INVERSE DESIGN OF PMUT USING DEEP REINFORCEMENT LEARNING WITH A VIEW TO CUSTOMIZED OPERATING FREQUENCY AND BROADENED BANDWIDTH

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ABSTRACT

This paper introduces an inverse design framework using deep reinforcement learning (DRL) to optimize Piezoelectric Micromachined Ultrasonic Transducers (PMUTs) through non-standard diaphragm geometries, moving beyond traditional circular or rectangular patterns. The framework achieves three key advances: 1) demonstration of -3dB fractional bandwidth reaching 113.7% in the array while maintaining precise frequency control (±0.1MHz) for the cells, 2) automated generation of PMUT design without prior training data, and 3) validation of practical feasibility through a fabricated 40-channel linear PMUT array.

KEYWORDS

Artificial Intelligence, Piezoelectric Micromachined Ultrasonic Transducers; Deep Reinforcement Learning; Fractional Bandwidth; Frequency Control

INTRODUCTION

Piezoelectric micromachined ultrasonic transducers (PMUTs) have become critical components in modern miniaturized systems, enabling advancements in medical diagnostics, fingerprint recognition, and industrial sensing [1]. Their compact size, low power consumption, low cost for mass production, and CMOS compatibility make them particularly attractive for portable devices and implantable medical tools [2]. In medical imaging, where PMUT arrays transmit and receive acoustic signals through biological tissues, fractional bandwidth (bandwidth over center frequency) directly determines two competing performance metrics: axial resolution (depending on bandwidth) and penetration depth (depending on center frequency) [3]. Conventional PMUT designs employing circular or rectangular diaphragms [4] struggle to balance these requirements due to inherent trade-offs in their vibration modes. For instance, circular diaphragms exhibit predictable resonance frequencies but suffer from limited bandwidth (<30% fractional bandwidth in typical configurations), while rectangular designs face challenges with mode coupling due to a higher density of vibrational modes within a given frequency range.

Efforts to overcome these limitations have focused on material selection, multilayer stacking, and array configurations [2,5-7], but geometric optimization of individual diaphragms remains largely underexplored. Irregular shapes—such as polygons, bone-like structures, or other symmetric profiles—could theoretically decouple competing eigenmodes or redistribute vibrational energy to broaden bandwidth [8,9]. However, manually designing such geometries is almost impractical due to the exponential design space and complex interactions between shape, stress distribution, and electromechanical coupling. Traditional finite-element analysis (FEA)-based optimization requires computationally intensive simulations, often taking days to evaluate subtle geometric variations in an array. This bottleneck has hindered progress in PMUT design, leaving a critical gap between theoretical performance potential and practical implementations.

Recent machine learning (ML) advances show promise for MEMS design automation, especially in deep reinforcement learning (DRL)-driven MEMS structure discovery [10-12]. However, existing ML methods mainly focus on single-objective optimization (e.g., maximizing the Q-factor) and often ignore fabrication constraints. PMUTs complicate this challenge by requiring optimization of operating frequency, fractional bandwidth, and manufacturability at the same time, which are tasks hardly accomplished by conventional ML frameworks. Furthermore, few studies validate ML-generated designs experimentally, raising concerns about practical feasibility. We address these gaps with a DRL framework that co-optimizes PMUT geometries for dual goals: precise resonance frequency (±0.1MHz error) and significant bandwidth improvement over circular designs. By interacting autonomously with a surrogate model predicting operating frequency and fractional bandwidth [9], the DRL agent discovers non-standard geometries while adhering to fabrication rules. Although fabrication experiments revealed deviations in cavity dimensions due to over-etching, post-fabrication simulations accounting for these process variations demonstrated strong agreement with experimental results, confirming the feasibility of the DRL-optimized PMUT designs.

