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Identification and Modeling of a Flute Source Signal

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Abstract

This paper addresses the modeling of the source signal of a flute sound obtained by «removing» the contribution of the resonator. The resulting sound has then a more regular spectral behavior and can be modeled using signal models. The decomposition of the source signal into a deterministic and a stochastic part has been made using adaptive filtering. The deterministic part can then be modeled by non-linear synthesis models, the parameters of which are obtained using perceptive criteria. Linear filtering are used to model the stochastic part of the source signal.

1. Introduction

When modeling sounds two main classes of models can be used, namely physical and signal models. The choice of the model depends on what the sound model is to be used to and on the «complexity» of the sound producing system. When interfaces are to be constructed to pilot a synthesis model with physically related parameters, physical models are very useful. However, when the physics is too complicated or demands measurements which are difficult to realize, signal models have to be used or can be mixed with physical models.

The work I describe here is part of my PhD project the aim of which was to construct a digital flute [Ystad, 1998]. The idea was to add sensors and a microphone to a traditional flute, making it possible to extend the performance possibilities of the traditional instrument while conserving the playing techniques.

Physical models such as the waveguide model wereused to model the wave propagation inside the resonator. This gave very satisfying results for resynthesis of transient sounds. However, for sustained sources this model was insufficient. I realized that the signal to be injected into the resonator- namely the source signal - had to be studied separately. Although, froma physical point of view, the resonator and the source cannot be separated, this procedure gave good results in our case. To model the source I decided to use a signal model, since the physical phenomena occurring when the air jet interacts with the embouchure are not fully understood.

In this article I first describe how the source signal was extracted from the flute sound, then I explain how it was separated into a deterministic and stochastic part, and how these parts were modeled separately.

2. Extraction of the source

As mentioned in the introduction, the resonator of the instrument was modeled by a waveguide model [Ystad, 1998]which consists in a recursive all-pole filter. The sound output y of thismodel can be written:

$$y(t) = (x * h)(t) \ ,$$

where $h(t)$ represents the impulse response of the resonant system and $x(t)$ represents the source signal. By removing the resonant systemfrom the sound, we obtain the source signal to be modeled. If $h^{-1}(t)$ such as $(h * h^{-1})(t) = \delta(t)$ exists, the source $x(t)$ can be obtained by deconvolution, that is:

$$x(t) = (y * h^{-1})(t)$$

This operation is legitimate since the transfer function of the resonant system has no zeros.

Figure 1 shows the spectrum of the source obtained by deconvolution for a flute sound. In this case we can see that the source signal contains both spectral lines and a broadband noise (whichin what follows respectively will be called the deterministic and the stochastic contributions). It is important to emphasize that the source signal contains no resonances anymore since they are removed by the deconvolution.

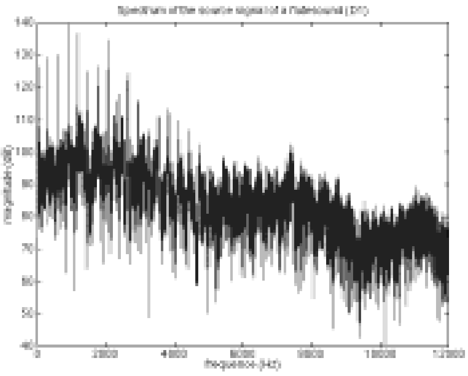

Figure 1: Spectrum of the extracted source

3. Splitting the deterministic and the stochastic contributions

To separate the deterministic and thestochastic contributions of the source signal, I first constructed an estimate of the deterministic part by selecting the corresponding spectral components. Further on, this deterministic contribution was used as a reference signal for an adaptive filter designed to extract the stochastic contribution. The LMS (Least Mean Square) algorithm was chosen for this purpose [Widrow, 1985]. This method is often used for active noise control, but is less known in connection with sound modeling. The stochastic contribution of a sound can then befound by removing the part of the original source signal which is correlated to the deterministic reference signal. In this case we suppose that the deterministic and the stochastic contributions of the source are not correlated.

