

Application of an Artificial Immune System in a Compositional Timbre Design Technique

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Abstract. Computer generated sounds for music applications have many facets, of which timbre design is of groundbreaking significance. Timbre is a remarkable and rather complex phenomenon that has puzzled researchers for a long time. Actually, the nature of musical signals is not fully understood yet. In this paper, we present a sound synthesis method using an artificial immune network for data clustering, denoted aiNet. Sounds produced by the method are referred to as immunological sounds. Basically, antibody-sounds are generated to recognize a fixed and predefined set of antigen-sounds, thus producing timbral variants with the desired characteristics. The aiNet algorithm provides maintenance of diversity and an adaptive number of resultant antibody-sounds (memory cells), so that the intended aesthetical result is properly achieved by avoiding the formal definition of the timbral attributes. The initial set of antibody-sounds may be randomly generated vectors, sinusoidal waves with random frequency, or a set of loaded waveforms. To evaluate the obtained results we propose an affinity measure based on the average spectral distance from the memory cells to the antigen-sounds. With the validation of the affinity criterion, the experimental procedure is outlined, and the results are depicted and analyzed.

1 Introduction

Computer music is an ever-growing field partly because it allows the composer such great flexibility in sound manipulation when searching for the desired result. Once the search space and the goals are defined, a technique for achieving the final product is required. Many different approaches have been proposed to meet the requirements of the process, i.e. creating interesting music, with results that vary from the unexpected to the undesired, depending upon a vast number of factors and on the methodology itself. Traditional sound synthesis techniques present limitations especially due to the fact that they do not take into consideration the subjective and/or the dynamic nature of music, by using processes that are either too simple or not specifically designed to handle musical sounds [14].

In this work, we are focusing primarily on the production of complex sounds for musical applications taking timbre design as paradigm. Complex sounds pertain to a distinctive class of sounds that present certain characteristics. Such sounds usually

have dynamic spectra, i.e. each partial has a unique temporal evolution. They are slightly inharmonic and the partials possess a certain stochastic, low-amplitude, high-frequency deviation in time. The partials have onset asynchrony, i.e. higher partials attack later than the lower ones. Our ears are highly selective and often reject sounds that are too mathematically perfect [4].

Music composition has been studied for a long time using many kinds of computational techniques, including statistic and stochastic methods [22][34], chaos theory [19], and other non-linear methods [21]. Many researchers have recently suggested the creation of Artificial Intelligence (AI) based systems for music composition [1][4][16][32]. Applications of AI in music composition involve artificial neural networks [6], cellular automata [3][23], and evolutionary computation (EC) [13][16][20][24][32]. Refer to the work of Santos et al. [29] for a detailed review of the application of EC in music systems.

As a preliminary step toward the current proposal, Caetano et al. [4] suggested the use of EC to pursue stationary/fixed target sounds that are considered the user's desired timbral outcome. The reported results can be interpreted as a sort of spectral blend between the initial and target sounds. An objective and a subjective criterion were adopted to evaluate the results. The approach of creating new timbres by the algorithmic evolution of a population of candidate solutions, having targets as references, presents a vast range of possibilities. It should be noted that, despite the fact that the process of algorithmic evolution searches for an optimum guided by the fitness function, this optimum cannot be properly specified from the musical point of view. So, the denoted targets should not be considered ideal solutions, but solely indicative modes.

Here, we present a timbre design method that allows the composer to express a certain degree of subjectivity by simply adjusting the input parameters according to prerequisites. The user is enabled to find candidate solutions that meet certain musical requirements by using a set of waveforms as examples of the desired timbre. Instead of describing the sounds using numerical parameters or any other linguistic tool, we used a set of sounds to characterize timbre. Smalley [31] declared that the information contained in the frequency spectrum cannot be separated from the time domain, because "*spectrum is perceived through time and time is perceived as spectral motion*". Thus, by specifying the target waveforms (antigen-sounds), the user is also specifying the spectral contents and the timbral characteristics of the tones. Grey [14] discusses the advantages of time domain representation. We aim at sound design by means of the specification of the spectral contents. In practical terms, the induced immune response will provide results (antibody-sounds) highly correlated with the target waveforms, albeit preserving local diversity.

