

# Efficient Speed Control of Ultrasonic Motor with Deep Reinforcement Learning Multi-Output Controller

Abdullah Mustafa<sup>1,†</sup>, Tatsuki Sasamura<sup>1</sup> and Takeshi Morita<sup>1,2</sup>  
<sup>(1</sup>Grad. School Frontier Sci., Tokyo Univ.; <sup>2</sup>Grad. School Eng., Tokyo Univ.)

## 1. Introduction

Efficiency optimization is a core requirement towards an optimal performance of Ultrasonic motors (USM). Efficient operation can reduce over-heating, prolong operation time, and extend the motor's lifetime. However, a single output controller (driving frequency) limits the motor's efficiency. For efficient tracking performance, multi-output control is proposed. This work focuses on efficient speed control through two control outputs; driving frequency and load torque. The proposed architecture can be further extended to additional control objectives and control outputs in future studies. This work introduces deep reinforcement learning controller for optimal nonlinear model-free efficient speed control.

## 2. USM Characterization

Driving voltage frequency and load torque are two main variables that control the USM performance, as shown in Fig. 1. Decreasing the driving frequency increases the speed and efficiency nonlinearly until sudden reduction around resonance due to the pull-out phenomena. Increasing load torque reduces maximum speed but increase driving efficiency due to increased output power. Yet, there is an optimal torque beyond which efficiency drops. By simultaneous control of frequency and torque, desired speed can be realized with maximum efficiency.

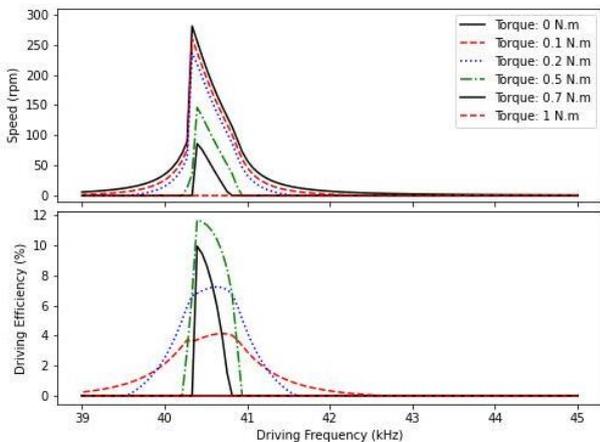


Fig. 1 Simulated USM speed response

## 3. DRL USM Efficient Speed Control

In our earlier work [1], deep reinforcement learning (DRL) was proposed for speed control of USM under varying torque. RL aims towards finding an optimal policy ( $\pi$ ) that maps state  $s_t$  to optimal action  $a_t$  that maximizes a sum of future rewards discounted rewards with factor  $\gamma$  [2]. Starting at state  $s$  and taking action  $a$ , a Q-value is an expectation of this sum, as in **Eq. 1**.

$$Q^\pi(s, a) = E_\pi\{\sum_{t=0}^{\infty} \gamma^t R_t | s_t = s, a_t = a\} \quad (1)$$

The Soft Actor-Critic (SAC) algorithm [3] is utilized as in our earlier work [1]. For USM efficient speed control, we redefine our input state, output action, and reward function to fulfill the needs of our modified objective. The USM efficient speed control problem is formulated as a Markov decision process (MDP), as in **Fig. 2**. The same Markovian input state is used as in [1]. This state includes driving frequency ( $f_t$ ), temperature ( $T_t$ ), load torque ( $\tau_t$ ), current speed ( $v_{r_t}$ ), and target speed ( $v_{target}$ ). The agent (controller) can infer the driving efficiency given the other state variables. The multi-output action is an update step to the current driving frequency ( $f_{t+1} = f_t + \Delta f$ ) and the current load torque ( $\tau_{t+1} = \tau_t + \Delta \tau$ ). Finally, the reward function should be defined to meet the requirement of speed tracking and efficiency optimization. The reward is defined as in **Eq. 2**. First, the root absolute speed error is penalized to optimize speed tracking objective. Second, the driving efficiency ( $\eta_t$ ) is rewarded with a weight ( $w_\eta$ ). Finally, the absolute action is penalized with weight ( $w_a$ ). Tuning these weights is necessary for reaching a compromise between minimizing speed error and maximizing efficiency.

