Chapter 7

A Biologically Inspired Evolving Spiking Neural Model with Rank–Order Population Coding and a Taste Recognition System Case Study

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ABSTRACT

The human brain has an amazing ability to recognize hundreds of thousands of different tastes. The question is: can we build artificial systems that can achieve this level of complexity? Such systems would be useful in biosecurity, the chemical and food industry, security, in home automation, etc. The purpose of this chapter is to explore how spiking neurons could be employed for building biologically plausible and efficient taste recognition systems. It presents an approach based on a novel spiking neural network model, the evolving spiking neural network with population coding (ESNN-PC), which is characterized by: (i) adaptive learning, (ii) knowledge discovery and (iii) accurate classification. ESNN-PC is used on a benchmark taste problem where the effectiveness of the information encoding, the quality of extracted rules and the model’s adaptive properties are explored. Finally, applications of ESNN-PC in recognition of the increasing interest in robotics and pervasive computing are suggested.

INTRODUCTION

Our sense of taste is a vital part of our existence. It discriminates between foodstuffs (such as vegetables, meats, tea, mineral waters), assesses their quality and nutritious content and detects potentially poisonous substances. In sharp contrast to its importance, the taste sensory system is poorly explored compared to other sensory systems such as the visual and olfactory systems. Only recently have studies started to paint a picture of taste biol-
ogy; and exactly how the taste signals are coded and transmitted to the brain is still unknown. For years, two biological models of taste-coding have been favored, namely the ‘labeled-line’ coding and the ‘cross-fiber’ coding (Chandrashekar, Hoon, Ryba, & Zuker, 2006; Reed, Tanaka, & McDaniel, 2006, Bradbury, 2004; Dulac, 2000; Margolskee, 1993). In ‘labeled-line’ coding the taste receptor cells (TRC) are specialized for responding to only one taste modality, either bitter, salty, sour, sweet or umami. In the ‘cross-fiber’ coding, the TRC are broadly tuned to more than one taste and a pattern of activity across a number of TRC characterizes the taste sensation.

Most taste recognition models use the ‘cross-fiber’ scenario. In these models broadly tuned TRC are simulated using an array of non-selective sensors with partially overlapping selectivity where the sensors’ electrical characteristics, for example capacitance, change under the influence of the chemical composition of a tastant. These arrays of sensors are called ‘electronic tongues’ (Cortina, Duran, Alegret, & del Valle, 2006; Gallardo et al., 2003; Riul Jr. et al., 2002). An ‘electronic tongue’ responds differently to different types of tastants forming unique taste signatures, which can be analyzed by a pattern recognition system as shown in Figure 1. The tasting of tastants must not be confused with the chemical analysis of tastants. Taste sensors do not provide a chemical composition of a tastant, i.e. what chemicals are present in the tastant, but rather produce responses closely associated with the tastant’s chemical composition. The pattern recognition system is usually based on a multilayer perceptron (MLP) neural network (Gutiérrez et al., 2008; Gütés, Ibáñez, Céspedes, Alegret, & del Valle, 2005; Riul Jr. et al., 2004; Gallardo et al., 2003; de Sousa, Carvalho, Riul Jr., & Matos, 2002). An electronic tongue together with a pattern recognition system is called an ‘artificial tongue’ (Riul Jr. et al., 2002).

While MLP have been found to be accurate taste classifiers, a number of difficulties associated with such networks have been reported: the rather limited exploratory capabilities (Varkevisser, 2001) linked to the ‘black-box’ property of these networks, the problems with tuning network parameters (Stitt, Gaumond, Frazier, & Hanson, 1997) and the problem of finding the appropriate size for the hidden layer (Gutiérrez et al., 2008; Cortina, 2006; Gallardo, 2003; de Sousa, 2002). The knowledge that an MLP acquires is hard or impossible to extract. Moreover, MLP are slow to learn. Training these networks consists of repetitively presenting the network with large training data sets where the number of repetitions (epochs) is usually found by trial-and-error. Furthermore, these networks must be retrained on old and new data every time a new data sample is obtained. In other words, they have a limited ability to learn new tastes as they become available. These problems hinder the MLP network from being an efficient taste classifier. Hence, the objective of this work is to tackle these problems.
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