CAREER: Robust Intelligence of Cyber-Physical Systems for Highly Automated Mobility

1. Project Overview and Significance

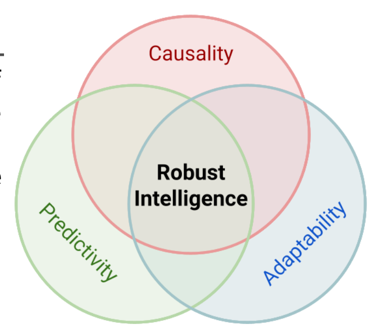
1.1. Overview

Over the past few decades, the intelligence of Cyber-Physical Systems (CPS) in perception, learning, and reasoning for highly automated mobility has been greatly enhanced by advances in Artificial Intelligence (AI) and Computer Vision, supported by new Machine Learning (ML) algorithms and parallel processing hardware. As the mobility of CPS, such as mobile robots and unmanned vehicles, becomes increasingly automated through AI, the robustness of CPS intelligence in perception and control is brought to the forefront in the safety-critical systems.

Traditional approaches to ensuring the robust intelligence of CPS for highly automated mobility involve complex modeling and hierarchical algorithmic architectures for perception and control. Such intelligence through these approaches is often fragile in real physical environments characterized by rapid changes, high uncertainty, indefinite righteousness, and limited availability. In these conventional approaches, intelligence is understood as the *mental* ability to perceive, learn, and reason through high-level cognitive functions [1], and its connections to the body and the world are of little theoretical importance [2]. The PI posits that such a separation between high-level cognitive functions and their bodies is deeply rooted in the Western philosophical tradition in scientific methodologies based on *Platonic* idealism [3] and *Cartesian* mind-body dualism [4], which is the proposition of the existence of ideal forms and abstract beings for mental activities. This perspective overlooks the importance of the interaction between CPS and their environment through their physical body and is linked to the view that mental activities can be implemented by solely making cognitive functions faster and more accurate without much consideration of the physical body's interactions with environments. The PI hypothesizes such *disembodiment* is the source of the fragility of intelligence because there is almost always a certain level of imprecision in modeling the rapidly changing and highly uncertain physical real world. Unlike the common belief that our internal representations of the real world are rich and detailed, they are actually rather sparse [5]. Therefore, *experiencing* the outside world through sensors must be understood as not just something that CPS *feels (passive perception)* but something CPS *does (active embodied cognition)* [5]. To employ such embodiment, researchers have made many efforts individually and sporadically in neuroscience, neurorobotics, action generation and recognition, and control theories. Yet, no significant integrated and synergistic work has been done in CPS for mobility.

The objective of this CAREER is to <u>develop the scientific foundation for robust intelligence of CPS for highly automated mobility</u>, such as unmanned vehicles and mobile robots, and <u>integrate interdisciplinary research with the education of high school, undergraduate, and graduate students to foster them to be ready for the next generation of CPS with robust intelligence</u>. The anticipated outcomes of this research and education plan include the development of new robust intelligence frameworks of CPS based on *causality*, *predictivity*, and *adaptability* for highly automated mobility, contributing to saving human lives through robust perception and control systems and reducing greenhouse gas emissions through reducing energy consumption. The transformative impact of this CAREER will be on research and education communities with new and better insights to create and teach robust intelligent systems in safety-critical environments.

1.2. Research Statement



The long-term goal of this CAREER is to advance the breadth and depth of understanding how to guarantee the robustness of intelligence in CPS. The PI proposes a set of research thrusts that are interdisciplinary and innovative toward robust intelligence of CPS for highly automated mobility. The proposed research investigates a fundamentally robust intelligence framework to achieve highly automated mobility in CPS, anchored by the three research hypotheses: Causality, Predictivity, and Adaptability. (1) ***Causality*** is a fundamental building block of robust intelligence. Deep Learning (DL) methods rely on reasoning by data-driven *association* that is nothing but *"curve fittings,"* [6] resulting in unavoidable edge cases. This hypothesis posits that causal reasoning is a key to true intelligence, enabling the system to overcome limitations and handle uncertain scenarios effectively. (2) ***Predictivity*** is another key ingredient of robust intelligence. Inspired by the brain's predictive mechanisms, this hypothesis states that robust intelligence should possess the ability to generate predictions of future states caused by actions, enabling proactive decision-making and preparedness for unknown future states. (3) ***Adaptability*** is an essential element of robust intelligence. A real intelligent system should not be broken with slight changes in input. Generative AI can be used to fill the gap of imperfect or tainted input to support the adaptability of intelligent systems. The aforementioned three research hypotheses will be concurrently investigated and then integrated to develop a robust intelligence framework through this CAREER proposal, and this results in a novel and robust perception system and control architecture of CPS for highly automated mobility.

1.2.1. Expected Outcomes from Research Hypotheses

(1) ***Causality***: The outcome of this research hypothesis will be a novel robust AI control architecture based on a causality model using forward/inverse internal models in physiological motor control [7–10] for highly automated mobility. (2) ***Predictivity***: The outcome of this research hypothesis will be a novel robust perception and control framework that can predict future states. The novel framework will be able to be used to enhance the stability of mobility in fast-changing environments, and it can also be used to compensate for delayed feedback signals by providing probable near-future sensory situations. (3) ***Adaptability***: The outcome of this research hypothesis will be an adaptable and flexible perception system for a robust intelligence framework of CPS. ***The results from the proposed research*** will be related to diverse application domains, including next-generation unmanned vehicles and mobile robots. The proposed research hypotheses have been validated with preliminary studies, and the expected outcomes will be orchestrated and systematically integrated to have a transformative impact on the ways of designing and operating future CPS for mobility.

1.3. Educational Statement

The long-term educational goal of this CAREER is to attract more diverse students to STEM (science, technology, engineering, and math), make them stay by giving them positive hands-on experiences, and encourage them to pursue their careers in STEM. The primary objectives are as follows. The first is to teach students, particularly those from underrepresented groups in the Detroit metropolitan area, and share the PI's passion for research on intelligent systems. This will foster diversity in STEM and prepare them for future industries that are yet to emerge in the United States. The second is to let students enjoy learning STEM through experiential learning, which will introduce STEM to them with positive involvement. The third is to train and enable students to be able to engage in lifelong learning. By fostering a proactive and adaptive mindset, students will be equipped to study and understand new technologies even after their graduation. The PI's educational hypothesis is that teaching in engineering and science can be improved by means of Project-Based Learning, Hands-on Experiences, and Preparation for Lifelong Learning. (1) ***Project-Based Learning (PBL)*** is about learning by doing. Faculty guides students on projects and helps them to apply classroom learning to current real-world challenges. (2) ***Hands-on Experience*** is based on the idea that learning is facilitated by body engagement. (3) ***Preparation for Lifelong Learning*** means education must provide a strong foundation for lifelong learning, where students can continue updating their knowledge and skillsets.

1.3.1. Expected Outcomes from Education Hypotheses

(1) ***Project-Based Learning (PBL)*****:** The outcome of PBL will be (i) new course modules in the final project components for undergraduate robotics and computer engineering curricula and (ii) new graduate courses, including seminar series. New components for PBL will be open as a form of standardized templates using an online shareable documentation platform for other faculty members. (2) ***Hands-on Experience*****:** The outcome will be new lab materials to ensure hands-on experience for undergraduate and graduate courses: robotics, embedded systems, and pattern recognition and neural networks. In addition, the PI will organize and host summer engineering camps for high school students. (3) ***Preparation for Lifelong Learning***: The outcome of lifelong learning is full-stack open-source hardware and software, focusing on reproducibility only through online documentation and video tutorials. This method ensures students can learn the materials and try their own ideas. ***The results from the proposed educational plan*** will be integrated into the proposed research thrusts by adding the topics of robust intelligence, automated mobility, and bio-inspired machine

learning to each of the plans. The expected outcomes will be essential components of a diverse and highly-skilled workforce to help us to build CPS mobility with robust intelligence.

