Hebbian learning for online prediction, neural recall and classical conditioning of anthropomimetic robot arm motions

Hebbian Learning for Online Prediction, Neural Recall and Classical Conditioning of Anthropomimetic Robot Arm Motions

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Abstract

Classical Conditioning plays a vital role for learning in every mammal. It is is based on unsupervised neural learning embodied in a physical body that is in continuous interaction with the environment. Embedding the Hierarchical Temporal Memory (HTM) in the closed-loop of the sensorimotor space of a Myorobotics tendon-driven robotic arm we demonstrate learning, prediction and control of biomimetic body motions. Experiments finally lead to conditioned reactions in natural interaction with a human partner.

The HTM is able to learn arm movements generated by interaction with a human partner in a short time. It predicts future positions in different time scales up to seconds in advance. Closing the loop we utilize HTM predictions for motor control. Hereby learned motions are recalled from synaptic connections proactively continuing motion execution. Association, prediction and control requisite the HTM for conditioning according to Pavlovian: Neutral stimuli get associated to motions, after learning sensor impulses can trigger single arm lifting motions. Hereby, both the motions and the stimuli are learned from the environment and get associated efficiently. We can demonstrate high biological plausibility as for example even input variations result into similar variations in the action output. The robotic system consisting of biologically derived hardware and software components utilizes only usupervised Hebbian Learning to act autonomously. Learning is executed in real-time, can handle natural variations of human motions and takes morphologically plausible sensor input into account. The setup is fully scalable due to its modularity. Hereby, novel applications for the HTM are opened: It can be used in musculoskeletal robot control scenarios and robots being able to interactively learn from human partners and the environment.

Index Terms

Hierarchical Temporal Memory (HTM), Myorobotics, Musculoskeletal Robots, Artificial Neural Network, Classical Conditioning, Hebbian Learning, Associative Memory, Embodiment, Morphological Computing

I. Introduction and Motivation

The human musculoskeletal system differs distinctly from todays classical robots used for industrial purposes, and so does sensing and control. In particular, humans are able to predict and learn from the environment. A biological body focuses less on a highly precise and accurate motion repetition. Instead, mammals are compliant, adaptive to the environment as well as interaction partners and therefore highly flexible. To enable robots for close Human Robot Interaction scenarios and behaving autonomously in a complex world these characteristics are highly desired. Therefore, imitating the human musculoskeletal system in robotic systems is of special interest. Considering the concept of embodiment and exploiting morphological computing, the body plays an essential role in what kind of motions can be learned [1]. It becomes clear that only an adequate conjunction of hardware and software concepts can exploit the full prospects of a biomimetic robotic systems with particular interest in learning as the most intuitive way to acquire new skills. In this paper we exploit the unsupervised behavioral learning concept of Classical Conditioning that describes the association of sensor stimuli to motion execution. In this way new action and reaction scenarios can be learned, a first step towards autonomous task execution in interaction with the environment.

Our experiments are based on the closed-loop sensorimotor setup we introduced in [2]. An artificial neural network connects sensor and motor space while the world representation gets stored in the synaptic connections. We utilize a musculoskeletal humanoid arm that is built out of the modular toolbox Myorobotics [3]. The tendon driven actuation, imitating human muscles, affects a 1 Degree of Freedom (DOF) revolute elbow joint and a 3 DOF ball and socket shoulder joint. The Hierarchical Temporal Memory [4] artificial neural network is an associative memory based on Hebbian Learning and inspired by the neocortex. While manually interacting with the robotic arm the artificial neural network is exposed to the sensory space of the robotic system. The neural network predicts future motion states and the forecasts later are used to control one of the Myorobotics motor units.

In this paper we introduce the first application of the Hierarchical Temporal Memory in combination with a musculoskeletal robot. The HTM is a popular neo-cortex inspired artificial neural network demonstrating good prediction results, but so far only used for sensory prediction and classification tasks. The Myorobotics arm was built as a robot to safely collaborate with a human user. The compliant structure has not yet been utilized to let users teach motions by demonstration. Exploiting the HTM in a closed loop setup for robot control is presented here for the first time. We hereby mimic embodied associative learning: Sensory stimuli from the body are learned and a learned motion can executed. We carry on the experiments towards autonomous robot behavior learning and execution in a Classical Conditioning stimulus reaction scenario.

With the conducted experiments we can conclude three results. The Hierarchical Temporal Memory performs well on sensory input of a periodically moving musculoskeletal robotic arm. In particular, motions can be predicted in different time steps online and in real-time. Hawkins hypothesis generating motor commands is similar to making predictions [5] is proven in our experiments. We demonstrate that motions stored in the synaptic connections of the HTM can be recalled successfully as a learned trajectory can be executed by retrieval from the HTM. After learning predictions can be directly applied to motor setpoints, the current sensor input triggers the next action. Both results set the requirements to execute learning experiments analogue to the psychological concept of Classical Conditioning: Exploiting the associative memory capabilities of the HTM single non-periodic motions can be conditioned to sensor stimuli. After learning a similar impulse recalls the manually taught motion sequence while stimuli derivations retrieve similar motion variations. Proceeding the experiments in interaction with a human subject result in a very natural behavior which emphasizes the biological plausibility of the introduced setup.

Our results tackle the question of how to control a complex musculoskeletal robot by using brain inspired learning algorithms, and vice versa help to understand the underlying brain learning concepts for conditioning in mammal behaviors. From the application side, this enables interactively teaching of robots by demonstration which does not require any expert knowledge. With further research in this direction robot usage may be opened for a wider user community.

In our initial experiments on the one hand we demonstrate the good ability for Myorobotics robots as a basis for interactive teaching experiments as well as its controllability with artificial neural network controller. On the other hand we emphasize that the HTM can be used for robot control scenarios enabling interactive learning experiments. This work may also contribute to a better understanding of the human motion learning abilities, as both the robot and learning algorithms are highly inspired by the human body and brain. The presented work may open novel application scenarios for the HTM and enables new control strategies for musculoskeletal robots in Human Robot Interaction scenarios.

In this paper of biologically derived learning with a musculoskeletal robotic arm we first introduce the technologies in terms of robotic hardware and neural network implementation as well as the psychological concept of Classical Conditioning. Due to its first application of the HTM in combination with a musculoskeletal robot, two experiments prove the HTM pre-requesites to be used for conditioned learning in a robots applications. On the one hand the ability of the HTM to learn temporal motion patterns of the robotic arm is shown, on the other hand the possibility to recall a learned motion is demonstrated. section V then describes the integration of both pre-experiments to a conditioning experiment teaching a motion that can be intuitively recalled by sensor stimuli. Results are discussed in the conclusion. Here we point out the highly biomimetic nature of the experiment, further development and application scenarios of the results are presented.

II. Biomimetic Technology Concepts

Motion learning in human beings is twofold including the body and neural learning. We introduce technology counterparts for both to mimic the musculoskeletal system of mammals and learning in the neocortex, respectively.

A. *Myorobotics Anthropomimetic Robotic Arm*

The human musculoskeletal system is able to execute sophisticated motions while being highly flexible and compliant. Individual joints are actuated by multiple muscles that only apply contracting forces, on the contrary also multiple joints can be controlled by the same muscle unit. Exploiting the antagonist principle pretension on muscles can vary the stiffness of the actuated body parts and hereby sign highly adaptable to environment interactions. Energy stored in the visco-elastic muscles can be efficiently recuperated in periodic motion execution such as walking and jumping. Feedback in terms of applied forces and muscle contractions can serve as inputs for control procedures.

