Complex Preferences for the Integration of Neural Codes

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Abstract

This paper presents a complex preferences framework of integrating pulsed neural networks into neural/symbolic hybrid approaches. In particular, we introduce an interpretation of neural codes as multidimensional complex neural preferences and preference classes which allow the integration of knowledge from different neural and symbolic models. We define some basic operations on complex preferences and preference classes that allow them to be directly integrated into symbolic models. Furthermore, we show the interpretation of mean firing rate, time-to-first-spike, synchrony and phase codes as complex neural preferences and the interpretation of the operations on preference classes of these codes. To the best of our knowledge this is the first work that addresses the integration of pulsed neural networks into hybrid approaches, in particular the symbolic interpretation and simultaneous processing of mean firing rate and pulse coding schemes in a preferences framework.

1 Introduction

The development of hybrid models, integrating neural and symbolic approaches, has received a fair amount of interest. Some significant work has been done in this area [Medsker, 1995, Dorffner, 1997] but much less has been done on fundamental principles of neural/symbolic hybrid systems [Smolensky, 1988, Sharkey and Jackson, 1995, Wermter, 1995].
Furthermore, most neural network models considered in hybrid approaches use the mean firing rate as a concept of encoding the information. Recently, however, there is an increasing amount of evidence from the field of computational neuroscience which suggests that the firing rate alone is not sufficient for encoding all the information that is processed in the real neural networks. Some of this evidence shows that the neurons use alternative types of coding [Thorpe et al., 1996], while other research suggests that the neurons can simultaneously process firing rate and spatiotemporally encoded information [Araki and Aihara, 1999]. This evidence initiated experimental and theoretical work that outlines the computational limits of using firing rate alone and the advantages of using alternative or complimentary coding schemes in the framework of pulsed neural networks [Maass and Bishop, 1999].
The integration of pulsed neural networks into the hybrid approaches is one of the priorities of our approach. This paper presents an important step towards such an integration, theoretically addressing the fundamental issue of symbolic interpretation of pulse neural codes and their combination with firing rate code. Furthermore, we provide an introduction of the general concept of multidimensional complex neural preferences and preference classes. The concept of preference classes allows a clear link to symbolic interpretations. Furthermore, we show how mean firing rate, time-to-first-spike, synchrony and phase codes can be interpreted in our new neural preferences framework.

2 Complex Neural Preferences

In previous work we have introduced preference-based processing [Wermter, 1999] and here we would like to extend this work substantially towards integrating firing rate and pulse coding schemes. While usually the processing and representation in the brain are believed to be task-dependent, a common neural/symbolic interpretation of the neural code is possible and crucial for hybrid systems.

Definition 1 (Complex Preference, briefly C-Preference) *A complex preference of level l is represented by an $l \times m$-dimensional matrix $a \in [0,1]^{l \times m}$.*

The special case of a c-preference of level one is called simple neural preference, or just preference. As we will show in the following sections, some single neural coding schemes can be interpreted as a simple preference, i.e. an m-dimensional analog vector in $[0,1]^m$. Other single coding schemes can be interpreted as c-preferences where the simple preference at each level represents a given internal state of the code. Furthermore, multiple coding concepts can be integrated and can be simultaneously processed in a c-preference where each level (or several levels) represent a single coding scheme.

Definition 2 (Next Corner Reference) *The next corner reference $r(a) \in \{0,1\}^{l\times m}$ of the c-preference $a \in [0,1]^{l\times m}$ is determined for $i \in \{1,\ldots,l\}$ and $j \in \{1,\ldots,m\}$ as:*

$$r_{ij}(a) = \begin{cases} 0 & \text{if } a_{ij} < 0.5 \\ 1 & \text{if } a_{ij} \geq 0.5 \end{cases}$$

The introduction of the next corner reference allows us to associate each c-preference with a particular corner of the $[0,1]^{l\times m}$ hypercube, i.e. a discrete symbolic representation.

Definition 3 (Preference Value of a C-Preference) *A preference value of a c-preference $a \in [0,1]^{l\times m}$ with respect to its next corner reference $r(a)$ is defined as:*

$$pref(a) = 1 - \frac{distance(a, r(a))}{\frac{\sqrt{lm}}{2}} \quad \text{, where } distance(a, r(a)) = \sqrt{\sum_{i,j}(a_{ij} - r_{ij}(a))^2}$$

is the distance between the c-preference a and its next corner reference.

