Artificial Neural Network Controller Using Sensory Motor Contingency For Highly Automated Mobility

Jaerock Kwon, PhD - University of Michigan-Dearborn, USA

DEARBORN

Problem Statement

- Deep Neural Network (DNN) controllers gain popularity thanks to their performance in complex problems.
- Yet, It is challenging to answer why certain output is better than others.
- In some edge cases, an inference output of a DNN controller can be not optimal. This may result in catastrophic consequences in safety-critical systems such as autonomous vehicles.
  - (e.g.) Edge cases cannot be perfectly prepared for the DNN model training.

Figure 1. 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.

Method

Sensory Motor Contingency (SMC)

- To mitigate the above problems and provide a new learning method, we propose a novel neural network architecture that utilizes the simulation theory (simulation of actions, simulation of perceptions, and anticipations) of cognitive brain function.
- The simulation theory is largely based on the Sensory Motor Contingency (SMC) theory, which considers perception a form of embodied know-how constituted by lawful regularities in the sensorimotor flow in an active and situated agent.
- The proposed neural network architecture inspired by forward and inverse models of the cerebellum, generates an appropriate sequence of motor actions to achieve a desired state through a pseudo-inverse model.
- A forward model, trained in the form of the Variational Auto-Encoder (VAE), infers future states caused by the motor actions. The proposed neural network architecture is capable of showing how and why a certain sequence of actions must be applied to a certain task, which means that the decision-making process is transparent as it retains highly adaptive and robust DNN-based methods.