Various approaches exist to mimic these characteristics in technical systems. Hydraulic approaches surpass pneumatic ones in terms of strength, while novel electrically actuated soft materials are developed. Tendon-driven systems implement flexibility with springs and are well controllable as the system dynamics in terms of differential equations are known. Examples for full humanoid musculoskeletal robotic bodies can be found for pneumatic approaches [6][7] and in the tendon-driven robot Kenshiro [8]. All musculoskeletal robots share the principle of morphological computing: outsourcing control to the morphology, executed motions behave naturally smooth and human-like. In contrast to nowadays industrial robots, the intrinsic compliance enable safe human-robot interaction.

The Myorobotics project (Make Your Own - Robot-Toolkit Myorobotics) „is strongly inspired from the human and animal musculoskeletal system“[3]. It integrates the tendon-driven muscle approach for high modularity into a comprehensive and lightweight toolbox of design primitives. The cost-efficient and reconfigurable components allow building bio-inspired robots as well as industrial ones that exploit the introduced and desired human characteristics [3]. Four Design Primitives are provided: bones out of light-weight carbon fiber, 3D printed joints, muscle units and Myo-Ganglion serving as lower-level control boards running PID (proportional-integral-derivative) controllers adapting for the control error.

Figure 1 shows the physical muscle setup, including non-linear flexibility by routing the tendon via a series elastic element in a triangular way. Feedback is provided by sensors for spring elongation (muscle force), motor encoder (muscle contraction) and absolute joint position sensors (body pose).

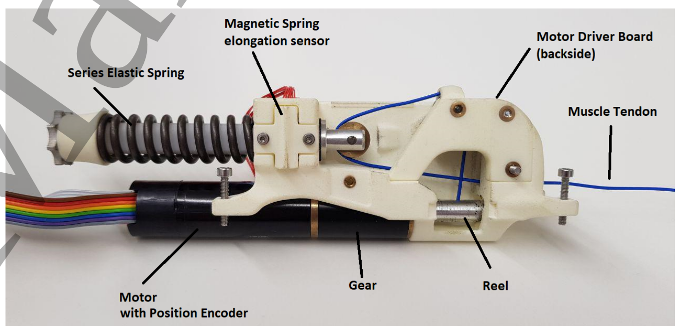

Figure 1: A technical Myorobotics muscle unit that imitates biological muscle characteristics. Contraction and non-linear flexibility are implemented by rolling up a tendon with a brushless motor and triangular routing along a spring, respectively. Proprioception in accordance to biology is included in terms of position (muscle afferent type 1a) and force (muscle afferent type 1b) feedback with motor encoder and magnetic measurement of the spring elongation.

Starting with the ECCE project [9] of building a humanoid musculoskeletal robot, enhancements in 3D pinting technologies evolved the Anthrob Arm [10] and a modularization with the Myorobotics toolkit lead to the latest version of a biologically derived arm. A 1 DOF asymmetric revolute elbow joint and a 3 DOF spherical ball and socket shoulder joint imitate the skeletal structure of a humanoid arm. 11 Myorobotics muscle units are arranged circular around the shoulder according to the biological rotatory cuff and antagonistically at the upper arm imitating biceps and triceps.

Due to cross control of multiple muscles and joints the purely contractile control of tendon-driven systems is increasingly complicated compared to standard joint controlled robots. As a first step Jaentsch in [11] provided an advanced controller design and approaches for friction compensation using machine learning techniques. However, with an increasing number of muscles fibers approaches for autonomously learning or by demonstrating play an essential role.

Using a robotic arm that imitates the human musculoskeletal system is of great benefit in our experiment setup. Due to the mechanically compliant character people can safely interact with the arm. Interaction is possible dynamically while applied forces are sensed and serve as additional HTM input to improve the learning accuracy.

B. *Hierarchical Temporal Memory*

The brain continuously processes a variety of sensory input from different proprioceptive and exteroceptive modalities in parallel to understand time event sequences and hereby reason about future activities. Learning spatio-temporal patterns to predict future outcomes, sensor stimuli are adaptively associated with each other to recognize coherences as events can only be fully understood in the context of all sensor inputs. As a fundamental learning rule for unsupervised learning processes, Donald Hebb in 1949 [12] spotted the basic concept of „neurons wire together if they fire together“[13]. This Hebbian Learning rule could be refined thanks to advancements in brain recording. Putting more detail in particular on the time factor of synaptic spike occurrences STDP (Spike Timing-Dependent Plasticity) was found fundamental as described in [14] and [15].

Various concepts have been developed for time-series understanding. In an analytical way mathematical concepts estimate model parameters as with „Moving Average“, „Autoregressive Model“or a combination of both „Autoregressive Moving Average Model“[16][17]. Considering biological findings a more general non-parametric approach in temporal learning extending prediction for non-linear dynamics is introduced with Recurrent Neural Networks in the 1980s. This approach was further refined to the Long Short-Term Memory by Schmidhuber and Hochreiter in 1997. Single memory units equipped with input, output and forget gates better handle the vanishing gradient problem in backpropagation learning. In 2003 it has been „used as a controller for a real robot“[18] for the first time in combination with reinforcement learning for path planning of a mobile robot platform in a maze. However, these types of neural networks require a huge training set and pre-learning. In contrast, online learning, which is essential in robotics application, can only be achieved with techniques such as sliding window or batch learning [19].

The „Hierarchical Temporal Memory“(HTM) claims to be highly inspired by findings in the sensory-motor layers two and three of the Human Neocortex. According to the whitepaper „cells used in the HTM cortical learning algorithms are far more realistic than the artificial neurons used in most neural networks“[5].

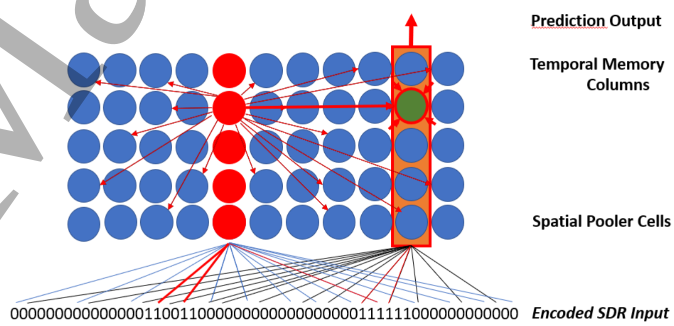

Figure 2: Principle network connectivity and data processing in the Hierarchical Temporal Memory. The HTM implements technical equivalents for sensory organs and learning of spatio-temporal sequences in the neocortex. Raw sensory data is processed by encoders and fed into the Cortical Learning algorithm consisting of Spatial Pooler and Temporal Memory cells. The network is initially randomly connected and weights adapted by variations of unsupervised Hebbian Learning. The output is classified to predict future occurrences in the sensory space.

Analogue to Hebbian Learning the strength of connections between single cells is continuously updated and the hereby learned spatio-temporal patterns can provide future prediction states.

As visualized in Figure 2, in each processing iteration step a sampled data row is fed through the different components and a prediction value is calculated. A brief description of their functionality is depicted here:

Encoder Encoders imitate the functionality of sensory organs such as retina and cochlea where native real world physical input is continuously converted to electrical signals [21]. Preserving semantic characteristics of the input data, here a bio-inspired Sparse Distributed Representation (SDR) [22] ensures noise handling by bit overlapping.

