Proposal: Deciphering Electrocommunication with MARL and Unsupervised Machine Translation

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Abstract

Unsupervised machine translation (UMT) has recently been proposed as a tool for deciphering animal communication. Previous efforts, however, have attempted to align animal signals directly with human language, introducing large ecological and representational gaps that inevitably limit success. We argue that a more promising path is to generate synthetic corpora through *rich, situated, biologically realistic* multi-agent reinforcement learning (MARL). Such simulations yield emergent communication signals that share statistical and functional properties with real animal data, thereby narrowing the gap that hampers translation. As a case study, we present MARL agents inspired by pulse-type weakly electric fish (WEF), which rely on electric organ discharges (EODs) for both sensing and social communication. WEF provide an ideal test case because their communication signals are tightly coupled to collective behaviors such as foraging, resource sharing, and dominance interactions. Our MARL agents reproduce key features of real WEF behavior and communication, including socially aware foraging strategies, heavy-tailed EOD interval distributions, and context-dependent shifts in EOD rate. These synthetic corpora can be generated at scale, with complete access to both neural and behavioral variables, and allow for mechanistic interpretation and virtual interventions that are expensive or infeasible in vivo. We propose a methodology to combine the MARL-generated emergent communication with UMT techniques to decipher real fish EOD data. This integration opens a path toward AI-assisted deciphering of animal communication, with WEF as a proving ground and strong potential for extension to other species.

1 Introduction

Unsupervised machine translation (UMT) has recently emerged as a tool for deciphering animal communication [1, 2]. Most existing proposals attempt to align animal signals directly with human language [3]. This direct alignment introduces ecological and representational gaps that limit success, since the latent structure of human language differs from that of animal signals [4, 5].

We propose a different strategy. Rather than forcing alignment to human words, we first generate synthetic corpora using *emergent communication* arising among agents trained with multi-agent reinforcement learning (MARL) in *rich, situated, biologically realistic simulations*. When placed in ecologically grounded environments, with realistic constraints on motion, sensing, and energetic cost, agents generate emergent communication signals that more closely resemble animal signals than human text.

Here we present a case study focused on pulse-type weakly electric fish (WEF) [6, 7]. These fish use electric organ discharges (EODs) for both active sensing and social communication, signals that are central to collective behaviors such as foraging, resource sharing, and dominance [8, 9].

Submitted to the AI for Non-Human Animal Communication workshop (NeurIPS 2025). Do not distribute.

By combining MARL with UMT, we aim to bridge simulation and biology, enabling structured interpretation of animal signals in their ecological context. In the remainder of this proposal, we outline a research design and UMT-based translation framework, present early results from MARL simulations of WEF communication, and discuss key considerations for integrating MARL with UMT.

2 Unsupervised Machine Translation (UMT)

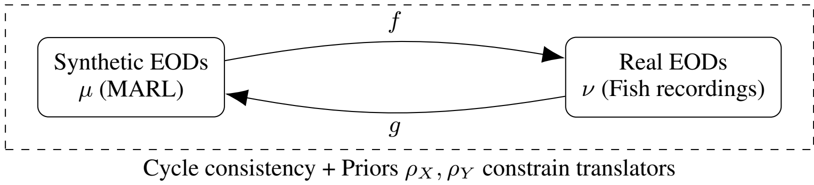

Figure 1: Two-domain UMT framework. Synthetic EODs generated by MARL (μ) and real EODs recorded from weakly electric fish (ν) serve as two monolingual corpora. Translators f and g are trained with priors for fluency and cycle-consistency for information preservation.

Unsupervised machine translation (UMT) seeks to learn a mapping between two monolingual corpora in the absence of parallel pairs. In our case, one corpus is composed of synthetic electro-communication signals generated by MARL agents, while the other consists of real EOD recordings from weakly electric fish. We denote the synthetic distribution by μ over alphabet Σ_X and the real distribution by ν over alphabet Σ_Y. The goal is to find a translator $f : \Sigma_X^\star \to \Sigma_Y^\star$ that maps synthetic sequences to real ones (and vice versa via g), such that the translation preserves semantics of ecological context.

