Sound Texture Synthesis
(revision 2)

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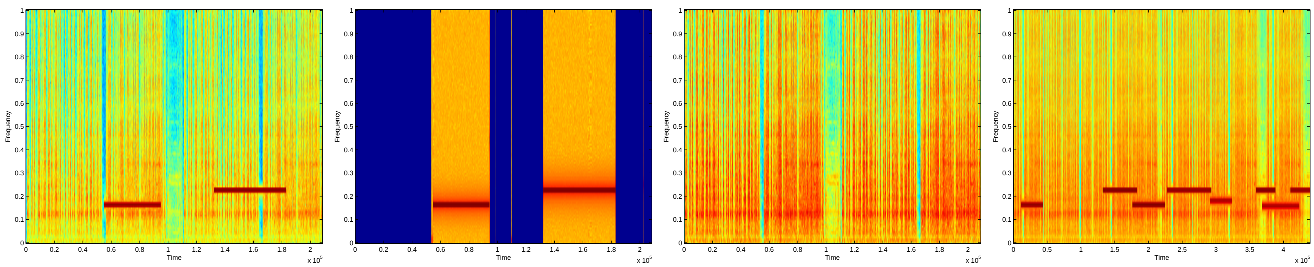

(a) original (b) foreground (c) background (d) synthesized

Figure 1: *The original sound texture (a) is separated into deterministic foreground events (b) and stochastic background texture (c). A new texture (d) is generated.*

Abstract

‘ We describe a framework for synthesizing perceptually-convincing sound textures of unlimited length, with fine control over the characteristics and occurrences of individual foreground events and the qualities of the background sound. Given an example texture, the system can automatically locate and isolate sinusoidal events, transient events, and background textures into reusable templates. Our framework also allows users to interactively highlight points of interest in the sound for event isolation, manipulate events independently, change the density of events, and even create new sound textures by combining elements of different source templates.

Our general approach models foreground events and background sound separately. We apply spectral modeling to extract sinusoidal or deterministic events and a stochastic residue from the given sound. The deterministic events are then generated to order, possibly after spectral transformations, using sinusoidal resynthesis. The stochastic component may also contain non-sinusoidal events, known as *transients*. We generate the stochastic component using wavelet tree learning. The resulting system provides a new paradigm for interactively synthesizing high-quality sound texture with flexible control over the variety and quality of the synthesized sound.

Keywords: sound texture, synthesis, sinusoidal modeling, wavelet

1 Introduction

Many sound synthesis techniques focus on generating foreground sounds such as voices, music or sudden events that easily hit the ear. These sounds alone do not generally give the listener a strong sense of being in a real-world environment where there are many background noises as well. The totality of sounds that compose an auditory environment are an example of sound textures.

A sound texture can be described as a sound with structural elements that repeat over time, but with some randomness. The randomness prevents it from being modeled well by strictly deterministic techniques. On the other hand, the sound cannot be modeled as a purely random process since on some level it appears stationary, or has an almost stable structure.

Sound texture synthesis is the creation of perceptually convincing sound based on a set of example sounds. The generated sound should be sufficiently like the original to be perceived as another instance of it. However, merely repeatedly playing the original sound is not convincing, so the synthesis should also involve some randomness.

Given one or more example sound textures, we would like to generate from these an unlimited supply of non-repeating, perceptually convincing sound that can be parametrically controlled to fit the user's specifications. One of our goals is to give sound designers for entertainment (movies, TV, and games), Virtual and Augmented Reality, and art projects such as live performance and installations, an automation tool for easily modeling and generating sound textures.

Our general approach is based on the notion that sound textures are composed of events as well as background sound, which are best modeled separately. We apply spectral modeling [Serra 1989] to extract sinusoidal or deterministic events and a stochastic residue from the given sound. The deterministic events are then generated to order, possibly after spectral transformations, using sinusoidal resynthesis. The stochastic component may also contain non-sinusoidal events, known as transients. We generate the stochastic component using a wavelet tree learning algorithm by Dubnov et. al. [2002]. Feeding it the residue, with no sinusoidals or harmonic events, allows the wavelet tree learning to operate on the type of data with which it works best. SMS techniques has been primarily used for analysis/modeling of foreground musical sounds. We

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are the first (and the last probably) to use it for event separation in texture synthesis.

