SPECTRAL SYNTHESIS AND CONTROL WITH CELLULAR AUTOMATA

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ABSTRACT

This paper presents a new method for sound synthesis. The method consists in mapping the histograms sequence of a cellular automata evolution onto a sound spectrogram. The data obtained from the histograms are in the form of sound spectral structures evolving in time in a natural fashion. The main problem of cellular automatas is the difficulty of control due to its unpredictability property. This mapping offers significant controllability characteristics which allow flexible processes for sound and instrument design. The sounds obtained with this mapping present natural behaviour and are capable of simulate acoustic instruments and other real sounds.

1. INTRODUCTION

Effective use of any digital synthesis technique depends on having good Control Data for the synthesis instrument. Control Data can be obtained from several sources. One approach commonly followed is to import them from another domain and to map them into the range of synthesis parameters [7]. In this research, Cellular Automata [1], or CA, will be considered as to be the Source of Control Data for sound synthesis & processing applications.

The CA chosen for this study is based on the Gerhard & Schuster's hodge-podge machine [2]. A slightly different version of this CA was successfully used in a granular synthesis system called Chaosynth [4]. The states of a cell can be interpreted as follows: the state characterized by a minimum value 0 is called "healthy". The state given by a maximum value *V*-1 is called "ill". All other states in between are called "infected". The transition rules are expressed as follows:

$$m_{x,y}[t+1] = \begin{cases} \text{int}(A/r_1) + \text{int}(B/r_2) & for\ \ m_{x,y}[t] = 0 \qquad RULE\,1 \\ \text{int}(S/A) + K & for\ \ 0 < m_{x,y}[t] < V \quad 1 \qquad RULE\,2 \\ 0 & for\ \ m_{x,y}[t] = V \quad 1 \qquad RULE\,3 \end{cases}$$

where the state of a cell at a time step *t* is denoted by $m_{x,y}$[t]; *x* and *y* are the horizontal and vertical coordinates of the location of the cell in the CA. *A* and *B* represent respectively the number of 'infected' and 'ill' cells in the neighbourhood, r_1 and r_2 are constants, *S* stands for the sum of the states of all cells in the neighbourhood, and *V* is the number of possible states that a cell can adopt.

We have chosen this CA mostly for its cyclic nature (Figure 1) which, among other things, easily allows us to work with different and, as large as we wish, range of cell values. The cyclic nature in a CA is characterized by two end states, positive feedback mechanisms and negative feedback mechanisms. By respecting this scheme it is possible to modify or create different CA rules for designing new cyclic CAs.

Figure 1. One period of a cyclic CA

2. MAPPING HISTOGRAMS ONTO SPECTROGRAMS

We devised a mapping method based on a statistical analysis of the CA evolution. We estimate the Probability Distributions of the cell values for each CA generation by Histogram measurements of each CA image [5]. The histogram of a digital image with grey levels in the range [0, *L* - 1] is a discrete function

$$p(r_k) = n_k / n \qquad (1)$$

where r_k is the kth grey level, n_k is the number of pixels in the image with that grey level, n is the total numbers of pixels in the image, and $k = 0, 1, 2, \ldots, L - 1$. Loosely speaking, $p(r_k)$ gives an estimate of the probability of occurrence of grey-level r_k [3].

We have found zones in the histograms consisting in narrow bands (sometimes with a width of just one colour) clearly separated one from the others. By examining the evolution in time of those narrow bands, we surprisingly found that their envelopes were very similar to the amplitude envelopes of sounds partials. With this in mind, our mapping will be to consider the Histograms Sequence of the CA evolution as to be a Sound Spectrogram. Considering that the time domain is common for both, the histograms sequences and the spectrogram, the histogram's sample space domain maps onto the spectrogram's frequency domain and, the histogram's probability domain maps onto the spectral magnitude domain.

