Effectiveness of a Coupled Oscillator Network for Surface Discernment by a Quadruped Robot based on Kinesthetic Experience

Andrew H. Toland\textsuperscript{1}, Lars A. Holstrom\textsuperscript{2}, George G. Lendaris\textsuperscript{3}

Abstract—Inspired by examples of oscillatory circuits in biological brains, we explore a hypothesis that one role of dynamical neural networks observed in biological sensory systems is to amplify subtle differences in sensory data, which in turn simplifies the task of classifying external stimuli. The authors recently developed a method for classifying the surface walked upon by a quadruped robotic dog \[9\]. The method developed utilizes time series data from the dog’s joint sensors (kinesthetic vector). Employing the same data, an experiment was set up to explore the above hypothesis, comparing the relative accuracy of classifying (discerning) the surface type experienced by the robot, both with and without the inclusion of a system of coupled nonlinear oscillators in the data processing stream. These experiments demonstrated a significant increase in classification rate (on average) when the sensory data was passed through a coupled oscillator system to precondition the signals prior to inputting to a PNN type neural network classifier, in comparison with the result obtained by feeding the data to the PNN without preconditioning. From an implementation point of view, it is significant that these results were obtained via a coupled oscillator whose inter-oscillator weights were randomly instantiated. Some of the results are provided in terms of the Lyapunov Exponent and the spectral radius of the inter-oscillator weight matrix.

I. INTRODUCTION

A long-standing research goal of the authors laboratory (NWCIL) has been to build into machines the ability to employ experiential knowledge in a human-like way to rapidly select effective models and/or controllers for the current context (from a memory repository). A key to this approach is the notion of context discernment \[8\][13][15]. A recent NWCIL result demonstrates the ability of a neural-network based agent to efficiently discern which surface type, from among a set of candidates, a quadruped robot experiences in real-time. This information is subsequently used to select the appropriate walking gait (for a Sony AIBO dog robot) as the robot moves from one surface type (context 1) to another surface type (context 2) \[9\].

The purpose of the present research is to explore the utility of a biologically-plausible coupled-oscillator circuit to carry out some of the computations important to the experience-based/context-discernment process.

Motivation for the exploration reported here derives from a hypothesis we made that one role of dynamical neural networks observed in biological sensory systems may be to amplify subtle differences in sensory data, which in turn simplifies the task of classifying external stimuli. We tested this hypothesis by comparing the relative accuracy of classifying (discerning, in the vocabulary of the authors research) environmental parameters experienced by a robotic dog, based on the robots sensor data, both with and without the inclusion of a system of nonlinear coupled oscillators (COs) in the processing stream. The classification rate was significantly increased (on average) when the sensory data was passed through the COs. From an implementation point of view, it is significant that these results were obtained via COs whose inter-oscillator weights were randomly instantiated.

From a computational intelligence perspective, it is of interest to examine learning systems that have biologically plausible architectures. A key challenge is to develop learning algorithms and meaningful interpretations of the biologically inspired unit. Even at the current early stage of our research with the experience-based/context-discernment process mentioned above, the latter shows promise of an important functionality observed in sensory systems: that of rapid association of input patterns with learned behaviors and memories.

The architecture selected for the present study was inspired by knowledge available about the olfactory sensory system \[3][4][10][20\]. The olfactory system seems to epitomize the above-mentioned rapid association property. The olfactory bulb contains networks having locally inhibitory and globally excitatory neurons forming coupled oscillatory systems. Even in the early stages of sensory processing in the olfactory bulb, patterns are extracted and synchronized with activity in the olfactory cortex \[4\]. The network of coupled oscillators in the olfactory bulb is able to distinguish subtle input patterns and quickly evoke associations to learned responses.

