COMPILING SIGNAL PROCESSING CODE EMBEDDED IN HASKELL VIA LLVM

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ABSTRACT
We discuss a programming language for real-time audio signal processing that is embedded in the functional language Haskell and uses the Low-Level Virtual Machine as back-end. With that framework we can code with the comfort and type safety of Haskell while achieving maximum efficiency of fast inner loops and full vectorisation. This way Haskell becomes a valuable alternative to special purpose signal processing languages.

1. INTRODUCTION
Given a data flow diagram as in Figure 1 we want to generate an executable machine program as in Figure 4. First the diagram must be translated to something that is more accessible by a machine. Since we can translate data flows almost literally to function expressions we choose a functional programming language as the target language, here Haskell [1]. The result can be seen in Figure 2. This translation must be done manually but in future it could also be supported by a flow diagram editor like PureData [2] or Gems [3]. The second step is to translate the function expression to a machine oriented presentation. This is the main concern of our paper.

Since we represent signals as sequences of numbers, signal processing algorithms are usually loops that process these numbers one after another. Thus our goal is to generate efficient loop bodies as in Figure 3 from a functional signal processing representation. We have chosen the Low-Level Virtual-Machine (LLVM) [4] for the loop description, because LLVM provides a universal representation for machine languages of a wide range of processors. The LLVM library is responsible for the third step, namely the translation of portable virtual machine code to actual machine code of the host processor.

Our contributions are
• a representation of an LLVM loop body that can be treated like a signal, described in Section 3.1
• a way to describe causal signal processes which is the dominant kind of signal transformations in real-time audio processing and which allows us to cope efficiently with multiple uses of outputs and with feedback of even small delays, guaranteed deadlock free, developed in Section 3.2
• a handling of internal filter parameters in a way that is much more flexible than traditional control rate/sample rate schemes, presented in Section 3.3
• support for the vector units of modern processors both for non-recursive and recursive signal processes as derived in Section 3.4
• a method for compiling a signal processing algorithm once and run it with different parameters as shown in Section 3.5
• and a speed comparison with well established signal processing packages in Section 5

Figure 1: Data flow for creation of a very simple percussive sound

Figure 2: Functional expression for the diagram in Figure 1

Figure 3: Simplified LLVM assembly code to be generated from the function expression in Figure 2. In our example scalar and vectorised loop are the same.
Figure 4: Intel x86 assembly loop for Figure 3 using SSE vector instructions.

2. BACKGROUND

We want to generate LLVM code from a signal processing algorithm written in a declarative way. We like to write code close to a data flow diagram and the functional paradigm seems to be appropriate.

We could design a new language specifically for this purpose, but we risk the introduction of design flaws. We could use an existing signal processing language, but we are afraid that it does not scale well to applications other than signal processing. Alternatively we can resort to an existing general purpose functional language, but we are afraid that it does not scale well to applications other than signal processing. Alternatively we can resort to an existing general purpose functional language, but we are afraid that it does not scale well to applications other than signal processing. Alternatively we can resort to an existing general purpose functional language, but we are afraid that it does not scale well to applications other than signal processing. Alternatively we can resort to an existing general purpose functional language, but we are afraid that it does not scale well to applications other than signal processing. Alternatively we can resort to an existing general purpose functional language, but we are afraid that it does not scale well to applications other than signal processing.

In this terminology “embedded” means that the domain specific (or “special purpose”) language is actually not an entirely new language, but a way to express domain specific issues using corresponding constructs and checks of the host language. For example, writing an SQL command as string literal in Java and sending it to a database, is not an EDSL. In contrast to that, Haskell [6] is an EDSL because it makes database table rows look like ordinary Java objects and it makes the use of foreign keys safe and comfortable by making foreign references look like Java references.