Spatial Pooler In the Spatial Pooler cells which initially connected to ta random subset of the input space specialize on semantically similar patterns and hereby pool a wide input space to a small cell representations. The cell connection, technically „permanence values“in $]0, 1[$, is reinforced or weakened according to Hebbian Learning.

Temporal Memory The Temporal Memory extends cells to columns learning the temporal context of the forwarded activation. First, the activity of Spatial Pooler cells is propagated along the synapses according to connection strength. Active columns exceeding an activation threshold serve as the prediction output. Second, analogue to Hebbian learning the most active cells reinforce their connections that led to its activation and decrease weights of not involved synapses.

Figure 3 visualizes processing of a contextual input sequence: After learning specialized predictive cells get active depending the current sensory input (D). A typical HTM implementation with 40 active columns and 32 cells region theoretically allows to store patterns in 3240 different contexts [4], SDR encoding allows multiple simultaneous predictions.

Classifier The classifier inverts encoding to output a prediction in the input metric. The calculated Anomaly Score is not considered here, but can give additional feedback about the learning quality.

More details and a formal description of HTM cells, connectivity and learning rules can be found in [24] [25]. [25] indicates reasonable performance in comparison to other time-series learning methods on training data sets.

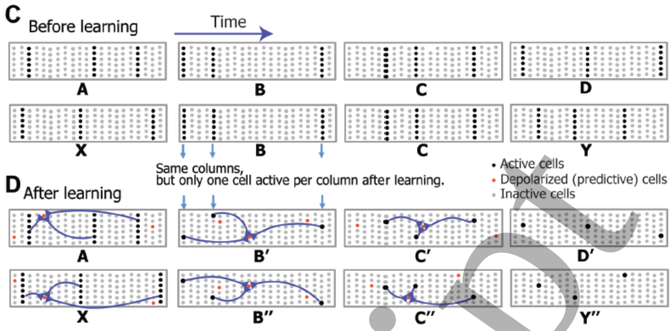

Figure 3: Sequence Learning in the Hierarchical Temporal Memory: Spatial and temporal correlations in the sensory space are learned by means of modified Hebbian Learning rules, patterns are stored distributed in synaptic connections between cells of columns. Accordingly, the time association is utilized to output predictions of future occurrences from the given input (figure from [4])

Being highly inspired by the neocortex, for engineering reasons the implementation includes several added non biological features for better performance. As the HTM is limited to only a few sensory inputs, we exploit the provided „Swarming“algorithm based on Particle Swarm Optimmization (PSO) to preselect the best sensory input spaces.

Nearly all applications of the HTM such as prediction of CPU power consumption, stock prices and language processing are purely sensory. A first step towards sensory-motor integration can be found with an extension for 3D object representations in the real world in [23]. In contrast, for our experiments the HTM is embodied into the control loop of the robotic arm, actively controlling motors.

For this purpose four HTM learning characteristics are of special interest:

- *online*: no split between test and training set, instant and continuous prediction allows real-time application in robotics
- *unsupervised*: heavily relying on the local learning rules adaptation to the environmental input without any goal-definition
- *spatio-temporal*: association of sensory and motor events as well as sequences can learn trajectories
- *noise tolerance*: handling high variation in sensor values that particularly arise with musculoskeletal robot and human motions

In this paper we focus on how the HTM deals with musculoskeletal motions and in particular try to imitate biological behaviors with our test setups and executions. The HTM implementation itself has not been changed for the executed experiments, rather its setup, input and encoder specification is objective of the following experiments. For all experiments we used a HTM network with common parameters according to Table I.

Parameter	**Value**
Number of columns	2048
Number of cells per column	32
number of active columns per inhibition area	40
maximal number of segments per cell	128
permanence decay	0.1
permanence incrementation	0.1

Table I: Main HTM parameters used for the experiments

III. Classical Conditioning

Conditioning describes a class of lifelong learning procedures in mammals such as humans. In contrast to Operant Conditioning where rewards reinforce behaviors, we here focus on Classical Conditioning as an unsupervised learning principle associating sensory signal inputs and action outputs.

A. Psychological Concept

The brain is an associative memory that continuously correlates stimuli and behaviors [26]. In fact, implicitly stored behaviors can be triggered for execution by peripheral stimuli which also may hold for voluntary movements [26, p. 656]. Classical Conditioning has initially been studied by Ivan Pavlov on the salivation process of a dog. Basis are an unrelated *Neutral Stimulus* and an *Unconditioned Stimulus* which naturally leads to an *Unconditioned Reaction*. Presenting specific sequences of stimuli to the subjects sensory space, the Neutral Stimulus gets conditioned as the *Conditioned Stimulus* directly causing the *Conditioned Reaction*. In Classical Conditioning the chronology of stimuli distinguishes different types. We here focus on the most common Forward Conditioning. In general, the fastest learning can be achieved if Conditioned Stimulus and Unconditioned Stimulus are presented without delay, in the best case they overlap slightly. Conditioning plays a key role in mammalian behavior generation only combining natural reactions with environmental stimuli.

B. Robotic Implementations

In robotic applications a lot attention has been drawn to Operant Conditioning. To achieve a goal autonomously in an efficient way, a multitude of implementations well known as reinforcement learning are proposed. A popular example is the Q-Learning [27] implementation e.g. used for robot path planning.

Far less implementations exist for Classical Conditioning, still it gets more relevant within human robot interaction scenarios which nowadays draw special interest. [28] underlines the importance of Classical Conditioning for social robots and introduces a probabilistic architecture implementation. More biologically derived models can be found in STDP implementations such as [29]. In [30] a spiking neural network lets an icub robot learn the association of tactile and visual information to verbal action.

Due to its unsupervised character enabling stimuli association, Hebbian like learning plays an important role in Classical Conditioning. In addition, all neural network based models compared in [4] are based on Hebbian Learning. The implementation in the HTM demonstrates capabilities for learning spatial as well as temporal patterns, hereby the network fulfills the requisites for a Classical Conditioning procedure. After the prerequisite tests, our final experiment is inspired by a Classical Conditioning example from [26, p. 1244] including hand lifting motions and electrical stimuli: „A subject lays her hand, palm down, on an electrified grill; a light (Conditioned Stimulus) is turned on and at the same time she receives an electrical shock on on finger - she lifts her hand immediately (Unconditioned Response). After several light-shock conditioning trials she lifts her hand when the light alone is presented“.

IV. Learning, Prediction and Control of Musculoskeletal Robotic Motions

The implementation of the HTM embodied in a closed-loop of the sensorimotor space of a Myorobotics arm has been introduced in [2]. To verify its applicability with reasonable solutions for sensing and control tasks, we demonstrate its performance with two experiments, respectively. While the first can be considered as a typical usage of the HTM here applied to a novel type of data input, the second one puts the HTM in a new and embodied context scenario for control purposes. On the one hand we demonstrate the performance of learning and prediction on the specific sensory motion patterns generated by the robotic arm. Hereby, we first question its capabilities for robotics applications in terms of online learning, real-time performance and handling of natural highly deviating motions including drift. On the other hand closing the control loop, we introduce the novel use case of HTM for control tasks utilizing predictions as motor commands. We try to recall learned motion patterns from the HTM synapses to autonomously continue learned motion patterns. For both experiments its biologically derived context in terms of setup, execution and learning procedure is outlined before results are presented.