3.1 Modeling of the deterministic part

In many cases, sounds generated by an excited resonant system behave nonlinearly since the evolution of the spectrum is not a simple amplification.This is the case for most musical sounds for which the dynamic way of playing dramatically acts on the resulting sound. However, this non linear behavior is often related to the excitation, even though some non linearities sometimes appear during propagation [Gilbert et al.,1997]. I have only considered non linearities generated by the excitation system. In order to model the deterministic part of the non linear source signal, I chose to use the waveshaping synthesis [Arfib, 1979][Le Brun, 1979] since this method makes itpossible to generate complex spectra from easy calculations using a small number of operations. As mentioned earlier, the source signal does not contain resonances because of the deconvolution with the resonator. This makes the waveshaping synthesis well adapted.

3.1.1 Waveshaping synthesis

The waveshaping synthesis consists in distorting a sinusoidal function with a variable amplitude $I(t)$ by a non-linear function γ. The synthetic sound is then given by:

$$s(t)=\gamma(I(t)\cos(\omega_0 t))$$

The variable amplitude I(t) called distortion index should be chosen so that the timbre of the synthetic sound varies in the same way as the timbre of the real sound as the dynamic level changes.

The first step consists in constructing a non-linear function so that the «richest»spectrum obtained by playing the instrument corresponds to a wave-shaping index $I=1$. This spectrum is obtained when playing fortissimo (ff). The function γ corresponding to the flute is represented in *Figure 2.*

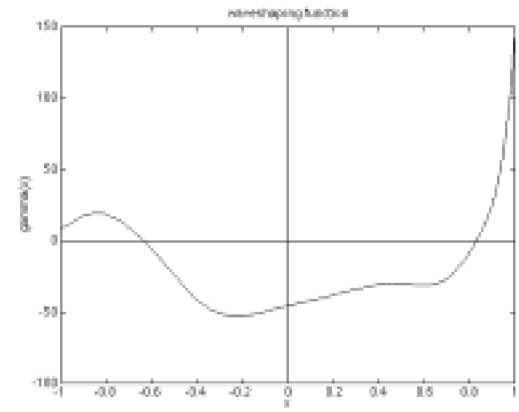

Figure 2:Waveshaping function for a flute sound.

One note that the value of the function γ is different from zero when the argument is zero. This means that if the input of the non-linear system is zero, the output will be non-zero. This phenomena can cause saturation problems and a bad use of the dynamics provided by the digital representation. One can avoid this difficulty by forcing the function γ to be zero when the argument is zero. This can be done by modifying the signs of the coefficients of the decomposition of γ into Chebychev polynomials $(T_k(x))$. Only even coefficients have an influence on $\gamma(0)$, since the value of $T_k(0)$ is zero when k is odd, and $(-1)^{k/2}$ when k is even.One can then minimize the value of $\gamma(0)$ by modifying the signs of the even k's, and then use the coefficient of T_0 to cancel $\gamma(0)$. Altering the signs of the coefficients which corresponds to altering the phase of the sound does not modify the sound since it is periodic. Furtheron, the mean value of the signal should also be minimized to minimize the DC bias when the index of distortion is non- zero. Since this value is related to the integral of the non-linear function, this corresponds to minimizing this integral on the subset *(-I,I)* corresponding to the current index. To minimize this integral, one can make the function fluctuate as much as possible. This can be done by acting on the signs of the coefficients of the non-linear function. This time the signs of the odd coefficients should be modified, since the signs of the even coefficients were modified to cancel the DC bias. A criterion for finding the signs of the coefficients leading to a minimum DC bias is to minimize $\gamma(\pm 1)$. *Figure 3* represents the same non-linear function as above, obtained this way.

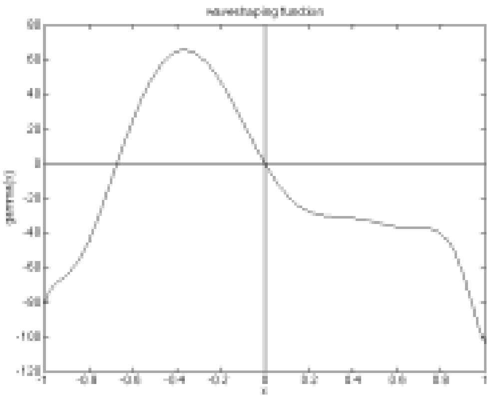

Figure 3:Waveshaping function with g(0)=0 and $\gamma(\pm 1)$ *minimized.*

A great disadvantage of the global synthesis techniques is that the representation of signals is not complete, meaning that one can not reconstruct any spectral evolution by changing the distortion index. Nevertheless, it can be estimated so that the reconstructed signal satisfies perceptive criteria. In the following section I give some examples of the non linearities measured on the flute signal and describe how the distortion index can be estimated using perceptive criteria.

