Learning a musical sequence by observation: A robotics implementation of a dynamic neural field model

Flora Ferreira*, Wolfram Erlhagen*§, Emanuel Sousa‡, Luís Louro‡ and Estela Bicho‡

* Dept. of Mathematics and Applications, Center of Mathematics, University of Minho, Portugal

‡ Dept. of Industrial Electronics, Center Algoritmi, University of Minho, Portugal

§ Email: wolfram.erlhagen@math.uminho.pt

Abstract—We tested in a robotics experiment a dynamic neural field model for learning a precisely timed musical sequence. Based on neuro-plausible processing mechanisms, the model implements the idea that order and relative timing of events are stored in an integrated representation whereas the onset of sequence production is controlled by a separate process. Dynamic neural fields provide a rigorous theoretical framework to analyze and implement the necessary neural computations that bridge gaps between sensation and action in order to mediate working memory, action planing, and decision making. The robot first memorizes a short musical sequence performed by a human teacher by watching color coded keys on a screen, and then tries to execute the piece of music on a keyboard from memory without any external cues. The experimental results show that the robot is able to correct in very few demonstration-execution cycles initial sequencing and timing errors.

I. INTRODUCTION

Learning sequential activities such as music, sports or speech requires the ability to represent the order of component actions and the intervals separating them. In many situations, ordinal and timing information must be unified for smooth and skillful performance. Playing a recognizable melody on a piano for instance requires a series of precisely timed finger movements. The neuro-cognitive mechanisms supporting an efficient acquisition of interval and ordinal properties of complex sequences like music are still a matter of debate [1]. It has been suggested that a single learning system might be responsible for integrating sequencing and timing information [2]. Experimental support for this integrated view comes from studies with the classical serial reaction time paradigm (SRT, [3]) in which subjects learn the associations between a series of spatial cues and corresponding response keys. Learning appears to be facilitated when the stimuli are presented in a fixed order compared to a random order. The depended measure of skill acquisition is a gradual reduction in response time that takes place across the sequential trials, indicating that participants develop a temporal expectation of the subsequent stimulus and/or associated motor response without becoming aware of it. Moreover, a variant of the SRT paradigm in which subjects are exposed to sequences with temporal structure, ordinal structure, or both showed that learning for a temporal pattern does not occur independently from the ordinal dimension ([4], [5]). However, since in the

SRT protocol responses are made as quick as possible to external cues and no precise timing is needed for accuracy, the question to which extent order and timing information are integrated in the memory of musical sequences remains unsolved. In fact, several observations in the acquisition and performance of music have been used as argument against the fully integrated view. When learning a melody, the pitch sequence is typically acquired first irrespectively of temporal constraints (intervals and rate, [6], see also [7]). Once learned, a piece of music can be easily recognized and performed across a whole range of production rates (for a discussion see [8]). Substantial changes in the temporal structure of a musical sequence may thus occur with no or only little impact on serial order.

Here we address the problem of the neural representations supporting the learning and production of a novel melody in an approach that combines theoretical modeling and testing in a real-world robotics experiment. The model based on the theoretical framework of dynamic neural fields implements three key processing principles that are in line with neuro-physiological findings. First, the memory of the sensory cues defining the sequential order is represented by self-sustained activity of neural populations tuned to the continuous stimulus dimension (e.g., pitch or color). The persistent stimulus-dependent activity is however not static but increases monotonically as a function of elapsed time since stimulus onset ([9], [10]). As a result, the neural field dynamics establishes an activation gradient over sub-populations that not only encodes the content but also the relative timing of stimulus events. Second, sequence planning starts from a subthreshold activation of all sequence elements in a decision field which mirrors the activation gradient of the sequence memory [11]. Third, sequence recall from memory is associated with a release of pro-active global inhibition in the decision field which leads to a monotonic buildup of activity of all sub-populations [12]. When a certain sub-population reaches a fixed activation threshold, the motor response generating the planned musical event is initiated[13]. To test the various hypothesis of the dynamic field model under real-time constraints of sensing and acting, we conducted an experiment with the humanoid robot ARoS [14]. We used a learning by demonstration paradigm with color coded events in which ARoS learns to perform the

Happy Birthday melody.