The main objective of this paper is to verify the music potential of an immune inspired clustering technique in the specific task of timbre design by simulating the process under different conditions, and posteriorly showing that the results are consistent with the expected outcome. Artificial immune systems (AIS) for data clustering are generally based on the immune network theory of Jerne [18], thus producing a self-organizing process with diversity maintenance and a dynamic control of the network size [10].

Concerning the application of immune-inspired approaches in the aesthetical domain, we may emphasize two initiatives. AISArt [17] is an interactive image

generation tool. The user conducts the system according to the aesthetic appreciation of areas of the images, which is also an original approach in the context of interactive evolutionary systems [1]. Chao and Forrest [5] also describe an interactive search algorithm inspired by the immune system, devoted to synthesizing biomorphs [9]. They report that this algorithm is capable of consensus solutions, given that distinct selection criteria may be associated with modules that compose the biomorph. To the best of our knowledge, there has been no previous application of AIS in timbre design.

The next section describes theories of timbre and how they are related to the development of sound synthesis techniques. Then, the fundamentals of AIS are briefly reviewed and the proposed approach is presented. The experiments performed are described and the outcomes, followed by analysis, are presented. Finally, concluding remarks and perspectives for further research are considered.

2 Timbre Design

2.1 Musical Timbre

Timbre is defined by the ASA (American Standard Association) as “that attribute of the auditory sense in terms of which the listener can judge that two sounds similarly presented which have the same intensity and pitch are dissimilar” [28]. Therefore, musical timbre is the characteristic tone quality of a particular class of sounds. As a diverse phenomenon, timbre is more difficult to characterize than either loudness or pitch. No one-dimensional scale – such as the loud/soft of intensity or the high/low of pitch – has been postulated for timbre, because there exists no simple pair of opposites between which a scale can be made.

Because timbre has so many facets, computer techniques for multidimensional scaling have constituted the first major progress in quantitative description of timbre [14], since the pioneering work of Hermann von Helmholtz [33] in the nineteenth century. From then on, researchers have determined a more accurate model of natural (complex) sounds. Digital recording has enabled the contemporary researcher to show that the waveform (and hence the spectrum) can change drastically during the course of a tone. Risset [27] observed that complex sounds have dynamic spectra and the evolution in time of the sound’s spectrum plays an important part in the perception of timbre. Timbre variations are perceived, for example, as clusters of sounds played by a particular musical instrument, or said by a particular person, even though these sounds might be very distinct among themselves, depending upon its pitch, intensity or duration. In fact, the concept of timbre has always been related to sounds of musical instruments or voice, and it is in this scope that the majority of research on timbre has been developed [14][15][27]. These works identified innumerable factors that form what is called timbre perception.

2.2 Theories of Timbre

2.2.1 Classical Theory of Timbre

Herman von Helmholtz [33] laid the foundations for modern studies of timbre. He characterized tones as consisting of a sum of sinusoidal waves enclosed in an amplitude envelope made up of three parts: the attack, the steady-state, and the decay as shown in Figure 1.

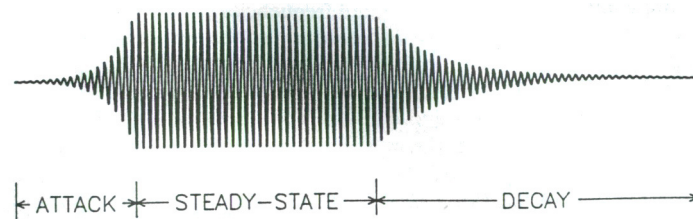


Fig. 1. A simplified Helmholtz model: the three principal segments of a tone.