3.1.2 Perceptive criteria

The second step in modeling the deterministic part of the source signal of a flute consists in estimating the wave-shaping index and to link it to a measurable value such as the driving pressure. In the first register there is an important exchange of energy between the first spectral components, while the other components increase rather monotonically with the energy of the driving pressure. This causes a problem when using the spectral centroid criterion [Beauchamp, 1982], since the brightness changes very little with increasing driving pressure, corresponding to small changes in the waveshaping index [Ystad, 1998]. This means that the spectral centroid criterion is not convenient for flute sounds. In fact, this criterion is suitable for sounds whose spectral components globally increase and not for sounds whose spectrum dramatically changes during the play.

Another criterion should therefore be used to find the waveshaping index of a flute as a function of the driving pressure. For a flute sound the most important exchange of energy appears between the first and the fifth or sixth components. More importance should therefore be given to these components than to the higher ones. The tristimulus criterion therefore turns out to be well adapted to a flute sound, since it divides the spectrum into three groups: one where the evolution of the fundamental component is considered, one where the evolution of the second, third and fourth components is considered, and one where the evolution of the rest of the components is considered [Pollard et al., 1982]. By minimizing the difference between the tristimulus of the real sound and the tristimulus of the synthetic sound the evolution of the waveshaping index as a function of the driving pressure is found. As a result, in the flute case, the waveshaping index should vary from I=0.5 to I=1 as the logarithm of the driving pressure increases from a pianissimo to a fortissimo level.

In order to equalize the changes in amplitude induced by the variations of the distortion index, the output signal must finally be adjusted by a post correction.

3.2 Modeling the stochastic part

In this section the stochastic part of the source signal is characterized so that the resynthesis satisfies perceptive criteria. Stationary and ergodic processes are here considered since such processes generally correspond to steady state sounds of musical instruments. This non deterministic part has been extracted using the LMS algorithm described above.

The probability density function $f_B(x)$ is related to the histogram of the values x taken by the noisy process B [Schwartz, 1970]. It can be easily estimated as soon as the random process can be separated from the deterministic one, which is generally the case for source signals. The histogram of the flute noise is symmetric and follows an exponential law. This means that the noise to be generated when modeling a flute sound should have the following probability density function:

$$f_e(x) = \frac{\lambda}{2} e^{-\lambda|x|}$$

At this stage, one may notice that the probability density function of a process is not invariant by linear filtering;

except in the case of the normal law (Gaussian probability density function). Nevertheless, if the correlations induced by the filtering are weak, then the probability density function is almost unmodified. This is the case for the flute signal where the non deterministic part of the source corresponds to a slight low-pass filtering of a white noise.

As an example *Figure 4* shows the power spectral density of the stochastic part of the source of a flute sound.

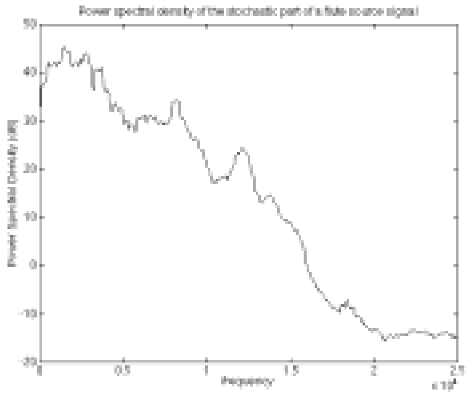

Figure 4: Power spectral density ofthe stochastic part of the source of a flute noise.

The stochastic part of the source signal can now be modeled by linear filtering of a white noise. This model together with the model of the deterministic part of the source signal gives a general model of the source signal based on signal modeling.

4. Conclusion

In this paper I have shown how a source signal can be extracted from a real sound by «removing» the resonance due to the resonator. Such a signal can be easily modeled using non-linear signal models the parameters of which can be obtained by perceptive criteria. By combining the source model with the physical model simulating the behavior of the waves during propagation in the medium, very general sound models can be constructed.

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