II. MODEL DESCRIPTION

Dynamic neural fields provide a rigorous theoretical framework to analyze and implement neural computations that bridge gaps between sensation and action in order to mediate working memory, action preparation, and decision making (for review see [15]). Localized bumps of activation within the field represent metric information about continuous dimensions such as color or pitch. In analogy to the concept of neural population coding, a single bump may be interpreted as the activation pattern of a pool of neighboring neurons with similar tuning properties in an otherwise inactive population ([15], [16]). Crucial for the present learning experiments, bumps that initially evolve under the influence of sufficiently strong transient inputs from connected populations or external sources may become self-sustained due to strong excitatory and inhibitory interactions within the neural populations. Fig. 1 depicts an overview of the model architecture with several interconnected fields representing the feature color that we used for the learning experiments. The three fields on top of the figure implement the learning by demonstration of the musical sequence whereas the two bottom fields become active during recall.

A bump in the perceptual field u_{per} representing the sensory information provided by the vision system triggers through excitatory connections (solid line) the evolution of localized activity pattern at the corresponding site in the present sequence memory layer u_{mem}. Inhibitory feedback (dotted line) from u_{mem} to u_{per} in turn destabilizes the existing bump in the perceptual field. This feedback inhibition ensures that newly arrived localized input to u_{per} will automatically create a bump at a different field location even if the color information is repeated during the course of the sequence. The multi-bump pattern in u_{mem} stores all demonstrated sequence elements with a strength of activation decreasing from element to element as a function of elapsed time since sequence onset. The decision field u_{de} receives this multi-bump pattern as tonic subthreshold input. During sequence recall, the buildup of activity in u_{de} brings all subpopulations closer to the threshold for the evolution of self-stabilized bumps. When the currently most active population reaches this threshold, the corresponding motor response is triggered. At the same time, the excitatory-inhibitory connections between associated populations in the decision field u_{de} and the working memory field u_{wm} guarantee that the suprathreshold activity representing the latest decision becomes first stored in u_{wm} and subsequently suppressed. Once the activity is below threshold, the population representing the next sequence element develops a bump [17].

A key role in the robot's ability to improve its performance in successive demonstration-execution cycles plays the past sequence memory field u_{pa}. It gets excitatory input from corresponding populations in u_{mem} and has excitatory connections with the perceptual field u_{per}. During successive sequence demonstrations, a fading memory trace of the multi-bump

in u_{pa} builds up. The preshaping of neural populations in the perceptual field u_{per} creates an expectation about future stimulus events which manifests in a significant speed up of the evolution of suprathreshold activity in response to an external input [18]. This change in the time course of the population dynamics allows the system to correctly memorize both the order and the timing of the demonstrated events.
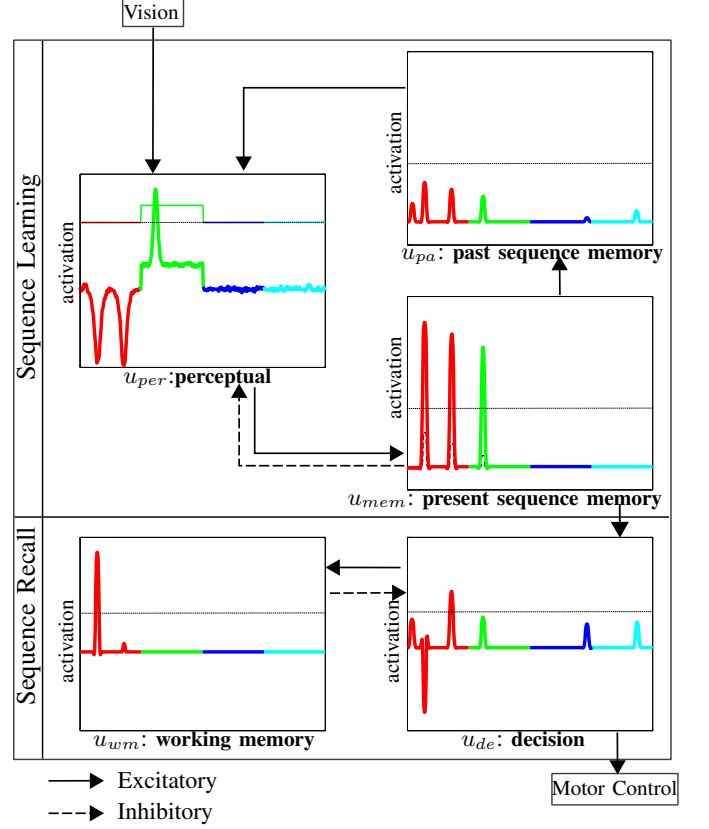

Fig. 1. Sketch of the distributed architecture of the field model. Dashed lines indicate inhibitory connections, solid lines excitatory connections. For details see the text.

