Perception of Simple Rhythmic Patterns in a Network of Oscillators

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Introduction

Recently several computational models of the perception of rhythm based on oscillators have been proposed. Oscillator models capture the cognitive predisposition to discover periodicity in auditory patterns, and models in which oscillators exhibit phase and/or period coupling with inputs also tolerate deviations from perfect periodicity.

However, current oscillator models only address tempo and meter perception. In this paper we are concerned with a more complex capacity, the ability to recognize and reproduce rhythmic patterns. While this capacity has not been well investigated, in broad qualitative terms it is clear that people can learn to identify and produce recurring patterns defined in terms of sequences of beats of varying intensity and rests: the rhythms behind waltzes, reels, sambas, etc. Our short-term goal is a model which is "hard-wired" with knowledge of a set of such patterns. Presented with a portion of one of the patterns or a label for a pattern, the model should reproduce the pattern and continue to do so when the input is turned off. Our long-term goal is a model which can learn to adjust the connection strengths which implement particular patterns as it is exposed to input patterns.

Approach

We have developed a connectionist architecture which realizes our short-term goal. The model consists of a single input/output unit and network of coupled oscillators of varying resting periods. These periods are expected to capture the micropulse and harmonic periods characterizing various rhythmic patterns. An identified familiar pattern takes the form of a stable pattern of activation across the network of oscillators.

The network consists of two types of oscillators, pulse oscillators and continuous oscillators.

Pulse oscillators provide an interface between the pulse-like world and internal continuous oscillators. They are activated by the input unit and by other oscillators only when they are near their zero phase angle. They also adjust their phase angle in response to an activated input or oscillator, but again, only near their zero phase angle. Pulse oscillators exhibit a periodic output which activates the network's output unit, as well as other oscillators. At a given period, there is an inhibitory cluster of pulse oscillators which is reponsible for finding a downbeat. Other pulse oscillators at a given period are responsible for beats and rests at points within the measure. Beat pulse oscillators excite and are excited by the input/output unit; rest pulse oscillators inhibit and are inhibited by the input/output unit.

Unlike pulse oscillators, continuous oscillators do not connect directly to the input/output unit. Instead they connect to other continuous and pulse oscillators, responding throughout their phase cycle rather than only near their zero phase angle. Their function is to represent recurring subpatterns of beats and rests which provide the building blocks for complex patterns. Each subpattern is handled by a cluster of continuous oscillators which is stable when the oscillators' phase angles are evenly distributed throughout the phase cycle. Each oscillator in such a cluster is associated with a beat or rest pulse oscillator. For example, the 3/4 pattern consisting of two quarter notes followed by a quarter rest would be handled by three continuous oscillators, each with a period equal to the measure and spaced 1/3 of a phase (one quarter note) away from the others. Two of these oscillators would be connected to a beat pulse oscillator and the other to a rest pulse oscillator. This cluster of six oscillators would take part in turn in more complex 6-beat patterns.

We have tested hard-wired versions of the model on simple 3- and 4-beat patterns, which it is able to distinguish and to continue to reproduce when the input is turned off. It also handles these patterns in the presence of temporal noise.

The model makes numerous predictions about relative pattern difficulty and error types. For example, it predicts errors with complex patterns which result from the substitution of one subpattern for another.