A. Proprioceptive Pose Prediction

Learning by self-motivated exploration of the own body and the surrounding environment is very time consuming. It highly depends on the strength of intrinsic curiosity and is limited to the capabilities gained by the slow process of evolution. Humans have gained a lot of knowledge not being transferred via evolution but passed to next generations by narration and demonstration. Big development steps occur lifting a child to force walking, putting it into another room to explore a new environment or directly guiding body parts to point out possible actions. Such guidance can either improve already learned motions in terms of precision or as teach completely new actions.

We generate motions manually by direct interaction with the robotic arm, concurrently the HTM is exposed to the generated sensory signals. While the HTM has been validated for sensory prediction, we here question its performance on the specific characteristics of natural muscle generated motions.

Experiment and Results: Body posture in mammals is guaranteed by permanent muscle ground tension. Consequentially exploiting the antagonist principle, pretension on the Myorobotics muscle units ensure a stable initial arm position. Imitating a motion similar to an inter human handshake, we take the robots tip and move it in an ellipsoidal way as visualized in Figure 4 on the left.

We see the resulting elbow joint position in Figure 5 in blue as a deviating periodic wave that stabilizes after some iterations and hereby demonstrates natural characteristics of a human supervised motion. Feeding the sensory data into the HTM, the filtered HTM prediction (red) of the elbow joint position is plotted shifted in time to compare actual values and the corresponding forecast. We observe the prediction is very unsure in the beginning leading to wrong and peaked output values as the motion is never seen before and hereby at first unpredictable. However, after only a very short learning time the predicted values converge to the actual sensory data. It takes only about four motion iterations until the prediction gets close to the waveform motion. Finally, after four motion iterations a prediction accuracy better than $\pm 10\%$ is reached including only a few outliers appearing as spikes in the analogue output.

For the introduced experiment, three aspects are of special interest:

a) Sensor Input: The heuristic „Swarming“algorithm based on Particle Swarm Optimization is applied to preselect input fields as the HTM input. The algorithm selects the elbow position and the applied force on the biceps (Bizeps Breve) as input fields that can best support the pose prediction. This selection is meaningful from an anatomical perspective as well: The biceps muscle is directly affected when moving the arm and therefore can support a motion prediction.

b) Online real-time learning: The experiments are executed online feeding the sensory dataset S of the robot into the HTM in every control cylce step of 20 ms, leading to a new prediction output in every iteration. We here only demonstrate the results with 10 time step predictions (10* 20ms = 200ms), however also different step sizes have been successfully applied. The general hypothesis of smaller step sizes leading to more accurate results, bigger ones to less accurate predictions is supported by our data.

c) Prediction Filter: The prediction output of the HTM is generally infiltrated by short error

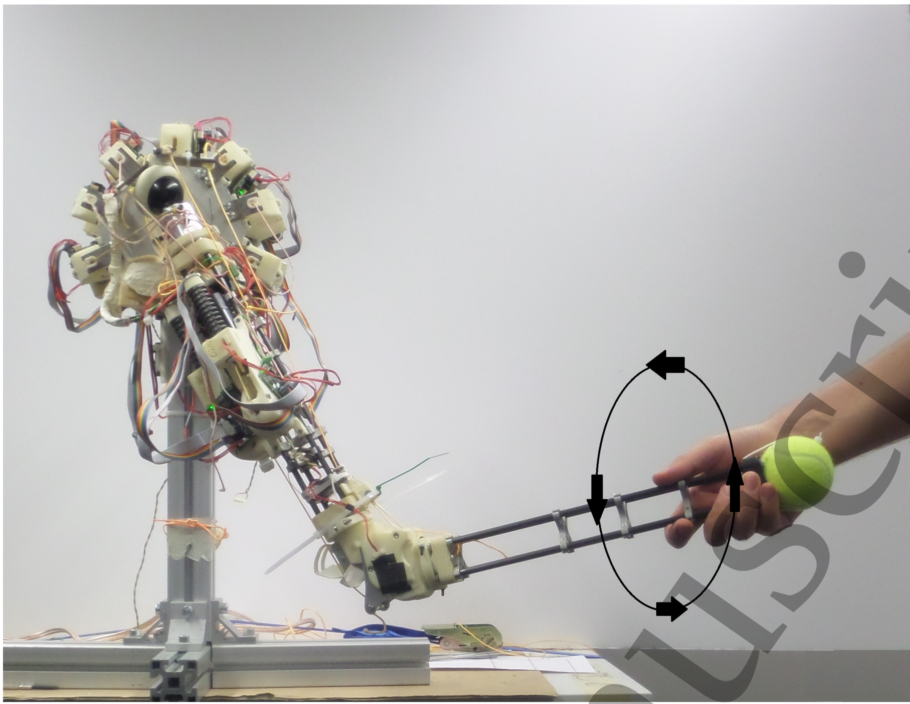

Figure 4: Proprioceptive Pose Prediction: In a Human Robot Interaction experiment (left) the user guides the compliant robot forearm in an ellipsoidal way, very similar to shaking hands with another person. The proprioceptive sensory feedback is fed into the HTM to predict the elbowjoint joint position.

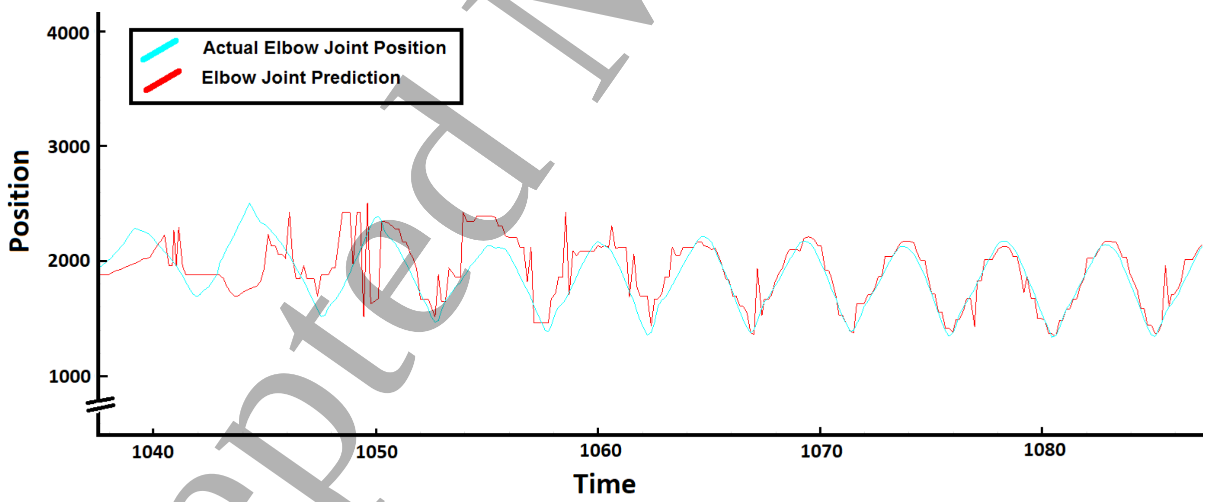

Figure 5: Proprioceptive Pose Prediction: The proprioceptive sensory feedback generated by the ellipsoidal arm motion is fed into the HTM to predict the elbowjoint joint position. The HTM (red, shifted in time) predicts the periodic motion (blue) very fast, and after about four repetitions reaches an accurracy better than $\pm 10\%$. The experiment is executed online in real-time

spikes, in our particular use case of robotic motions we know such characteristics are physically not possible. Filtering the output leads to a suppression of spikes increasing the quality of the prediction significantly. This is demonstrated with a mean filter that takes into account stored last prediction outputs according to Equation 1.

$$p_{t,mean} = \frac{p_{t-2} + p_{t-1} + p_t}{3} \tag{1}$$

with: p_x = Prediction for timestep x
t = prediction step time

As the HTM can predict multiple steps ahead simultaneously, a wider basis for a filter mask including also future prediction values can be applied. Due to the increased computation time exceeding the robot control cycle time of 20ms, we demonstrate the enhancement by a median filter according to Equation 2 in an offline analysis.

$$p_{t,median} = median(p_{t-2}, p_{t-1}, p_t, p_{t+1}, p_{t+2}) \tag{2}$$

The prediction results (top) in Figure 6 of a slightly more complex arm motion in comparison to its non-filtered equivalent (below) emphasize a decreased spike rate down to less than 20%. As well the accuracy of the prediction can be improved and a smoother prediction in particular in the beginning is observed.