Another key motivator for the present line of research is the potential (based on theoretical knowledge) for systems comprising coupled oscillators that are poised in an attentive state and characterized by behavior that is consistent with a dynamical system in a chaotic attractor to exhibit the rapid associations mentioned above. Such coupled oscillators are observed to have evolved in living systems (e.g., in the olfactory bulb), apparently utilizing certain properties of complex dynamical systems. It is hypothesized that they appear where there is a biological imperative to rapidly make strong distinctions between weak inputs, and to si-
multaneously excite associations with other systems [7]. Our exploration of coupled-oscillator systems is further motivated by the fact that a similar imperative is expected to be operative in context-discerning control systems.

There are challenges that face the implementation of complex dynamical systems as elements of control systems. Besides the problem of how to train such systems, there is the problem of how to interpret their output(s). Despite these seeming difficulties, a strong incentive is provided by properties of chaotic systems [2] that suggest the tantalizing possibility of dense associational storage with rapid recall. The ubiquity of oscillating systems in the brain suggests the nervous system may be making use of their rapid switching-between-states and synchronization of dynamical systems properties [18].

II. THE OLFACTORY BULB [1][4][6][7][12][19]

The olfactory bulb (OB) is organized by laterally inter-connected, loosely columnar structures. In the columnar organization of the bulb, mitral cells form the main columns. The mitral cells form local dendrodendritic inhibitory connections with granule cells, and global excitatory synaptic connections with other mitral cells. In engineering terms, the olfactory systems may be seen as containing a large number of coupled-oscillator circuits with which it creates a dynamical representation upon reception of an odorant. A spatially extended, amplitude-modulated pattern may then be thought to synchronize with downstream neural processing units, and thus form contextual awareness associated with the odorant. Projections from the anterior olfactory nucleus also extend back to the granule cells in the bulb. These projections serve to provide reinforcement signals to the bulb so that novel odors may be recognized.

III. THE COUPLED OSCILLATOR NETWORK

The pattern of locally inhibitory and globally excitatory connections between the cells in the OB forms an oscillatory network that can be expressed by an instance of the Wilson-Cowan model [10], (the form of which is here specifically inspired by the Hayashi model [17]):

\[
\begin{align*}
\dot{x}_i &= -x_i + S \left( \rho_i + \sum_{j=1}^{n} a_{ij} x_j - b_i y_i \right) \\
\dot{y}_i &= -y_i + S \left( c_i x_i \right)
\end{align*}
\]

(1)

In these equations, \(x_i\) represents the activity of the \(i^{th}\) mitral cell; and \(y_i\), the activity of the \(i^{th}\) granule cell. The external input present on the \(i^{th}\) mitral cell is represented by \(\rho_i\). Activity of the neural elements in this model can be thought of as average spike rate of real neurons. The function \(S\) is a sigmoid (in this case, the hyperbolic tangent). The equations (1) were implemented in discrete form for the experiments carried out for the research reported here. For simplicity, each oscillator was given the same local connection weights. The inter-oscillator weight matrix, \(A = a_{ij}\) for \(i, j = 1...n\), was randomly instantiated, with the weights selected from a normal distribution \(N(0, 0.5)\). The values of the inter-oscillator weights were at least an order of magnitude less than the values of intra-oscillator connections.

IV. RECURRENT NEURAL NETWORKS

Recurrent neural networks (RNNs) can generate complex dynamics. As a result of this behavior, it has been proven that (analog) RNNs are capable of super-Turing computational power [16]. However, the achievement of super-Turing computability comes at the price of losing programmability. Achieving control over the input-output relations in RNNs is the main impediment to their utility.

In the (special) case of coupled oscillator systems, limited learning algorithms have been proposed [5][11][18]. Strategies also exist for controlling chaotic coupled oscillator systems by carefully perturbing them into periodic orbits [14]. Typically, such approaches involve either extensive training periods, or make limited use of the full range of dynamical behavior.