Helmholtz concluded that sounds which evoke a sensation of pitch have periodic waveforms (refer to Figure 2 (b) for an example) and further described the shape of these waveforms as fixed and unchanging with time. He also established that the nature of the waveform has great effect on the perceived timbre of a sound. To determine which characteristics of a waveform correlate best with timbre, he made use of the work of Fourier and concluded that the spectral description of a sound has the most straightforward correlation with its timbre. As a consequence, almost every synthesis technique proposed is concerned with the production of a signal with a specific spectral content, rather than a particular waveform.

The spectral envelope of a sound is one of the most important determinants of timbre [12], because it outlines the profile of energy distribution in a frequency spectrum.

2.2.2 Modern Studies of Timbre

Since then, researchers have determined a more accurate model of natural sound. Digital recording has enabled researchers to show that the waveform, and hence the spectrum, can change drastically during the course of a tone. Such changes can be visualized by a plot of the evolution of the partials in time, herein denoted dynamic spectrum and depicted in Figure 2 (c).

The Fourier transform enables researchers to obtain the spectrum of a sound from its waveform. Risset [27] obtained the spectral evolution of the partials of trumpet tones, being able to determine the time behavior of each component in the sound. He found that each partial of the tone has a different amplitude envelope.

This clearly contrasts with the basic Helmholtz model in which the envelopes of all the partials have the same shape. Grey [15] wondered whether such fine-grained, intricate evolution of the partials could be approximated and still retain the tone's characteristic timbre. He found out that of the three forms of simplification attempted with the tones, the most successful was a *line-segment approximation* to time-varying amplitude and frequency functions for the partials.

Although this method does decrease dramatically the amount of data required to reconstruct the tones, it still takes a large number of oscillations to satisfactorily accomplish the desired result. In computer music, synthesis algorithms that directly recreate the partials of a tone generally use data stored as line segments. It is important to be aware that this methodology is usually effective only within a small range of frequencies. For instance, a tone based on the data but raised an octave from the original will most often not evoke the same sensation of timbre.

Application of an Artificial Immune System in a Compositional Timbre Design Technique

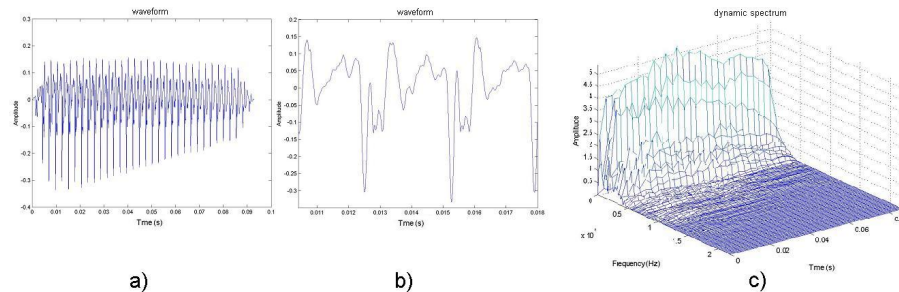


Fig. 2. Example of a waveform and dynamic spectrum of a natural (complex) sound (tenor trumpet). Part (a) shows the waveform and (b) a detail of the periodicity, characteristic of the harmonic spectra of musical instruments. Part (c) emphasizes the evolution of the partials in time (dynamic spectrum).

When presented with a group of spectral components, a listener may or may not fuse them into the percept of a single sound. One of the determining factors is the onset asynchrony of the spectrum that refers to the difference in entrance times among the components [15] (see Figure 2(c)). The fluctuations in frequency of the various partials are usually necessary for the partials to fuse into the percept of a single tone [7].

3 The Artificial Immune Musical System

The immune system is a complex of cells, molecules and organs with the primary role of limiting damage to the host organism by pathogens, which elicit an immune response and thus are called antigens. One type of response is the secretion of antibody molecules by B cells. Antibodies are receptor molecules bound on the surface of a B cell with the primary role of recognizing and binding, through a complementary match, with an antigen. Antigens can be recognized by several different antibodies. The antibody can alter its shape to achieve a better match (complementarity) with a given antigen. The strength and specificity of the antigen-antibody interaction is measured by the affinity (complementarity level) of their match [11].

