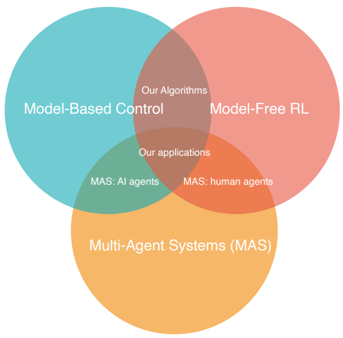
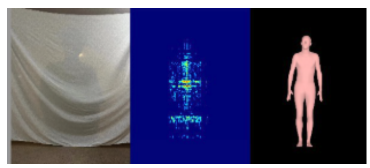
RESEARCH STATEMENT

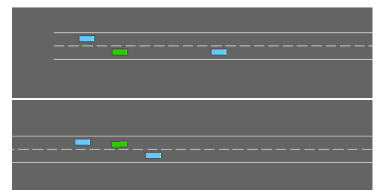
In my doctoral research at University of Illinois Chicago, I have applied *model-based Reinforcement Learning* (RL), *switched control theory*, *stochastic game theory*, and *composite optimization* to develop algorithms that leverage model information to accelerate the training of learning-based model-free algorithms (Fig. 1a), achieving greater sample efficiency. Additionally, we extended the algorithm to hybrid multi-agent systems involving humans, where humans are treated as black-box agents (model-free) while other agents follow a model-based approach, enabling effective collaboration between the AI and human agents without the need to control or model human behavior (Fig. 1c). I also collaborate with researchers at University of Massachusetts to build a system that can reconstruct human meshes in extreme environments using acoustic signals (Liang et al., 2025) (Fig. 1b).



(a) Hybrid systems that combine model-based control and model-free reinforcement learning



(b) Reconstruct human mesh in extreme environments using acoustic signals



(c) Green: AI agents; Blue: Human agents. The AI agent successfully changed the lane.

Figure 1: Summary of Research

We also extend the design of hybrid systems to the frontier of Large Language Models (LLMs) in decision-making systems. We created the first system to integrate LLMs into real-world, closed-loop vision-based autonomous driving (Dong et al., 2024). Our architecture resolves the fundamental latency challenges that previously prevented LLMs from being used in real-time systems by strategically positioning them as high-level instructors while maintaining rapid local control mechanisms (Fig. 2).

Looking forward, I am expanding these methodologies to empower a broader range of end-users in deploying AI systems. This work draws on my entrepreneurial experience as a co-founder of LIII NETWORK, where we developed GNU $\mathrm{T_EX_{MACS}}$/Mogan—a WYSIWYG $\mathrm{T_EX}$-like editor that accelerates academic writing—and Goldfish Scheme, an interpreter that bridges the gap between Scheme and Python ecosystems. Particularly notable is our implementation of literate programming (Knuth, 1984) in Goldfish Scheme, which exemplifies my commitment to making complex systems more comprehensible and maintainable (Shen* et al., 2024).

These varied projects share a common thread: making sophisticated AI-involved systems more practical and accessible while maintaining their theoretical rigor. As AI continues to evolve, I am dedicated to developing hybrid approaches that combine the best aspects of different methodologies, ultimately creating AI systems that can be effectively deployed in real-world applications ranging from autonomous vehicles to healthcare, scientific, media and art research.

1 AI APPLICATIONS IN EXTREME CASES

Human mesh reconstruction using acoustic signal Recovering a complete 3D mesh of human bodies from fragmented RGB data is challenging. Data can be compromised by issues such as occlusions, where parts of the body are hidden from view, and variations in body poses and shapes across individuals. Additional complications include the complexity of clothing and accessories, as well as the inherent ambiguity in inferring depth information from 2D images in computer vision. We developed a novel neural network architecture, SonicMesh (Liang et al.,

(a) Training environment for end-to-end purely vision-based autonomous driving

(b) Testing environment for LLMs-assisted end-to-end autonomous driving

Figure 2: Training and testing environments (the experiment is conducted in real-world, closed-loop; this image is for presentation purposes only). The LLMs enhance the generalization of purely vision-based autonomous driving systems.