DRL MODEL ARCHITECTURE AND SYSTEM WORKFLOW

The proposed DRL framework, illustrated in Figure 1, operates through a six-step cycle to automate PMUT design:

1. State Initialization: The environment provides a starting point (representing the PMUT's current geometry) for the design.
2. Action Selection: A decision-making component called the actor network proposes a geometric adjustment to improve performance.
3. Feedback Generation: The environment updates the geometry based on the action and returns two key indicators of information:
   a) A reward R (a numerical score reflecting how well

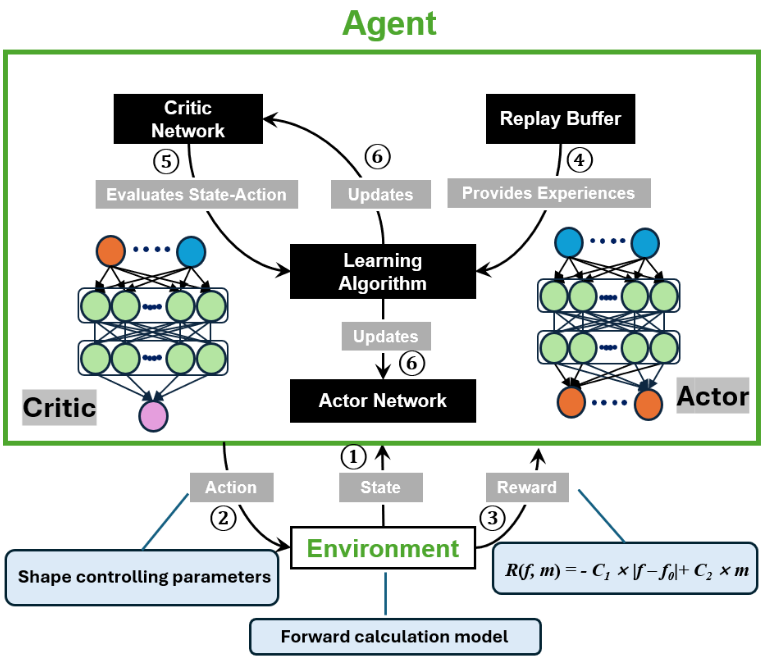

Figure 1: DRL model architecture with 6 steps denoted.

the new design meets targets like frequency accuracy or bandwidth).

b) The new state (updated geometry).

4. Experience Storage: These interactions (current state, action, reward, new state) are stored in a replay buffer, a dataset that collects past design attempts for later training.
5. Critic Evaluation: A second component, the critic network, evaluates the long-term impact of each action by estimating Q-values—a metric predicting how beneficial an action will be over time, considering future rewards.
6. Network Updates: Both actor and critic networks are iteratively trained using the collected data. The actor learns to propose better design changes, while the critic network improves its ability to predict outcomes.

The implemented environment we refer to [9]. This reference details the parametric control of the diaphragm geometry and the forward surrogate model that accurately predicts resonant frequencies and fractional bandwidth based on geometrical features. It provides the fundamental modeling framework upon which our current optimization approach is constructed.

Reward R is calculated by equation (1):

$$R(f, m) = -C_1 \times |\, f - f_0 \,| + C_2 \times m \qquad (1)$$

where f_0 represents the target resonant frequency, f is the frequency of the current design, m denotes the broadband factor (with higher values corresponding to enhanced bandwidth performance), and C_1 and C_2 are weighting coefficients that balance the trade-off between frequency accuracy and bandwidth maximization. This formulation creates a dual-objective optimization landscape that rewards designs meeting the frequency targets while, at the same promoting expanded operational bandwidth.

This cycle is depicted in Figure 1 and is repeated until the PMUT design converges to meet the target specifications. In this study, the framework is applied in three stages:

1. Optimizing Individual PMUT Cells: The DRL model designs two PMUT cells with distinct target frequencies (4.5 ± 0.1 MHz and 5.0 ± 0.1 MHz) while maximizing bandwidth.
2. Array Integration: The optimized cells are combined into a single array. Their intentional frequency separation minimizes crosstalk—interference caused by neighboring transducers—by ensuring their signal peaks do not overlap.
3. Validation: The final design is rigorously tested using numerical multiphysics simulations and experimental fabrication, ensuring practical feasibility.

RESULTS AND DISCUSSION

DRL-Driven Optimization

To demonstrate the effectiveness of our DRL approach, we present a representative optimization case for a PMUT designed to operate at 4.5±0.1MHz. Figure 2 illustrates the convergence process during training, with panel (a) tracking the resonant frequency evolution across training steps. As shown, the algorithm successfully navigates the design space to stabilize within our target frequency range. Concurrently, Figure 2(b) depicts the progression of the broadband factor—a critical performance metric where higher values indicate enhanced bandwidth capacity. Notably, this factor reaches convergence after approximately 500 iterations, suggesting an optimal balance between exploration and exploitation in the learning process.