3.1 Artificial Immune Network (aiNet)

AISs are adaptive procedures inspired by the biological immune system for solving several different problems [10]. Dasgupta [8] defines them as “*a composition of intelligent methodologies, inspired by the natural immune system for the resolution of real world problems*”.

The aiNet is an artificial immune network whose main role is to perform data clustering by following some ideas from the immune network theory [18], the clonal selection [2], and affinity maturation principles [25]. The resulting self-organizing

system is an antibody network that recognizes antigens (input data set) with certain (and adjustable) generality.

The clonal selection principle proposes a description of the way the immune system copes with the pathogens to mount an adaptive immune response. The affinity maturation principle is used to explain how the immune system becomes increasingly better at its task of recognizing and eliminating these pathogens (antigenic substances). The immune network theory hypothesizes the activities of the immune cells, the emergence of memory and the discrimination between reactive and tolerant regions in the shape-space [26] [30].

The aiNet clusters will serve as *internal images (mirrors)* responsible for mapping existing clusters in the data set (Figure 3 (a)) into network clusters (Figure 3 (b)). The resultant memory cells represent common features present in the data set that were extracted by aiNet. Let us picture a set of sounds as antigens and its internal (mirror) image as variants. Inspired by Risset’s sound variants idea [27], it is possible to imagine, for example, variants as a type of immune-inspired transformation applied to the sound population. Smalley’s time and spectrum integration [31] also induces a timbre adaptation in time or, using a more suitable terminology for the context, a dynamic process in which an immunological timbre is generated. In this sense, the waveforms can be regarded as the repertoire to which the system is exposed, and the associated timbre may be linked to the specific response it elicits. It is of critical importance to notice that when an antibody-sound is representing more than one antigen-sound, it is placed in such a spot in soundspace that allows it to present features that are common to all the sounds it is representing. Figure 3 (c) depicts the intersection of characteristics shared by three different sounds.

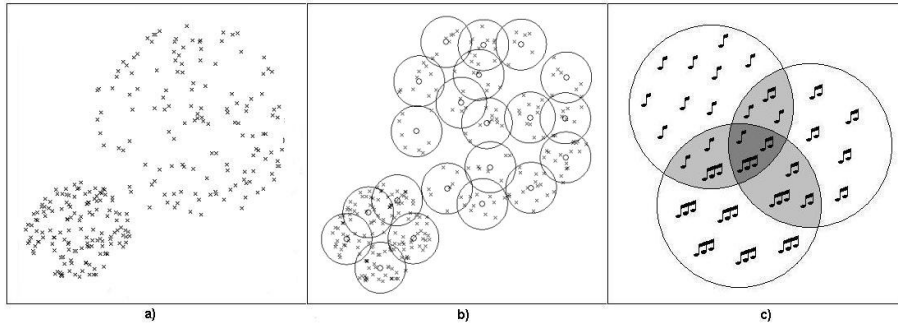


Fig. 3. Depiction of the feature extraction capability of aiNet. Part (a) shows the original data, part (b) shows the resultant memory cells representing the original data, and part (c) illustrates the common timbral features of three classes of sounds.

3.1.1 Representation

The input parameters of the present implementation are shown in Table 1. Each individual is codified as a vector composed of L samples of a given waveform at a sampling frequency of FS samples per second. The individuals are, thus, represented in time domain, as vectors in \mathbb{R}^L . The affinity is given by the multidimensional Euclidean distance between antigen-sounds and antibody-sounds and is shown in equation (1). This is the time-domain evaluation of distance.