3. HISTOGRAMS AND BEHAVIOURS

Different CA behaviours offer different histogram typologies. A 'quasi-synchronic' behaviour (in which all the cells reach the maximum state almost at the same time) offers a type of histogram from which we can obtain sets of structured data for both, sinusoidal and noise sound components. After the maximum state is reached, "distorted circumferences" patterns will appear. The contours of these shapes will create narrow bands or peaks in the histogram. From here, the cell values grow towards the maximum state and the boundaries of the

distorted circumferences become "blurred", creating wide bands in the histogram (see Figure 2). At each cycle of the CA this process is repeated with the following interesting characteristics: A) At each cycle, the CA self-organizes through the same set of predominant colours. These set of colours vary depending on the CA parameter values. That will create the time evolving structures in the histograms sequence. B) At each cycle, the distorted circumferences adopt slightly different shapes. That will create time varying amplitudes in the structures.

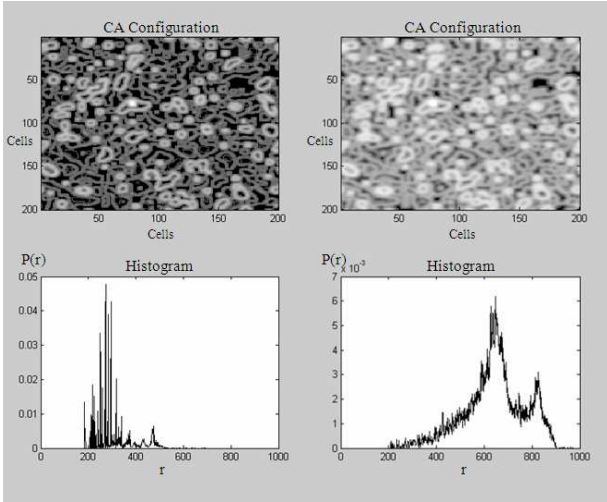

Figure 2: Different CA configurations in the 'quasi-synchronic' behaviour and the histograms they produce: narrow bands (left) and wide bands (right).

Figure 3 shows the histograms sequence of a CA evolution and the different zones we can find on it. SC1 and SC2 are zones consisting of narrow band structures which represent Control Data suitable for sinusoidal sound components. NC Zone consists of wide bands correlated in amplitude with the previous structures and can provide Control Data for correlated noise bands.

We can see also that the histograms sequence is a good reflect of the CA rules, parameter values, and hence of the CA behaviour. Peaks E1 and E2 are the probabilities of the two end estates. There is a GAP with zero probabilities due to the addition of constant K in Rule 2 (like an offset) and due to the end of SC1 Zone which has a maximum value due to r_1 and r_2 in Rule 1. This behaviour is achieved by many combinations of the CA parameters: CA size around 200x200 cells; by working with thousands of states (V), the histogram space is enlarged fostering interesting structures for sinusoidal components to appear in SC2 Zone. K as 20~30 % of V, and r_1 and r_2 can be set to 2.

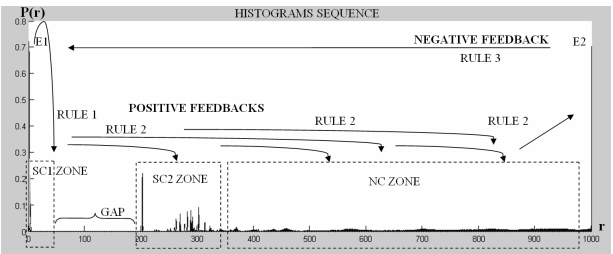

Figure 3. Frontal plot of the histograms sequence with the effects of the rules ('quasi-synchronic' behaviour).