A recent neural network formulation that respects the broader range of dynamics available to recurrent systems is the Echo-state network (ESN) [6]. The ESN represents a significant simplification to the challenge of training recurrent neural network structures. Echo-state networks utilize the complex dynamics of a large collection of sparsely connected nonlinear units. When active, the collection of neurons creates a reservoir of dynamics from which a function approximation system can draw. Rather than attempting to tame the dynamics in the reservoir, the ESN approach linearly combines characteristics of the dynamics using linear output units to match a desired target. This simple training algorithm has shown results that can rival state-of-the-art Extended Kalman Filter Back Propagation Through Time (EKF BPPT) training of RNNs, although apparently at the expense of requiring a greater number of neural units [14].

The approach taken in this study was to treat a fully coupled system of neural oscillators as a dynamical reservoir. We do not encode the outputs, per se; instead we show the feasibility of including a reservoir network in an experience-based/context-discernment type of process mentioned in Section I. We cluster the outputs of the coupled oscillator network (CONN) according to a metric we define, and then classify the clusters using probabilistic neural networks (PNNs).

V. CONTEXT DISCERNMENT

The notion of context as used here entails declaration of perspective. For a setting in which the task is to design a controller for a plant, the key factors from the perspective of the entity performing the design or selection (from a collection of already designed controllers) that would influence the design/selection process are the plant being controlled, the criterion function (CF) used to stipulate control objectives and to measure how well the controller/plant combination achieves design objectives, and the environment in which the controlled plant is functioning. Stated more concisely: context for control design / selection = (plant, CF, environment). Discernment of the current context is a prerequisite
VI. EXPERIMENTAL CONSIDERATIONS

A. Data Collection

An AIBO ERS-7 robot was used for the experiments; description of the data collection and control aspects of the process may be found in [9]. Briefly, the AIBO was trained via genetic algorithm to develop a gait for each of four distinct surface types that are better than the AIBO’s default gait; the metrics used involved speed and sway of the AIBO. The four surfaces included: plywood board, thin foam, short carpet, and shag carpet; these were selected to represent a range of surface characteristics that would allow (possible) generalization to novel surfaces. Ten sample runs were taken of each gait on the surface for which the gait was crafted to be best, and then augmented with ten sample runs of each gait on each of the other three surfaces; this yielded 10 data realizations for each of the 16 possible gait/surface combinations (contexts). The data comprised about 10 seconds of time series values of the relative angular positions of the AIBO’s 12 leg joints, collected at a rate of 31.25 Hz, with the period of each gait fixed at 670 ms.

B. Classification

A full step is defined as a ‘cycle’. Time series data from a small number of cycles from a run were averaged, modulo one cycle, to form a characteristic step for each gait/surface combination. A separate characteristic cycle (comprising \( n \) interpolated data points) was computed for each of the 12 joints. The resulting characteristic cycles were stored in a separate matrix for each gait/surface combination. Each matrix comprised 12 columns, each column containing the \( n \) averaged data points of the corresponding characteristic cycle, yielding an \( n \times 12 \) dimensional matrix. Each of the \( n \) rows of the data matrix thus contained data from the 12 joints at the same instant in time.

The data were split up into a training set (60\% of the data) and a test set (the remaining 40\%). The training data was employed to train a probabilistic neural network (PNN) to discern which of the 16 possible gait/surface conditions the AIBO was experiencing, both with and without use of a coupled-oscillator neural network (CONN) as an intermediary processor before the PNN received the joint data.

The CONN was constructed with 12 inputs. To activate the CONN, an input matrix was fed row-wise to the CONN, with \( m \) passes through the matrix, so the CONN received \( mn \) of the \( 1 \times 12 \) input vectors, where the number \( m \) was chosen large enough for the dynamics of the CONN to settle into an input-specific attractor within \( mn/2 \) presentations. Usually the dynamics settled into an attractor after a few presentations of the matrix. Thus, the attractors were subsequently represented using (just) the last half of the recorded time series for each oscillator’s excitatory unit – i.e., \( mn/2 \) data values for each attractor.

