# GPU-accelerated Action Acquisition Through Multiple Time Scales Recurrent Neural Network

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## Introduction

•Humans are able to acquire many skilled behaviors during their life-times. The learning of complex behaviours is achieved through a constant repetition of the same movements over and over, with certain components segmented into reusable elements known as motor primitives. These motor primitives are then flexibly reused and dynamically integrated into novel sequences of actions [1].

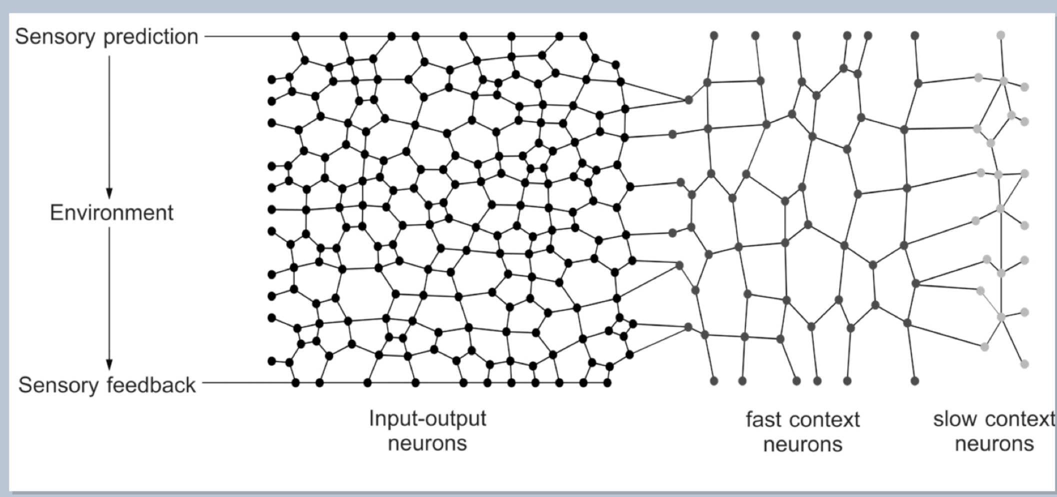
•For example, the action of lifting an object can be broken down into a combination of multiple motor primitives. Some motor primitives would be responsible for reaching the object, some for grasping it and some for lifting it. These primitives are represented in a general manner and should therefore be applicable to objects with different properties.

•The Multiple Timescales Recurrent Neural Network (MTRNN) attempts to overcome the generalisation-segmentation problem of previous action learning models based on explicitly structured functional hierarchies (e.g. MOSAIC). This is achieved through the realisation of functional hierarchy that is neither based on separate modules nor on a structural hierarchy but rather on multiple timescales of neural activities implementation of which was inspired by the biological findings [2].

•This work presents novel results of complex action learning based on an extended MTRNN model. The results showed that the system was able to learn eight different sensorimotor patters, which form the basis of our next experiments on action and language compositionality, which involves the use of three additional self-organising maps (SOM), linked to the MTRNN, and trained to represent simple linguistic inputs, as well as the object shapes and colours, obtained from images fed through logpolar transform inspired by human visual processing.

## Method

•The preliminary experiment presented in the poster implements the extended MTRNN model embodied in the iCub humanoid robot. The model was implemented as part of Aquila cognitive robotics toolkit [3] that makes use of massively parallel GPU devices that significantly outperform standard CPU processors on parallel tasks. This allowed for the extension of the previously used MTRNN model [4] with a higher number of neurons and sensorimotor sequences.



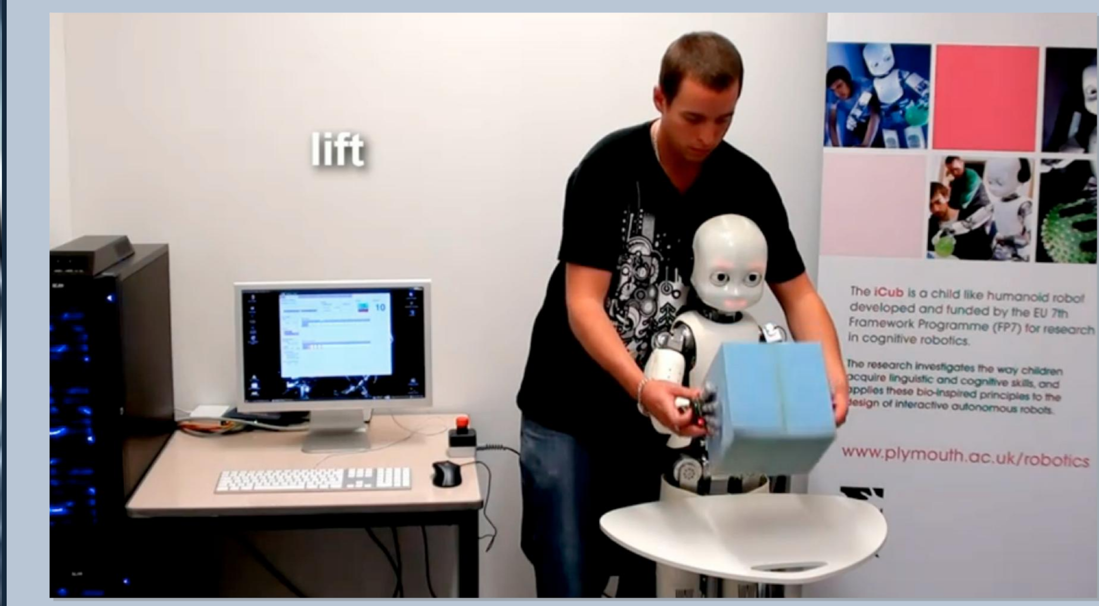

•The MTRNN's core is based on a continuous time recurrent neural network characterised by the ability to preserve its internal state and hence exhibit complex dynamics. The system receives sparsely encoded proprioceptive input from the robot, which is used to predict next sensorimotor states and it therefore acts as a forward kinematics model.