CAs present different forms of long-term behaviours. Regarding sound evolution, we can differentiate two generic forms: long-term behaviours that will bring structures for sustained sounds and long-term behaviours that will bring structures for non-sustained sounds. The previously mentioned CA behaviour is an example of the formers. CA definitions with few neighbours are likely to give structures for non-sustained sounds. That is the case of considering Neumann neighbourhoods [2], or even fewer neighbours, for example considering the case where the central cell is not a neighbour. Due to considering fewer neighbours, the divisor of Rule 2 is lower than with Moore neighbourhoods, and thus, 'infected' cells have great chances of getting immediately 'ill'; there are many combinations in the neighbourhoods that induce this effect. In the neighbourhood, 'ill' cells make the numerator higher, whereas the denominator does not grow by 'ill' or 'healthy' cells. Thus, having just one 'ill' neighbour, then in case of not having any other 'infected' neighbour than the central cell, this cell becomes automatically 'ill'. That makes that the CA reaches a long-term behaviour with cells that oscillate only in between 0, cell values corresponding to SC1 Zone and V-1. While reaching this long-term behaviour, the rest histogram's bins fade out to zero, creating structures of sound releases. These structures are interesting because there appear different release times for different histogram bins. It is also clear this process in the images of the CA evolution (Figure 4). There will remain structures in the first, the SC1 Zone and the last histogram's bins. All the CA cells are concentrated in these few positions, so their time evolution will be very flat, and can be discarded.

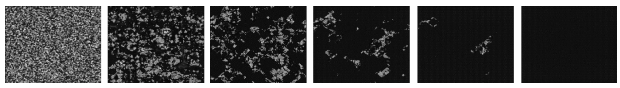

Figure 4. CA evolution that creates non-sustained structures in the histograms sequence.

4. SPECTRAL STRUCTURES

As we have already seen in previous section, with different CA behaviours we can find many types of structures with different time evolutions.

Time varying amplitudes can be considered in different ways. The original amplitude evolution of the histogram's bins usually present oscillatory shapes, and it could be desired to perform an amplitude envelope extraction to get a smoother evolution (Figure 5).

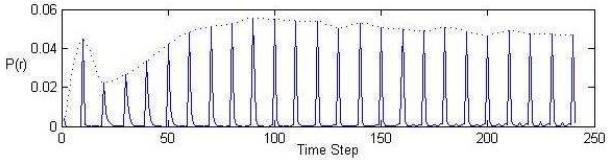

Figure 5. Time evolution of one histogram's bin from SC2 Zone in the 'quasi-synchronic' behaviour (solid line), and its amplitude envelope (dotted line).

When the partials are in the form of narrow bands, it is possible to obtain frequency trajectories. Especial attention deserves some correlated glissandi appearing in attacks (Figure 6).

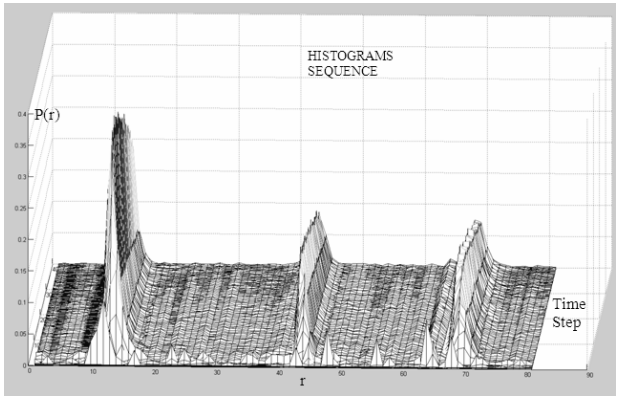

Figure 6. Structures from SC2 Zone showing glissandi and a noisy structure in the attack.

The Self-Organization process of CAs also gives other interesting noisy structures. In Figure 6 and 7 we can see a noisy structure in the attack that disappears while the partials emerge. Here, there are sets of peaks that may be candidates for Transients.

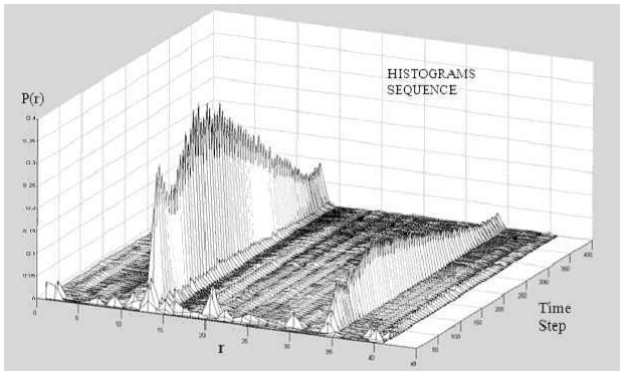

Figure 7. Structures from SC2 Zone showing correlated amplitudes and a noisy structure in the attack.