The population dynamics in each field is governed by a model equation first proposed and analyzed by Amari [19]:

$$\tau \dot{u}(x,t) = -u(x,t) + S(x,t) - h + \int w(x-y) f\left(u(y,t)\right) dy$$

$$(1)$$

where $u(x,t)$ represents the activity at time t of a neuron encoding feature value x. The constant $\tau > 0$ defines the time scale of the field dynamics. The global inhibition $h > 0$ determines the baseline level to which field excitation decays without external stimulation. $S(x,t)$ represents the time dependent localized input at site x from the vision system and/or connected fields. The firing rate function $f(u)$ is taken as the Heaviside step function with threshold 0. The interaction kernel $w(x-y)$ defines the coupling between neurons within the field. For the decision field in which only one bump at a time should evolve, we use a standard kernel of lateral inhibition type [19]. To enable multi-bump solutions in the memory fields, we adopt an interaction function with

oscillatory rather than monotonic decay described in [20]:

$$w(x) = A e^{-b|x|} \left(b \sin |\alpha x| + \cos(\alpha x) \right), \qquad (2)$$

where the parameter $b > 0$ controls the rate at which the oscillations in w decay with distance. The parameters A and α are added to control the amplitude and the spatial phase of w [17]. A rigorous analysis shows that stable multi-bumps exist over a whole range of parameters defining the inputs and the intra-field interactions (Ferreira et al., in preparation).

To establish an activation gradient in u_{mem} which represents the relative timing of events, we chose the baseline activity to be time dependent, $h = h(t)$. Note that by including $h(t)$ in the definition of the firing rate function $f = f(u - h(t))$ it becomes clear that changing the baseline level is functionally equivalent to changing the threshold of the transfer function $f(u)$. Following the idea of a phenomenological model for threshold accommodation in dynamic fields discussed by Coombes and Owen [21], we apply the following state-dependent dynamics for h_{mem}:

$$\dot{h}_{mem}(x,t) = \left(1 - f(u_{mem}(x,t))\right)\left(-h_{mem}(x,t) + h_{mem_0}\right)$$
$$+ \frac{1}{\tau_{h_{mem}}} f(u_{mem}(x,t)), \qquad (3)$$

where f is again the step function, $h_{mem_0} < 0$ defines the level to which h_{mem} converges without suprathreshold activity at position x and $\tau_{h_{mem}} > 0$ measures the growth rate when it is present. The release of proactive inhibition in the decision field, which results in a monotonic increase of population activity until a threshold is reached, is modeled as a simple linear dynamics of the baseline activity with time constant $\tau_{h_{de}>0}$ (for a discussion of neural evidence see [12]):

$$\tau_{h_{de}} \dot{h}_{de}(t) = 1, \quad h_{de}(t_0) = h_{de_0} < 0. \qquad (4)$$

Assuming that $\tau_{h_{de}}$ may depend on task demands allows us to recall the learned musical sequence with different speeds while preserving the relative timing of tones (see the result section below).

III. PIANO PLAYING TASK

To test the efficient acquisition of order and timing information in a real-word learning experiment, we integrated the model in the cognitive control architecture of the humanoid robot (ARoS) built in our lab [14]. The goal was to teach ARoS to play a simple melody on a keyboard using one or two of its 3-fingered hands. We adopted a learning by observation approach since evidence from SRT experiments suggests that knowledge of serial order can be acquired perceptually even in the absence of a motor response if the stimulus-response mapping is relatively simple (e.g., [22]). We used for the demonstrations a display with color coded events as sensory modality and not the auditory channel since color was easier to detect for the robot than pitch. A key stroke by the human teacher produced not only a sound but also activated a colored square on a computer screen (red for C, green for D, blue for E and cyan for F see Fig. 2). It is important to stress that the choice of the sensory modality does not affect the

learning principles implemented in the DNF model since only the dimension over which the fields are spanned have to be adapted accordingly. The visual cues on the display matched the relative position of the keys. In addition, the fingers where positioned directly above the keys to execute a pre-defined movement with negligible delay whenever the associated population activity in decision field reached a threshold value.