Table 1. Input parameters that can be controlled by the user

L	Number of samples per individual
FS	Sampling rate
G	Number of antigens
ts	Suppression threshold
$number$	Initial number of antibodies
n	Number of best-matching cells selected
gen	Number of generations
CM	Clone number multiplier
qi	Percentile amount of clones to be re-selected
sc	Minimum distance between antibodies and antigens

$$d(ag, ab) = \sqrt{\sum_{n=1}^L (ag_n - ab_n)^2} \quad (1)$$

3.1.2 Methodology of Analysis

A measure of spectral distance was developed to verify whether approaching the target sounds in time domain also corresponds to approximating the desired timbral attributes in virtue of this spectral distance measure. It measures the distance from the antigen-sound's dynamic spectrum to the dynamic spectrum of each antibody-sound it represents, as shown in equation (2), which utilizes the same notation of Figure 4. Figure 4 depicts a schematic representation of a dynamic spectrum matrix. The parameters are explained in Table 2.

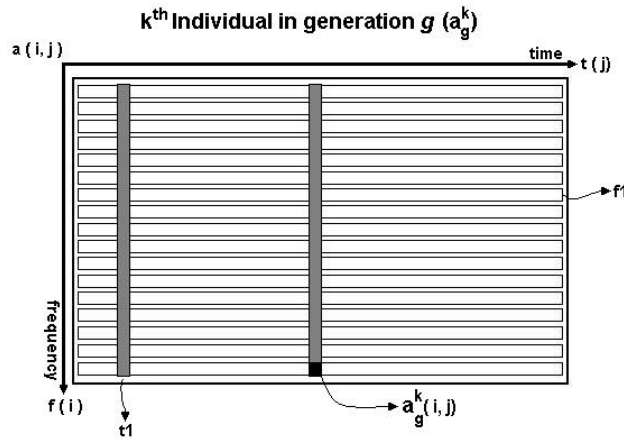


Fig. 4. Depiction of a dynamic spectrum matrix representation. X-axis represents time domain by the index j . Y-axis represents frequency domain by the index i . Each white row is a frequency (partial) temporal evolution (e.g. f_1). The gray columns are instantaneous spectra in determined moments (e.g. t_1). The intersection of row and column gives the amplitude of a given partial (frequency) at a given moment, represented by $a(i,j)$ (black square).

$$\alpha_g^{kh} = \sqrt{\frac{1}{FT} \sum_i^F \sum_j^T (|a_g^k(i, j)| - |a_g^h(i, j)|)^2} \quad (2)$$

Table 2. Parameters of Equations (2) and (3)

k	k^{th} antigen
h	h^{th} antibody
g	Generation
F	Dimension of frequency vector
T	Dimension of time vector
D	Number of antibodies representing antigens

Then, the minimum distance for each antigen and the respective antibody-sound set representing it are extracted from α_g^{kh} , obtaining a subset $\tilde{\alpha}_g^{k_1}$, where $k_1 \leq k$ because one antibody-sound may be representing more than one antigen-sound (data compression). In the latter case, the distances are averaged for each antigen-sound. Finally, this vector of values is averaged for each generation, as shown in equation (3).

$$\bar{A}_g = \sum_{k_1}^D \tilde{\alpha}_g^{k_1} \quad (3)$$

This way, an average spectral distance from the potential solutions to the target spectrum is obtained at each generation. Two different experiments were performed to validate the method. They will be explained in what follows.

Experiment 1:

The spectral distance can be used to test whether the suppression threshold (ts) would produce the expected result. The suppression threshold (ts) controls the specificity level of the antibodies, the clustering accuracy and network plasticity. Refer to de Castro & Von Zuben [11] for sensitivity analysis of the parameters. One can conclude that decreasing ts , the antibody-sounds are expected to become more specific, decreasing the average distance from the antigen-sounds they represent while increasing in number. As a consequence, the resultant waveforms approach the target sounds as close as the user wishes.