Our method also allows users to have control over the characteristics of their synthesized texture. Separating the events provides a framework in which to manipulate events individually, and to request more occurences of some events and less of others in the final texture. It also offers the option or creating new sound textures by mixing the backgrounds and deterministic events from several example textures.

2 Related Work

Previous work on synthesizing sound to match a given environment has involved simulation or model-based methods for generating interactive contact sounds, or the analysis and resynthesis of existing sounds. While our work draws on ideas from the former, we focus more on the analysis and resynthesis of environmental sounds.

2.1 Simulated and Model-based Sounds

Interactive contact sounds such as scraping, rolling and walking have been synthesized by modeling the physics or spectrum of the sound source.

The FOLEYAUTOMATIC software system by Doel et. al. [2001] uses dynamic simulation with a modal audio model based on contact forces and a graphics renderer to create interactive simulations with high-quality audio.

In the Sounding Object project by Rocchesso et. al. [2003], physically based models are applied to generate complex sounds.

A related area is perceptual rendering, where the sound sources correspond to actual entities in the virtual environment. They are manipulated or combined based on the listener's position in the model. Tsingos et. al. [2004] demonstrated a method to efficiently render many (hundreds of) moving sound sources, using auditory culling and spatial clustering.

The advantage of this approach is that sound can be directly infered/synthesized, given a model. sounds can be "intuitively" modified by modifying the model. The downside is that you need a model in order to generate sound so it's hard to generalize.

2.2 Environmental Sounds

The ultimate goal in sound texture synthesis is to generate an unlimited supply of non-repeating, perceptually convincing, parametrically controlled sound, based on a given set of example sound clips. This method assumes no prior knowledge of the geometry of, or the objects in, a particular environment.

Existing work includes various ways of analyzing, transforming and resynthesizing the source sound.

Athineos and Ellis [2003] used cascading time-frequency linear prediction (CTFLP) to model very brief granular events known as *micro-transients*. Examples include fire crackling, people applauding, or soda being poured out of a bottle. Performing linear prediction in both the time and frequency domains captured these sounds that normal time-domain linear prediction misses. This method is effective on textures that primarily contain micro-transients, but does not generalize well to other sounds and the output texture is limited to the same length as the source sound.

Zhu and Wyse [2004] extended the cascading time-frequency linear prediction technique and applied it to separate the foreground transient sequence from the background din in the source texture. Their method performs a frame-based CTFLP analysis and observes the change in the gain of the time-domain linear prediction across frames to detect events. It then segments these out to obtain a background. A background sound of the desired length is generated using a noise excited time-domain linear predictive filter, while events are generated using the CTFLP method on clusters of the CTFLP coefficients. The background and events are then combined to obtain the final texture. However, this method does not take frequency into account while identifying events, and hence does not distinguish spectral events. Moreover, since it extends CTFLP, its effectiveness is also limited to sound containing mostly micro-transients.

Miner and Caudell [1997] used wavelets to decompose, transform or modify, and resynthesize various background sound textures including rain, wind, crackling fire, etc. Their work concentrated on the perceptual effects of various transformations. The use of wavelets instead of the Fourier transform allowed them to model the time varying nature of the sounds, since it provided variable-sized time windows for studying information at variable frequencies. With this method, they showed that the wavelet coefficients at different frequencies could be manipulated to alter the sound. The parameters to be manipulated did not directly map to the audible characteristics of the resulting sound, so some high-level knowledge was required for obtaining specific results. Also although this was a method for transforming sound, it didn't generate more of a texture.

Dubnov et. al. [2002] also used a wavelet decomposition to analyze the temporal and spectral structure of a sound texture at various resolutions. Treating the input sound texture as a sample of a stochastic process, they performed stochastic learning to generate wavelet coefficients for the synthesized texture. The synthesized texture could be controllably close to the source by some measure of error. This technique focused on generating a sound texture close to the original rather than on transforming the original sound texture. The results were best for sounds with periodic or pitched components of short duration, and for mostly stochastic sounds. However, synthesizing mixtures of stochastic and continuous pitched sounds, or periodic sounds of strong temporal coherence in this way sometimes resulted in the undesirable chopping up of continuous sounds. This happened due to the small amount of randomness permitted in learning the wavelet coefficients. Even though this measure of error could be controlled, setting it to an extremely low value produced sound textures almost exactly identical, temporally as well as spectrally, to the original.