Fig. 2. Experimental setup: Human and robot playing a melody on a keyboard.

As an example of an easily recognizable musical sequence we selected the "Happy Birthday" melody. To keep the presentation of results simple, we focus here on the learning of the first part composed of six elements with three repetitions of the note C (C-C-D-C-F-E, for a video of the whole learning experiment with 12 tones see http://marl.dei.uminho.pt/public/videos/PianoTask.mp4). To quantitatively validate the model in terms of its ability to produce the correct series of pitches with the demonstrated temporal pattern, we compared the interval between successive tones (in percentage of sequence duration) in the demonstrations with the model predictions. In the majority of the experiments, the robot was able to reproduce the melody after only three (shorter sequence) or four (longer sequence) demonstrations.

IV. RESULTS

Music provides a challenge for any sequence learning model since pitches repeat often within a melody, yet people do not confuse their sequential ordering and timing. Most modeling approaches assume some form of pre-processing of the input sequence to deal with the problem of repeated elements (e.g., [23], [24]). The population dynamics in the distributed model architecture resolves the problem of item repetition without the need to refer to additional processing or learning mechanisms. Fig. 3 shows a snapshot of a model simulation in which the same sensory input is applied twice to the perceptual field u_{per}. The inhibitory feedback from the memorized first event in u_{mem} guarantees that the second bump evolves at a different position within the range of the external stimulation. With respect to the buildup of the sequence memory in u_{mem}, there is no difference whether the currently processed item is a repeated item or not. What determines the ordinal position of the item is the time at which population activity reaches the threshold and not where in the field the localized pattern evolves.
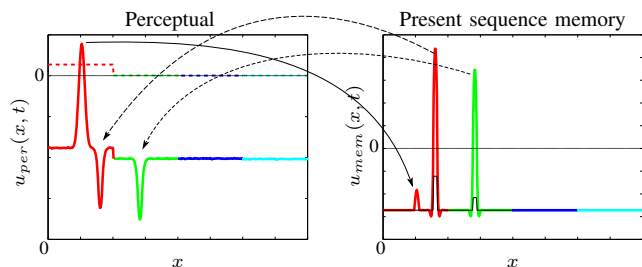
Fig. 3. Snapshots of the activation of the perceptual field, u_{per} (left, solid line) in the presence of external input (dashed line), and the activation of the present sequence memory field, u_{mem} (right) are shown. The dashed arrows indicate inhibitory connections and the solid arrow excitatory connections between the two fields.

The top panel of Fig. 4 shows for three successive demonstrations the activation pattern in the present sequence memory field, u_{mem}. Due to the threshold accommodation dynamics, the peak amplitudes reflect the order and timing memorized musical events. The bottom panel compares the exact point in time in which each note was played by the teacher (vertical lines) with the time course of the maximal activation of the corresponding population representation in u_{mem}.
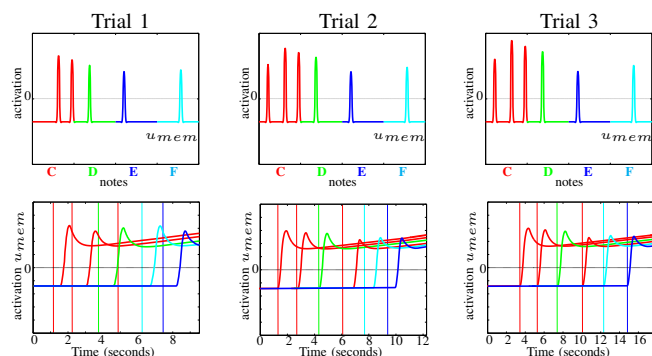

Fig. 4. Comparison of population activity in u_{mem} in 3 successive demonstration trials. *top panel*: Self-stabilized activation pattern. *bottom panel*: Time course of population activity representing the different sequence elements, and timing of notes during demonstration (vertical lines).