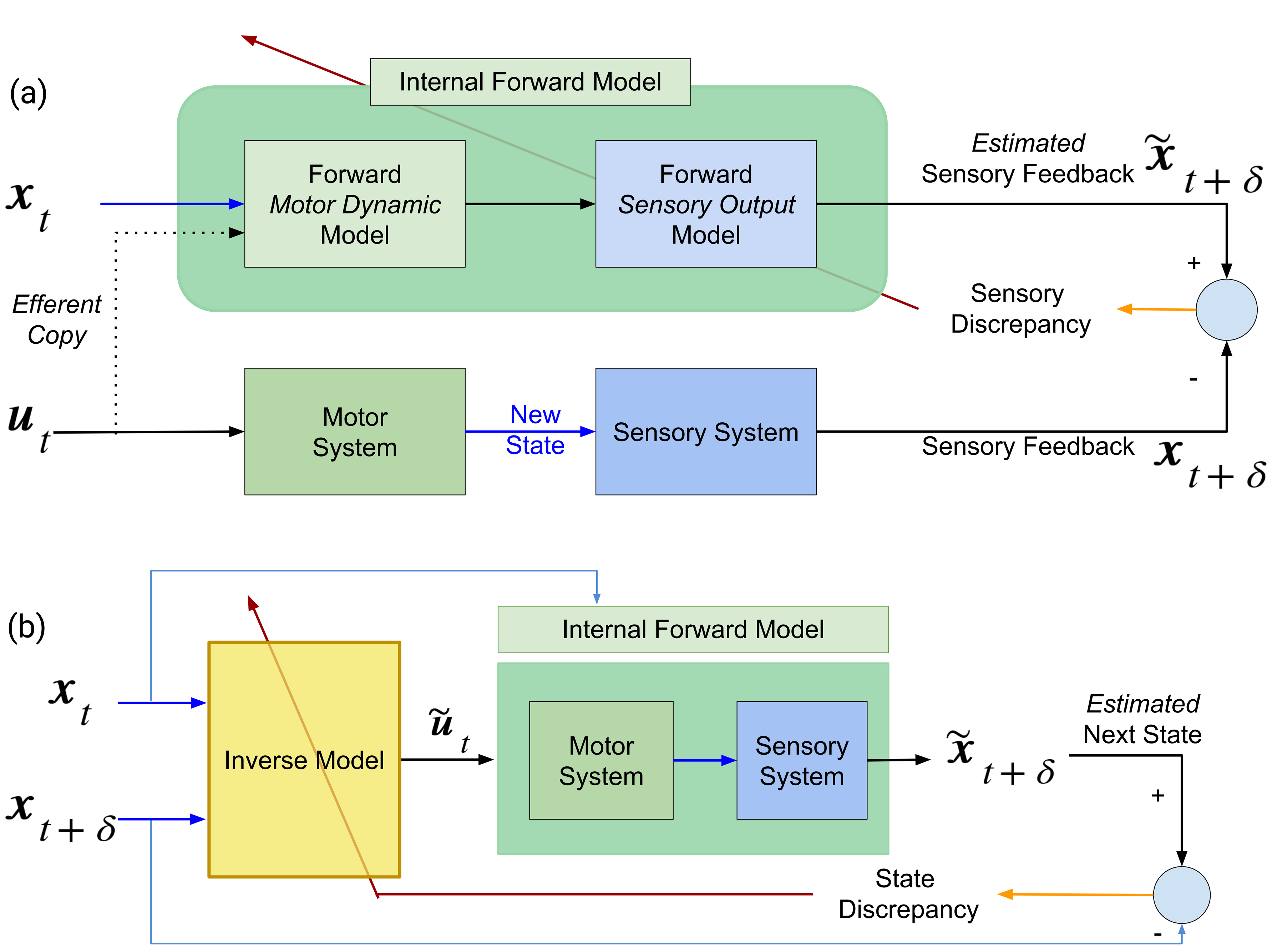


Figure 2. Training a forward model. (a) A forward model can be trained using sensory discrepancy between a predicted next sensory situation and the ground truth sensory situation xt + δ. (b) Training Inverse Model. An Inverse Model can be trained using state discrepancy between an estimated next sensory situation and the ground truth sensory situation xt + δ..

Variational Auto Encoder (VAE)