2. Intellectual Merits

***Novelty*:** Conventional methods associated with designing and building a perception and control system for highly automated mobility are mostly limited to putting efforts into making a system faster and more accurate. Such approaches show weaknesses in terms of the robustness of the decision-making system. The PI hypothesizes the robustness in intelligence for CPS can be transformatively improved by investigating using three fundamental research thrusts: causality, predictivity, and adaptability. The proposed novel and holistic approaches are inspired by physiological motor control and sensory-motor contingency that have not been elaborated together in CPS for highly automated mobility. Thus, the research projects to be enabled by this CAREER will have a transformative impact on CPS for highly automated mobility. ***Critical Needs*:** The proposed research will advance knowledge on how to ensure the robustness of intelligence for highly automated mobility, which will save more human lives by providing safer decision-making systems and reduce the emission of greenhouse gasses by cutting energy consumption. By addressing the broader research issues, direct contributions will be made to the following research areas: (a) Better safety in mobility control and perception by causality study, (b) Novel control architectures where significant feedback delay persists by predictivity study, (c) Robust perception systems by adaptability study. ***Qualification*:** The proposed research requires knowledge of a wide span of work. The PI has pursued in his earlier career in computational neuroscience [11–17], robotic microscope design and implementation [18–21], automatic large volumetric data acquisition [22–25], visualization and analyses for large volumetric datasets [24, 26–30], robotics and autonomous vehicles [31–54], and cybersecurity in energy systems and mobility [55–58]. The PI is in the *Goldilocks Zone* [59], where his unique experiences in these wide varieties of research topics make him well qualified for the proposed inter/multidisciplinary research. The results from the proposed research and education plans will lead to a fundamental change in understanding the robustness of intelligence for highly automated mobility systems.

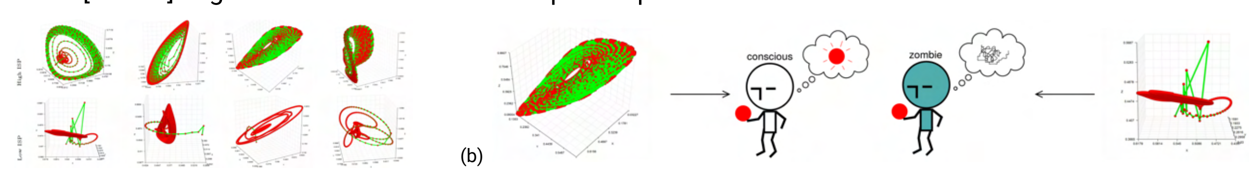
3. Broader Impacts

***Scientific/Technological Impact*:** The proposed project will contribute to a more in-depth scientific understanding how to ensure robustness in intelligent systems for CPS. It will also provide new pieces of knowledge and useful tools to educate future engineers and researchers using the proposed open-source software and hardware platform. ***Education*:** The PI will develop new educational materials about intelligent CPS for high school, undergraduate, and graduate students. The PBL components will be deployed to the PI's undergraduate and graduate courses, and the PI will be a facilitator of campus-wide PBL efforts. The PI will develop and host summer engineering camps for high school students in the Detroit area. Detroit, Michigan is known as the automotive headquarters, and 77.9% of the residents are Black or African American [60]. In Michigan, 26 manufacturers including the *Big Three* (General Motors, Ford Motor Company, and Stellantis) have headquarters or tech centers, and they employ more than 100K engineers [61]. For lifelong learning for undergraduate and graduate students, several media types (text, pictures, videos) of educational materials, including hardware and software design and source code for the proposed research and education, will be prepared and open to the public. The software code will be on a public repository, and hardware design documents will be in an online format (Read the Docs [62] and GitBook [63]). So the resources for studying robust intelligence will be available for even the general public to promote lifelong learning. ***Qualification*:** The PI has a wide variety of work and research experiences, spanning computational neuroscience, robotic microscope, robotics, cybersecurity, and mobility, which is crucial for the proposed interdisciplinary research and education. The PI is also a scholarship recipient of the Defense Advanced Research Projects Agency (DARPA) *AI Forward* [64] in-person workshop in Boston, MA, in 2023. AI Forward is DARPA's initiative to explore new directions for AI research that will result in trustworthy systems for national security missions. The PI has intensive experiences with high school students through summer computer engineering camps (Computer Engineering I and II) from 2011 to 2019 [65–67], where students build a robot with electrical and computer knowledge and program a smartphone app to control the robot via Bluetooth communication. ***Collaboration*:** The PI also has a strong record of domestic and international collaborations with universities and companies for several years. Recent collaborators are as follows: Mr. Paul Fleck, CEO/Founder of

Dataspeed Inc. for advanced mobility research and sensor fusions. Mr. John Moore, Ford Motor Company, *AI System Security Detection Monitoring Research*, in 2022 - 2024. Hyundai MOBIS Technical Center North America, *Detection and tracking of vehicles using Lidar point clouds for autonomous lane-changing system*, in 2021. Dr. J. Chung, Tilda [68] on an optimized solution for ESG, manufacturing, logistics, and dynamic pricing using Machine Learning. Dr. Eric Moon, JM Smart [69] on AI solutions for their IoT service platform. Dr. J. Lee, Smart Radar System [70] on sensor technologies. Prof. Y. Lee, Grand Valley State University, MI, on the following collaborative research activities: *Development of Markerless 3D Human Motion Capture Framework from 2D Videos Using Deep Learning*, in 2022. Prof. H. Nam, Hanyang University-ERICA, Korea, on perception and navigation systems for autonomous vehicles: *Robot Operating System, Cooperative Perception and Navigation for Multiple Vehicles Using Deep Neural Network,* in 2020 - 2021. Prof. Y. S. Cho, Wonkwang University, Korea, on sensor networks and agricultural electric vehicles: *Development of machine learning algorithm for electric autonomous agricultural vehicles*, in 2023. ***Integration of Research and Education*****:** The integration will be smooth since the PI has a sturdy background in teaching from his previous institute and also strong research activities both in the previous and the current institute. Simulation framework and mesoscale electric autonomous vehicle platform will be utilized in pre-college camps and undergraduate education. Two full-scale vehicles with a Drive-by-Wire (DBW) system from the PI's previous NSF award and an internal grant from the PI's home institute will be used for graduate research and education. ***Effectiveness of Evaluation and Assessment Plan*****:** The proposed projects will be evaluated and assessed both qualitatively and quantitatively with a clear metric table to ensure the effectiveness of those plans. The initial validations of the proposed research will be done inside a simulated environment [71] developed by the PI. Then further validation will be conducted with an outdoor mobile robot to ensure the safety of the researchers. As the last step, the PI will use a plug-in hybrid Chrysler with a sensor suite (NSF-MRI #2214830) as well as his Drive-by-Wire (DBW) equipped Kia Soul Electric to test further and validate the feasibility of the proposed research thrusts.

4. Relevant Prior Research

The PI has unique and combined multidisciplinary experiences in computer engineering and science, computational neuroscience, and robotics: (i) computational neuroscience [11, 11–17], (ii) robotic microscope design and implementation [18–21], (iii) automatic large neuroanatomical volumetric data acquisition [22–25], visualization and analyses for large neuroanatomical volumetric datasets [24, 26–30], (iv) mobile robotics and autonomous vehicles [31–46, 48–54, 72], and (v) cybersecurity in energy systems and mobility [55–58]. ***Computational neuroscience*****:** Study on predictive neural dynamics for delay compensation [11, 13], Predictictable internal brain dynamics and consciousness [11, 12, 14, 16]. See Figure 1 for further details. ***Robotic microscope, brain scanner, and neuronal data analysis tools*****:** An Internet-enabled robotic microscope for brain study through NSF-funded development proposal, *Development of High-Throughput and High-Resolution Three-Dimensional Tissue Scanner with Internet-Connected 3D Virtual Microscope for Large-Scale Automated Histology* (National Science Foundation Award No. ECCS-1337983, PI: Kwon), robotize the brain scanner [19–21, 23, 25], data acquisition and visualization, data analyses [27–30]. See Figure 2 for details. ***Robotics and mobility*****:** The designs of sensor packages for robots and their validation, smartphone-based educational robots, 2D SLAM studies, and vision-based localization [34, 49, 50, 52, 53]. ***Autonomous vehicles*****:** Lane detection algorithms, autonomous vehicle control design, a design of a simulation framework, behavior cloning-based lateral motion control, an incremental end-to-end learning framework, Drive-by-Wire system design for mesoscale electric vehicles [37–43]. ***Cybersecurity and energy systems*****:** deep-learning-based fault event analysis, threat analysis for autonomous vehicle perception systems [55–58]. Figure 3 illustrates some examples of prior research on this thread.



(a) (b)

Figure 1. The PI's prior research on computational neuroscience. (a) Different internal neural dynamics study from the same high-performance individual agents. The upper row shows more predictable neural dynamics. The lower row shows less predictable neural dynamics. (b) Conscious being vs. zombie. From the outside, a conscious being and a zombie (a philosophical zombie) may

seem indistinguishable. Yet, internally, one might have phenomenal experience (left) while the other might lack this kind of experience (right). These internal characteristics may be determined in part by the internal state dynamics.