In synthesis it is common to perform a reorganization of the structures (by frequency assignment) in order to design the spectrogram.

5. CONTROL

The predictability of the outcome of a CA evolution is an open problem [11]. Music & Sound Systems based on CA may offer more or less degree of flexibility; but being under unpredictability conditions implies control limitations and thus, restrictions in the Design Process. Consequently, a high factor of aleatority is present in the output. Our work gives improvements in this issue. Firstly, the mapping presented in this paper links to a CA analysis giving structured data in the form of Spectral Magnitude. Thus, we can establish a sound design process from here using many of the existing spectral signal processing techniques [9]. Secondly, with this mapping it is possible to work with a certain degree of predictability. As we have seen, the CA rules and parameters are very well reflected in the histograms. Thus, it is possible to find direct relations between the CA parameter values and their effects in the histograms. Most of them refer to the spectral dimension, and very little to the time dimension. For instance, the lower K's value is, the lower the GAP is. As a consequence, in the 'quasi- synchronic' behaviour, we will have more noise bands in NC Zone. It is also very intuitive to see that with a large GAP we may lose noise bands. K also contributes to the attack delays; the lower K's value is, the more delay (in these cases, delays are also proportional to the histogram bins). r_1 and r_2 control the tendency for a 'healthy' cell to be infected by 'infected' neighbours and by 'ill' neighbours respectively. When working in the 'quasi- synchronic' behaviour, we could consider they act in parallel; the lower the values, the wider SC1 Zone is. If the values are extremely low, the histograms sequence will evolve presenting only two peaks in the first and the last bins. On the contrary, if the values are higher than the number of neighbours, the histograms sequence will evolve blocking in the first bin. About the time domain, we have seen that by considering few neighbours it is possible to control, in general terms, the time-evolution of the amplitude envelopes. Once analyzed how non-sustained structures appear, it is possible to induce the same effect working with Moore neighbourhoods, by modifying the rules. One way we can simulate fewer neighbours is by dividing A and B by two. With this we can get the same kind of non-sustained structures than working with Neumann Neighbourhoods.

We have found an Invariance Property in the Histograms by performing the following experiment: different runs of the same CA definition, with enough time to reach the long-term behaviour, and each one starting from different initial configurations consisting of noisy images generated with uniform random distributions. By looking in the histogram at a zone of narrow bands (peaks of prominent colours like SC1 or SC2 in the 'quasi-synchronic' behaviour) we have observed that the histograms' structure in terms of peak locations remains exactly the same (all the CAs self-organize through the same set of prominent colours). Apart from this, the relative amplitude of the peaks remains very similar. The time variations of the amplitude envelopes (fluctuations included) are slightly different for every CA. This invariance property remains present even with changes in the CA sizes (as long as these changes do not induce a different behaviour).

Thus, this is a degree of predictability with applications, for example in the context of our Mapping; this Invariance Property is useful for Instrument Design. Considering that every process done from the histograms' data can be "recorded", once it is designed a sound with a desired structure, it will be possible to automatically obtain multiple instances of the original sound. Each instance will have the same structure of the original sound, but with differences in the time varying amplitude envelopes. Thus, we can design an instrument that will not ever output the same exact sound twice and therefore, capable of generating more natural sequences of notes.

6. SYNTHESIS

We have tested the CA Control Data with two synthesis & processing techniques: additive synthesis with bank of oscillators and subtractive synthesis by FFT convolution.

