# Cognitive Neurorobotics Study Using Predictive Coding Framework

**Jun Tani (tani1216jp@gmail.com)**
Cognitive Neurorobotics Research Unit, Okinawa Institute of Science and Technology
Onna-Son, Okinawa 904-0495 Japan

**Abstract:**

**The current paper proposes that the mind is comprised of emergent phenomena, appearing via intricate and often conflictive interactions between top-down intentions for acting on the external world and the bottom-up recognition of the resultant perceptual reality. It is presumed that the neural structure necessary for autonomously generating complex actions as well as for recognizing such intentions in others naturally develops through interactions entangling these two processes. This hypothesis is evaluated by reviewing a set of neurorobotics experiments performed by the author's group which use predictive coding as the principle guiding embodied cognition.**

**Keywords: predictive coding; recurrent neural network; humanoid robot; top-down and bottom-up process**

## Predictive Coding and MTRNN Model

Sensory-motor mapping has for a long period dominated the study of neurorobotics. However, sensory-motor mapping schemes cannot achieve human-level thinking and acting because they fail to be proactive toward the future as well as reflective of the past. On the other hand, according to predictive coding (Rao & Ballard, 1999; Friston, 2005; Tani, 2016) intention for action is generated via prediction of an action's consequences while actual consequences of the action are recognized in the open environment and influence current intention through regression of prediction error. Yamashita and Tani (2008) instantiated predictive coding in the multiple timescale recurrent neural network (MTRNN) (see Figure 1 (a).) The MTRNN model uses multiple timescale constraints, with higher level activity forming intention through slower timescale dynamics, and lower level activity dealing with visuo-proprioceptive sequence patterns through faster timescale dynamics.

## Robot Experiments

The MTRNN model was tested in a humanoid robot experiment involving developmental tutoring of multiple object manipulation tasks.

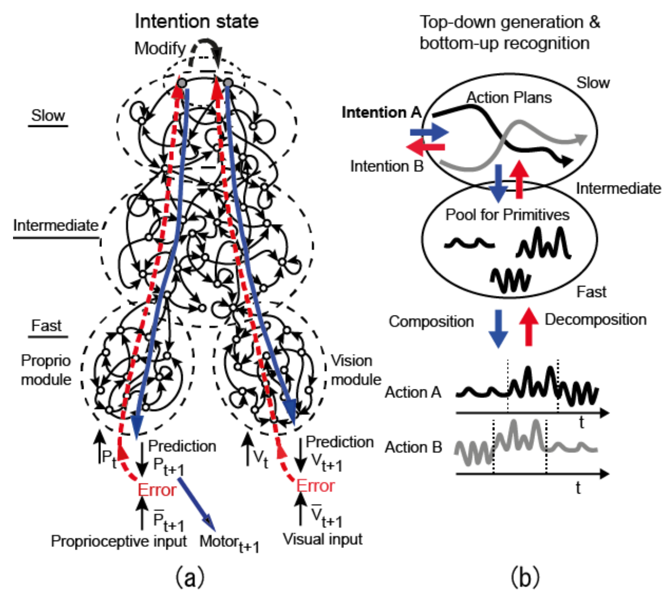


Figure 1: (a) Predictive coding implemented by the MTRNN and (b) development of the functional hierarchy generating and recognizing compositional actions.

Each task was designed as a different concatenation of behavior primitives: reaching for an object, grasping the object, rotating the object, lifting the object, etc. After supervised training of each task's visuo-proprioceptive sequence, all learning parameters of the network including synaptic weights and the intention state for each task converged, with prediction error minimized using the back-propagation through time algorithm (BPTT). It was found that all task behaviors were successfully generated through top-down neuronal dynamics as activated by intention states set with proper values (see Figure 1 (b)). Analysis of network dynamics indicated that a set of behavior primitives developed in the lower level network, while task sequences of these primitives developed in the higher level. The analysis concluded that behavior compositionality as represented in concatenations of primitive actions developed by means of a self-organizing functional hierarchy due to timescale differences demarking different levels of network activity.

Namikawa et al. (2011) examined the same model for its ability to learn to imitate probabilistic transitions of behavior primitives. It was found that the network could learn to imitate such probabilistic transitions by self-organizing deterministic chaos in the higher level network. It can be said that the spontaneous selection of actions can be mechanized by chaotically fluctuated dynamics developed in the higher level.

Murata et al. (2017) extended this study with an online error regression scheme to include the self-modification of own intention according to the perceived intentions of others. In this study, a robot was initially trained to move its arm spontaneously toward the left or right with a 50 percent probability either way. Simultaneously, it predicted arm movement generated by another robot with the same probability. Where its prediction was in error, movement was corrected to follow the movement of the other through self-modification of intention. In the case of behavioral conflict, the robot could immediately correct action by applying BPTT to update its intention state in the direction of minimizing prediction error. Furthermore, it was found that this immediate correction of action could not be achieved when a conventional sensory-motor mapping scheme was used instead.

## Discussions and Summary

In the experiment by Murata et al. (2017), intention spontaneously generated by means of chaos is modified in a postdictive manner according to error between the predicted and perceived actual movement of the other robot. This result may help to account for the mechanisms underlying autonomous generation and self-awareness of intention in voluntary actions, such as reported by Libet (1985). Using scalp electrodes, Libet showed that awareness of intention to perform an action is delayed around 500 msec after the development measured in the supplementary motor area (SMA) of the readiness potential for that action. In light of the MTRNN model, it can be speculated that neural activity in SMA (presumably with slower dynamics) fluctuates slowly by cortical chaos until confronted with upsurge in fluctuated activity exceeding a certain threshold, at which point this activity may propagate downstream possibly to the parietal cortex (with intermediate dynamics) as an intention to drive motor movement (with faster dynamics). The parietal cortex typically deals with dynamic and noisy perceptual reality due to the openness of embodiment to the real world, and may find its ongoing operations in conflict with the suddenly arriving top-down signal. This conflict between what is ideally intended and its practical exercise corresponds with the prediction error in the system. When it is back-propagated to the SMA, the original intention state is modified in the direction of minimizing the error. At this moment of modification, the intention state might become an object of conscious awareness.

The current paper has shown that interaction between top-down forward activation and the bottom-up error back-propagation processes such as that instantiated in a predictive coding type neural network model like the MTRNN may be essential to the development of compositional actions, to the spontaneous generation of intentions for actions, and to the postdictive conscious recognition of such intentions. Future study promises to bridge the gap between two different approaches, one based on deterministic dynamics (including chaos) and the other based on stochastic dynamics, in order to further study learning of naturally fluctuating temporal patterns.

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