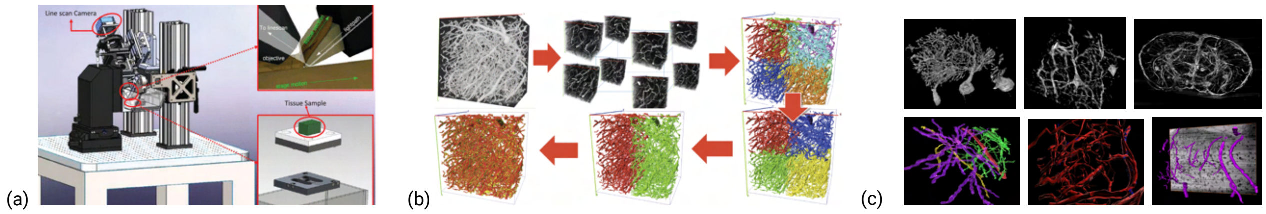


Figure 2. The PI's prior research on neuroanatomy and robotic microscope. (a) A new Knife-Edge Scanning Microscope (KESM). The original design is from [73, 74]. (b) The flow of the divide-and-conquer algorithm from data to result [30]. (c) Examples of acquired samples: Purkinje cells, microvasculatures, whole mouse brain blood vessels, and neuronal structures.

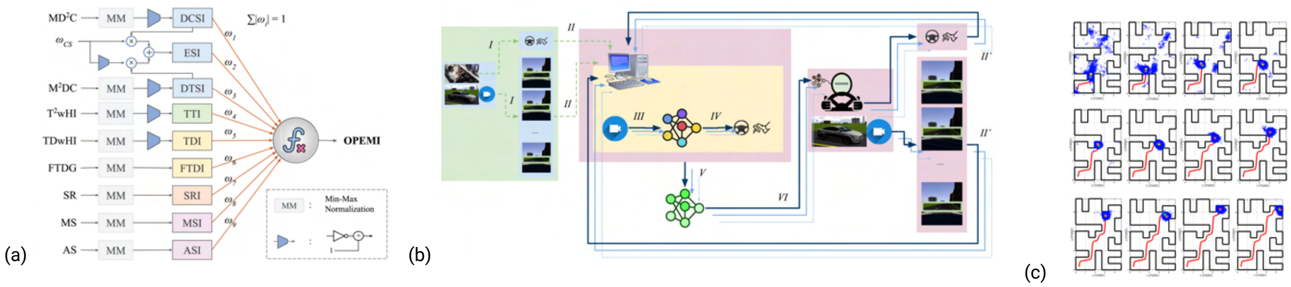


Figure 3. The PI's prior research on robotics. (a) OPEMI: Online Performance Evaluation Metrics Index. For more details, refer to [31]. (b) System overview of the incremental End-to-End learning [32]. (c) Localization results using particle filters [35].

5. Research Plan and Preliminary Data from Feasibility Validation

The primary research objective of the proposed project is to investigate the robustness of intelligent systems for highly automated mobility systems and propose a fundamentally novel approach to the topic. There will be three thrusts to provide propulsion for robust intelligence of CPS for highly automated mobility.

5.1. Thrust 1: Causality Study in Sensorimotor Loop via Forward and Inverse Models

Overview: Judea Pearl [75], who is a Turing Awardee computer scientist and philosopher known for probabilistic approaches to AI, said, "*to build truly intelligent machines, teach them cause and effect*" [6]. In conventional end-to-end systems based on Deep Neural Networks (DNN), ML models can only *associate* an input with a desired output. For example, a DNN model maps an image from a front-facing camera to a steering angle value [76, 77]. The DNN model can automatically find useful features (e.g., lane marks, the curvature of lanes, etc.) from an input image that can be used to determine a steering angle through convolutional layers. Thus we can safely tell the DNN model can *associate* an input image with a corresponding steering angle. However, the ML model does not *understand why* a certain steering angle is good for keeping lanes. The *association* assumes all possible cases were in the training data, which is not practically viable. There will be almost always edge cases. Figure 4 illustrates an example of the association problem. The PI hypothesizes causality models can mitigate the aforementioned association problem and proposes to investigate forward and inverse internal models of physiological motor control.

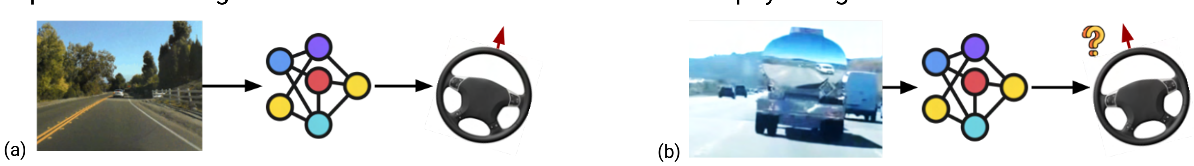


Figure 4. ML model problem due to simple association of input with output. (a) An ML model trained with pairs of images from a front-facing camera and steering angle. The ML model works well as long as the input has a similar distribution to training datasets. (b) Even a successful model will show unexpected behaviors when the input data has a significant distributional shift (a reflected road image on the car in front) from the training datasets.

Scientific Premise: In neurophysiology and cognitive robotics, paired forward and inverse models have been extensively studied for motor control, adaptation, and learning [7–10, 78]. Using the physiological sensorimotor loop in action execution through motor control and learning could shed light on mitigating the *association* problems. To employ causality in intelligent systems, the PI also investigates Sensorimotor Contingency (SMC), which is defined as *"acquired law-like relations between movements and associated changes in sensory inputs* [5]." SMC was originally proposed for visual consciousness. Then, it has been extended to action prediction, planning, generation, recognition, and even cognition [79, 80]. Most control architectures for highly automated mobility rely on internal representations of the outside world, and reliable state estimation from the internal representations is only possible for highly controlled environments [79]. Partially Observable Markov Decision Processes (POMDP) [81], a probabilistic approach, may mitigate this problem, but it requires various approximations due to its computational complexity. Therefore, the PI hypothesizes that SMC can also be a sturdy foundation for building causality of robust CPS intelligence.

This research lineage has been investigated from various disciplines with different viewpoints: Embodied cognition [82, 83], Neurorobotics [84], Kalman Filters [85], and Active Inference [86–89]. Yet, integrated computational frameworks of sensorimotor loops are very rare in CPS for highly automated mobility due to their multifaceted nature and cross-discipline topics. In CPS for highly automated mobility, the PI hypothesizes that the causal inference means it knows what would happen to sensory input if a certain ego action is made. In conventional frameworks, perception and decision-making are two separate intelligent activities. Perception is often understood as combined information about the physical world by modeling sensor signals in mathematical forms, and a higher-level decision-making system uses the models to understand the environment. Such a separation between perception and decision-making has been taken for granted. However, the physical world cannot be perfectly represented by models, and the PI considers that this is a fundamental reason for the fragility in intelligence. The world must be perceived by embodied methods, where the *brain*, the main controller in CPS, must be mounted in a moving body, and the world must be perceived through the sensorimotor loop. The PI hypothesizes that intelligence for mobility must be implemented through motor learning to ensure causal inference, which is a key ingredient in building robust intelligence. Infants acquire their body dynamics through so-called *motor babbling*. Through their random and exploratory body movements, infants learn the causal relationship between their body movements and the resulting sensory changes [90–93]. The skills to interact with the outside world emerge through two sensorimotor schemes: forward and inverse internal models [7–10]. The idea was proposed by [78] as a supervised learning method. The forward model is an internalized incorporated causal knowledge about sensor changes induced by an ego action [94]. Given a sensory situation $\boldsymbol{x}_t$ and a motor command $\boldsymbol{u}_t$, a forward model is a predictor, $y_t = f_F(\boldsymbol{u}_t|\boldsymbol{x}_t)$ presenting the causal relationship between an action through $\boldsymbol{u}_t$ and its consequence at the next time step *t+δ*. A sensory situation and motor command can be specified in the context of CPS for ground mobility. Let $\boldsymbol{u}_t$ be $\boldsymbol{u}_t \in \mathbb{R}^3,\ \boldsymbol{u}_t = [s_t,\ r_t,\ b_t]^T$, where $\boldsymbol{s}_t$ is a steering angle, $\boldsymbol{r}_t$ is a throttle, $\boldsymbol{b}_t$ is a brake. Let $\boldsymbol{x}_t$ be $x_t = [I_t,\ v_t,\ a_t]^T,\ I_t \in \mathbb{R}^{W\times H\times 3}$, where $\boldsymbol{I}_t$ is an input image, $\boldsymbol{v}_t$ is a speed, and $\boldsymbol{a}_t$ is an acceleration. In CPS for ground mobility, $\boldsymbol{y}_t \equiv \tilde{\boldsymbol{x}}_{t+\delta}$, the output of the forward model at time *t* is a predicted sensory situation at time *t+δ*. While a forward model acts as a predictor for the consequences from the ego action, an inverse model is a controller, $y_t = f_I(x_{t+1}|x_t)$ that provides CPS with $\tilde{\boldsymbol{u}}_t$, a motor command to transit from the current sensory situation, $\boldsymbol{x}_t$ to a desired one $\boldsymbol{x}_{t+\delta}$. The output of the inverse model is $\boldsymbol{y}_t \equiv \tilde{\boldsymbol{u}}_t$, the necessary motor command for the sensory situation transition. Figure 5 (a) illustrates the training of a forward model. Once the forward model is successfully trained, then an inverse model can be trained using the trained forward model (See Figure 5 (b)).