These existing approaches do not allow much control over the output - either the entire texture is transformed (Miner et. al) or segments are shuffled and concatenated blindly. There's an extra dimension that they don't take care of, and that's different events happening simultaneously. For example, *what example?* Our approach overcomes these limitations by isolating pitched sounds, performing wavelet tree learning on the remaining stochastic part, and re-inserting the pitched components afterwards. We separate the pitched components from the sound texture using spectral modeling.

2.3 Spectral Modeling

Spectral modeling builds on the notion that some components of sound fit a sinusoidal model while others are modeled better by spectrally shaped noise. The Fourier transform allows us to observe the spectrum of a sound and identify the components that would best be modeled by sinusoids. These are also known as the deterministic components of the sound. We can then subtract these components from the original sound and ideally end with only the noise component, also called the residual or stochastic component.

Xavier Serra and Julius Smith [1989] posed and implemented the concept of "sines plus noise" modeling in the Spectral Modeling Synthesis (SMS) system. The SMS system also offers options for modifying the original sound before resynthesis, for instance by pitch-shifting and time-stretching.

Thornburg and Leistikow [2003] developed a hybrid state-space sinusoidal model that uses an iterative filterbank to split the sound into subbands. In each subband, the instantaneous sinusoidal phase and frequency are estimated and the latter is used to set parameters for the next iteration. They employed this method for modeling signals that are "quasi-harmonic", with a loose harmonic structure and some possible inharmonicity.

Traditional methods for obtaining a signal's spectrum often assume that the data is stationary and has uniform spacing between samples. This is not always the case for real data. Qi et. al. [2002] address this by using a non-stationary Kalman filter within a Bayesian framework to estimate spectral coefficients.

3 Overview of our Approach

To demonstrate how the system works, we give an example that begins with an existing sound texture, and shows the stages involved in generating new sounds textures. While the system can operated unsupervised from beginning to end (given a set of parameters), it is possible to interact with it at various points in the pipeline. We will highlight the control points and the parameters as appropriate.

The system starts with an existing sound texture, which we will refer to as the *template*. An example template may be the sound of a city street, a factory environment, seagulls by the ocean, a sporting event, or anything other ambient or semi-ambient sound. The duration of the template may be around 30-45 seconds or more, depending on the contents of the sound. Sound events in the street template, for example, may include (1) car horns, (2) screeching of vehicle brakes, (3) engines accelerating (4) cars passing by with dopplar shift, (5) engines starting, and (6) random bangs and pops. Background textures might include indistinct chatter of pedestrians and the general hum/din of the surrounding/city.

No *a priori* knowledge about the existing sound is necessary, though users may (interactively) direct the analysis and synthesis in ways that are specific to the content of the sound and the desired output - for example "pointing out" part(s) of the sound to extract or segment.

We hand the template to the system, which then prepares the template through a sequence of automated preprocessing stages - sample rate/data depth conversion (as needed), sub-band correlation for stereo or multi-channel data, and also extracts basic audio features (see subsections 4.1 and 4.4), which may serve as hints in the analysis stage.

Next, the sound template undergoes analysis (sinusoidal modeling, classification, segmentation), which performs the following tasks: (1) It isolates *deterministic*, foreground events (i.e. car horns, loud engine accelerating, brakes screeching, cars passing). The are stored/represented as event templates, which can be transformed and reused in the reconstruction/synthesis stage. Statistics about their frequency of occurence is also gathered and stored. (2) The analysis also isolates the background texture (general "hum" of the surroundings, indistinct chatter, etc.) The component of the sound is said to be *stochastic*. (3) It also segments the stochastic background texture according to event boundaries, and also mark portions of the background texture that "stand out" as potential events (somehow different from the deterministic, foreground events). These are called *transient events*. The user can listen to each component, and also "fine-tune" the isolation (filtering etc.) as needed. The analysis stage is described in detail in Section 4.