$\sqrt{lm}/2$ is the maximum distance in the $l\times m$-dimensional c-preference space, that is the distance from the center of the hypercube to any corner. If the c-preference a is close to its next corner reference then its preference value $pref(a)$ will be close to 1 and if it is close to the center then $pref(a)$ will be close to 0. For a *neural interpretation* the preference value is a measure of how far away a neural c-preference is from the discrete representation indicating for example the strength of the neural response. For a more symbolic *fuzzy interpretation*, the preference value is a measure of how far away a fuzzy set is from the corresponding symbolic sharp set which represents the corner reference.

Definition 4 (C-Preference Class) *Let $a \in [0,1]^{l\times m}$ be a c-preference with next corner reference $r(a) \in \{0,1\}^{l\times m}$. Then the class of complex preferences of a is called c-preference class $c(a)$ and contains all those c-preferences with next corner reference $r(a)$, which have the same distance from $r(a)$ as a.*

The *preference value of a class of c-preferences* is the preference value of an arbitrary c-preference which belongs to this class. This follows directly from the definitions of c-preference classes and the preference value.

Definition 5 (Order of C-Preference Classes) *Let $a, b \in [0,1]^{l\times m}$ be two c-preferences with common corner reference $r \in \{0,1\}^{l\times m}$. Then the corner reference order of classes of c-references $\geq_{pc}$ is defined as follows: $c(a) \geq_{pc} c(b)$, if $distance(a, r) \leq distance(b, r)$.*

Theorem 1 *The corner reference order for c-preference classes is a partial ordering.*

Directly applying the above definitions it is straightforward to show reflexivity, antisymmetry and transitivity for the order of c-preference classes. Therefore, we fulfill the minimum requirement for the definition of all fuzzy sets with multidimensional goal domains.
We can also say that a class of c-preferences $c(a)$ is unambiguously specified by the pair $(r(a), pref(a))$, where $r(a)$ is the next corner reference of all c-preferences in the class and $pref(a)$ is their preference value. Furthermore, union and intersection operations can be specified for c-preference classes.

Definition 6 (Union of C-Preference Classes) *The union of two c-preference classes $(r(a), pref(a)) \in [0,1]^{l\times m}$ and $(r(b), pref(b)) \in [0,1]^{l\times m}$ is a c-preference class $(r(c), pref(c)) \in [0,1]^{l\times m}$ with reference $r_{ij}(c) = max(r_{ij}(a), r_{ij}(b)), i = 1\ldots l, j = 1\ldots m$ and preference value $pref(c) = max(pref(a), pref(b))$.*

Definition 7 (Intersection of C-Preference Classes) *The intersection of two c-preference classes $(r(a), pref(a)) \in [0,1]^{l\times m}$ and $(r(b), pref(b)) \in [0,1]^{l\times m}$ is a c-preference class $(r(c), ref(c)) \in [0,1]^{l\times m}$ with reference $r_{ij}(c) = min(r_{ij}(a), r_{ij}(b)), i = 1\ldots l, j = 1\ldots m$ and preference value $pref(c) = min(pref(a), pref(b))$.*

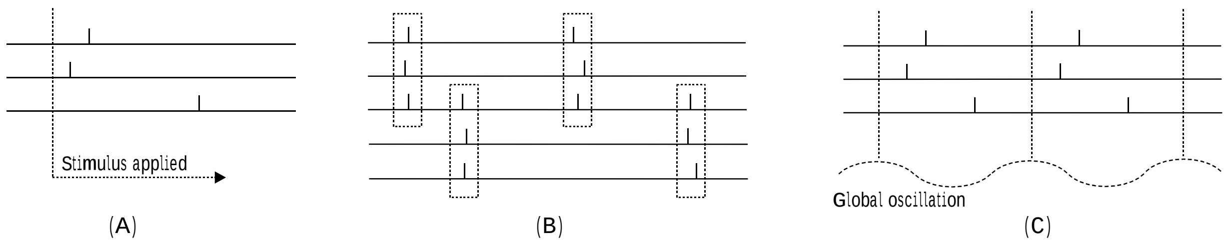

Figure 1: Examples of Pulse Codes: (A) Time-to-First-Spike Code. (B) Synchrony Code. (C) Phase Code.

3 Firing Rate Code in C-Preferences

The firing rate hypothesis has been used in describing the behavior of neurons in many sensory [Adrian, 1926] and cortical regions [Hubel and Wiesel, 1962]. It is based on the average spike count of a neuron in a given time window. Extensions of this concept include averaging over a number of units or over several stimulation repetitions. The mean firing rate coding concept has been successfully applied to some computational neuroscience models and most of the connectionist models. Firing rate code can be modeled with simple neural preference. In our previous work on neural preferences we have focused on firing rate codes [Wermter, 1999], which is why we emphasize pulse coding schemes in the following sections.