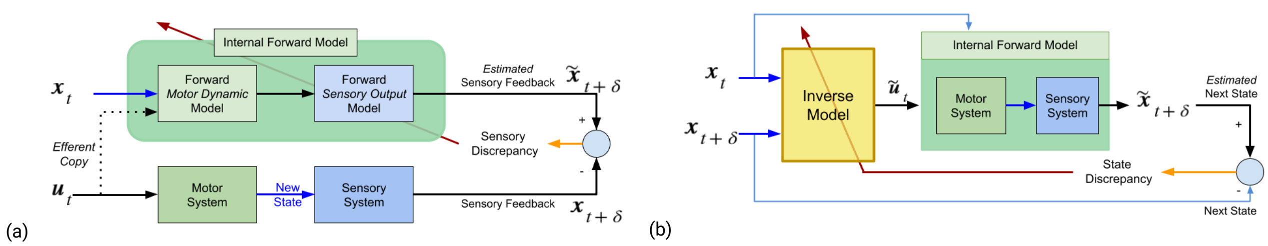


Figure 5. Training a forward model. (a) A forward model can be trained using sensory discrepancy between a predicted next sensory situation $\tilde{\boldsymbol{x}}_{t+\delta}$ and the ground truth sensory situation $\boldsymbol{x}_{t+\delta}$. (b) Training Inverse Model. An Inverse Model can be trained using state discrepancy between an estimated next sensory situation $\tilde{\boldsymbol{x}}_{t+\delta}$ and the ground truth sensory situation $\boldsymbol{x}_{t+\delta}$..

Sensorimotor Contingency (SMC) [95–97] is also an option to implement causality for robust intelligence. Sensorimotor contingencies are defined as "*the regularities in how sensory stimulation depends on the activity of the perceiver*" [97]. This idea was applied to the perception of spatial arrangements in mobile robots [98] and presented a computational model to train a quadruped robot to discriminate between different types of terrain and adapt its walking behavior accordingly, using the concept of SMC [99]. By training the robot to anticipate changes in its visual input as a result of movement orders, the author was able to perform two perceptual tasks. The first task is judging the distance to an object and the second is to recognize dead ends. A discrete computational model of SMC for visual perception and robot control was built and tested [100], showing actions are an essential part of their robot vision. They considered SMC as a multi-step and action-conditional probability of future sensory observations. These probabilities were formally described by a collection of n^{th}-order Markov models. They demonstrated how the model can learn to anticipate the effects of its own behavior and use this knowledge to achieve its goals. A developmental approach to SMC was used by [101] to formalize a single and generic learning framework that would account for the acquisition of any contingency. They developed the idea that SMCs define a perceptive ontology, introduced predictive modeling as a computational implementation of contingencies, and described an approach to allow a naive agent to build its own predictive models and interpret the world with which it interacts.

Validation: The PI has worked on this research thrust with collaborators [37, 38]. To computationally implement a forward model, several generative machine learning models have been tested and validated: U-Net [102], Conditional GAN (cGAN) [103], Pix2PixGAN [104], and VAE [105]. U-Net is a convolutional neural network that was originally developed for biomedical image segmentation. The encoding path and the decoding path make up the two fundamental components of the U-Net design. Convolutional layers form the encoding path, which gradually lowers the input image's spatial resolution while raising the number of feature mappings. Another sequence of convolutional layers makes up the decoding path, which successively lowers the number of feature mappings while raising their spatial resolution. In order to retain the spatial information lost during downsampling (encoding path), the U-Net design additionally contains skip connections between matching layers in the encoding and decoding paths. Two GAN [106] networks, cGAN and Pix2PixGAN were tested as well for a forward model. cGAN proposes a modification to the original GAN architecture to allow for the generation of samples based on a specific condition or label. Pix2Pix GAN was also tested for a forward model. It addresses the problem of translating an input image from one domain to another, where both domains have a distinct visual appearance. The generator network of Pix2PixGAN is a U-Net, and the discriminator is a Markovian discriminator (PatchGAN) [107]. With preliminary testings and validations, Variational Autoencoder (VAE) was determined as the best option for a forward model. VAE is a type of neural network model that can be used for unsupervised learning and generative modeling. It is based on the autoencoder architecture, which consists of an encoder network that maps the input data into a lower-dimensional latent space and a decoder network that maps the latent space back to the original data space. In a VAE, the encoder network maps the input data to a probability distribution over the latent space, rather than directly mapping it to a specific point in the latent space. This probability distribution is typically a Gaussian distribution with a mean and variance, which allows for stochasticity in the encoding process. The decoder network then maps samples from the latent space to the original data space, producing a reconstructed output that is similar to the input data. The model is trained to minimize the reconstruction error between the input and output data, as well as the Kullback-Leibler (KL) divergence between the learned latent distribution and a prior distribution (usually a standard Gaussian).

Figure 6 (a) illustrates a VAE architecture for a forward model. Figure 6 (b) shows preliminary results. The pictures are examples of *effective* future sensory situations (generated by the VAE) by *causal* actions. Given input images (i) at time *t*, predictions at *t* + 100 ms are at the (ii)'. Compare the predictions with the ground truth (ii). Time at *t* + 300ms is also tested (iii)' and (iii). The results are very promising because the predictions are more similar to the ground truth rather than the input images. These generated future images were tested in steering angle predictions and compared with the ground truths. The steering angle prediction differences between the generated images by a forward model and the ground truths are as follows. The mean absolute error was 0.032, the mean squared error was 0.034, and the standard deviation was 0.034. Since the unit is a steering angle (-1 to 1), these error values are a strong indication that the forward model was well trained. <u>These preliminary results indicate that the proposed forward model can be successfully</u>

<u>trained using VAE, and *effective* future sensory situations can be generated based on the current sensory information and *causal* actions</u>.

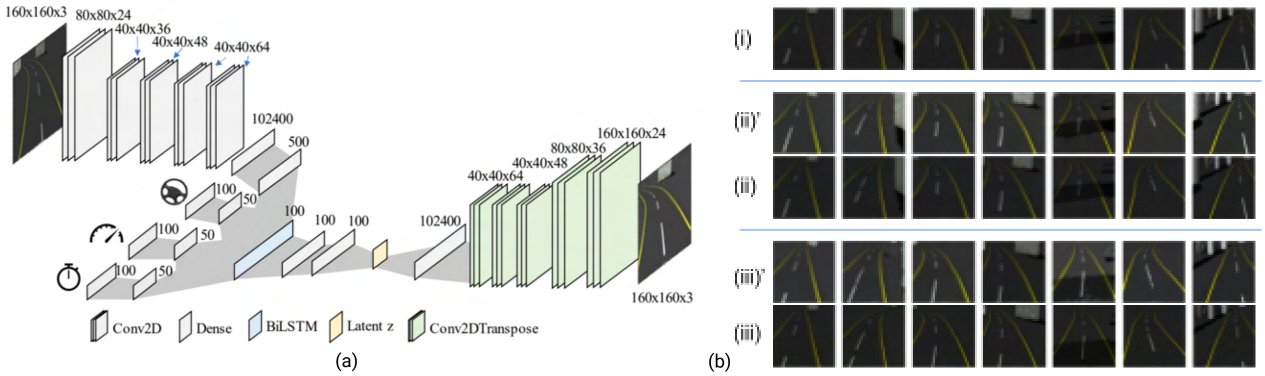


Figure 6. (a) Proposed Variational Auto-Encoder (VAE) architecture for a forward model and results. (b) The output of the VAE is part of the future sensory situation, which is an image that would be seen due to the motor command $\boldsymbol{u}_t$.