In this joint position prediction scenario, the HTM demonstrates good performance on proprioceptive sensory data of robotic motions for arm pose predictions in different time steps. The neural network runs online and adapts very fast to a novel motion. The prediction quality could be even improved in particular in terms of non plausible peak value errors by the introduced mean or median filtering techniques.

B. *Synaptic Motion Recall for Muscle Control*

While the multitude of neural networks as well as the HTM is applied to sensory data only, in robotics closed-loop scenarios for controlling motors depending on the given sensory input are required. Summarizing findings in neuroscience, processing of sensory and actuation is considered similar [26, p.33]. In particular, it can be seen a the inverted process whereas both regions are highly interlinked and the connections define its purpose. The brain as well receives an efferent copy that is exploited for predictive control.

Even though the HTM is optimized for sensory processing, its developer Hawkins proposes the neocortex is able to directly control body limbs. More specific, he thinks the neocortex could directly be able to control body limbs [5][31]. By spotting the similarity of motor commands and predictions he suggests adding output for motor control directly to the HTM.

Experiment and Results: From the introduced neuroscientific findings we can derive three statements that serve as a basis to utilize a learning algorithm such as the HTM for muscle control:

1) Motor and sensory regions are fully interconnected
2) The brain receives a copy of motor control commands
3) Predictions can be seen similar to motor control activation

In this experiment a motion is generated by actuating the central biceps longum muscle with a sinusoidal position setpoint command that pushes the whole arm in a similar behavior. After the learning phase the control input is substituted by directly applying motor position predictions as control commands. In this phase the HTM runs in a closed loop generating the next motor commands based on the current sensory input. In this experiment the biceps motor setpoint is the only network input, the encoder SDR is spread on 396 input cells.

Figure 7 visualizes the takeover process after learning: The red line shows the actual control setpoint of the biceps, the blue line is the prediction (here the prediction is not shifted in time, so a correct prediction is one step ahead).

As we can see the HTM takes over the control for the robotic arm in a fluent way, no delay or any deviation in the sinusoidal motion is visible. In the plotted run the motion continues for about half a sinewave period which means about 40 HTM predictions were used for control.

Hereafter, slightly wrong predictions lead to direction change of muscle activation. Nevertheless, the HTM still finds back into correct predictions.

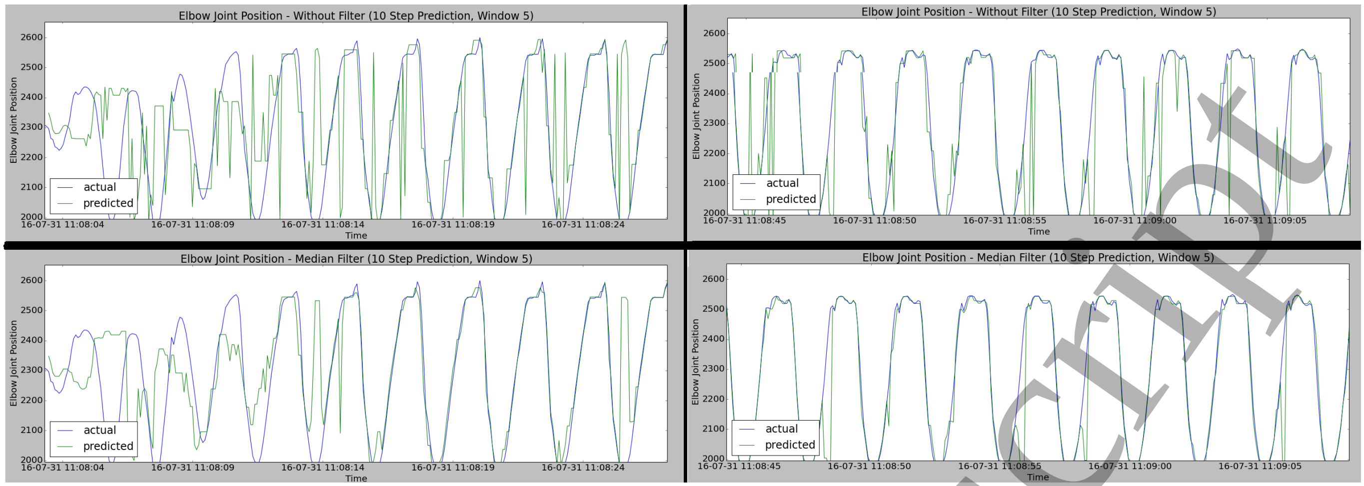

Figure 6: Spike Reduction by Filtering the HTM Prediction Output: HTM predictions are characterized by a spiky errors (top) which are obviously non plausible in natural motion execution. Applying a median filter (window size = 5, bottom) improves the prediction output in terms of a smoother prediction being more accurate in shorter time (bottom left) and reduced spike error rate all over the prediction periode (bottom right).

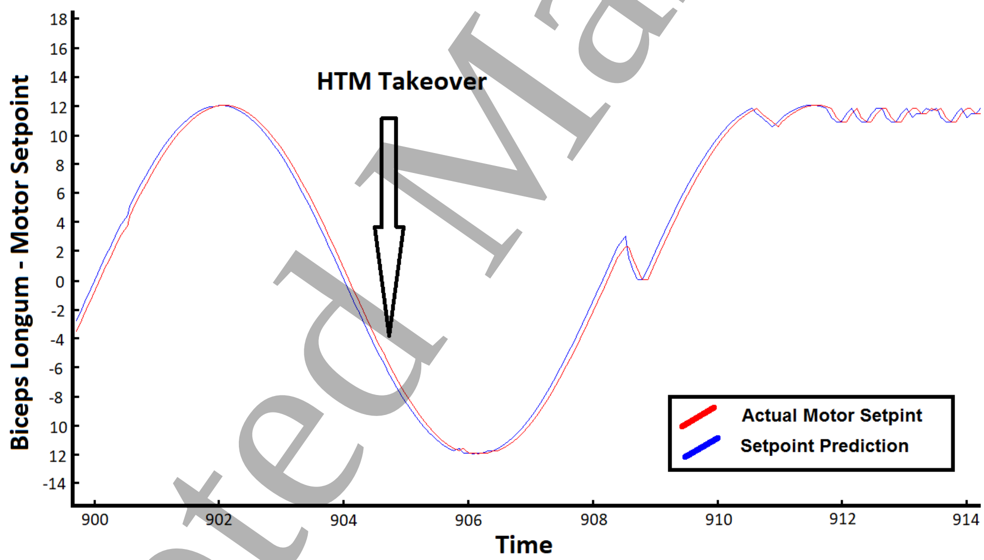

Figure 7: Synaptic Recall of Motions: The HTM learns to predict the next time step of a sinusoidal motor motion, here only the last iteration is plotted. Learning is turned off at the black error and from here the HTM prediction is used to directly control the motor. We see the fluent continuation of the processed motion for about 40 timesteps, and even after some wrong predictions different patterns of the original motion is recalled. We conclude that synaptically stored motions can be recalled from the HTM and predictions be directly utilized as motor control commands.