•The MTRNN needs to be trained via an algorithm that considers its complex dynamics changing through time and for this reason we used a backpropagation through-time (BPTT) algorithm as it has been previously demonstrated to be effective with this recursive neural architecture [4].

•A self-organising map was used as the input to the MTRNN system to help preserve the topological relations in the multidimensional input space by reducing the possible overlaps between various sensorimotor sequences. The SOM was trained offline using a conventional unsupervised learning algorithm implemented in Aquila SOM module.

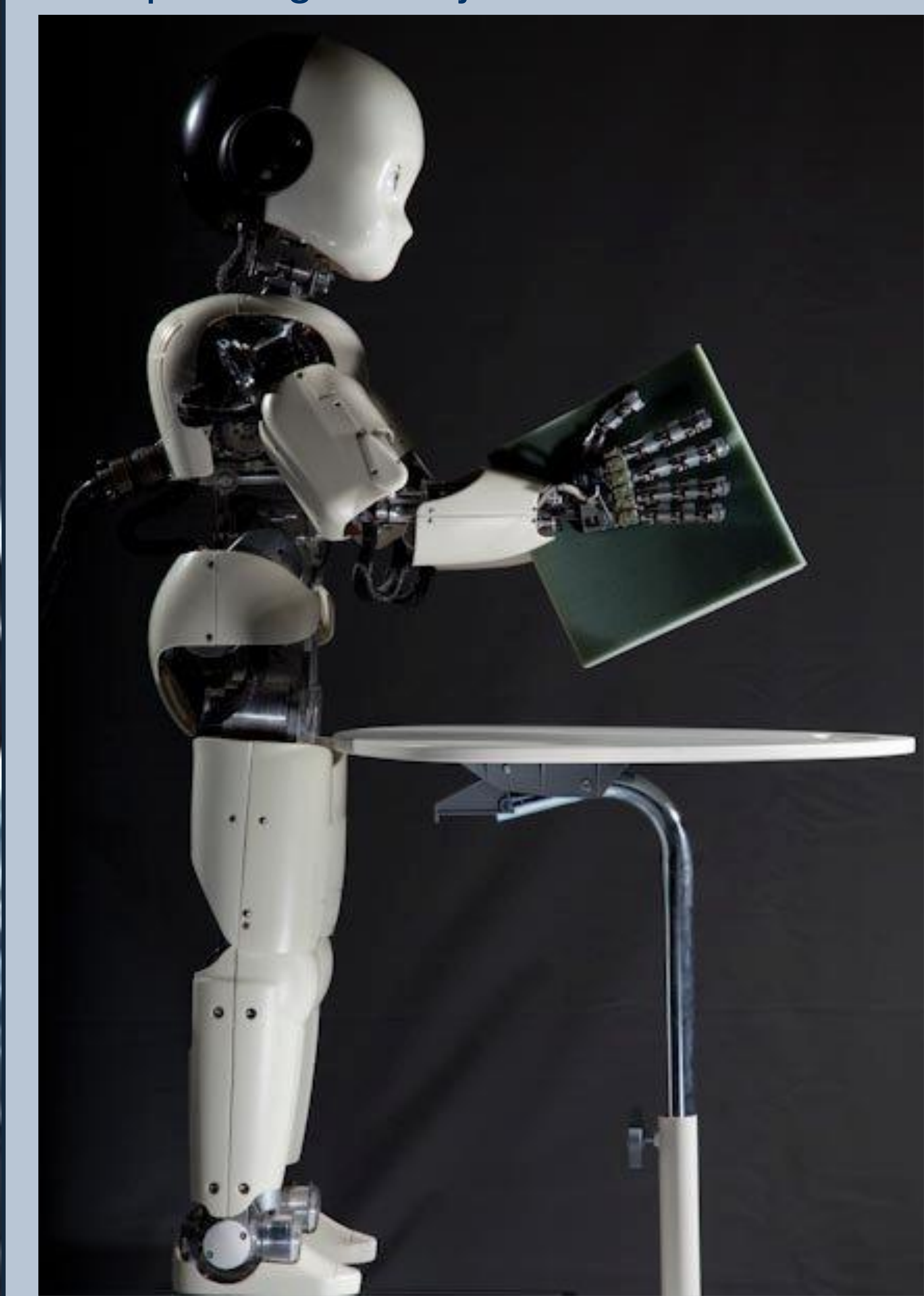
## Experiments and Results

•The experimental task required the MTRNN system to learn the eight sensorimotor patterns: slide box left/right, swing box, lift box up/left/right, push/pull box.




The Sequence Recorder module of Aquila was used to record these sensorimotor patterns while the experimenter was guiding the robot by holding its arms and performing the actions.

•At the end of the training, the learned neural network was tested on the iCub in the same setup as that during the tutoring part. The results showed that the MTRNN system was able to replicate all the eight sequences while successfully manipulating the object.



Testing the trained MTRNN system on the iCub humanoid robot in an object manipulation task scenario.

•Our preliminary benchmark tests showed 12x speedup of the training algorithm and 75x speed-up of the neural network forward pass when using GPUs and MTRNN with 336 neurons.

## References

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## Acknowledgment

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