Experiment 2:

In this experiment we wish to verify the potential of the method to generate high quality variants, regardless of the type of initialisation of the antibody network, i.e. regardless of the initial spectral content. We used three types of initialisation: white noise (a vector randomly generated), pure tones (sinusoidal waves with random frequencies from 180 Hz to 16 kHz) and complex sounds (loaded waveforms of another musical instrument). The spectra used in the experiments can be seen in Figure 5. They represent the dynamic spectra of the original antibody-sounds, that is,

Application of an Artificial Immune System in a Compositional Timbre Design Technique

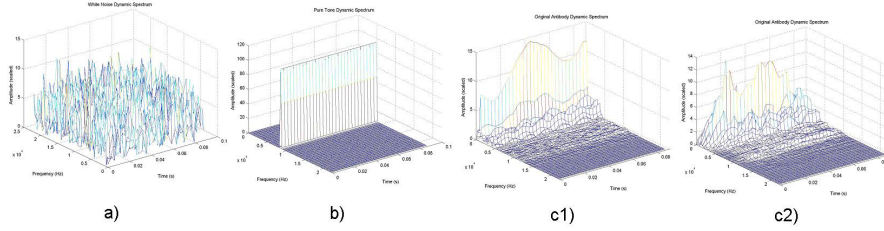


Fig. 5. Dynamic spectrum of the original antibody-sounds used in experiment 2. Part (a) shows white noise; Part (b) a pure tone and parts (c1) and (c2) show examples of the dynamic spectrum of a harmonica representing a natural (complex) sound.

the spectral content which will be moulded into the target spectra by means of temporal immunological manipulation.

The dynamic spectra of four antigen-sounds are shown in Figure 6. They represent the target spectra, the ultimate goal of the method. We expect to obtain immunological internal images, which would represent timbral variants.

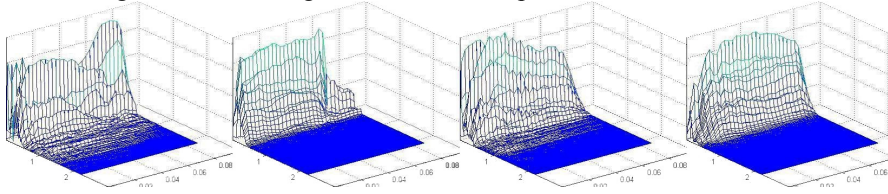


Fig. 6. Example of dynamic spectra of the tones used as antigens

4 Results

The parameters used in all experiments were as follows in Table 3. Refer to Table 1 for the definition of all input parameters. These values of L and FS represent a wave-format sound segment of approximately 0.1s. In experiment 1, the value of ts varies as shown in Table 4.

Table 3. Parameters utilized in both experiments (1) and (2)

L	FS	G	$number$	n	gen	CM	qi	sc
4096	44100	10	5	1	50	7	70%	0.1

4.1 Experiment 1

In this experiment we wished to confirm the data compression capability of the method. This characteristic allows the user to choose how close to the target sounds one wishes the results to be. The smaller the number of memory cells (resultant antibody-sounds), the farther they are from the antigen-sounds they represent for they represent more than one antigen-sound. The results shown in Table 4 confirm this assertion both in time and in spectrum domain. Due to the relatedness of the spectral contents and the associated timbre, it can be inferred that the same holds true for the

Table 4. Result of Experiment 1

ts	D	Distance	
		Temporal	Spectral
0.5	4	3.16	41.89
0.3	6	1.44	35.46
0.1	9	0.49	21.66
0.05	10	0.27	20.05

corresponding timbral space. That is, this representation contains characteristics that are common to all the sounds it is representing (Figure 3).

Figure 7 (a) shows an antigen-sound’s dynamic spectrum and its memory cell representation when ts is 0.05 (b) and 0.5 (c). Part (d) shows the result of randomly perturbing the antigen-sounds, i.e. adding a gaussian-noise (white-noise) vector (with variance 0.1) to it. Clearly the result is very different between Figures 7 (c) and (d). Psychoacoustically, the resultant sound in Figure 7 (c) is a timbral merger of the corresponding antigen-sounds. In Figure 7 (d) it is a noisy version of Figure 7 (a). It is interesting to notice that the spectral result was achieved through waveform (temporal) manipulation.