The canonical UMT formulation balances three ingredients: *(i) Language priors*, ensuring that translations resemble valid samples in the target domain; *(ii) Cycle consistency*, ensuring that $x \to f(x) \to g(f(x)) \approx x$ and $y \to g(y) \to f(g(y)) \approx y$; and *(iii) Optional denoising/back-translation*, where pseudo-parallel pairs are generated by translating monolingual examples and training conditional models on them [10, 11].

Formally, the two-domain UMT objective is

$$\max_{f,g}\ \mathbb{E}_{x\sim\mu}[\log \rho_Y(f(x))] + \mathbb{E}_{y\sim\nu}[\log \rho_X(g(y))] - \lambda_{\mathrm{cyc}}\,\mathcal{L}_{\mathrm{cyc}}(f,g), \tag{1}$$

$$\mathcal{L}_{\mathrm{cyc}}(f,g) = \mathbb{E}_{x\sim\mu} d_X\big(g(f(x)), x\big) \ + \ \mathbb{E}_{y\sim\nu} d_Y\big(f(g(y)), y\big). \tag{2}$$

where ρ_X, ρ_Y are language-model priors trained on synthetic and real corpora, and $d_X : \mathcal{X} \times \mathcal{X} \to \mathbb{R}_{\geq 0}$ and $d_Y : \mathcal{Y} \times \mathcal{Y} \to \mathbb{R}_{\geq 0}$ are distances (or divergences) defined on the synthetic EOD sequence space $\mathcal{X}$ and real EOD sequence space $\mathcal{Y}$ respectively.

The objective in Eq. 1 can be seen as encouraging three things simultaneously: translations should be *fluent* in the target corpus, *information-preserving* under round-trip translation, and *robust* to noise or mismatch via back-translation. Eq. 2 measures how close a round-trip translation is to the original sequence. Similar formulations have been shown to succeed in both word-level alignment and sentence-level UMT [10, 11].

3 MARL for Weakly Electric Fish

Weakly electric fish are an ideal case study for our proposal. They emit EODs that are tightly coupled to ecological and social behavior. EODs serve multiple roles, from electrolocation to communication with conspecifics, and have been extensively studied in both ethological and neurophysiological contexts [12, 13, 6]. The frequency, interval distribution, and context-dependent motifs of EODs vary with foraging, resource sharing, and dominance interactions. Decades of work have shown how temporal patterning in EODs encodes social and ecological information [14, 15, 16]. More recently, studies have revealed collective sensing and group-level coordination in electric fish [9].