<u>Potential Challenges</u>: The inverse model should still need to be tested and validated to complete this sensorimotor loop approach to implementing causal inference in mobility. Yet, the PI expects that training the inverse model can be less challenging since the output is a much smaller dimension compared to the forward model's output. Another potential challenge is that a full causality model has not been tested. These preliminary results, however, are promising. Therefore, the PI's anticipation regarding potential challenges is optimistic.

<u>Expected Outcome and Assessment</u>: The expected outcome from this thrust is a novel control architecture inspired by physiological models for CPS for highly automated mobility. This proposed causality-based system will be a foundation of robust intelligence since, unlike association-based methods, understanding causality makes a control system adaptable and agile to edge cases. The outcome will be validated by applying it to the control system of mobile robots and ground vehicles to see if the causality helps implement robust intelligent control for mobility.

5.2. Thrust 2: Predictivity of Machine Learning-based Control

<u>Overview</u>: An intelligent being senses time: past, present, and future, and believes in living in the present. It is, however, not possible to live in the present, precisely speaking. According to studies [108, 109], an intelligent organism's conscious perception system is always lagging behind. This delayed perception is unavoidable since it takes time for an organism's perception system to process sensory information to make the sensory stimuli meaningful to the organism.

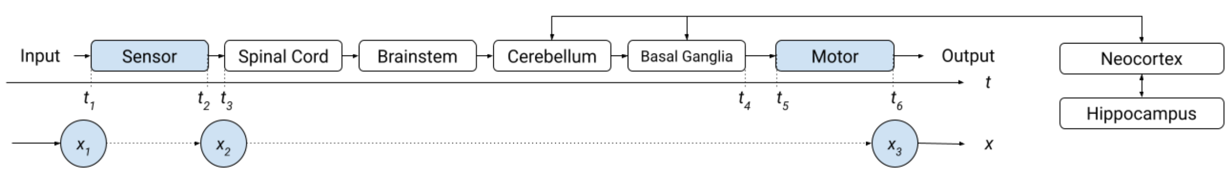


Figure 7. Neural transmission delay and a moving object. Suppose a moving object is going to be located along with the *x*-axis as time goes by on the *t*-axis accordingly. The moving object was located at x_1 at time t_1, and the particular sensory information travels to the central nervous system. The object keeps changing its position while the neural signal (position of object = x_1) travels through the sensory pathway. When a motor output is activated, the object is no longer at position x_1. It will be located at x_3 at time t_6.

In Figure 7, the neural transmission delay is illustrated. In monkeys, the time for visual signals from the eyes to the prefrontal cortex is approximately 100 to 130 milliseconds [110]. Then, how can organisms precisely react to the *current* environment based on information from the *past*? To fill the gap between the *current* state of the environment and the *past* sensory information, the brain must have a prediction mechanism that utilizes the *past* sensory information to predict the *not-yet-to-come current* state. When we drive a car, for example, we sense our environment, assess it, make a decision, and then act on that decision. The action we take, however, is based on an earlier observation since by the time we act, the state has already changed, and we have a new observation. If we get an observation of the environment at time t_1, our brain needs time δ to process the observation, so we take action at time $t_1+\delta$. However, at time $t_1+\delta$, the vehicle has moved, the environment has changed, and we have a new observation. There have been debates on how the brain produces present conscious awareness using past sensory information. One of the hypotheses is that visual perception is predictive, so sensory information is extrapolated ahead of the perceived event. In autonomous driving, the latency due to *lagging behind* is present, determined by the amount of time the control algorithm needs to process information before acting. This algorithmic perception latency δ is inevitable [111]. The PI hypothesizes a predictive neural mechanism can be emerged through internal simulation of perception and control behaviors.

Scientific Premise: Using massive computing power via GPUs, FPGAs, and multicore CPUs may reduce the latency. In training a deep neural network, such a high computing power system can be a choice. Yet, in actual inference, computing resources are limited in automobile platforms. Thus, it is a reasonable assumption that there will be an unavoidable latency in the perception and actuation cycle. Most vision-based lateral control studies assume no delay between observation and action [32, 77, 112–117]. Most vision-based neural network driving models from various research [32, 76, 77, 114–116, 118, 119] were developed without taking the algorithmic perception latency δ into account. Instead, latency in autonomous driving has been discussed from different perspectives. The majority of the work concentrates on deployment-related computational latency (i.e., hardware) [120–123] and network-related latency (i.e., communication) [124–128], occasionally both [129, 130]. Li et al. [126] emphasized how the problem of algorithmic latency should not be overlooked in online vision-based perception. Taking this latency into consideration, they presented a method for measuring the real-time performance of perception systems that quantifies the trade-off between accuracy and latency. Their approach might be a strong solution for well-defined problems but is not ideal for safety-critical systems such as automotive platforms. Mao et al. [131] investigated the algorithmic latency for video object detection, comparing the detection latency of several video object detectors. They proposed a metric to measure the latency, not a solution to deal with the latency. Kocic et al. [132] attempted to reduce the algorithmic latency in driving by modifying the DNN architecture. This approach may reduce the latency, but it is challenging to maintain the original accuracy. Wu et al. [116] highlighted that control-based driving models (image → control signal) have algorithmic latency and may fail since they focus on the current time step. To address this issue, they created Trajectory-guided Control Prediction (TCP), a multi-task learning system that combines a control prediction model with a trajectory planning model. Their approach requires extracting the exact trajectory, which can be challenging. The PI accepts that this latency is inevitable and tries to reduce its effect by adaptively combining predicted future actions with the current action.

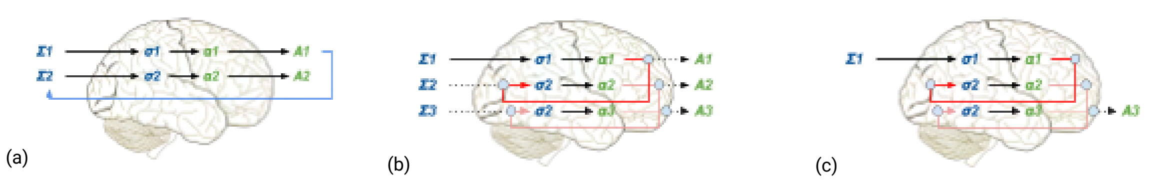


Figure 8. Internal simulation theory. (a) Sensorimotor loop. Σ is sensory input from an environment. σ is an internal representation of the sensory input. *a* is an internal representation of an action. A is an actual motor output. The loop of $\Sigma \rightarrow \sigma \rightarrow a \rightarrow A$ is repeated as new sensor input comes. (b) As the repeat of the sensorimotor loop, action feedback starts being internalized, and the sensory input caused by the action also starts being internalized as well. (c) After internalization is established, perception *"would have occurred if the action had actually been performed*[133]."

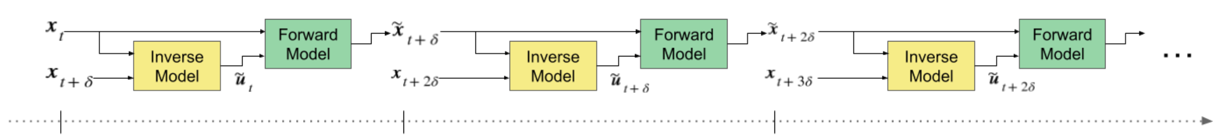


Figure 9. Recursive simulation of the sensorimotor loop for an action. $\boldsymbol{x}$ is a vector of sensory situations, and $\boldsymbol{u}$ is a vector of motor outputs (or actions). The forward model (green box) generates predicted sensory situations for the next time step using the current state and a predicted motor action from the inverse model. The pairs of the forward and inverse models are recursively repeated to simulate future sensory situations and motor actions.