In the same way we want to cope with signal processing in Haskell. In the expression

amplify

{exponential halfLife amp}

{osci Wave.saw phase freq}

the call to osci shall not produce a signal, but instead it shall generate LLVM code that becomes part of a signal generation loop later. In the same way amplify assembles the code parts produced by exponential and osci and defines the product of their results as its own result. In the end every such signal expression is actually a high-level LLVM macro and finally, we pass it to a driver function that compiles and runs the code. Where Hibernate converts Java expressions to SQL queries, sends them to a database and then converts the database answers back to Java objects, we convert Haskell expressions to LLVM bitcode, send it to the LLVM Just-In-Time (JIT) compiler and then execute the resulting code. We can freely exchange signal data between pure Haskell code and LLVM generated code.

The EDSL approach is very popular among Haskell programmers. For instance interfaces to the CSound signal processing language [7] and the real-time software synthesiser SuperCollider [8] are written this way. This popularity can certainly be attributed to the concise style of writing Haskell expressions and to the ease of overloading number literals and arithmetic operators. We shall note that the EDSL method has its own shortcomings, notably the sharing problem that we tackle in Section 3.3.

In [9] we have argued extensively, why we think that Haskell is a good choice for signal processing. Summarised, the key features for us are polymorphic but strong static typing and lazy evaluation [10]. Strong typing means that we have a wide range of types that the compiler can distinguish between. This way we can represent a trigger or gate signal by a sequence of boolean values (type Bool) and this cannot be accidentally mixed up with a PCM signal (sample type Int8), although both types may be represented by bytes internally. We can also represent internal parameters of signal processes by opaque types that can be stored by the user but cannot be manipulated (cf. Section 3.3). Polymorphic typing means that we can write a generic algorithm that can be applied to single precision or double precision floating point numbers, to fixed point numbers or complex numbers. Static typing means that the Haskell compiler can check that everything fits together when compiling a program or parts of it. Lazy evaluation means that we can transform audio data as it becomes available while programming in a style that treats those streams as if they were available at once.

The target language of our embedded compiler is LLVM. It differs from CSound and SuperCollider in that LLVM is not a signal processing language. It is a high-level assembler and we have to write the core signal processing building blocks ourselves. However, once this is done assembling those blocks is as simple as writing CSound or SuperCollider/SCLang programs. We could have chosen a concrete machine language as target, but LLVM does a much better job for us: It generates machine code for many different processors, thus it can be considered a portable assembler. It also supports the vector units of modern processors (Sec-
3. IMPLEMENTATION

We are now going to discuss the design of our implementation [1][2].

3.1. Signal generator

In our design a signal is a sequence of sample values and a signal generator is a state transition system that ships a single sample per request while updating the state. E.g. the state of an exponential curve is the current amplitude and on demand it returns the current amplitude as result while decreasing the amplitude state by a constant factor. In the same way an oscillator uses the phase as internal state. Per request it applies a wave function on the phase and delivers the resulting value as current sample. Additionally it increases the phase by the oscillator frequency and wraps around the result to the interval \([0,1]\). This design is much inspired by Haskell.

According to this model we define an LLVM signal generator in Haskell essentially as a pair of an initial state and a function that returns a tuple containing a flag showing whether there are more samples to come, the generated sample and the updated state.

```haskell
    data Generator a =
      (state,  
        state -> Code (Value Bool, (a, state)))
```

The lower-case identifiers are type variables that can be instantiated with actual types. The variable \(a\) is for the sample type and \(state\) for the internal state of the signal generator. Since Generator is not really a signal but a description for LLVM code, the sample type cannot be just a Haskell number type like Float or Double. Instead it must be the type for one of LLVM's virtual registers, namely Value Float or Value Double, respectively. The types Value and Code are imported from a Haskell interface to LLVM [13].