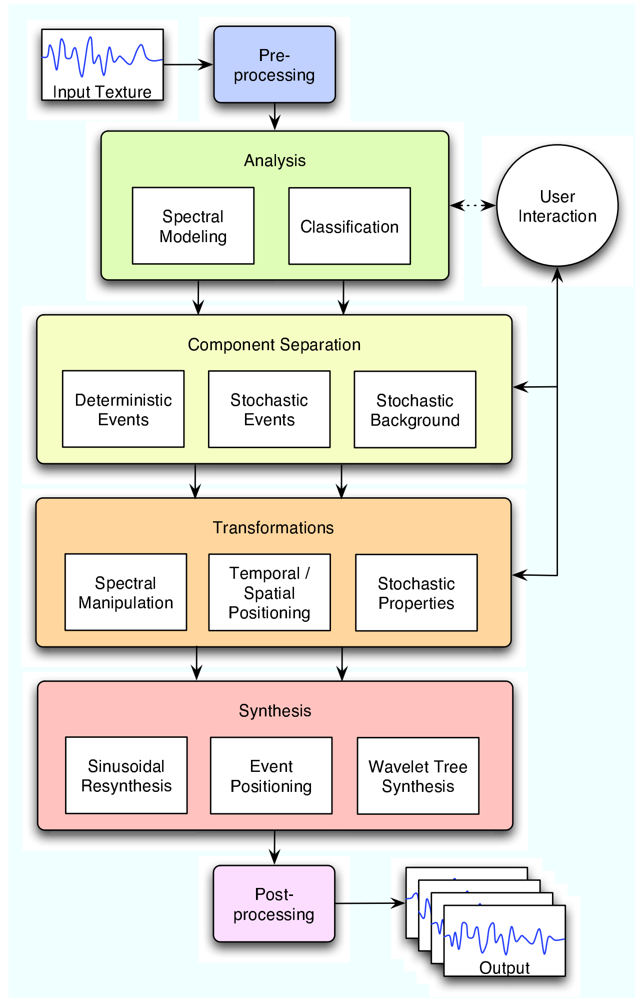

Figure 2: *Our pipeline.*

During transformation, the system or user parametrically specify how to construct and synthesize the output sound texture(s). For foreground events, transformations include high-fidelity frequency/magnitude-warping, time-stretching, and transformations that controls the temporal and spatial density of event instances. For background textures, it is possible to parametrically alter the density of the sound, as well as "similarity" to the original template.

For example, if we take the engine accelerating event template from our street scene, we make difference instances of the event with varying loudness, frequencies and durations. We can then specify for them to occur according to some probability, or as a group (cars at a traffic light accelerating together from rest). Furthermore, we can place each instance "sonically" in space. The user can experiment with each of these and preview the result before the final reconstruction / synthesis stage. Transformations on events and background are discussed in Section 5.

(TODO: need to show scripting language or user interface here or earlier)

The reconstruction / synthesis stage takes event and background templates, and produces the output texture according to specification. The stochastic background texture is repeatedly decomposed and recomposed (using wavelet tree learning and or dafxtflp) into new, perceptually similar, non-repeating stochastic background textures, which are layered with the foreground of deterministic events. From the original street sound template, it is possible to generate an arbitrary length sound texture with similar background and distribution of events. Also, the loudness, frequency-content, density, and spatialization of each component can be controlled and modified independently. From the same template, we can generate a new sound texture that gives the impression of many more cars and bus, or that of a sparse, quieter intersection, and vary the parameters dynamically to go from one to the other.

4 Event Identification and Isolation

The first step in our framework is to identify and separate the *deterministic events* from the background noise. In this context, deterministic events are the sinusoidal or pitched components of a sound. We separate these since listeners perceive them as distinct occurrences against the background of more stochastic, unpitched parts of the sound texture. A texture may also contain transient, non-sinusoidal events such as footsteps. Hence our event identification is based on sinusoidal extraction methods and on further analysis of the stochastic component (TODO: write this).

4.1 Preprocessing

We are considering several ways of preprocessing the given sound texture to enhance deterministic and transient event extraction. One strategy is to bandpass-filter the sound and perform event detection separately on each subband. This could be useful because what is perceived as an event may differ according to the spectral range in which it takes place. For example, high-frequency sounds are easier to detect than low-frequency sounds of the same magnitude (I think). So processing each subband separately allows for better fine-tuning of the event detection / tracking parameters.

Another form of preprocessing is to intelligently segment the given sound texture using the MARSYAS framework. Each segment could then be processed separately. Since each segment is a contiguous-time clip with uniform features, doing this could also aid event identification.