Another direction to mitigate latency issues for robust intelligence is the internal simulation theory [134, 135], which is also called the simulation hypothesis, perception/motor imagery, and mental practice of action. The *simulation hypothesis* stems from David Hume and Alexander Bain, British empiricist philosophers in the 18th and 19th centuries [136, 137], and states that thinking is a simulated interaction with the environment [133, 134]. The core idea of the simulation theory is "*conscious thought as simulation of behavior and perception*" [133]. Figures 8 and 9 illustrate the idea in the form of a recursive simulation. The internal simulation theory of cognitive brain function is based on the following three assumptions. (i) Simulation of Action: motor actions can be internally simulated without their actual execution. (ii) Simulation of Perceptions: imagining perceptual activity is essentially the same as actual perception by external stimuli. (iii) Anticipation: association mechanisms exist by which a simulated action can invoke perceptual activities [138]. The association between the perceptual activity and covert movement can generate a simulated action that can evoke similar perceptual activity that "*would have occurred if the action had actually been performed* [133]." The PI investigates this internal simulation hypothesis to develop prediction mechanisms for highly automated mobility to ensure robust intelligence of CPS.

Validation: The PI conducted initial preliminary studies for this research thrust in finding predictive latent information in visual input of advanced mobility. The PI studies the latency effect on autonomous driving in the lane-keeping task. A larger effect of the latency δ can be expected in higher velocity and curved sections of the road. For instance, a model could be able to drive at a speed up to (v + 5) km/h, if it is trained at a maximum speed of v km/h, but it would likely not function effectively at higher speeds in a more dynamic environment. When vision-based neural network models, such as PilotNet [76, 77] and CNN-LSTM, were employed for racing [117], neither model was able to finish the course. A probable reason was the high speed that amplifies the effect of the latency. Yet, perception latency does not prevent human drivers from successful in-time decision-making. According to [139], when they looked at the gaze distributions of human drivers during lane keeping, they discovered that most of the time (assuming there is no lead vehicle), humans hold their gaze at a distance in front of their own vehicle, which aids in anticipating future actions. Inspired by this gaze distribution, the PI hypothesizes that visual input at time t has latent variables not only for the current state at time t but also for future states at time $t + \delta$, and the weight of importance of the future states varies with the current driving speed and curvature of the road. In this context, the PI proposed the Adaptive Neural Ensemble Controller (ANEC) to show that the algorithmic perception latency issue can be addressed by adaptively infusing the prediction action output into the baseline output. A paper based on this idea is accepted for the 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2023), one of the premier conferences of robotics alongside ICRA, (International Conference on Robotics and Automation). ANEC depends on combining the output of two driving models, the Base Model (BM), a reference model, and the Predictive Model (PM). BM is expected to focus on the near-point area like any vision-based neural network model. PM, on the other hand, is expected to cover the far-point area to extract latent variables for future actions. Note that near/far areas are not explicitly selected. BM and PM will figure out which areas are important to infer control output. A dynamic and adaptive weight, dependent on the vehicle speed, is assigned to each model to establish ANEC final output. The higher the speed, the greater the significance of future states and hence the greater the weight assigned to PM. ANEC was tested and validated through the following experiments. The trajectories of all three models (BM, PM, and ANEC) on a series of consequence turns while driving at a maximum speed of 90 km/h against the trajectory of the reference model while driving at an ideal maximum speed. The driving performance of all three models was compared at different maximum speeds (90, 94, and 97 km/h) to validate that the proposed method can address the algorithmic perception latency issue. The increase in speed amplified the latency effect, where the autonomy score significantly decreased from 93.33% to 76.67%. The trajectories of all driving models at a maximum speed of 90 km/h with the reference model trajectory were tested, and the trajectory of ANEC was the closest to the reference BM, qualitatively. The experimental data unambiguously demonstrated that ANEC performed better and was able to tolerate high speed to some extent compared to BM and PM. The results indicate that predictivity can play a pivotal role in enhancing the robustness of CPS intelligence for highly automated mobility.

Potential Challenges: Even with promising results from ANEC, a more direct exploration of the predictivity should be validated through an implementation of the internal simulation.

Expected Outcome and Assessment: The expected outcome of this research thrust is a novel perception and control framework that can predict future states. The novel framework will be able to be used to enhance the stability of mobility in fast-changing environments, and it can also be used to compensate for delayed feedback signals by providing probable near-future sensory situations. The output will be assessed by the prediction capabilities of CPS in mobility in terms of performance in driving conditions with mobile robots and ground vehicles

5.3. Thrust 3: Adaptability in Perception

Overview: The robust Intelligence of CPS is the ability to be able to adapt itself to a novel environment and ambiguous situations. Conventional ML algorithms, such as Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (K-NN), Decision Tree, Logistic, and Linear Regression, often show vulnerabilities against slight differences in training and test datasets. Perceptions of robust intelligence should not be broken due to a slight distribution shift of features. DNN models outperform such algorithmic approaches in perception and decision-making when the latent features in problems are more convoluted. Yet, even DNN models are fragile when an articulated adversarial attack is executed. This research thrust aims to investigate the adaptability of intelligence to pursue robust intelligence. Adaptability can be seen in individuals and systems who can flexibly adjust their cognitive abilities to varying environmental demands and challenges. Long-term objectives could be understanding the mechanisms and factors underlying adaptability by examining the neurobiological foundations of adaptability and designing/implementing algorithms aiming at improving adaptability and cognitive flexibility. To build a foundation for these long-term objectives, the PI started investigating methodologies to handle adversarial attacks. The PI proposes to use holistic and generative AI approaches to these adversarial attacks.

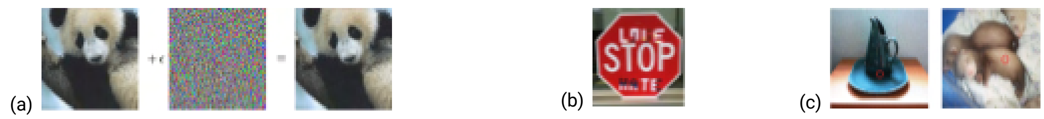
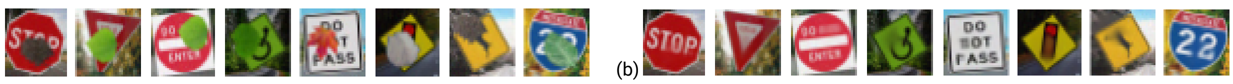


Figure 10. Examples of adversarial attacks. These examples show a lack of resilience in conventional DNN models. (a) A successful image classifier can be easily fooled by the addition of unnoticeable random noise. The classifier recognizes the original panda image but the noise-added image (no significant difference to human eyes) as a gibbon monkey with 99.3% confidence [140]. (b) The stop sign with stickers is recognized as a speed limit of 45 [141]. (c) One-pixel attack [142] is another example showing the vulnerability of DNN-based classifiers even if they showed comparable performance with trained human labelers [143]. By one-pixel attack, the teapot is classified as a joystick, and the hamster is classified as a nipple.

Scientific Premise: Resilience is one of the most important aspects of intelligence. Adversarial attacks can be a seminal example [140–143], and Figure 10 presents a lack of resilience in conventional DNN models with some examples. Another aspect of *adaptability* for robust intelligence can be investigated in terms of *interpretability*. There will be a higher chance to make CPS adaptable when the ML models are more interpretable. The PI hypothesizes a holistic and hybrid approach that ensures interpretability while leveraging the advantages of DNN models should be used for robust intelligence. Interpretability is defined as *"the degree to which a human can understand the cause of a decision* [144, 145] *or why and how the model generates prediction* [146]*."* Choosing DNNs for ML means, in many cases, sacrificing interpretability for performance. The model becomes harder to be understood why and how the model makes such decisions as given tasks are more challenging. In some applications, such as dogs-vs-cats classification, simply achieving higher accuracy is desirable. However, for safety-critical systems (e.g., self-driving cars and mobile robots), interpretability is also important unless its accuracy is always 100% under any circumstances since taking a left turn instead of a right or running over instead of stopping can determine life or death. The PI hypothesizes that generative AI can be a potential solution for ensuring adaptability. Generative Adversarial Networks (GAN) were introduced to show that a type of content can be generated by GAN [106]. A new network architecture, the Transformer, was proposed [147], and this attention mechanism-based model became a foundation of Large Language Models (LLM) that open up new opportunities where generative AI models can create texts [148] and photorealistic images [149]. The PI investigates generative models to ensure the adaptability of CPS for highly automated mobility. These studies showed neural network-based classifiers could be easily fooled by specially designed noise that does not make any significant difference to the human eyes but causes wrong classification results. Real intelligence should not have worked this way. The research thrust to address this vulnerability is to make the system use (i) a multimodal approach and (ii) a generative AI. (i) A multimodal approach is characterized as using methods where the system does not depend on a classification method that can be vulnerable. For example, a stop sign tainted by tapes or paint still has a clue to be properly classified, such as characters: S, T, O, and P. Even after one or two letters are obstructed, the sign input may have S, T, and O or T, O, and P, which can be a strong indication the input sign is a stop sign. Also, the shape of the sign is an octagon which can increase the probability of the input image being a stop sign. (ii) A generative method is to restore the obstructed area. Humans can easily reconstruct missing areas based on prior knowledge about traffic signs. Yet, the performance of classifiers trained by traffic signs easily deteriorated due to the obstructed area. True intelligence should not be broken by a slight chance in the input image. Masked Auto Encoder (MAE) is a self-supervised learning algorithm [150], by which obstructed areas (blocked by masks) can be reconstructed in ImageNet datasets.