In this section we show an example using real-time subtractive synthesis of white noise to produce the

spectra. The CA Control Data applied to this process is illustrated in Figure 8. It comes from a CA with modifications in the rules to get a non-sustained structure. Having discarded the firsts and the last bins, it results in a compact structure due to the low values of K and V (K=8, V=100, $r_1 = r_2 = 2$).

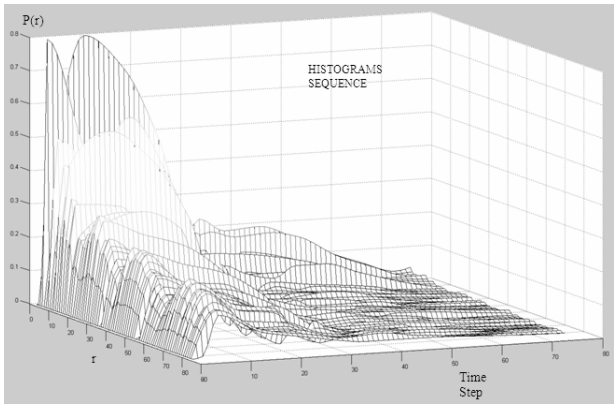

Figure 8. Non-sustained structure after envelope extraction.

Figure 9 shows the process. White noise is converted to the frequency-domain by the Short-Time Fourier Transform (STFT) using the Real FFT. We will proceed with the parameters mapping of our CA Control Data so as to become a frequency domain signal. We will consider the bins of the histogram as to be bins of the Real FFT; for each CA generation we will construct, with N points, one half of the symmetric FFT that would correspond to the analysis of a 2N-point real-valued input frame [6]. In our example, the value of N is 512, and the CA structure has around 90 bins, so we will have to add zero-valued bins up to get a structure of 512 bins. We adjust the CA structure as to start in the bin corresponding to the desired minimum frequency by adding the correspondent zero-valued bins to the left. Then we complete the FFT structure by adding zero-valued bins to the right up to N. We extract the amplitude envelopes and apply an appropriate amplitude scale. Then, at a certain ratio, the CA Control Data will be sent (for each CA generation) to the FFT convolution filter. Finally, the signal is converted back to the time-domain by Overlap-Add method (OLA).

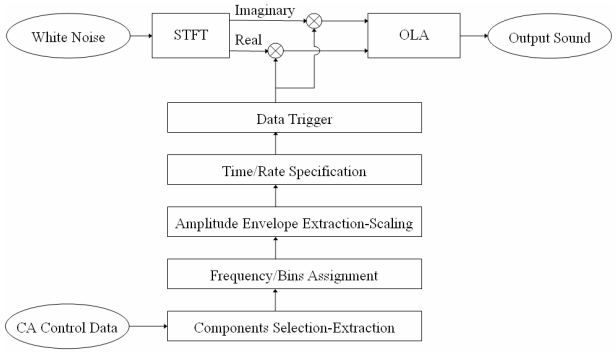

Figure 9. Real-Time Filtering of white noise with the CA Control Data.

With this CA structure and this process (establishing the duration in the range of 1 to 2 seconds) we obtained a reverberated explosive sound.

7. CONCLUSION AND FURTHER WORK

In this paper we have presented a new method for spectrograms design, based on histogram measurements of a CA evolution. We have described a number of ways for obtaining spectral structures for both, sinusoidal and noise sound components in both, sustained and non-sustained modes. We also have addressed controllability aspects useful for sound design and, we have presented an Invariance Property useful for instrument design.

The synthesis results obtained so far show great potential. Cellular Automatas are computational models inspired in Nature and with few parameter specifications we obtain complex structures evolving in a natural fashion. Also, with different rules and, modifications in other aspects like boundary conditions, initial CA configurations, neighbourhood specifications, etc. there is a great variety of possible structures to be obtained.

We are planning to test the potential of this method according to Spectral Modelling procedures and techniques [8, 10]. In the sound design processes we have not mixed synthesis techniques and we are also planning to do so within the context of Spectral Fusion studies.

8. REFERENCES

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