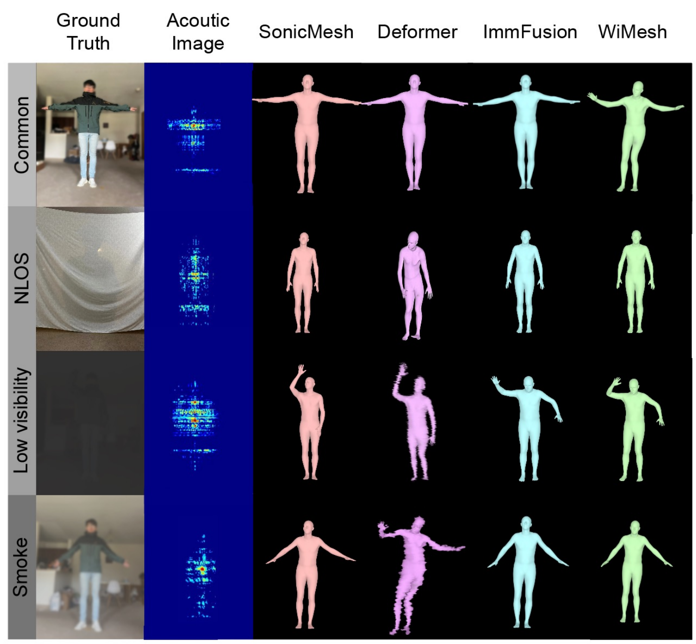


Figure 3: Our method, SonicMesh, can successfully reconstruct the human body with the help of acoustic signal in extreme environments.

2025), to enhance the human mesh reconstruction with the help of acoustic signals. Our method outperforms other state-of-the-art methods in terms of accuracy and robustness as shown in Fig. 3.

Training models to assist legacy devices Deploying complex machine learning models on resource-constrained devices is challenging due to limited computational power, memory, and model retrainability. To address these limitations, We developed a hybrid system, *learning to help* (Wu et al., 2025), that augments the local client model with a server-side model, where samples are selectively deferred by a rejector and then sent to the server for processing. Fig. 4 illustrates the Learning to Help framework for a fixed client model. We proposed several algorithms to train an optimal rejector and tested the framework on CIFAR100. The results demonstrate that the framework effectively utilizes the deprecated client model, improving overall performance on resource-constrained devices.

2 HYBRID SYSTEMS IN DECISION MAKING

My research designed hybrid systems to exploit model information in model-free learning regime. The exploration has led to solutions in human-AI collaboration and language model integration for autonomous systems.

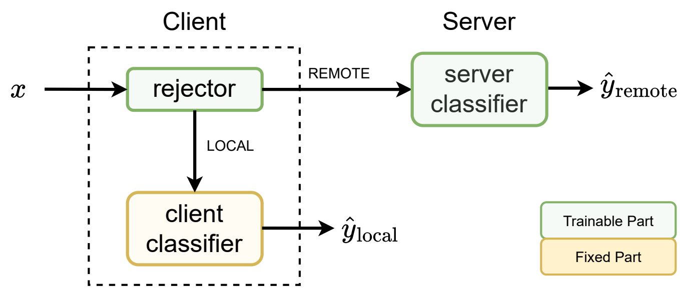


Figure 4: The learning to help framework with fixed client.

Multi-Agent Systems Involving Humans Human behavior presents a unique challenge in multi-agent systems due to its complexity and unpredictability. Rather than attempting to create precise models of human behavior, we developed a novel approach that treats humans as black-box components within the system. This perspective allows us to observe and adapt to human actions without making assumptions about their decision-making process. Meanwhile, we maintain explicit models for AI agents, creating an effective hybrid architecture. This approach led to two significant advances. First, we developed an algorithm for Stackelberg games (**Yansong Li*** and Han, 2023) that enables AI agents to collaborate effectively with human followers without modeling human behavior. We then extended this framework to handle the more complex domain of stochastic games (**Yansong Li*** and Han, 2024), demonstrating the adaptability of our hybrid approach.

Large Language Models for vision-based autonomous driving We applied a hybrid system to integrate LLMs into vision-based autonomous systems. Our key insight is that while LLMs excel at high-level reasoning, they are poorly suited for direct control tasks due to latency issues. This led us to develop a novel architecture for autonomous driving that leverages LLMs' strengths while avoiding their limitations. Our system (Fig. 2) represents a breakthrough in LLM application for autonomous driving. We created the first successful implementation of LLMs in closed-loop, real-world driving by decoupling high-level decision-making from direct control. The architecture combines multimodal LLMs for strategic decisions with rapid local control systems, effectively addressing the latency challenges that hindered previous attempts. Our experiments demonstrate that this hybrid approach significantly enhances the vehicle's ability to navigate novel environments (Dong et al., 2024).

3 LARGE LANGUAGE MODELS AND LITERATE PROGRAMMING

Modernizing Scientific Document Creation: GNU TeXmacs and Mogan The challenge of efficient mathematical writing has long been a bottleneck in scientific communication. GNU TeXmacs pioneered a solution with its WYSIWYG TeX-like editor, enabling users to type equations at handwriting speed. Building on this foundation, we developed Mogan Research, a fork of GNU TeXmacs. Our version maintains the core strength of rapid equation editing while implementing significant technical upgrades. Table 1 details these improvements, which span performance optimization, modernized framework adoption, and enhanced user interface design.