4 Time-to-First-Spike Code in C-Preferences

The Time-to-First-Spike coding paradigm is based on several analyses that most of the information about new stimulus is presented during the first 20-50 ms of the neural response [Kjaer et al., 1994, Tovee et al., 1993]. The coding of this type assumes that the time between the stimulus and the first spike of the neuron represents the strength of the response. The sooner the neuron fires, the stronger the response is. Respectively, a later first spike will mean a weaker response to the stimulus (Figure 1.A).

Neural Preference of Time-to-First-Spike Code. Let us consider a neural assembly of m neurons which have been stimulated with a new input at time t_0. We examine the spikes in the assembly in a time window Δt. Let t_i be the time of the first spike of neuron i in the examination time window ($t_0 \leq t_i \leq t_0 + \Delta t, i = 1 \ldots m$). We can define the *preference spike time* of a neuron i as $a_i = 1 - \frac{t_i - t_0}{\Delta t}$. Then the vector $(a_1, a_2, ..., a_m)$ is the neural c-preference for the time-to-first-spike-encoded responses of the neural assembly. Neurons with a stronger response to the stimulus will have values in the neural c-preference close to 1 and the ones with weaker (negative) response close to 0. This type of coding can be presented in simple neural preferences.

Preferences with a higher preference value will represent definite responses of the neural assembly, positive or negative. On the other hand, a low preference value will indicate that most of the neurons in the assembly have fired around the middle of the time window and therefore do not show a definite response.

Neural Preference Classes of Time-to-First-Spike Code. The above specified neural preferences for the time-to-first-spike code will form a class of preferences that have equal strength as response to the stimulus. We can abstract from the particular fluctuations in the order of firing on the neurons and symbolically interpret their responses as either strongly positive/negative or no-definite-response. Then, the class of preferences will contain all preferences that encode the same information with equal strength. The result of the intersection of c-preference classes will present the minimal strength response of the assembly. Respectively, the union will result in a maximum strength response.

5 Synchrony Code in C-Preferences

Neurons in many cortical and sub-cortical areas are found to fire synchronously during particular mental or behavioral tasks [Eckhorn et al., 1990, Vaadia et al., 1995, Riehle et al., 1997]. This phenomenon is more related to the internal functions in the brain rather than the responses to external events. One widely accepted idea is that neurons with synchronized firing with zero (or considered as zero) phase delay perform temporal binding of individual features in order to represent complex objects (Figure 1.B). Furthermore, with a time shift between the firing of different assemblies, information about complex events or group of objects can be processed without crosstalk between individual representations.

Neural Preference of Synchrony Code. We can define Δt as the time window in which all spikes can be considered as firing synchronously. In a simple scenario this could be at least the time from the first to the last spike of a given synchronous firing of a neuronal assembly and is usually determined empirically. Let t_s be the mean time of firing for all spikes in the defined time window Δt. Then, we can consider all spikes that have occurred in the time Δt before t_s and Δt after t_s, that is in a time interval $2\Delta t$. We define the *preference spike time* of neuron i as

$$a_i = \begin{cases} 1 - \frac{|t_i - t_s|}{\Delta t} & \text{if the neuron has fired in the time window } 2\Delta t \\ 0 & \text{if the neuron has not fired in the time window } 2\Delta t \end{cases}$$

Here, t_i is the firing time of neuron i. Then the vector $(a_1, a_2, ..., a_m)$ will be the c-preference vector for the synchrony code of m neurons. Again this type of coding can be presented as simple preference. The definition of a_i ensures that neurons which fire closely to the mean spike time will have values close to 1. In other words, higher density in the synchronous firing will lead to higher values for the neurons in the preference vector. This definition includes preference spike times of neurons that are not considered to be in the current synchronous firing. However, the values for such neurons will be less than 0.5 and usually close to 0. This way, by altering Δt we can combine the information encoded in multiple synchronous firings in one preference vector without causing confusion with the actual synchrony-encoded information.

The preference value will be higher if the neurons considered to fire synchronously have fired closely in time and no other neurons have fired closely to that time (with respect to the given time window). On the other hand, if the spikes of the synchronously firing neurons are distributed with low density over the time window and/or other neurons have fired close to the time window, the preference value will be low.

Neural Preference Classes of Synchrony Code. A neural preference class of a synchrony code can be interpreted as a set of all preferences that represent the synchrony code for the same information with equal strength. This interpretation of the classes allows us to abstract from the particular distribution of the synchronous spikes in the time window usually considered as noise in biological systems. Furthermore, with preference class operations like union and intersection we can operate with all features activated in multiple synchronous firings.

6 Phase Coding in C-Preferences

Global oscillations found in some areas of the brain are suggested to serve as a reference signal for neurons that can encode information in the phase of the firing times [Hopfield, 1995, Jensen and Lisman, 1996, Burgess et al., 1993]. In such a coding concept, neurons react to a new stimulus by adjusting the phase of their spike with respect to the background oscillation. If the stimulus does not change over time, the neurons carry on firing with the same phase (Figure 1.C).