Fig. 5 compares the relative timing of the played melody (white bar) and the model prediction when the fixed read-out threshold is applied to the evolving population activity in u_{mem} (black bar).
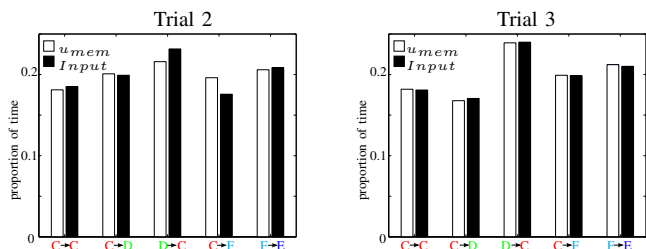

Fig. 5. Relative time intervals between successive tones (white) and predicted intervals from suprathreshold population activity in u_{mem} (black).

After the first demonstration, the robot has memorized only five of the six notes as shown by the five bumps in the top panel of Trial 1 (Fig. 4). The fourth note was lost, due to the time delay in encoding the first three notes (compare the time course in the bottom panel of Trial 1). When the fourth note is played, the population representation of the third note has just reached threshold and no suprathreshold activity representing the forth note evolves (Fig. 4, bottom panel, Trial 1). The processing delay in u_{mem} is due to a relatively slow formation of bumps in the perceptual layer which does not follow the pace of the demonstration.

During the second demonstration, the preshaping from the past sequence memory field lead to a much faster processing of the color information in u_{per}, and consequently also to a speeded processing in u_{mem} (Fig. 5, Trial 2). The robot is able to memorize all notes of the melody (Fig. 4, top panel, Trial 2). The difference in the relative timing compared to the demonstrated sequence, however, is still considerable (Fig. 4, bottom panel, Trial 2). When playing the musical sequence with the encoded temporal pattern, the perceptual difference to the demonstrated pattern is relatively easy to detect for a listener. In the third experimental trial, the processing of the preshape input and sensory input in u_{mem} results in a time course of suprathreshold activity of the different populations that matches very well the relative timing of all demonstrated pitch events. The experiments show that once the robot has memorized the series of pitches, it is able to follow even small expressive timing variations that the teacher may introduce on purpose.

The robot may produce the learned melody from memory in a duet with the teacher using one hand or alone using its two hands. Playing duet is possible by assuming that the populations representing pitch events assigned to the human receive additional pro-active inhibitory control. As a result, the population activity does not reach threshold for the imitation of the associated motor response.

Fig. 6 compares the time course of population activity in the decision field u_{de} (top panel) and the interval timing (bottom panel) for two different speeds. As can be nicely seen in the top panel, the population representations of all notes appear to be pre-activated at the time of sequence onset ($t = t_{on}$) with a relative strength reflecting the temporal order. This parallel planning of all sequence elements has been suggested as a general processing principle for the production of fast sequences such as playing a piece of music that cannot rely on sensory feedback [25].

Different execution speeds can be achieved by adapting the time constant of the baseline dynamics in the decision field, τ_{de}. If τ_{de} is chosen equal to the parameter τ_{mem} controlling the growth rate of the threshold accommodation dynamics, the recall dynamics nearly perfectly reproduces the stored timing of notes (Fig. 6, top left panel). If the time scale for the baseline dynamics is chosen smaller, the execution of the sequence is accelerated (Fig. 6, top right panel) . The characteristic temporal pattern of the melody appears to be preserved in the speeded execution since relative timing and movement onset are controlled by distinct but closely related mechanisms. A comparison of the two bottom figures of Fig. 6

shows that the pattern of interval timing between successive events in the two execution trials is nearly identical.
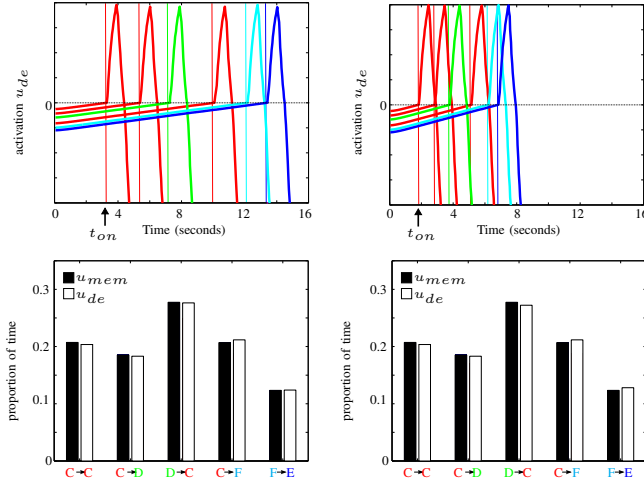