	GNU TeXmacs	**Mogan Research**
Performance	slow	fast
Qt Framework	mainly in Qt 4 (some in Qt 5)	mainly in Qt 6 (some in Qt 5)
Scheme Engine	GNU Guile 1.8.x (deprecated by GNU)	Goldfish Scheme (based on S7 Scheme)
Build Tool	GNU Autotools	xmake

Table 1: Comparison between GNU TeXmacs and Mogan Research

Literate Programming in the Era of LLMs: Goldfish Scheme as a Case-Study The evolution of Mogan required us to address a fundamental challenge in its architecture: the Scheme interpreter. While TeXmacs relied on the deprecated GNU Guile 1.8.x, our initial choice of S7 Scheme also proved limiting due to incomplete R7RS and Unicode support. This prompted us to develop *Goldfish Scheme*[1] (Shen* et al., 2024).

What sets Goldfish Scheme apart is its innovative development approach using literate programming, a methodology introduced by Knuth (1984). Building on Knuth's original vision (Knuth, 1984), we see literate programming not merely as a documentation method but as a fundamental shift in how code is organized and understood. Rather than following traditional top-down or bottom-up approaches, code becomes a "web" of interconnected ideas[2] that naturally aligns with how LLMs process and understand information. This alignment between literate programming and LLM capabilities has guided our development of Goldfish Scheme. Through our research, we raised a compelling hypothesis about the synergy between these two approaches:

> *Projects developed using literate programming are inherently more understandable for LLMs than projects containing even the most detailed comments.*

Our experiments in Shen* et al. (2024) provide strong evidence for this hypothesis. The narrative structure of literate programming, where code and documentation form a cohesive story, aligns naturally with LLMs' ability to process and understand natural language. This alignment suggests a promising future where literate programming could become the preferred methodology for creating AI-comprehensible software.

FUTURE RESEARCH DIRECTIONS

How can we deploy learning & vision-based methods in real-world real-time? The deployment of learning-based systems in real-world applications presents three fundamental challenges that drive my future research agenda:

- *Data requirements*: Real-world training demands extensive environmental interaction, making traditional learning approaches impractical for many applications.
- *Real-time performance*: The computational complexity of learning-based policies often conflicts with the strict timing constraints of real-world decision-making.
- *Adaptability to environmental changes*: Current learning systems struggle to generalize beyond their training data, limiting their effectiveness in dynamic environments. The issue becomes more severe in vision-based systems.

My research has already made significant strides in addressing these challenges through hybrid approaches. Our algorithms combining model-based control with model-free learning (**Yansong Li*** and Han, 2022; **Yansong Li***† et al., 2024) have successfully reduced data requirements, while our LLM-assisted driving framework has demonstrated improvements in real-time performance and environmental adaptability.

Looking ahead, I plan to expand this research to address two critical remaining challenges: the *exploration vs. exploitation balance* and *safety and stability* in real-world deployments. Through collaborations with experts in robotics, computer vision, and game theory, I aim to develop more robust AI systems that can safely and effectively adapt to real-world applications. This work will build upon my existing research while opening new avenues for investigation in autonomous systems, human-AI interaction, and safe AI deployment.

Can vision-based LLMs help for decision-making in real-world? Integrating Large Language Models into real-world decision-making systems requires careful consideration of their fundamental limitations. This conclusion stems from three critical constraints:

- *High Latency:* LLM inference creates response delays incompatible with real-time decision requirements. Also, vision-based LLMs require more time for inference.

[1] Goldfish Scheme is named with a playful reference to the idea that goldfish have a 7-second (7s) memory, the inverse of S7. In the future, we hope LLMs can help create new functions for Goldfish Scheme within those same 7s. The literate programming document for Goldfish is available in `https://github.com/LiiiLabs/goldfish/releases/tag/v17.10.9`.

[2] In our implementation, code exists in interconnected chunks that tell a story about their purpose and relationships. We provide this functionality as a Mogan plugin, automatically exporting chunks into organized project files and folders.

- *Limited Context Awareness:* Vision-based LLMs fail to understand dynamic situations from images, leading to disastrous decisions.
- *Reliability Concerns:* The sensitivity of LLM outputs to minor input variations introduces unpredictability that makes them unsuitable for critical decision-making roles.

These insights have led us to pursue hybrid system architectures where LLMs serve as strategic advisors rather than direct decision-makers. This approach parallels my earlier work on combining model-based and model-free methods, suggesting promising directions for integration. We can create more robust and reliable decision-making frameworks by leveraging LLMs' strengths in high-level reasoning while compensating for their limitations through specialized control systems. My future research will explore these hybrid architectures through collaborations that span machine learning, control theory, and systems design.

Renaissance of Literate Programming in the Era of LLMs The use of literate programming extends beyond traditional programming paradigms into the realm of prompt engineering, offering new ways to structure and communicate code. While challenges remain in areas such as collaboration workflows, version control systems, and standardization of writing practices, we are actively working with our colleagues at LIII NETWORK to address these issues. Our goal is to create a modern literate programming framework that fully harnesses the capabilities of LLMs while maintaining the practical needs of software development.

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