The thing we actually do is block DC.

4.2 Classification

As described earlier, classification of sounds can give us hints on the appropriate parameters or techniques to use for event detection and tracking. We can classify based on various features, including power, spectral centroid and rollof, spectral flux, zero crossing rate, and Mel-Frequency Cepstral Coefficients. For domain-specific tasks, features such as Parametric Pitch Histogram, and Beat/Periodicity Histogram can be calculated and used. These features also aid segmentation of the original sound, as described in Section 4.1.

4.3 Sinusoidal Modeling

To identify deterministic events, we perform sinusoidal analysis based on the spectral modeling framework. The sound texture is divided into possibly overlapping frames, each of which is transformed into the frequency domain using the FFT and processed separately by the sinusoidal analysis framework.

The maximum and average magnitudes of the spectral frame are computed and stored. The following steps are then repeated until either a specified maximum number of peaks have been located or no more peaks are present:

(1) The maximum-magnitude bin in the frame is located.
(2) If the ratio of its magnitude to the average magnitude of the frame is below a specified number, it is assumed to be noise and we deduce that no more peaks are present.
(3) If its magnitude is below a specified fraction of the stored maximum magnitude of the whole frame, it is not considered a peak and we deduce that no more peaks are present.
(4) Otherwise it is added as a sinusoidal peak, and the steps are repeated for the next highest magnitude.

Once all the peaks have been detected, we match them with the peaks from the previous frame. Over time this yields tracks of peaks as they shift slightly in frequency and magnitude from frame to frame. The matching and updating of tracks takes place in the following way:

(1) Each existing track from previous frames selects a current peak that is closest to it in frequency. (This may not work well in some cases but we believe it succeeds in the average scenario.) If the difference in frequency is above a reasonable error amount, that track is discontinued and the selected peak remains unmatched.
(2) All remaining current peaks that have not been matched to a track are added as new tracks, and all existing tracks that have not found a continuation are removed.

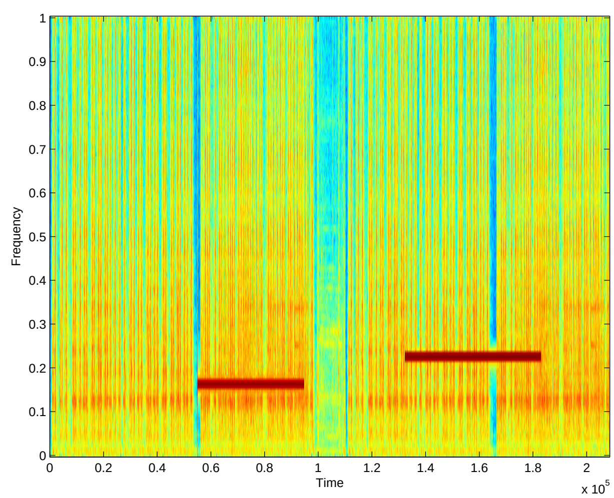

Figure 3: *Sinusoids - didactic sms figure waterfall.eps*

The presence of tracks makes it possible to specify that a sinuosoidal peak must exist across enough frames before it is accepted as an event, or that we can wait for a few frames before discontinuing it even if it vanishes temporarily. This in turn can make event representation more accurate/meaningful.

4.4 Transient Detection

This is a variant of transient dection.

4.5 Event Representation

Deterministic events are represented as sinusoidal tracks. For each event, we have access to a history of its frequency, phase and magnitude over frames, as well as the time of its onset, whether it is currently going on, and if not, the time when it ended. An extension based on this information would be to identify sinusoidal tracks that move in similar ways across the same frames, and group them as a single event or object.

Transient events are segmented and isolated sound events from the background texture. Since they are, by definition, not captured by deterministic event isolation, they cannot be represented as sinusoidal tracks. Once a transient event is detected in the background texture, it is isolated in both time and frequency range, and stored as frames of time-varying Fourier spectra. This representation is not as flexible as sinusoidal tracks but represents transients better, since they tend to be more noisy than deterministic events, and is amenable to spectral transformations.