To provide data in a form appropriate to the PNN that follows the CONN, a scalar metric was developed to characterize a distance between attractors. The process involves arbitrarily selecting one of the attractors, and using this as a ‘reference’ attractor. The data for the remaining attractors are then subtracted point-wise from the reference attractor. The absolute values of the differences are summed to form a 1x12 vector (a point in some 12-dimensional vector space). Thus the metric is similar to an \( l_1 \) norm. The PNN was then trained to classify the resulting clusters (in this vector space), with 60\% of the data used to train the PNN, and the remaining 40\% used to test classification performance.

Distinct CONNs were generated via randomizing the inter-oscillator connection weight matrix. Training/test runs were performed on each distinct CONN system.

The classification system is depicted in Fig. 1.

C. Auxiliary Experiments

Given that the 12 constituent oscillators of the CONN all interact with one another, it is in principle possible that sufficient information for the classification task is embedded within a subset of the 12 CONN outputs. If so, this would have the benefit of reducing the size of the (metric) space being explored, as well as the size of the PNN. Auxiliary experiments were run to test this possibility. One hundred random choices of output subsets were tested for all the previously acquired data. In addition, a set of experiments was also run wherein PNNs were trained and tested for each gait separately. Each of these modifications improved the classification performance (see next section).

Another set of auxiliary experiments involved adjusting some parameters of the CONN and noting their effect on classification performance. The adjusted parameters included the slope of the sigmoid activation function, the intra-oscillator weights, and the input weights. All oscillators within a given instantiation of a CONN were given the same sets of parameter values.

Yet another set of auxiliary experiments involved calculating the Lyapunov spectrum for each instantiated CONN system, to explore whether the CONN’s degree of chaoticity at the quiescent state of the CONN system correlated with classification performance. The quiescent state was defined for IJCNN, August 2007, Orlando, FL. Final manuscript date 04/25/07
Fig. 1. Schematic of the discernment system. A time signal is obtained from each of the robot’s joint actuators, as represented (for one joint) in the upper portion above. An averaging process is performed to yield a “characteristic” version of each signal. This signal is then fed to the “metricizer” box either through the CONN or directly, using the “Bypass” path. The output of this box provides the signals to the PNN for the surface classification (i.e., discernment).

as the state of the system under excitation with very small inputs. For the experiments, the quiescent state was excited with small sinusoidal inputs, all having the same frequency, phase, and amplitude. The frequency and phase of the inputs were arbitrary (but the same for all), and the amplitude was chosen to be about three orders of magnitude smaller than the amplitude of the inputs from the joint time series.

Finally, classification of the gait/surface context by the CONN/PNN system was compared to the classification of the gait/surface context by the PNN alone. In the PNN-only system, the inputs were clustered in a manner similar to that used in the CONN/PNN system, but instead of using a reference attractor to define a metric for input to the PNN, a reference cycle was chosen. All twelve dimensions were used in the classification of the PNN-only system.

VII. RESULTS

A. Classification results without CONN

The highest classification rate achieved by the PNN system without the CONN (Bypass path in Fig.1) was 82%. This result was achieved by training gait-specific PNNs.

B. Classification results with CONN

A classification rate as high as 97% was achieved via assigning each gait its own (arbitrarily selected) subset of four CONN output channels and its own PNN. This result is better than those reported in [9], in which AR filters were used to identify the surfaces. A full complement CONN (12-inputs/12-outputs) improved classification performance to 87.5%. This performance was taken as a baseline and was improved upon when only a subset of the 12 CONN outputs was selected for input to the PNN stage. For example, using six of the CONN’s outputs for input to the PNN (that has 16 outputs, one for each of the possible gait/surface contexts) yielded 90.6% correct classification.

Fig. 2 concisely illustrates the enhanced performance of the system with the CONN vs. without. The distributions in the figure represent classification rates of 100 different randomized subsets (of size 5) of the channels that feed the Metric unit (shown in Fig. 1).

Fig. 3 compares the highest performance value from the bypassed system to the highest performance values from 100 systems with different, randomized CONNs.