Validation: The proposed method reconstructs the areas and then feeds the restored images to the processing pipeline. The preliminary results show that the classifier trained with normal datasets is improved in performance. The PI constructed a new US traffic dataset for this research thrust since popular traffic sign datasets in the computer vision community are from Germany [151], China [152, 153], and India [154]. Interestingly, there are not many US traffic sign datasets in high resolution with various backgrounds. The PI is preparing an open dataset (not yet published as the proposal is being written). The PI created US traffic sign datasets (50 classes, 50,000 total images) with collaborators to conduct feasibility studies. With a pre-trained network model with ImageNet datasets [155], the MAE was tested to determine if randomly positioned obstructions could be reconstructed. As seen in Figure 11, the results are promising qualitatively. The PI built a DNN-based classifier (ResNet50 [156] architecture was used for convolutional layers) and tested with the obstructed and reconstructed ones. Without obstructions, the classification success rate was 100%, and it went down to 81.02% when obstructions were applied. The preliminary classification results with the reconstructed dataset showed 84.50%, which is an improvement of 4.3%. The amount of improvement is less than the PI's initial expectation but still noticeable. In addition, a multimodal approach, including Optical Character Recognition (OCR) method, will be tested and validated.



(a) (b)

Figure 11. Examples of reconstruction. (a) Traffic signs with obstructed images. (b) Reconstructed images using a pre-trained model.

Potential Challenges: The PI suspects some imperfection in the reconstructed images is because of using the pre-trained model with the ImageNet dataset, which does not have high-resolution traffic signs. To improve the reconstruction quality, the PI will train a new MAE DNN model with the US traffic sign datasets. A multimodal approach is also on the way, expecting a better perception performance. The PI expects classification accuracy would improve certain traffic signs, but there still could be some unseen challenges. But, even a small improvement in a perception system for highly automated mobility can have significant impacts on saving lives and energy consumption.

Expected Outcome and Assessment: This research thrust expects an adaptable and flexible perception system for a robust intelligence framework of CPS, and it will be a great addition to the robustness of intelligent CPS for highly automated mobility. The outcome will be assessed by the classification accuracy improvement by the proposed method.

6. Integrated Education and Outreach Plan

The PI is to integrate his research thrusts with education and outreach activities. There are three educational thrusts to propel the integration of research and education, where underrepresented groups, including african american high school students in Detroit Metropolitan areas and undergraduate and graduate women in STEM, will be prioritized. The PI will also apply for Dearborn Discovery Core [157, 158] with new undergraduate courses developed through this CAREER proposal. Dearborn Discovery Core is the campus-wide general education program that is designed to complement work in a student's chosen area of study. The three thrusts in education and outreach are as follows. (1) ***Project-Based Learning (PBL)***: Faculty guides students on projects and helps them to apply classroom learning to current real-world challenges. The University of Michigan-Dearborn (UM-Dearborn) has been a strong supporter of PBL for its colleges. Every year, the College of Engineering and Computer Science (CECS) exhibits exemplary work on PBL through faculty members. (2) ***Hands-on Experience***: Learning is facilitated by body engagement, according to research on embodied cognition [2, 159]. The PI hypothesized that STEM education should be more like musical instrument training. Charles Kettering once said that "*If we taught music the way we try to teach engineering, in an unbroken four-year course, we could end up with all theory and no music. When we study music, we start to practice from the beginning, and we practice for the entire time*" [160]. When we study engineering, we should start to practice from the beginning, and we have to practice for the entire time. (3) ***Preparation for Lifelong Learning***: STEM learning must be a self-initiated education, so-called lifelong learning. The world is changing at near-lightning speed. In STEM areas, it is even faster. Scientific facts may stay the same longer, yet, the ways of learning and utilizing them have drastically changed. A few years from now, probably, no one will need to write entry-level code due to generative AI such as OpenAI's ChatGPT [148], Google's Bard [161], and Meta's LLaMA [162].

6.1. Thrust 1: Project-Based Learning

Project-Based Learning (PBL) promotes critical thinking, teamwork, and practical skills to solve real-world problems by giving students chances to work on a project over several weeks during a semester. Faculty guides students on projects and helps them to apply classroom learning to current real-world challenges. However, due to the extra work and time/effort commitment for a successful project experience, it is sometimes difficult to implement for faculty to existing courses even if there is a strong initiative from their institute. Yet, the PI believes the topics of STEM education must be connected to real-world applications, and has a long history of working on Project-Based Learning (PBL), aiming at introducing the core concept of PBL, which is learning by doing to undergraduate and graduate students. From 2010 to 2019, when the PI worked at Kettering University, a national leader in experiential STEM education, most of his courses had final project components: ECE-450/650 Mobile Robotics (Spring and Winter 2019), CE-491 App Development for Mobile Devices (Winter 2016, Spring 2015, Winter 2014, Spring 2013, Winter 2012, Spring 2011, Summer 2010), CE-426/626 Real-Time Embedded Systems (Winter 2019, Spring and Winter 2017). The PI continues his efforts on PBL as working at UM-Dearborn: ECE-3641 Robotic Manipulation (Winter 2023, Fall 2022) and ECE-5831 Pattern Recognition and Neural Networks (Fall 2022) as soon as the COVID-19 pandemic situation was improved. The PI's home institute has been a strong supporter of PBL. CECS has had an annual PBL showcase to publicize the work. The PI participated in the 2023 PBL showcase with two-course projects [163]. See Figure 12 for examples. In 2023, CECS sent a group of faculty to the PBL workshop hosted by the Center for Project-Based Learning at Worcester Polytechnic Institute (WPI) [164]. The PI volunteered to attend the 2.5-day intensive in-person workshop at WPI. The proposed research thrusts will be integrated with the PBL efforts. The robust intelligence in terms of causality and adaptability in research will be integrated with potential student project topics in ECE-5831 (Pattern Recognition and Neural Networks) and ECE-505 (Introduction to Embedded Systems) for graduate students, and ECE-3641 (Robotic Manipulation), ECE-434 (Introduction to Machine Learning), and ECE-4641 (Mobile Robotics) for undergraduate students. If this CAREER proposal is awarded, the PI will significantly expand the PBL efforts to his other undergraduate and graduate courses and even more actively engage the institutional efforts on PBL.

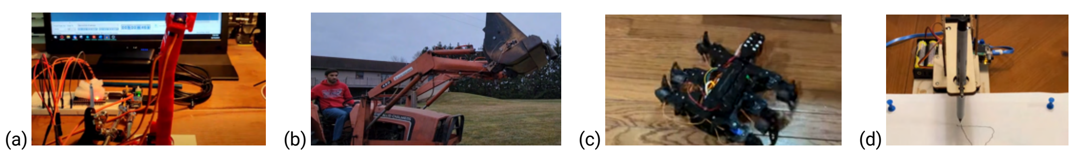


Figure 12. Examples of projects. (a) A robot arm remotely controlled by IMU sensors. (b) An automatic tractor bucket leveler. (c) A hexapod robot capable of avoiding obstacles. (d) A drawing robot using robot kinematics. Full code and demo videos are at [163].