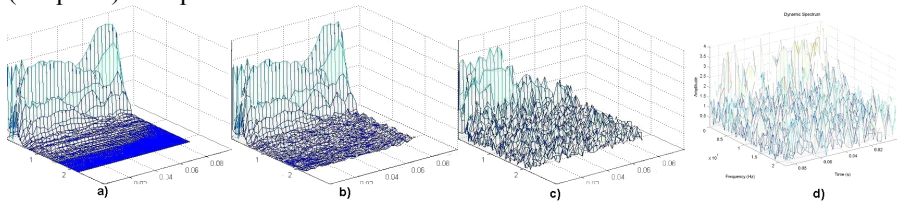


Fig. 7.Depiction of the different results obtained by adjusting the parameters and randomly perturbing the antigen-sounds.

4.2 Experiment 2

This experiment was set to prove the independence of the method from the type of initialization of the original antibody-sounds. All the parameters remained the same in experiment 2, except for ts that was set to 0.05. The results of the second experiment are depicted in Figure 8, which shows only four resultant antibody-sounds to illustrate the results. It is important to stress that 10 memory cells (resultant antibody-sounds) were obtained in all instances of this experiment. Compare the results with the antigen-sounds shown in Figure 6. In terms of spectral contents and dynamics, these antibody-sounds bear a striking resemblance to the antibody-sounds’ dynamic spectra, representing a variant

4.2.1 Generational Distance Analysis

This second result intends to show the rapid dynamics of the convergence process, independently from the initialisation, both in time and spectrum domain. It can also be inferred that the same holds true for the timbral domain. Figure 9 shows the adaptation of both the temporal and spectral affinity between antibody-sounds and the antigen-sounds they represent. Only the first generations are shown for the sake of clarity and to emphasize the rapid convergence in both cases. Notice that in all

Application of an Artificial Immune System in a Compositional Timbre Design Technique

instances convergence was achieved before the tenth generation. It means that, no matter the starting point in soundspace, the result can always be expected to be approximately the same (for the same input parameters). This is an extremely important characteristic of the method.

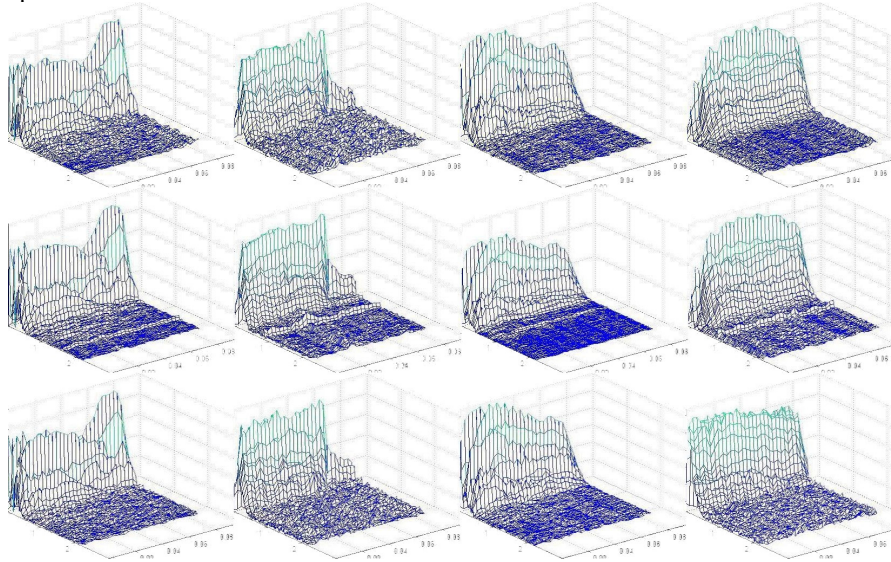


Fig. 8. Memory cells resulting from the initialization of the algorithm with white noise (top), pure tones (middle) and complex sounds (bottom).