Later on different motion patterns with a length of about 20, 10 and later less cycle times are recalled. Since we predicted the motor setpoint and directly used it for motor control the biceps muscle moved according to the visible motion pattern.

Repeating the test execution with same settings leads to different recalled sub-patterns of the learned sinewave motion. Even though jumping out of the pattern on every wrong prediction, multiple pattern parts can be recalled while the muscle is still moving. After emerging to noisy behavior no patterns are recalled any more.

This motor control experiment demonstrates that the predictions of the HTM can be directly used as the motor control commands and hereby puts the HTM in a closed-loop for applications in robot control tasks. In particular, one can actively recall and re-execute a motion that has been learned previously and is stored in the synaptic connections of the HTM. As a prerequisites for long-term control scenarios the HTM prediction output needs to be of very good quality, the characteristic spiking prediction output can disturb or stop the recalling process.

With the introduced experiments we demonstrate that the HTM can be exploited for learning, prediction and control of musculoskeletal robotic motions. It can be directly embedded in a closed loop, associating multiple reasonable sensory inputs to a learned motion. Hereby, an inner sensorimotor mapping is learned in the Neural Network based on variations of unsupervised Hebbian Learning. The introduced setup has potential for upscaling to routinely full body motions. In a first step here multiple HTMs could be used for multiple muscles, for future research the HTM needs to be adapted to be able to handle a multitude of sensory inputs in parallel.

V. Classical Conditioning of a Musculoskeletal Robotic Arm

The HTM performs well for prediction and control of repetitive motions, given the theoretical assumption of a perfect prediction motions could be continued forever. However, human behavior as well consists of many isolated actions that are executed individually. To recall and execute single motions, we utilize the psychological concept of Classical Conditioning. Hereby, the prerequisites of sensory association, prediction and motion control have been demonstrated. We now first break the periodic constraint of motions and afterwards execute a full conditioning experiment that shows a conditioned stimulus reaction.

A. Non-Periodic Motion Prediction

We break the periodic time constraint by modifying the pose prediction experiment. Instead of regular arm motions only a single lifting action is executed at a time followed by a pause of a random time in the range of 0 to 5s.

1) Predicting Random Occurrences: The left diagram in Figure 8 visualizes the irregular guided arm movements and the prediction after a long learning time of 2.5 minutes (about 30 repetitions): The prediction includes many spikes, in particular we see that the HTM can never adequately forecast the beginning of a motion and hereby the prediction gets disturbed for a long range. The obvious reason here is the randomly chosen starting time. A high anomaly score at the motion starting points underpins this observation.

2) Prediction support with Preceding Stimuli: We modify the experiment setup according Figure 9 by introducing an exteroceptive sensor stimulus. Just before every independent arm lifting motion (2), an additional neutral stimulus is generated by manually turning the exteroceptive sensor (1). Two scalar encoder are used for the biceps motor position and stimulus input each. Both use 272 cells, weighting both inputs equal.

In Figure 8 the right diagram demonstrates the online learning progress after only two minutes including about 24 repetitions of stimulus and reaction. While previously even after a very long time motions could not be predicted adequately, only supplemented with an additional stimulus we here see a good prediction after a short learning time. The HTM can especially predict the beginning of each arm motion quite accurately. In addition, it tracks the structure of the movement in general well considering the visible high variation in arm lifting execution.

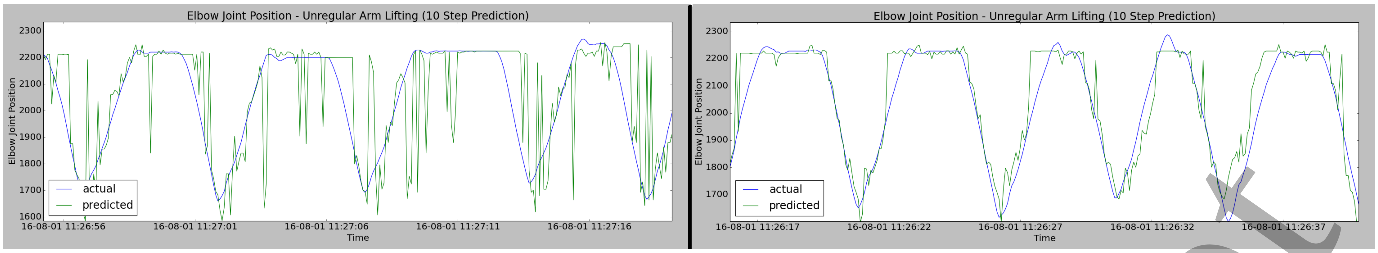

Figure 8: Non-Periodic Motion Prediction: If arm lifting motions are executed not periodically including random time gaps between every action, the HTM particularly cannot predict a motion starting point and the quality of prediction becomes insufficient spiking all along the motion (left). However, providing a previously neutral stimulus before every arm lifting leads to a significantly better prediction result and additionally shorter learning time (right). In especial the beginning of the variable arm lifting can mostly be predicted accurately and the results rise the hypothesis that the stimulus is conditioned to the lifting motion.

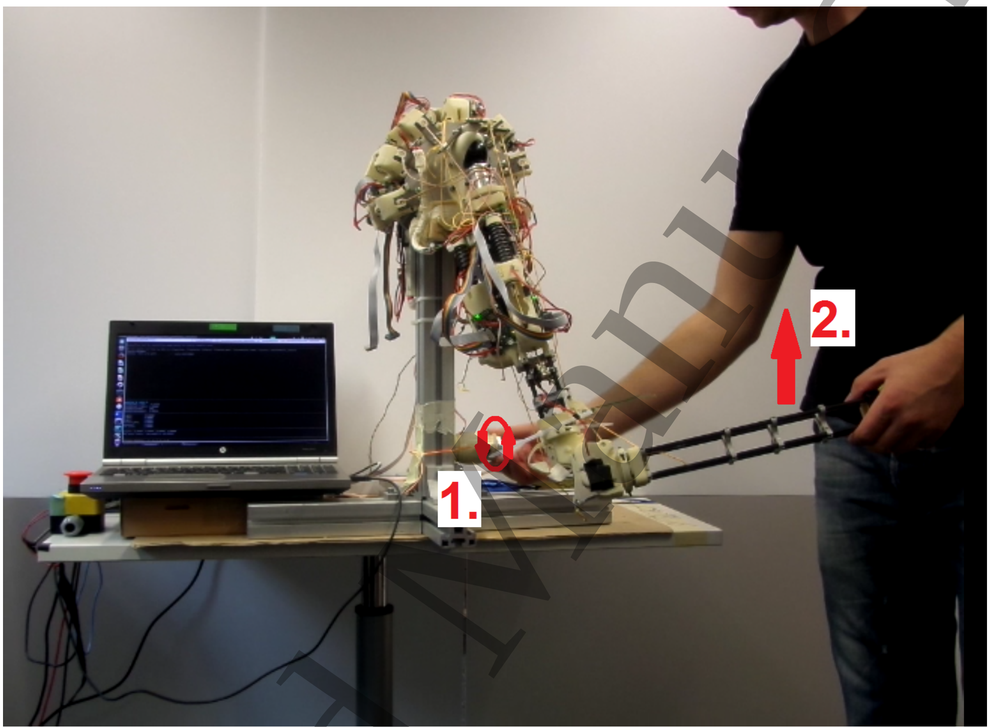

Figure 9: Experiment setup for Classical Conditioning: An exteroceptive sensor is turned and afterwards the arm is lifted manually. Sensory data is fed into the HTM network and after learning only stimuli are provided and the HTM predictions directly applied as the biceps motor control.