Neurons can also use the spikes from other neurons as a reference signal instead of global oscillation. In such a scenario, called correlation coding, the information is encoded in the time shift between the firing times of a pair or group of neurons. The interpretation of the phase code as neural c-preferences can be directly applied for correlation code.

Neural C-Preferences of Phase Code. Let us consider a pool of m neurons that use phase coding with respect to a global oscillation with a time period Δt. For each neuron we can define l distinguishable phase shifts of firing. This will lead to l subintervals of Δt so that firing of that neuron in this subinterval will represent a particular feature. We can define the neural c-preference of the phase code over a representative number of oscillation periods as a matrix $p \in [0,1]^{l \times m}$, where p_{ij} is the number of times neuron j has fired in its subinterval i, normalized with respect to the total number of spikes registered for that neuron during the observation. A representative number of oscillation periods could be one that ensures that the same stimulus is presented more than once to the neurons during the observation. In such a scenario, a neuron can be considered as responding with a phase code if it has fired with the same phase shift in most of the oscillation periods.

A direct interpretation of the preference value of phase code states that c-preferences with a high value will indicate a definite phase-encoded response of the neurons, and respectively, low preference value will indicate less phase-encoded information or a high level of noise in the pool. Therefore, we can consider the preference value as an indication of the strength of the neural response to a particular stimulus.

Neural C-Preference Classes of Phase Code. By constructing a class of neural c-preferences for a phase code we can abstract from the symbolically indistinguishable fluctuations in the neuron's firing time. The class will represent all c-preferences that encode the same object with the same strength of phase code. Furthermore, by applying the intersection or union operations over such classes we can respectively extract common features or extend the features of two different phase-encoded objects or events.

7 Simultaneous Processing of Multiple Neural Codes

Neuroscience evidence suggests that many neurons in the brain are not restricted to only one type of coding. These neurons are able to process different aspects of the information simultaneously using complimentary types of encoding. In fact many scientists believe that neurons use rate coding in parallel with a complimentary type of pulse code [Hebb, 1949, Recce, 1999]. Indeed, such a processing scheme is highly plausible and computationally effective, since without any significant increase in the computational cost it can implicitly combine the advantages of firing rate and spatiotemporal codes.

Neural C-Preferences of Multiple Neural Codes. For presentational purposes we will discuss the situation where neurons simultaneously use firing rate and synchrony coding schemes. The concept presented here, however, is general and can be applied to any combination of neural codes.

We would like to model the behavior of m neurons. Both types of codes that these neurons use can be modeled as simple preferences. Therefore we can specify the neural c-preference of this model as a matrix $a \in [0,1]^{2\times m}$, so that the simple preference $(a_{11}, a_{12}, \dots, a_{1m})$ will represent the rate code and $(a_{21}, a_{22}, \dots, a_{2m})$ will represent the synchrony code. Such an integration of c-preferences representing different codes allows us to have a unified symbolic interpretation of a complex neural code. We can simultaneously process and combine the information contained in the different codes. The definitions of c-preference classes provide that there will not be interference between the different codes.

Following the common features of the preference value for single codes, we can interpret the preference value of c-preferences of multiple codes as the strength of the neural response to the present stimulus.

Neural C-Preference Classes of Multiple Neural Codes. A class of neural c-preferences of multiple neural codes will represent all c-preferences that encode a particular object with equal strength of the response. Again, it allows us to abstract from the symbolically indistinguishable fluctuations in neural responses, and concentrate on the encoded objects/events and the strength of the representation.

The definitions of union and intersection of c-preference classes ensure that information from one type of encoding will not interfere with the other type. Therefore, these operations applied to c-preference classes of multiple codes will preserve the properties for each single code embedded into the c-preference classes.

8 Conclusion

We introduced the concept of complex preferences and c-preference classes as theoretical framework for symbolic interpretation of different neural codes. The corner preference order is a partial order and therefore c-preference classes can serve as a basic link between neural and symbolic fuzzy representations. The framework of complex neural preferences as symbolic interpretation of neural codes extends the scope of hybrid models as integration of pulsed neural networks, mean firing rate networks and symbolic approaches. For instance, the use of the presented results allows pulse neural codes or multiple neural codes to be used in symbolic models such as automata, sequential machines, fuzzy models, etc. To the best of our knowledge this is the first work that addresses the integration of pulsed neural networks into hybrid approaches, in particular a symbolic interpretation and simultaneous processing of mean firing rate and pulse coding schemes in a preference framework.

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