Fig. 6. Time course of the maximal activation of each element in the decision field (top). Relative timing of successive tones in u_{mem} and in u_{de} (bottom). t_{on} is the time of sequence onset.

V. DISCUSSION

Learning to play a piece of music is an excellent example for studying the intimate coupling between ordinal and timing properties of complex sequence behavior. The results of the present robotics experiments provide new insights about the open question to which extent the learning system relies on joint order-timing representations ([2], [4], [5]). The activation gradient of the memory field reflects the dominance of relative timing over global production rate in music performance [6]. To adapt the speed of performance, the only additional assumption to make is that a growing signal related to elapsed time is integrated with the memorized information about order and relative timing to control the initiation of the motor response. This is similar to the idea implemented in modeling studies of perceptual decision making that use elapsed time as additional input to control the rate at which sensory information is integrated until a threshold is reached (e.g., [26]). It is important to notice that the use of a simple linear dynamics for the threshold accommodation in the memory field and the adaptation of the resting state in the decision field is not a restriction, other growth models (e.g., exponential) could have been used as well. The robotics experiments also replicate observations in studies with human subjects indicating that the ordinal sequence is in general learned more quickly than the temporal sequence. A two-stage learning process can thus not be used as an argument against the development of integrated order-timing representations [7].

In the field of human-robot interactions, robot learning by observation is considered highly attractive since it allows in principle a normal user to teach a robot new tasks in an intuitive and simple manner ([16], for reviews and discussion see [27]). Importantly, since users will not likely invest time in many repeated demonstrations, the learning should be efficient and fast. The experiments with the dynamic field model proof that the memory of a complex sequence with repetitions can be acquired with very few demonstrations without the need to refer to additional learning mechanisms. This contrasts with other models of serial order that implement the learning of associations between sequence elements (e.g., neural network models, [2], [28], [29]) or between items and external cues indicating the position of the items in the sequence (for a robotics example see [30]). This associative learning usually needs a larger number of training trials. A second major distinction from associative models is the notion implemented in the field model that fundamentally parallel representations underlie serial behavior [25]. The model extends the idea of an activation gradient, which is the hallmark of so-called competitive cuing models (for a review see [31]), to include also the temporal dimension. The parallel planning of all items in the decision layer makes a fast production of the musical sequence possible since the execution of an individual motor event does not depend on feedback from previous events. This is in line with findings with pianists showing that the absence of auditory feedback has surprisingly little effect on performance [32].

In the present robotics experiments, we have focused on the efficient learning of order and timing information. We have therefore assumed that the robot had already acquired the knowledge about the arbitrary mappings between color cues and associated motor responses. Like in experiments with elementary music students [33], these stimulus-response mappings could be learned in a separate training session using simple associative learning rules. A second simplification of the present implementations concerns the impact of movement time on musical performance. The robot does not need to move its hand since the fingers are positioned over the keys, and the finger press can be executed with a negligible constant delay. In a more general situation, movement time has to be included in the sequence representation to guarantee the production of the correct temporal pattern. This could be achieved using sensory feedback to adjust the level and/or the rate of change of proactive inhibition in the decision layer which controls the time of movement onset. The melody used for the experiments was limited to up to 12 tones that the robotics system could learn and produce without errors. Typical musical sequences that can be readily memorized and recalled consist of hundreds of tones. The idea of a single activation gradient cannot be applied to robustly represent such high numbers of elements. The solution could be to exploit structural and relational aspects of individual elements to group them together to larger units [1]. We are currently exploring for our robotics work how "chunking" mechanisms may be integrated in dynamic neural field models of serial behavior to cope with this challenge ([34], see also [29].