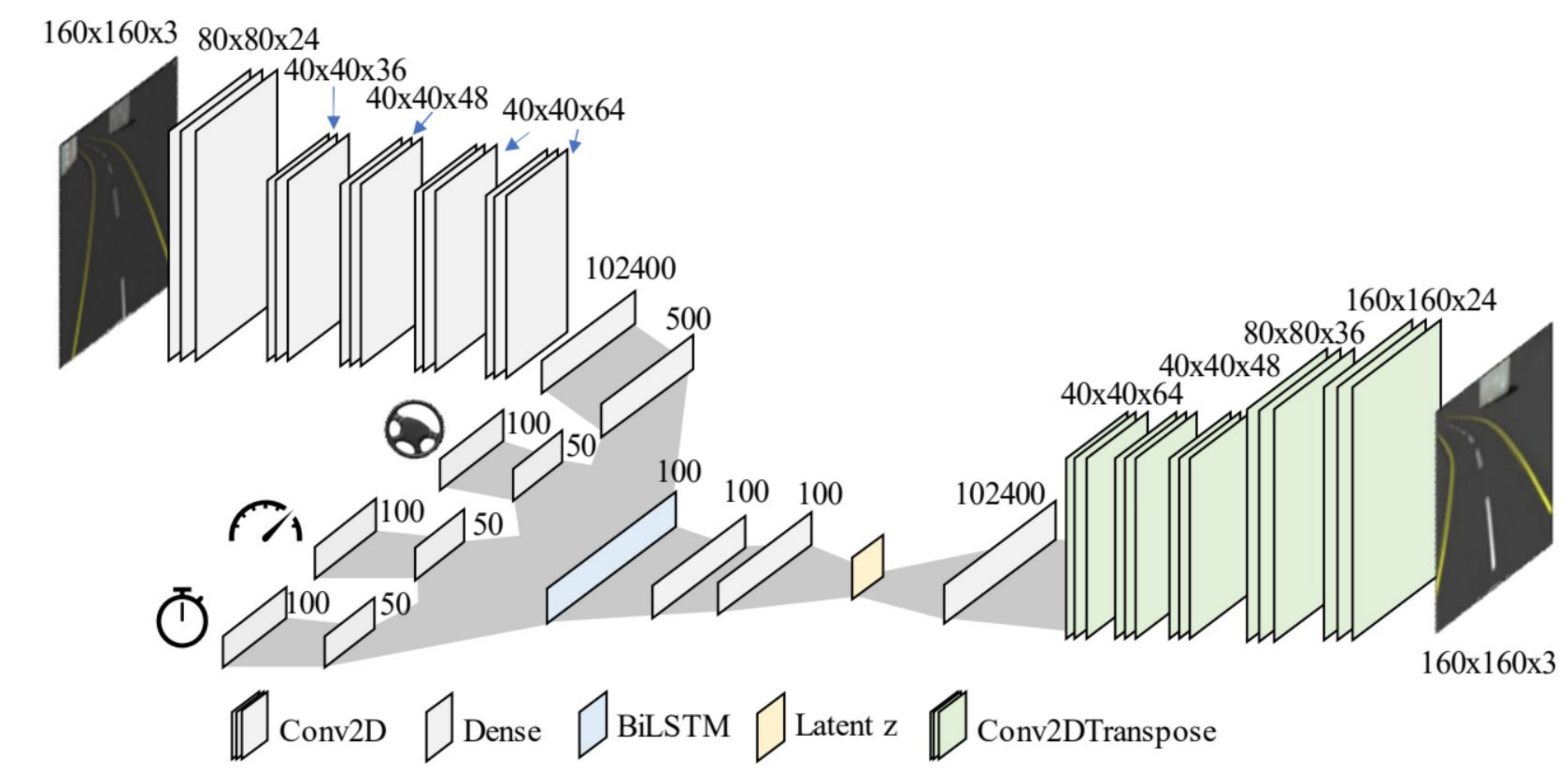


Figure 3. Proposed Variational Auto-Encoder (VAE) architecture for a forward model and results.

Results

Figure 4 shows 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.