The geometrical modifications driving these performance improvements become evident in Figure 2(c), which visualizes the progressive refinement of diaphragm geometries throughout the optimization process. These morphological adaptations directly influence the acoustic response characteristics, demonstrating how the DRL framework effectively learns the complex relationships between geometrical parameters and ultrasonic performance metrics.

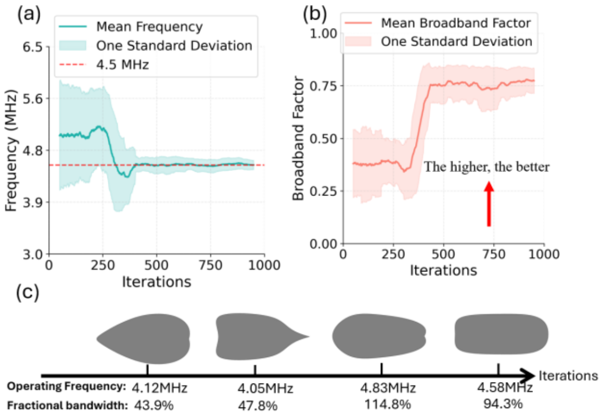

Figure 2: Convergence plots of (a) operating frequency and (b) broadband factor vs. number of iterations, with (c) evolution of PMUT diaphragm shapes and their performance metrics.

To validate training effectiveness, Figure 3 contrasts the broadband factors obtained through the DRL approach (red columns) with those from random generation (grey columns). The “random samples” were initially generated without frequency constraints, then filtered to the 4.5±0.1MHz range for fair comparison. The significant performance gap between DRL and stochastic policy confirms the optimization success.

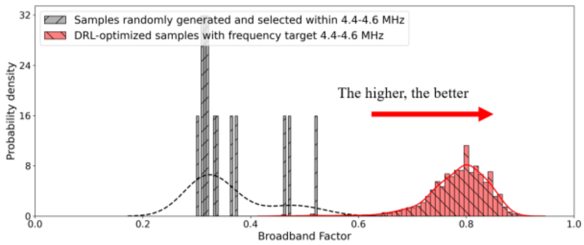

Figure 3: Comparison of the broadband factor of samples discovered via DRL and the stochastic policy.

Array Integration Leveraging Crosstalk Mitigation

Building upon our optimization results, we develop a heterogeneous array architecture to address the persistent challenge of crosstalk in PMUT arrays. Crosstalk—the undesired acoustic coupling between adjacent elements—typically reduces array performance by distorting vibration patterns and decreasing frequency bandwidth. Our approach strategically combines cells operating at two distinct resonant frequencies (4.58MHz and 5.02MHz) within a single array, as illustrated in Figure 4(a). This frequency diversity disrupts the interference patterns that typically amplify crosstalk effects in conventional homogeneous arrays.

Finite element simulations validate the effectiveness of this approach, with results presented in Figure 4(b). The heterogeneous array design achieves a remarkable fractional bandwidth of 113.7%, representing a 6.6-fold improvement over the 17.1% bandwidth observed in conventional PMUT arrays composed of identical circular cells. This substantial fractional bandwidth enhancement directly translates to improved axial resolution in imaging applications and expands operational flexibility in sensing contexts.

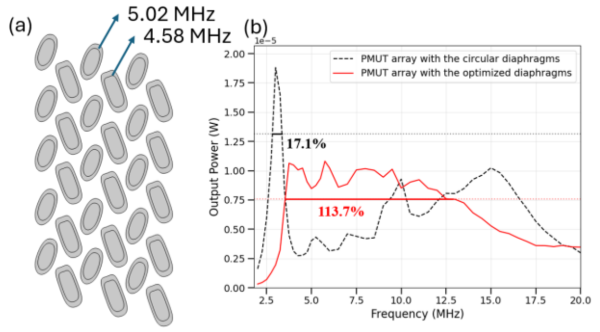

Figure 4: (a) PMUT array that combines DRL-optimized cells with a pitch size of 230 μm; (b) Comparison of power output and -3dB bandwidth between proposed and circular arrays from simulation results.