$$r_{t+1} = -\sqrt{|v_{err_t}|} + w_\eta \eta_t - w_a |a_t| \quad (2)$$

## 4. Results

The proposed controller was trained and evaluated under a simulated environment of USM as in [1]. Experimental validation is currently being researched. In addition to speed modeling in [1], the induced current ( $I$ ) is calculated knowing the

vibration amplitude ( $w$ ), voltage amplitude ( $V$ ),

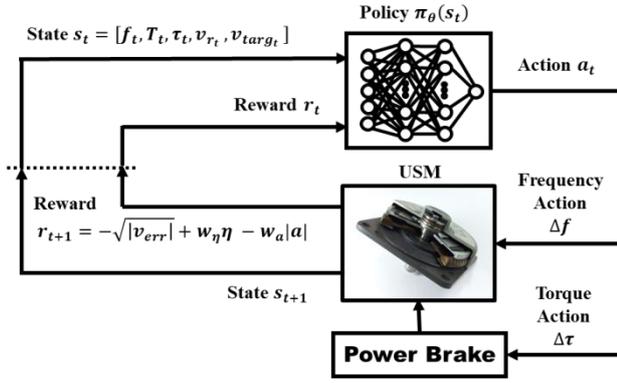


Fig. 2 MDP representation for USM efficient speed control

damped capacitance ( $C_d$ ), and coupling factor ( $\Theta$ ) as in Eq. 3. Given  $I$ , the input power ( $P_{in}$ ) and driving efficiency ( $p_{out}/p_{in}$ ) can be calculated.

$$I = C_d \dot{V} + \Theta \dot{\omega} \quad (3)$$

The agent training procedure was the same as [1]. Following agent training, it was evaluated by commanding a sinusoidal target speed varying between [0-300] rpm. During speed tracking, driving frequency and load torque are controlled as simultaneously in Fig. 3. The agent could realize perfect tracking and the speed error was minimized. Additionally, the driving efficiency was maximized whenever possible. The efficiency drops to zero in two cases; zero rotor speed and zero load torque (for high target speeds). The agent outputted optimal action that corresponded to changes in the driving frequency and load torque.

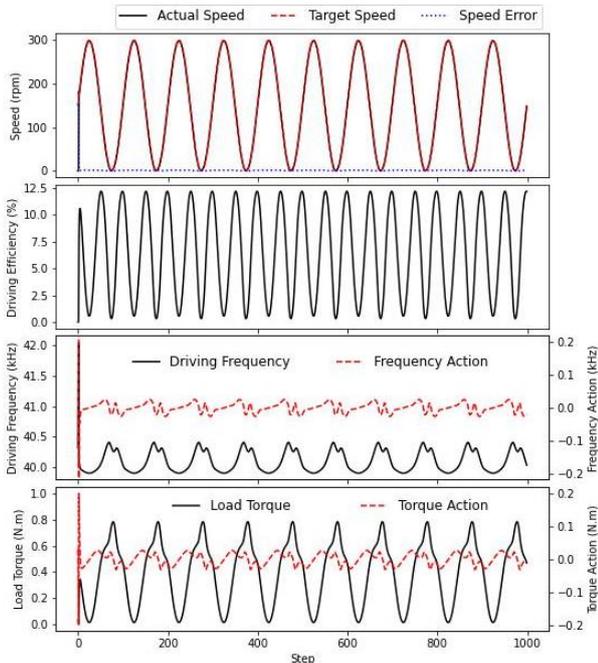


Fig. 3 Efficient speed tracking of a sinusoidal

target speed

To further validate the effectiveness of the proposed controller, we plotted the DRL agent performance curve against the USM best performance as in Fig. 4. First, we sampled multiple operation points of USM by sweeping over load torque and driving frequency. Then, samples that resulted in maximum efficiency were identified. Within the target speed range, the DRL agent realized a comparable maximum efficiency. For higher speeds, the driving frequency and load torque decreased. Maximum efficiency was realized at a moderate load torque (0.5 N.m) and target speed (150 rpm). Additionally, excessive load torques resulted in reduced efficiencies and may damage the motor.

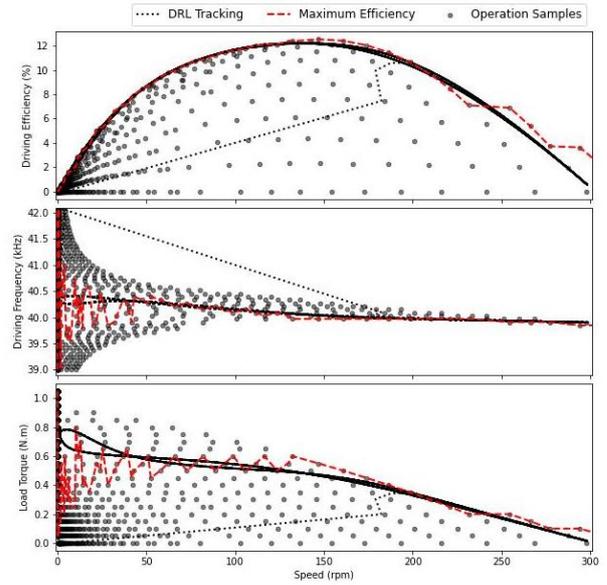


Fig. 4 DRL efficient speed tracking curve

## 5. Conclusion

In this work, DRL was proposed for efficient speed control of USM. The simulation results showed that DRL could track desired speeds while maximizing driving efficiency. Future research will focus on experimental validation of proposed controller as well as studying additional control outputs such as preload, phase difference, and voltage amplitude.

## References

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