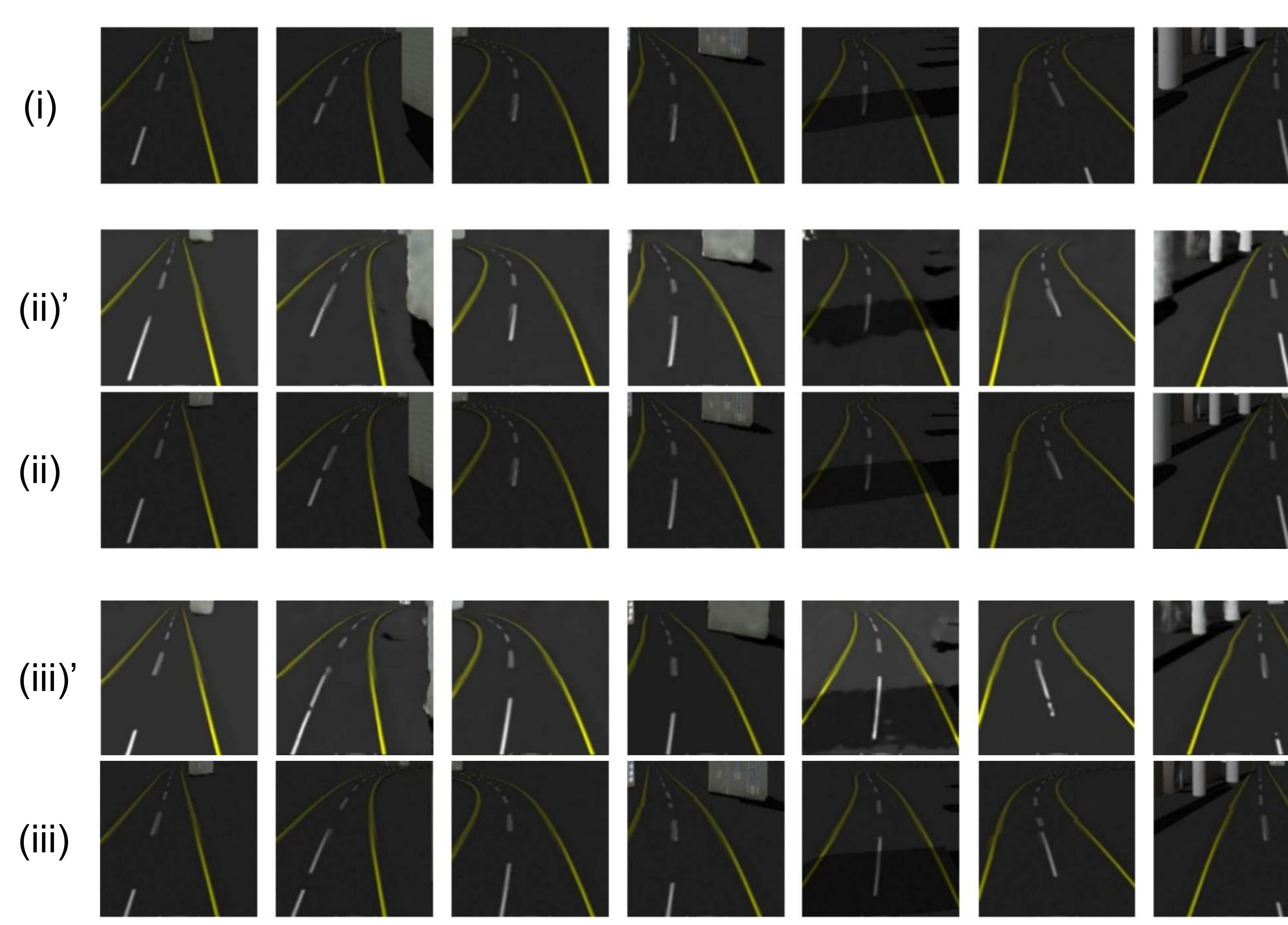
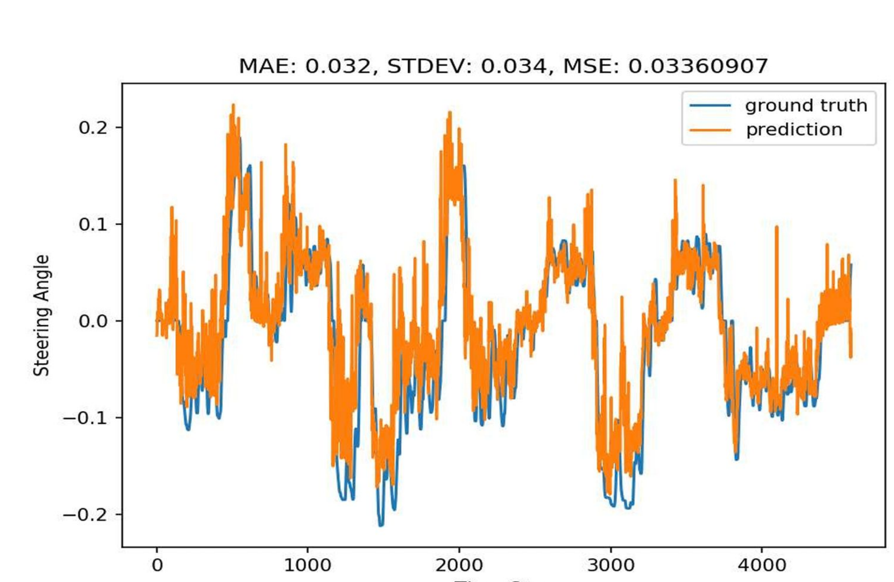


Figure 4. The output of the VAE is part of the future sensory situation, which is an image that would be seen due to the motor command ut .



Experimental Environments

- ROS Melodic/Gazebo 9
- Images: 744,180
  - Training:Validation = 85%:15%
- Input: front camera image, steering angle, velocity, time delay to predict
- Output: future image after the time delay.

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