Fabrication Feasibility Validation

To validate the practical implementation of our DRL-optimized design, we fabricate a 40-channel linear array of PMUT cells in house, as shown in Figure 5(a). Single PMUT cells with two resonate frequencies are also fabricated. Optical characterization using a laser-Doppler vibrometer confirmed the successful realization of the effective vibrational modes, with Figures 5(b) and 5(c) displaying the first and third eigenmodes of individual cells, respectively.

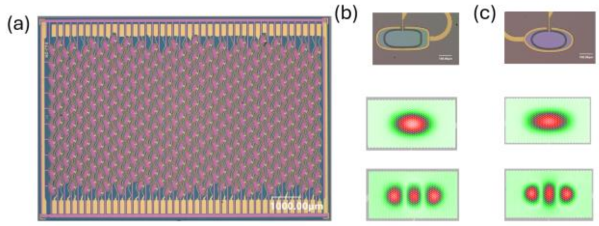

Figure 5: (a) Fabricated 40-channel linear PMUT array following Fig.4(a) design with a pitch size of 230 μm; laser Doppler vibrometer measurements showing a single PMUT cell with first and third eigen modes of the two devices working at (b) 4.58MHz and (c) 5.02MHz.

Acoustic performance is evaluated through underwater ultrasound transmission testing. Figure 6(a) presents the time-domain signals received from the fabricated array, while Figure 6(b) gives the measured frequency response spectrum (solid red curve). We observe some deviation from the expected performance shown in our earlier simulation results (Figure 4(b)). Subsequent analysis revealed that this discrepancy stems from fabrication-related over-etching in the cavity regions, resulting in expanded diaphragm boundaries. To confirm this hypothesis, we develop a modified simulation model that accounts for diaphragm expansion (approximately 12 μm outward from the original boundary), which shows excellent agreement with the experimental results (black dashed curve in Figure 6(b)).

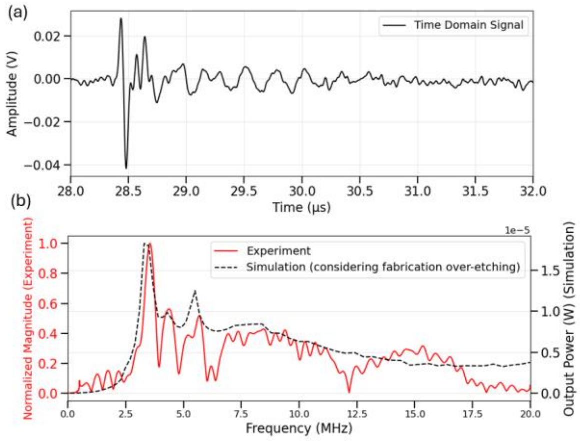

Figure 6. (a) Temporal evolution of an acoustic pulse recorded by a hydrophone at a depth of 20mm; (b) FFT spectrum of (a), with simulation results accounting for PMUT cavity over-etching.

CONCLUSION

This work demonstrates an effective DRL approach for optimizing PMUTs. Our autonomous design framework successfully achieves two key objectives: precise frequency control within ±0.1MHz and substantial bandwidth enhancement. Simulation results show that our optimized PMUT array design achieves a remarkable 113.7% fractional bandwidth, significantly outperforming conventional designs. We validate these findings through the fabrication of a 40-channel linear array, confirming the real-world feasibility of our computationally derived designs. Additionally, we discover that integrating cells with different resonant frequencies (4.58MHz and 5.02MHz) effectively mitigates crosstalk issues that commonly affect PMUT arrays. This approach demonstrates the potential of AI-guided design methods to overcome longstanding challenges in MEMS device optimization, offering a promising direction for future development of high-performance ultrasonic transducers for medical imaging and sensing applications.

ACKNOWLEDGEMENTS

Under grant 101096884, Listen2Future is co-founded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or Key Digital Technologies Joint Undertaking. Neither the European Union nor the granting authority can be held responsible for them. The project is supported by the Key Digital Technologies Joint Undertaking and its members (including top-up funding by Austria, Belgium, Czechia, Germany, Netherlands, Norway, and Spain).

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