B. Conditioned Prediction and Reaction

The drastically improved prediction is a good indicator that the exteroceptive stimulus is associated to the arm lifting action and hereby supports the prediction. However, a successful conditioning must be proven with actively triggering a behavior with the associated stimulus. This may be seen as the technical equivalent of collecting salivary from the Pavlovian dog.

1) Motion Expectation: Having learned non-periodic motions as described before, we now provide only sensor stimuli without moving the arm at all. The raw data input from exteroceptive stimuli and proprioceptive motion sensing is presented on the left in Figure 10: Only the last iterations of the learning procedure with impulses (blue) followed by arm motions (brown) are visualized. For the last three stimuli learning is turned off and no motion occurs to the robot. The resulting prediction in Figure 10 on the right clearly demonstrates an predicted arm motion on every presented stimuli even though the arm itself is not moved at all. Two of the three stimuli cause a complete prediction of the full arm movement being very similar to the one presented manually during the learning phase. In addition, even a modified stimulus leads to a reasonable output: The weaker second stimulus here predicts a weaker motion with reduced amplitude. Hence, we can conclude the lifting motion got successfully conditioned to the exteroceptive impulse.

2) Motion Reaction: Besides a motion expectation, in an original view of Classical Conditioning we expect a physically observable Conditioned Reaction to occur after every presented stimulus.

We integrate the successful motor control by recall of predictions from chapter Synaptic Motion Recall for Muscle Control so that now the HTM learns directly on the motor position. After learning the prediction value is utilized as the motor setpoint commands to move the robot. Figure 11 on the left demonstrates the prediction of non-periodic motor motions with sensor stimuli support, which is slightly worse than elbow position predictions. We observe that the elbow position is taken as network import. Being a delayed and smoothed version of motor motions it can support the prediction output.

We now apply the predicted motor position as the setpoint for the dedicated biceps muscle motor and run the learned HTM (learning turned off) in real-time. Figure 11 visualizes the results of the online experiment: On every exteroceptive impulse (brown line) we see the motor starting to move (blue line). Consequently, the robot lifts his arm similar to what we have taught before. In addition, the robot moves and the resulting sensory change is taken into account. Again, variation in terms of impulse strength compared to the learned ones we see a weaker movement or a full arm lifting.

The results reflect the behavior of Classical Conditioning. In particular, a previously Neutral Stimulus is conditioned to cause an expectation for a motion and in a second step caused the physical reaction of the arm itself. A robotic system has no intrinsic reaction that corresponds for example to the unconscious salivation process observed with the Pavlovian dog. However, in terms of conditioning the essential point of Unconditioned Stimulus and Unconditioned Reaction can be seen as something is happening with the subject's body the agent can not actively influence. In our case this is imitated by lifting the robotic arm. Therefore, biological primitives can find their substitutes with technical implementations:

- Neutral Stimulus:
  - Turning an exteroceptive sensor (1)
- Unconditioned Stimulus and Unconditioned Reaction:
  - Manually lifting the robotic arm (2)

After learning the Unconditioned Stimulus in terms of a humanoid intention to raise the arm, is superseded and the conditioned stimulus directly triggers the Conditioned Response lifting the arm.

In view of robotic applications, we stress that the Conditioning is executed online in real-time and therefore could be executed in a very intuitive human robot interaction scenario. Even though we presented highly variant motions as well as stimuli, after conditioning the robot reacts to every impulse. Hereby even weaker versions of the stimuli cause a reaction which is a weaker version of the learned arm lifting motion, which also can be seen in biological experiments.

A consolidated video documentation for the conducted experiments can be found as complimentary material with this paper.

VI. Conclusion

Classical Conditioning plays an important role in Mammals learning behavior. We here briefly summarize our experiments that demonstrate the ability to predict motions, execute motions by recall and trigger motions with conditioned sensor stimuli. All experiments are utilizing the HTM in combination with a Myorobotics arm. Afterwards we emphasize the highly biological inspired character of our setup and experiment execution, before we suggest possible future developments for the HTM in robotic conditioning tasks. A greater outlook for applications of the gained results is spotted.

A. Summary

Summarizing the experiment results, we successfully applied the HTM for musculoskeletal robot

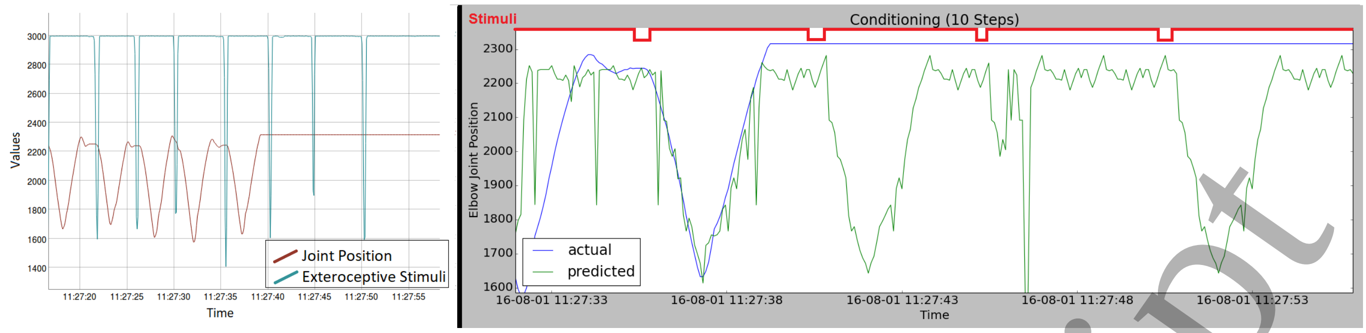

Figure 10: Motion Expectation on Conditioned Stimuli: After associating presented stimuli and a subsequent motion, learning is turned off and only stimuli are presented (HTM raw data input on the left). After learning is turned off (time 11:27:39) the HTM predicts full arm motions (right , green) on every stimuli even if the physical arm itself is not moved at all (right, blue). While a stimulus similar to the learned ones leads to a forecast of the full learned motion (first and last prediction), providing a weaker stimulus (second prediction) we see a weaker variation of the learned arm lifting.