4.6 Residual Extraction

The residue, or non-sinusoidal component, is extracted during the sinusoidal modeling. When a sinusoidal peak is discovered, the nearest local minima before and after the peak represent the peak's beginning and end respectively. We eliminate the peak from the spectrum by doing linear interpolation on the magnitudes of the bins between the its beginning and end. We also randomize the phase in these bins.

Some artifacts still remain in the resulting residual, so an alternative is to segment out frames that have many, or loud, events and to extract the residue from the remaining frames.

5 Transformations

Heading in the Transformation stage, we now have: (1) deterministic event templates, isolated in time and frequency from the background, (2) stochastic background sound texture, and (3) potential transient events.

During transformation, the system or user can parametrically specify how to construct and synthesize the output sound texture(s). The deterministic events, transient events and background can be modeled and transformed separately.

5.1 Event Transformations

Since both deterministic and transient events are modeled parametrically, we can leverage any number of powerful SMS techniques for transformation. They include high-fidelity time-stretching, frequency and magnitude warping, and cross synthesis. Since they are represented as individual events, we also use probability/statistics to model the frequency of their occurence as well as the overall density of many instances of the same event. Furthermore, it is possible to spatialize event instances, giving an impression of their respective spatial locations. Most of these transformations can be applied to both deterministic and transient event templates.

5.1.1 Sound Manipulation

Frequency/magnitude-warping - By stretching or compressing the spectral data, we can respectively raise or lower the frequency content, without affecting the duration of the sound. For deterministic events with sinusoidal tracks, we only have to shift the frequencies of the tracks and we can do this with high fidelity for almost any factor (limited by our range of hearing). For transient events, for which there is (more or less) only the raw spectral data, the spectrum of each will need to be shifted and interpolated (cite phase vocoder), and stretching by factor > 2.0 may produce artifacts. For any event instance, the magnitude (loudness) can be scaled uniformly or according to frequency.

Time-stretching - For events with sinusoidal tracks, we can modify the track's time-to-frequeny trajectory to increase or decrease the duration independent of the frequency. For track-based representation, it is robust to change the duration by almost any factor without producing artifacts. For example, (imagine that you) see figure below. For transient events, a new frame-based trajectory can be computed, which will be overlap/added to produce time-stretching. Once again, artifacts are likely beyond a factor of 2.0 to 3.0.

5.1.2 Sound Placement

Temporal placement - Explicitly place an individual event in time, or according to probability (need GUI or scripting language here). It is possible to explicitly script the occurrences of a particular event, and to apply other transformations independently on each event instance. It is also possible to specify a probability distribution, such as Poisson.

Spatial positioning - Explicitly place (or provide trajectory for) an event instance in space (in world coordinates), and assign a particular spatialization effect by providing something similar to an impulse response for the space. The system can place an event instance any where in world space (no occlusions), and calculate for distance attenuation, panning across any number of output audio channels, and spatialization if an impulse reponse is provided.

5.1.3 Group Control

Density - Specify density, or texture of a group of events, parameters include number of event instances and a probability distribution. While it's possible to achieve this control using temporal placement of individual event instances described previously, this offers a more globally-aware control of a sound "crowd". This lends to easier control and more potential for system optimizations for a large number of sound sources, such as in Tsingos et. al. Also, the size of the group can be varied dynamically.

Spatial density - Specify how to distribute group in space. (need interaction here).

(TODO: this should go somewhere else): The power of the parametric model comes from the fact that each transformation can be applied independently of others, and each component can be modified independent of other event and components (such as background sound)

5.2 Stochastic Background Transformations

Frequency/magnitude-warping - Similar to transient events' frame-based warping - modify the frequency/magnitude of the background texture (using spectral modeling). This can applied either before or after the stochastic modeling.

Time-stretching - Slow down or speed up the background characteristics, without changing the pitch.

Similarity to original sound - Modify how similar the new generated background will be to the original background. A lower index of similarity will allow more randomness in the synthesized texture.

6 Synthesis

Once the sound has been separated into events and background, and the transformation choices have been made, we can synthesize more of the sound texture to fit the user's preferences. We synthesize the background component and the events separately and combine them to produce the final texture. By default the synthesized texture emulates the original texture as much as possible.