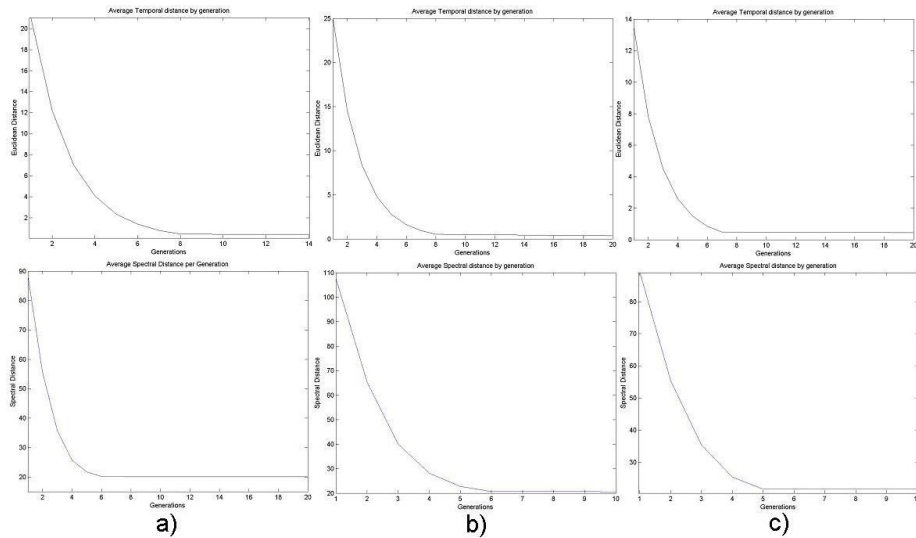


Fig. 9. Detail of the generational distance evolution. Top shows the temporal distance measure and bottom shows the spectral metric evolution. Column (a) shows the distances for the white-noise case; column (b) for the pure-tone case; and column (c) for the complex-sound case. Only the transient part of the curve is shown, i.e. the first generations.

5 Analysis

Both experiments base the method as a robust, yet flexible, timbre design technique. In experiment 1 we showed that the user can achieve a result that is as close as one wishes to the preset antigen population, depending on only one input parameter, the suppression threshold (t_s).

It should be noted that, in experiment 2, both distances decreased exponentially with the generations and stabilized fairly quickly. The measure of spectral distance developed confirms the temporal behaviour observed. Here we should stress the important fact that this is hardly the first proposal for a measure of timbral distance. Many other techniques are available, including multidimensional scaling [15] and subjective analyses [4], among others.

In experiment 2 the results show that the method does not depend on the initialisation of the original antibody-sounds. Also, the dynamic spectra obtained represent timbral variants of the antigen-sounds.

The experiments show that aiNet is capable of producing sounds that have the desired spectral content with flexibility and robustness. The method makes possible to avoid the burden of trying to describe the desired result in terms of timbral attributes or to exhaustively search the entire soundspace for the desired result interactively, such as is the case for Interactive Genetic Algorithms [1].

6 Conclusions

A novel method of timbre design was presented, which utilizes aiNet, an immune-inspired clustering technique, in the task of obtaining sounds. These sounds possess a set of desired timbral characteristics that are inherent to musical sounds and that cannot be precisely described due to the intrinsic multidimensional nature of timbre and the subjective characteristics involved. There is no consensus on how many or what these dimensions are, let alone their subjective relation to the spectral contents of the tone. A spectral measure of distance was developed to confirm the results. It is a mathematical measure that can be linked to the subjective, aesthetic percept of timbre.

We showed that the method is robust in original spectral content to be transformed, as well as it is adjustable according to the input parameters. We also demonstrated that random variation alone is not enough to produce the same results, generating only noisy results. The characteristics of maintenance of diversity and the adjustable size of population provided by aiNet are essential in the results.

Many extensions can be envisaged and tested. It can be used to compose soundscapes, as a timbre design tool or in live electroacoustic music where an immunological timbre is generated, which evolves in real time along with other music materials. Future trends might include using the technique in AI-based musical systems and adapting the method for dynamic environments, i.e. using time-varying antigen-sounds.

7 Acknowledgements

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