Fig. 4 illustrates the classification capabilities of the four possible configurations of Bypass vs. CONN path selection (cf. Fig. 1) and single PNN vs. gait-specific PNNs. The four different curves are plotted against the number of randomly selected output channels.

C. Spectral radius of weight matrix

The average classification performance deteriorated as the spectral radius of the (randomly selected) weight matrix exceeded about 1.8. Classification performance versus the spectral radius of the weight matrices for the experiments performed is shown in Fig. 5.

D. Lyapunov exponent

A range of consistently high average classification rates persisted up to Lyapunov exponent values of about 0.3, where
the Lyapunov exponent was measured on quiescent-state dynamical behavior. The largest Lyapunov exponent for each of the 100 weight matrix instantiation versus classification performance is shown in Fig. 6.

E. Mechanism: added specification through nonlinear transformation?

The question remains of why inserting the CONN improves the classification performance. Our conjecture is that the dynamics of the coupled-oscillator system provides a mechanism for sufficiently transforming what otherwise appear to be small differences in the joint-sensor (kinesthetic) realm to allow correct discernments – akin to the ability of the olfactory bulb mentioned in the introduction to distinguish between subtle input patterns and quickly evoke associations to learned responses. Further research is planned to test this conjecture.

As a first step toward that end, we can examine the spectra of the signals that are fed to the PNN, as shown in Figs. 7 and 8. Power spectra of two signals obtained via the Bypass path (cf. Fig. 1) are shown in Fig. 7, and the signals obtained via the CONN are shown in Fig. 8. These two signals correspond to two of the gait/surface combinations. A range of ±1 standard deviations about the average (calculated from 10 sample data sets) is shown in the graphs. Note that most of the variability occurs in and between the upper harmonics.

The signals in Fig. 8 appear to have undergone a process that includes the sharpening of harmonics, low-pass filtering, and frequency mixing, as compared to those in Fig. 7. The most significant differences (between the two plots in Fig. 8) appear to occur around (and below) the fundamental (at 1.49Hz) and the first few harmonics.

F. Computational Expense

The computational cost of running several hundred iterations of a 12-dimensional fully-coupled oscillator network is high, and makes this method seem unattractive in comparison to more straight-forward techniques that achieve a similar level of performance. As with any network topology, the simulation of the CONN on serial processors yields one measure of computational cost. Another might be made on dedicated custom hardware. Also it should be noted again that coupled oscillators are abundant in the nervous system, but possibly for reasons extending beyond computational efficiency, such as energy efficiency or adaptability.

VIII. Conclusion

Our motivation for the experiments described here has been to demonstrate that a biologically-plausible circuit comprising coupled oscillators can successfully perform pattern classification tasks in a context-discernment system.
The employed coupled-oscillator neural network (CONN) and classification performance were observed. The classification performance remained in a performance range greater than 80% when the largest Lyapunov exponent of the CONN under small-signal stimulation remained less than about 0.3, and the spectral radius of the inter-oscillator weight matrix in the CONN remained less than about 1.8.

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We demonstrate that attractors arising in systems of coupled-oscillator neural networks (CONNs) are distinct enough to improve the performance of a classification system. The inclusion of a CONN in the experimental system resulted in higher classification rates. Random instantiation of the weight matrix in a 12-dimensional coupled oscillator yielded classification performance of an impressive 97% when the coupled oscillator network was fed time-series inputs from the joint sensors of an AIBO robot walking on various surfaces, and components of the CONNs output (represented as appropriate) fed to a PNN neural network. This is significantly better than the 82% classification performance using the PNN neural network alone (which was fed the AIBO joint sensor data directly, represented as appropriate).

Statistical relationships between invariant parameters of the gait/surface 1

Fig. 7. Power spectra of characteristic signals from two of the 16 gait/surface combinations.

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Statistical relationships between invariant parameters of the gait/surface 2

Fig. 8. Power spectra of the CONN output, given input from the characteristic signals depicted in Fig. 6.