreich, P. A., Harrington, R. A., Liang, D. H., Ashley, E. A., & others. (2020). Video-based AI for beat-to-beat assessment of cardiac function. *Nature*, *580*(7802), 252–256. https://doi.org/10.1038/s41586-020-2145-8

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Köpf, A., Yang, E. Z., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., … Chintala, S. (2019). PyTorch: An Imperative Style, High-performance Deep Learning Library. In H. M. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. B. Fox, & R. Garnett (Eds.), *Advances in neural information processing systems 32: Annual conference on neural information processing systems 2019, NeurIPS 2019, december 8-14, 2019, vancouver, BC, canada* (pp. 8024–8035). https://proceedings.neurips.cc/paper/2019/hash/bdbca288fee7f92f2bfa9f7012727740-Abstract.html

Penninga, S. W., Gorp, H. V., & Sloun, R. J. G. van. (2025). Deep Sylvester Posterior Inference for Adaptive Compressed Sensing in Ultrasound Imaging. *2025 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2025, Hyderabad, India, April 6-11, 2025*, 1–5. https://doi.org/10.1109/ICASSP49660.2025.10888253

Rodriguez-Molares, A., Rindal, O. M. H., Bernard, O., Nair, A., Lediju Bell, M. A., Liebgott, H., Austeng, A., & LØvstakken, L. (2017). The UltraSound ToolBox. *2017 IEEE International Ultrasonics Symposium (IUS)*, 1–4. https://doi.org/10.1109/ULTSYM.2017.8092389

Schaft, V. van de, Nolan, O., & Sloun, R. J. G. van. (2025). Off-grid Ultrasound Imaging by Stochastic Optimization. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, *72*, 1245–1255. https://doi.org/10.1109/TUFFC.2025.3586377

Sloun, R. J. G. van. (2024). Active inference and deep generative modeling for cognitive ultrasound. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, *71*(11), 1478–1490. https://doi.org/10.1109/TUFFC.2024.3466290

Smistad, E. (2021). FAST: A framework for high-performance medical image computing and visualization. In S. McIntosh-Smith (Ed.), *IWOCL'21: International workshop on OpenCL, munich germany, april, 2021* (pp. 14:1–14:2). ACM. https://doi.org/10.1145/3456669.3456717

Stevens, T. S. W., Meral, F. C., Yu, J., Apostolakis, I. Z., Robert, J.-L., & Sloun, R. J. G. van. (2024). Dehazing Ultrasound Using Diffusion Models. *IEEE Trans. Medical Imaging*, *43*(10), 3546–3558. https://doi.org/10.1109/TMI.2024.3363460

Stevens, T. S. W., Nolan, O., Robert, J.-L., & Sloun, R. J. G. van. (2025). Sequential Posterior Sampling with Diffusion Models. *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Hyderabad, India*, 1–5. https://doi.org/10.1109/ICASSP49660.2025.10889752

Stevens, T. S. W., Nolan, O., Somphone, O., Robert, J.-L., & Sloun, R. J. G. van. (2025). High Volume Rate 3D Ultrasound Reconstruction with Diffusion Models. *IEEE Trans. Medical Imaging*. https://doi.org/10.1109/TMI.2025.3645849

Stevens, T. S. W., Overdevest, J., Nolan, O., Nierop, W. L. van, Sloun, R. J. G. van, & Eldar, Y. C. (2025). Deep generative models for Bayesian inference on high-rate sensor data: Applications in automotive radar and medical imaging. *Philosophical Transactions A*, *383*(2299), 20240327. https://doi.org/10.1098/rsta.2024.0327

Treeby, B. E., & Cox, B. T. (2010). K-Wave: MATLAB toolbox for the simulation and reconstruction of photoacoustic wave fields. *Journal of Biomedical Optics*, *15*(2), 021314–021314. https://doi.org/10.1117/1.3360308