Although the present sequence model has been developed with the goal to apply it for the learning of short musical sequences, it can be easily adapted for many others situations in which ordinal and timing information are tightly coupled. For in-

stance, for a fluent and pleasant human-robot cooperation in routine service tasks such as preparing the dinner table or handing over a set of objects, a judgment about the ordinal sequence structure but also a metrical judgment that involves the analysis of elapsed time between routine events is essential. Moreover, the robot should be able to synchronize its actions and decisions with different users, making the capacity to adjust its timing of actions a central one. With an adaptive integrated representation of ordinal and timing properties, the robot would be able not only to anticipate what the user needs next [35], but may also predict the moment in time when it should start an object transfer.

ACKNOWLEDGMENT

REFERENCES

[1] P. Janata and S. T. Grafton, "Swinging in the brain: shared neural substrates for behaviors related to sequencing and music." *Nature Neuroscience*, vol. 6, no. 7, pp. 682–687, 2003.

[2] P. F. Dominey, "A shared system for learning serial and temporal structure of sensori-motor sequences? Evidence from simulation and human experiments." *Cognitive Brain Research*, vol. 6, no. 3, pp. 163–172, 1998.

[3] M. J. Nissen and P. Bullemer, "Attentional requirements of learning: Evidence from performance measures," *Cognitive Psychology*, vol. 19, no. 1, pp. 1–32, 1987.

[4] J. C. Shin and R. B. Ivry, "Concurrent learning of temporal and spatial sequences." *Journal of Experimental Psychology: Learning, Memory, and Cognition*, vol. 28, no. 3, pp. 445–457, 2002.

[5] J. X. O'Reilly, K. J. McCarthy, M. Capizzi, and A. C. Nobre, "Acquisition of the temporal and ordinal structure of movement sequences in incidental learning." *Journal of Neurophysiology*, vol. 99, no. 5, pp. 2731–2735, 2008.

[6] C. Drake and C. Palmer, "Skill acquisition in music performance: relations between planning and temporal control." *Cognition*, vol. 74, no. 1, pp. 1–32, 2000.

[7] F. Ullén and S. L. Bengtsson, "Independent processing of the temporal and ordinal structure of movement sequences." *Journal of neurophysiology*, vol. 90, no. 6, pp. 3725–35, 2003.

[8] C. Palmer and P. Q. Pfordresher, "Incremental planning in sequence production." *Psychological Review*, vol. 110, no. 4, pp. 683–712, 2003.

[9] C. D. Brody, "Timing and Neural Encoding of Somatosensory Parametric Working Memory in Macaque Prefrontal Cortex," *Cerebral Cortex*, vol. 13, no. 11, pp. 1196–1207, 2003.

[10] A. Genovesio, S. Tsujimoto, and S. P. Wise, "Neuronal activity related to elapsed time in prefrontal cortex." *Journal of Neurophysiology*, vol. 95, no. 5, pp. 3281–3285, 2006.

[11] B. B. Averbeck, M. V. Chafee, D. A. Crowe, and A. P. Georgopoulos, "Parallel processing of serial movements in prefrontal cortex," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 99, no. 20, pp. 13 172–13 177, 2002.

[12] C. Wardak, S. Ramanoël, O. Guipponi, P. Boulinguez, and S. Ben Hamed, "Proactive inhibitory control varies with task context." *The European Journal of Neuroscience*, vol. 36, no. 11, pp. 3568–3579, 2012.

[13] J. I. Gold and M. N. Shadlen, "The neural basis of decision making." *Annual review of neuroscience*, vol. 30, pp. 535–74, 2007.

[14] E. Bicho, W. Erlhagen, L. Louro, and E. C. e Silva, "Neuro-cognitive mechanisms of decision making in joint action: a human-robot interaction study." *Human Movement Science*, vol. 30, no. 5, pp. 846–868, 2011.

[15] G. Schöner, "Dynamical systems approaches to cognition," in *The Cambridge Handbook of Computational Psychology*, R. Sun, Ed. Cambridge: Cambridge University Press, 2008, pp. 101–126.

[16] W. Erlhagen and E. Bicho, "The dynamic neural field approach to cognitive robotics." *Journal of Neural Engineering*, vol. 3, no. 3, pp. R36–54, 2006.