6.1 Stochastic Background Generation

The background is generated using an extension of the wavelet tree learning algorithm by Dubnov et. al. [2002]. The sound is decomposed into a wavelet tree, where each node represents a wavelet coefficient and its depth corresponds to its resolution. The wavelet coefficients are computed using the Daubechies wavelet with 5 vanishing moments. A new wavelet tree is then built where each node is picked based on the similarity of its ancestors and its first k predecessors (nodes at the same depth) to corresponding sequences of nodes in the original tree. The learning algorithm also takes into account the amount of randomness desired.

We added the option of incorporating randomness into the first step of the learning and modified k to be a fraction of the total number of nodes at the current depth, instead of a fixed number. We also found that we can avoid learning the coefficients at the highest resolutions, without perceptually altering the results. Since the wavelet tree is binary, every additional level learned approximately doubles the running time. So not learning the highest level decreases the running time accordingly. This optimization allowed us to build a real-time version of the wavelet tree analysis and synthesis.

6.2 Event Synthesis

The deterministic events are synthesized from their representative tracks with sinusoidal resynthesis. We linearly interpolate frequency and magnitude between consecutive frames before computing the time-domain sound from these.

Deterministic events can be placed in the synthesized texture according to their distribution in the original texture, as shown by Zhu and Wyse [2004]. But the user can also request more instances of a certain type of event or less of another, for a customized sound texture. For example, a view of the spectral domain over time shows distinct peaks, or events, that the user can select. If an event lasts long enough, it can also be synthesized and played in isolation so that the user can decide its role in the final texture.

Transient events can be directly mixed in to the output after all the appropriate frequency-warping, time-stretching, and spatialization effects are applied.

6.3 Putting It All Together

The background and events are mixed. At this point the user can sit back and enjoy the display, or interactively fine-tune it, depending on the degree of involvement with which he is most at ease. Minimal involvement entails stating the parameters at a high level and allowing the various components to do their job. More low-level control would involve listening to and adjusting the synthesized components separately, and then doing the same with the combined sound texture. Some hybrid between these two approaches may also be possible.

7 User Interface

Unofficially known as abuser interface.

figure goes here. it looks like this:

... (each dot is a track)

8 Results

Figure 1 describes the effect of sinusoidal separation. Figure 1(a) shows the spectogram of a sound texture made up of two tones (the red horizontal lines) played separately against the background of a typewriter sound. After sinusoidal analysis and resynthesis, the tones are isolated, as shown in the spectogram in Figure 1(b). Since the typewriter noise (Figure 1(c)) is stochastic, it becomes the background, although the individual typewriter clicks could also be interpreted and generated as stochastic events. Figure 1(d) is our visualization of a synthesized texture based on the sinusoidal separation. The synthesized typewriter background is similar but not identical to the original background in Figure 1(c). The sinusoidal events are made to occur at different time intervals, and last for different amounts of time. Some of them are also pitch-shifted.

more figures and results go here. use imagination.

8.1 Sound Examples

Objectively describe example sounds and results. Have some figures.

8.2 Evaluation

Evaluate above examples. Shirley's idea of having someone construct a new sound texture from existing ones and an example to replicate.

9 Conclusion and Future Work

We have described a framework for synthesizing unlimited length, perceptually-convincing sound textures with separate control over individual foreground events and the background. Given an example sound texture, the system can automatically locate and isolate deterministic and stochastic events, which can then be transformed and placed into new sound textures as individual occurrences or in groups. Our framework also allows users to interactively highlight points of interest in the sound to isolate as events. The background texture is also isolated and segmented into reusable templates. The separations allows for components to be transformed independently and provides a means to combine specific elements from completely different sound textures.

Unlike existing approaches, our framework separates a given sound into well-defined deterministic, transient, and stochastic components, which fundamentally allows a greater level of control over the variety and quality of the synthesized texture. We also demonstrated an interactive paradigm for building new sounds textures, which include iterative refinement of events, interact previews of transformations, grouping, and placement in time and space. Due to the separation, our system is effective in analyzing and synthesizing many classes of sounds (this is not true at the moment).

While our system has no fundamental restriction on the type of input sound texture to model, there are limitations, such as when two events have overlapping spectra, it's hard for the analysis to tell them apart. What about events that have strong deterministic and stochastic components? What about long time-scale events with complex temporal and spectral behavior? Example: like a motorcycle? Also, foreground vocals (such as children singing/yelling) or many musical sounds are difficult to capture faithfully.

(TODO: future work)

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