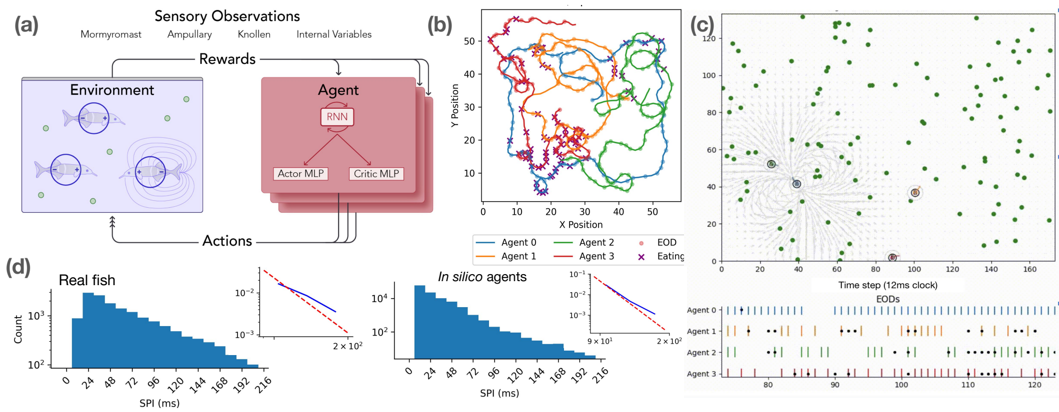

Figure 2: Overview of our MARL framework for modeling weakly electric fish communication. **(a)** Schematic of the training loop, where agents interact with a simulated arena, emitting and sensing electric organ discharges (EODs) through weakly electric fish-inspired sensors. Rewards encourage successful foraging and penalize aggressive encounters. **(b)** Example trajectories from four agents in a single foraging episode, showing exploration and food acquisition. **(c)** Snapshot of the arena (top) showing agents, food sources, and simulated electric fields; bottom shows temporally-structured EOD spike trains across individual agents. **(d)** Sequential Pulse Interval (SPI) distributions from real fish (left) and MARL-trained agents (right), showing that in silico agents reproduce the heavy-tailed statistics observed in biological data. Insets show log-linear curves compared to empirical curve fits.

Our MARL environment instantiates these ecological and biological priors (Figure 2). Agents are recurrent actor–critic networks that receive egocentric observations from simulated electrosensory modalities and generate actions including movement, turning, EOD emission, and biting [7]. EODs induce fields that interact with food objects, walls, and other agents, which are then sensed by different receptor types on each agent's body. Agents are trained using Multi-Agent Proximal Policy Optimization [17, 18, 19] with rewards that encourage successful foraging and provide asymmetric penalties during aggressive encounters between fish of different dominance levels. Trained MARL agents develop socially aware foraging strategies, dominance displays, and context-dependent EOD modulation. The resulting synthetic corpora reproduce power-law–like SPI distributions and other temporal motifs observed in real fish, while providing complete access to neural, behavioral, and environmental variables. Full observability and controllability of the artificial neural network enables mechanistic interpretation and in silico ablations [20, 21, 22].

4 Key Considerations

A key theoretical insight is that UMT performance depends on two properties of the signal distributions [1]. *Complexity* (d) captures the richness of statistical structure: context-dependent signals restrict the set of valid translators. *Common ground* (α) quantifies structural overlap between synthetic and real signals. Translation error decreases with both d and α: if signals are too simple or the domains share little overlap, degenerate translators can satisfy the UMT objective without preserving semantics.

Our design follows directly from the above. Generate MARL corpora under ecologically rich conditions (to raise d), and embed in the simulation constraints known from fish ethology so that synthetic motifs share structure with real EODs (to increase α). By doing so, the UMT alignment problem becomes not only feasible but biologically interpretable.

Several research questions guide our proposal: How do emergent motifs in MARL align with those observed in real fish? Can UMT trained on MARL corpora decipher real EOD recordings into structured behavioral descriptors? How does task context, e.g. competition versus cooperation, or group size, affect translatability?

5 Discussion

Traditional UMT approaches have struggled with the mismatch between animal signals and human text [3]. We propose bridging this gap with *rich, situated MARL*, using weakly electric fish as a case study. Our simulations generate communication corpora closer to real biology, enabling UMT to map signals into structured, situated descriptors.

The approach offers several contributions. First, it demonstrates how MARL can create interpretable corpora that reproduce known features of fish behavior and communication while allowing controlled virtual interventions. Second, it outlines a principled UMT framework to align synthetic and real signals into structured descriptors of ecological context. Third, it contributes datasets, both simulated and empirical, that can serve as benchmarks for future work on AI-assisted animal communication [23, 24].

The implications extend beyond weakly electric fish. Any species with structured signals embedded in social contexts, such as birdsong, primate calls, dolphin whistles, or sperm whale clicks, could be studied with this framework [25, 26, 27, 28]. By embedding ecological realism into MARL simulations, we generate corpora that are both interpretable and aligned with biology. Combined with UMT, this approach opens a general path toward AI-assisted translation of animal communication [29]. While our case study focuses on EODs from weakly electric fish, the same MARL–UMT framework can generalize to other modalities of animal communication.

Ethical considerations

Our framework reduces invasive experimentation on live animals by generating large synthetic corpora through simulation. By grounding AI models in ecological realism, we also reduce risks of anthropomorphizing or over-interpreting signals, instead situating interpretation in the behavioral context of the species. All experimental data used in this paper were collected by collaborators for previous neuroscientific studies of weakly electric fish.

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