[17] F. Ferreira, W. Erlhagen, and E. Bicho, "A dynamic field model of ordinal and timing properties of sequential events," in *Artificial Neural Networks and Machine Learning -ICANN 2011*, ser. LNCS, T. Honkela, W. Duch, M. Girolami, and S. Kaski, Eds. Springer Berlin Heidelberg, 2011, vol. 6792, pp. 325–332.

[18] W. Erlhagen and G. Schöner, "Dynamic field theory of movement preparation." *Psychological Review*, vol. 109, no. 3, pp. 545–572, 2002.

[19] S. Amari, "Dynamics of pattern formation in lateral-inhibition type neural fields," *Biological Cybernetics*, vol. 27, no. 2, pp. 77–87, 1977.

[20] C. R. Laing, W. C. Troy, B. Gutkin, and G. B. Ermentrout, "Multiple Bumps in a Neuronal Model of Working Memory," *SIAM Journal on Applied Mathematics*, vol. 63, no. 1, pp. 62–97, 2002.

[21] S. Coombes and M. Owen, "Exotic dynamics in a firing rate model of neural tissue with threshold accommodation," *AMS Contemporary Mathematics*, vol. 440, pp. 123–144, 2007.

[22] J. H. Howard, S. A. Mutter, and D. V. Howard, "Serial pattern learning by event observation." *Journal of Experimental Psychology: Learning, Memory, and Cognition*, vol. 18, no. 5, pp. 1029–1039, 1992.

[23] D. X. Shieh and J. L. Elman, "The Divergent-Reconvergent Model of Serial Order Encoding and Retrieval The Divergent-Reconvergent Model," in *Proceedings of the 29th annual meeting of the cognitive science society*, 2006, pp. 786–791.

[24] G. Bradski, G. A. Carpenter, and S. Grossberg, "STORE working memory networks for storage and recall of arbitrary temporal sequences," *Biological Cybernetics*, vol. 71, pp. 469–480, 1994.

[25] K. S. Lashley, *The problem of serial order in behavior*. Jonh Wiley & Sons, New York, 1951, no. 7.

[26] D. Standage, H. You, D.-H. Wang, and M. C. Dorris, "Gain modulation by an urgency signal controls the speed-accuracy trade-off in a network model of a cortical decision circuit." *Frontiers in computational neuroscience*, vol. 5, no. February, p. 7, 2011.

[27] K. Dautenhahn and C. L. Nehaniv, *Imitation in animals and artifacts*. MIT Press, 2002.

[28] A. Cleeremans and J. L. McClelland, "Learning the structure of event sequences," *Journal of Experimental Psychology: General*, vol. 120, no. 3, pp. 235–253, 1991.

[29] Y. Yamashita and J. Tani, "Emergence of functional hierarchy in a multiple timescale neural network model: a humanoid robot experiment." *PLoS computational biology*, vol. 4, no. 11, p. e1000220, 2008.

[30] Y. Sandamirskaya and G. Schöner, "Dynamic field theory of sequential action: A model and its implementation on an embodied agent," in *2008 7th IEEE International Conference on Development and Learning*. IEEE, 2008, pp. 133–138.

[31] B. J. Rhodes, D. Bullock, W. B. Verwey, B. B. Averbeck, and M. P. a. Page, "Learning and production of movement sequences: behavioral, neurophysiological, and modeling perspectives." *Human Movement Science*, vol. 23, no. 5, pp. 699–746, 2004.

[32] S. Finney and C. Palmer, "Auditory feedback and memory for music performance: Sound evidence for an encoding effect," *Memory & Cognition*, vol. 31, no. 1, pp. 51–64, 2003.

[33] G. L. Rogers, "Effect of Color-Coded Notation on Music Achievement of Elementary Instrumental Students," *Journal of Research in Music Education*, vol. 39, no. 1, pp. 64–73, 1991.

[34] E. Sousa, W. Erlhagen, and E. Bicho, "On observational learning of hierarchies in sequential tasks: A dynamic neural field model," in *Computational Models of Cognitive Processes*. World Scientifc, 2014, pp. 196–210.

[35] E. Bicho, L. Louro, and W. Erlhagen, "Integrating verbal and nonverbal communication in a dynamic neural field architecture for human-robot interaction." *Frontiers in neurorobotics*, vol. 4, 2010.