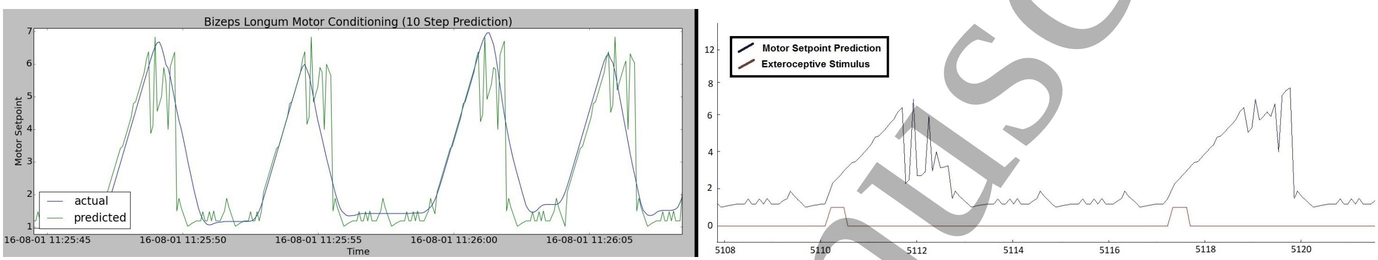

Figure 11: Stimulus Reaction in Classical Conditioning: The proprioceptive muscle position is predicted including preceding sensor stimuli. After learning, predictions are applied as motor setpoints. We observe a Conditioned Reaction on every Conditioned Stimulus, in particular the robot lifts its arm on every presented exteroceptive stimulus (right)

motion learning, prediction and control. The HTM predicts highly deviating motions online in real-time multiple time steps ahead. Filtering the output can help to improve the prediction quality. Additionally we introduced a new application field: With our experiments we demonstrate that the HTM can not only passively learn motions, but implicit knowledge that is stored in the synaptic connections can also be recalled afterwards. Hawkins suggestion of motor control commands being similar to predictions is proven as we use HTM predictions directly as motor control commands and hereby fluently recall and continue learned motions. Classical Conditioning can be found important in every mammal. According to this behavioral concept the robot associates stimuli and actions meaningfully. The HTM can learn the temporal and spatial relation of a previously neutral stimuli and executed motions. After the conditioning phase, the robots expects motions on every stimuli or even reacts proactively on every provided and sensor impulse.

Characteristics that highlight the beneficial combination of Myorobotics and the HTM include:

- *Noise Handling* The HTM can deal with the typical inaccuracy and drift of human motions.
- *Real-time execution* Learning runs in realtime allowing natural human robot interaction.
- *Embodiment* The prediction is supported by morphologically relevant sensory inputs which are autonomously selected.
- *Modularity* All hardware and software components are modular, thus results can be generalized and the setup upscaled.

In addition, the experiments successfully tackle relevant problems such as the control of a complex tendon-driven robot, recall of learned motions from a neural network and robot learning by demonstration.

B. Biological Plausibility

The hardware setup as well as used software components are biologically derived and lead to a technical equivalent of the biological behavior of Classical Conditioning. The Myorobotics Arm imitates the lightweight skeletal structure of a human arm and shoulder and its joints. The tendon driven actuation imitates body control with contractile muscle fibers. Morphological computation lets generated behaviors look humanoid. The HTM is highly inspired by learning in the third and fourth layer of the human neocortex and applies variations of the neural Hebbian Learning found in the brain. It processes sensory information continuously in associative manner and is highly adaptive as neural processing. The close-loop sensorimotor association of morphologically relevant inputs demonstrates the embodiment of adaptive learning in a biomimetic body.

The conducted experiments reproduce biological learning characteristics. The human brain is aware of own future body states in dynamic motions which we demonstrate with continuous prediction of joint positions in different time scales. Body motions are stored in neural circuits while a tied sensor to motor coupling can recall learned behaviors with triggering impulses. The main principles of Classical Conditioning are met in our robotic counterpart of arm motions: A temporal relation between sensor stimuli and motor action is learned by unsupervised association. A conditioned stimuli triggers a learned reaction, while even variations of the stimulus trigger similar variations of the reaction. Arm position prediction, recall and continuation of motions and Classical Conditioning with a biomimetic arm find there equivalent in human behaviors:

1) A subject receiving a handshake, unconscious prediction ensures mental and proactive adaptation to the periodic motion.
2) A sudden break in the periodic handshake leads to a confusion, a subject automatically continuous the learned motion recalling the learned pattern
3) Non-peridodic arm lifting can not be predicted and therefore no adequate adaptation can occur. However, giving a stimuli such as a fillip just before a motion, the stimulus gets conditioned. With this stimulus prediction leads to proactive arm liftings, and after some learning time fillips can trigger the motion execution similar as learned before.

Demonstrating the general behavior with a simplified experiment setup, various components can be refined to improve the given results.

C. Discussion

In this paper we introduce a biologically derived implementation for behavior prediction, recall and Classical Conditioning.

In contrast to analytical models for prediction [16][17] our approach is capable of non-linear prediction and continuously adapts to the given sensory input. Exploiting neural networks for predictions usually requires pretraining of the network or time quantization for batch learning, in contrast here we could execute our experiment online in realtime. The high adaptability comes with a fast fading memory which requires improvement.

The most common way to store and recall multiple motions in a neural network is to save the weights in a database and reload them into the network. In [32] Jaeger introduces Conceptors, embedded in every control update step and being tested on a humanoid character simulation demonstrates fluent transitions between multiple motion patterns. In contrast to this approach, we claim to not analyse the neural network analytically but exploit the network learning mechanisms itself. Exploiting only Hebbian Learning we can demonstrate a more biologically plausible approach, that leads to a natural human robot interaction scenario. A Classical Conditioning experiment in interaction with a humanoid robot and spiking neurons has been executed in [30]. However, in our approach we physically interact with a robot and hereby even teach the novel conditioned reaction by motion demonstration.

The current setup is limited to a few sensory inputs and was tested with learning a single behavior at a time only. A clear drawback is the limitation to short term memory storage. Learning can be turned of to store behaviors, otherwise associations may be overwritten shortly.

We can consider our approach as one of few to control a robot online in realtime to generate a biologically plausible behavior in interaction with a humanoid user. Hereby neither high performance computing nor batch learning is required.

D. Outlook

We demonstrate a very good performance of the HTM in this initial application for Classical Conditioning of a robot. this is particularly interesting since the developmental focus of the HTM so far has mainly been on sensory data processing. We therefore propose some further development with focus on robotic specific characteristics. Robots offer a wide and divers sensory space. As the HTM is designed for multiple sensory input the pre-selection currently executed by swarming shall be handled by learning in the HTM itself. To utilize learned behaviors the currently short term memory learning needs to be extended for long-term capabilities remembering a multitude of learned behaviors. A concept for great variance, here in terms of motion execution speed needs to be developed.

Despite having a powerful learning algorithm, learning ability was clearly defined by the sensory input and motion capabilities. Utilizing the modularity of the full concept both can easily extended, finally upscaling to a full humanoid robot body. On this multitude of sensory inputs and motion scenarios, sophisticated stimulus reaction scenarios can be learned by means of association and conditioning.

Considering the important role of Classical Conditioning for behavior learning we emphasize the big potential of the HTM in nowadays crucial robotic application for intuitive Human Robot Interaction scenarios. Utilizing the HTM motions can be predicted and an expectation about sensory states can be analyzed for adequate actions. Finally, Conditioning abilities in robots allow intuitive robotic teaching procedures: Without any expert knowledge new motions can be taught by guiding the robot and associating it to a provided stimuli. The same stimulus can recall the motion later in time. In the future learning can be based on a wide sensory and action space, providing novel stimuli combinations. In this way even totally different motions can be generated as a mix of the previous learned ones.

VII. Acknowledgments

Our experiments are based on the NuPIC Open Source implementation [33] of Hierarchical Temporal Memory (download 2016/08/16) provided by Numenta Inc. which also included basic evaluation tools we extended for the demonstrated experiments. The research leading to the demonstrated results has received funding from the European Unions Horizon 2020 Research and Innovation Program under Grant Agreement No. 720270 (Human Brain Project SGA1) and No. 785907 (Human Brain Project SGA2).

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