6.2. Thrust 2: Hands-on Experience

STEM education requires hands-on experiential training because most STEM fields assume the theory will be applied to solve real-world problems. In this context, hands-on educational modules will be developed as part of this CAREER award. STEM education should be more like musical instrument training. Knowing theories is not enough for musicians to play instruments. Musicians must practice hands-on with the instrument. Likewise, hands-on experiences are essential through project-based learning. Established courses in higher education often lack systematic coverage of robotic hardware and software. Hand-on Experience can be achieved through PBL, inclusive teaching [165], and active learning in the flipped classroom [166]. The lab materials for existing courses will be developed as hands-on modules. The courses include but are not limited to, ECE-3641 (Robotic Manipulation), ECE-4641 (Mobile Robotics), ECE-505 (Introduction to Embedded Systems), ECE-5831 (Pattern Recognition and Neural Networks). In addition, the PI will organize and host summer engineering camps for high school students if this CAREER award is granted. From 2011 to 2019, the PI hosted pre-college computer engineering summer camps at Kettering University, Flint, Michigan. Curriculum materials, developed by the PI, include robotics, computer engineering, and smartphone programming [65]. A small-scale mobile robot was designed and built with DC motors, and students wrote a mobile app to control the robot through Bluetooth connections. According to a post-program survey in the study [65], more than 90% of participants showed satisfied or positive responses. Figure 13 shows some pictures from the computer engineering summer camp 2019. With this CAREER award, the PI will redesign the materials and expand outreach opportunities to Detroit Metropolitan areas by showcasing work at Michigan Pre-College & Youth Outreach Conference [167]. The PI also has actively participated with students in various types of challenges: (i) Indy Autonomous Challenge in 2020 - 2021 [168] (advanced to the second round), which is a collaborative effort to challenge university students to imagine, invent and prove a new generation of automated vehicle software (ii) SAE Mobility Forward: AI Mini Challenge in 2021 (3rd Places in Showcase Booth, Solutions Presentation, and Solutions Report). (iii) Battery Workforce Challenge in 2023 (to be announced), sponsored by the Department of Energy (DOE) and Stellantis, which is a three-year collegiate engineering competition to prepare a diverse workforce for future battery engineering and manufacturing careers.

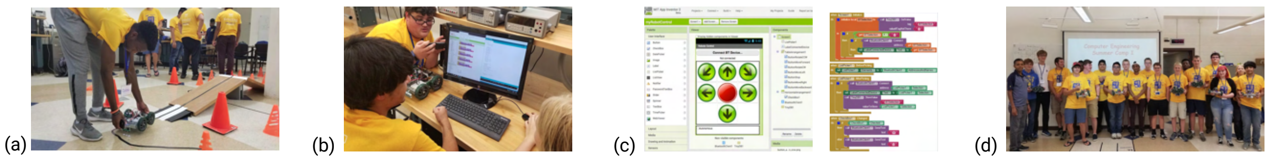


Figure 13. Computer engineering summer camp in 2019. (a) Students are testing their robots. (b) Robot programming and smartphone app for controlling the robot through Bluetooth. (c) Programming example code. (d) A group picture after the camp.

For a new hands-on experiential learning, integrated with the proposed research thrusts, the PI will start using a simulated robot in a simulated environment for initial algorithm tests to ensure the safety of the students. The proposed research thrusts will be integrated with the hands-on educational modules. After validating algorithms in a simulated environment, a physical mobile robot (requested through this CAREER proposal) will be used for a hands-on experience of students. As additional resources for hands-on experiential learning, the PI will use one electric vehicle, Kia Soul with the Sygnal DBW (a Drive-by-Wire system), and one plugin hybrid Chrysler Pacifica [169] with a sensor package for Simultaneous Localization and Mapping (SLAM). See Figure 14 for the details. These two programmable vehicles will be used in an NSF Research Experiences for Undergraduates (REU) Site program, which will be applied as part of the effort to build hands-on educational modules.

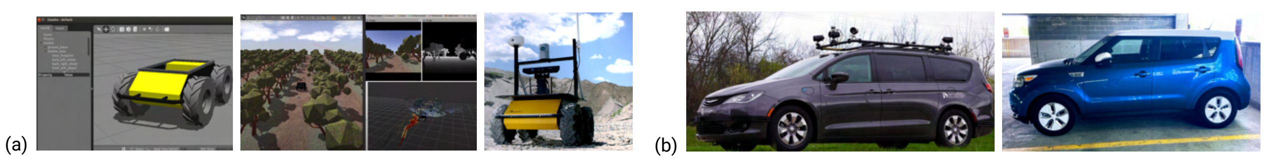


Figure 14. (a) Students will start with simulated robots and environments for their initial algorithm tests. After their validations are done, a real robot will be used. The robot will be purchased through this CAREER proposal. (b) A plugin hybrid Chrysler Pacifica (Supported by an NSF-MRI awarded (#2214830) and Kia Soul Electric (ECE departmental support + the PI's startup package).

6.3. Thrust 3: Preparation of Lifelong Learning

To support lifelong learning, educational modules must be available even after this CAREER award, and the modules should be easy to use without much cost and effort. The PI will provide the design of a mesoscale electric vehicular hardware platform along with open-source software that can be built at a low cost and be used for robust intelligence study on a smaller scale. The PI has a strong record in designing and implementing a ride-on electric vehicle [170, 33, 171], which can be controlled by high-level signals on Robotic Operating System (ROS) [172], an open-source robotics middleware suite. These educational modules will have documents, videos, and code. With the support of this CAREER award, the documents will be created and managed by the online documentation tool, ReadTheDocs [62], so they can always be up-to-date. Instruction videos will be posted and shared via YouTube, and code will be shared via GitHub [173], an online code repository management tool for broader dissemination. The PI will focus on the reproducibility of the design. There are some available small-scale vehicular platform designs. They are, however, tricky to be replicated due to many small custom parts and circuit boards. The PI's initial efforts were to minimize using customized parts in designing a new platform for lifelong learning. The Mesoscale Robotic Open-source Vehicle for Education and Research (M-ROVER) was designed and validated for various tasks [171]. M-ROVER uses Pixhawk PX4 hardware along with Autopilot, an open standard for aerial, underwater, and ground vehicles. The new design will increase accessibility to the platform, so more people can use it to study intelligence for mobility. To support the hardware and software, the PI has been working on a software framework, the Open-Source robotic Car Architecture for Research and education (OSCAR) [71], which is an open-source and full-stack robotic car architecture to advance robotic research and education (Figure 15).

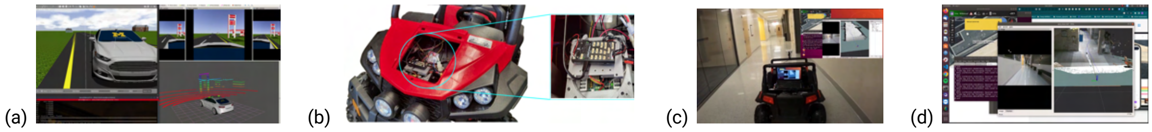


Figure 15. Preliminary work of software and hardware platform for education. (at) Open-source software, Open-Source robotic Car Architecture for Research and education (OSCAR) [71] (b) Drive-by-Wire (DBW) design for a mesoscale electric model vehicle, powered by OSCAR [171], Pixhawk 4 [174], and PX4-Autopilot [175]. (c) A test run in a hallway with visualization of a map. (d) SLAM test.

6.4. Assessments and Evaluation Plan

To improve the integration of the proposed research and education, an assessment of educational thrusts will be conducted. The PI will collect course evaluation results from the courses that PBL materials were introduced, and assess their effectiveness, and additional survey-type evaluation metrics will be developed. The PI will also work with the Diversity, Equity & Inclusion (DEI) office to improve engagement levels of underrepresented group students. The result will be submitted to ASEE Annual Conference & Exposition to share the PI's effort with broader communities.

7. Project Management

	Tasks	CAREER Grant Years					Beyond CAREER
		1	2	3	4	5	6 ~ 10 Years
Research							
1	Causality Study in Sensorimotor Loop						
	Design and development of forward and Inverse model						
	Computational model of sensory motor contingency theory						
	Test and validate in robots and vehicles						
2	Predictivity of Machine Learning-based Control						
	Latency compensation study						
	Develop computational models of simulation theory						
	Test and validate in robots and vehicles						
3	Adaptability in Perception						
	Robust classification of traffic sign						
	Generatvie AI						
	Test and validate in robots and vehicles						
Education							
1	Project-Based Learning						
	Design and Development of PBL modules for courses						
	PBL workshop for UM-Dearborn						
2	Hands-on Experience						
	Design and development of course modules						
	REU Site proposal and implementation						
3	Lifelong Learning						
	Development of M-ROVER, OSCAR						
	Online documentation and video instructions						

8. Results of Prior NSF Support

NSF Major Research Instrument Award # 2214830: (PI, $244,610.00, 9/01/2022 - 8/31/2025), *"MRI: Acquisition of Autonomous Plug-In Hybrid Vehicle Platform for Multidisciplinary Research and Education at the University of Michigan-Dearborn"* This NSF MRI project aims to acquire a high-performance autonomous electric vehicle platform with a sensor suite for research and education to advance fundamental science and engineering research and education. **Results:** This instrument is in the middle of the procurement process.