The type parameter is not restricted in any way, thus we can implement a generator of type Generator (Value Float, Value Float) for a stereo signal generator or Generator (Value Bool, Value Float) for a gate signal and a continuous signal that are generated synchronously. We do not worry about a layout in memory of an according signal at this point, since it may be just an interim signal that is never written to memory. E.g. the latter of the two types just says, that the generated samples for every call to the generator can be found in two virtual registers, where one register holds a boolean and the other one a floating point number.

We like to complement this general description with the simple example of an exponential curve generator.

```haskell
exponential ::
  Float -> Float -> Generator (Value Float)
exponential halfLife amp =
  (valueOf amp, \y0 -> do
    y1 <- mul y0 (valueOf (2**((-1/halfLife) :: Float)))
    return (valueOf True, (y0, y1))
```

For simplification we use the fixed type Float but in the real implementation the type is flexible. The implementation is the same, only the real type of exponential is considerably more complicated because of many constraints to the type parameters.

The function valueOf makes a Haskell value available as constant in LLVM code. Thus the power computation with ** in the mul instruction is done by Haskell and then implanted into the LLVM code. This also implies that the power is computed only once. The whole transition function, that is the second element of the pair, is a lambda expression, also known as anonymous function. It starts with a backslash and its argument \(y0\) which identifies the virtual register that holds the current internal state. It returns always True because it never terminates and it returns the current amplitude \(y0\) as current sample and the updated amplitude computed by a multiplication to be found in the register identified by \(y1\).

We have seen how basic signal generators work, however, signal processing consists largely of transforming signals. In our framework a signal transformation is actually a generator transformation. That is we take apart given generators and build something new from them. For example the controlled amplifier dissects the envelope generator and the input generator and assembles a generator for the amplified signal.

```haskell
amplify ::
  Generator (Value Float) ->
  Generator (Value Float) ->
  Generator (Value Float)

amplify (envInit, envTrans)
  (inInit, inTrans) =
  ((envInit, inInit),
    \(e0,i0\) -> do
      (eCont,(ev,e1)) <- envTrans e0
      (iCont,(iv,i1)) <- inTrans i0
      y <- mul ev iv
      cont <- and eCont iCont
      return (cont, (y, (ev, i1))))
```

So far our signals only exist as LLVM code, but computing actual data is straightforward:

```haskell
render ::
  Generator (Value Float) ->
  Value Word32 -> Value (Ptr Float) ->
  Code (Value Word32)
render (start, next) size ptr = do
  (pos,_) <- arrayLoop size ptr start $ \ptri s0 -> do
    (cont,(y,s1)) <- next s0
    ifThen cont () (store y ptri)
    return (cont, s1)
  ret pos
```

The ugly branching that is typical for assembly languages including that of LLVM is hidden in our custom functions arrayLoop and ifThen. Haskell makes a nice job as macro assembler. Again, we only present the most simple case here. The alternative to filling a single buffer with signal data is to fill a sequence of
chunks that are created on demand. This is called lazy evaluation and one of the central features of Haskell.

At this point, we might wonder whether the presented model of signal generators is general enough to match all kinds of signals that can appear in real applications. The answer is yes, since given a signal there is a generator that emits that signal. We simply write the signal to a buffer and then use a signal generator that manages a pointer into this buffer as internal state. This generator has a real-world use when reading a signal from a file. We see that our model of signal generators does not impose a restriction on the kind of signals, but it well restricts the access to the generated data: We can only traverse from the beginning to the end of the signal without skipping any value. This is however intended since we want to play the signals in real-time.

### 3.2. Causal Processes

While the above approach of treating signal transformations as signal generator transformations is very general it can be inefficient. For example for a signal generator \( x \) the expression \( \text{mix} \ x \ x \) does not mean that the signal represented by \( x \) is computed once and then mixed with itself. Instead, the mixer runs the signal generator \( x \) twice and adds the results of both instances. I like to call that the sharing problem. It is inherent to all DSLs that are embedded into purely functional languages, since in those languages objects have no identity, i.e. you cannot obtain an object’s address in memory. The sharing problem also occurs if we process the components of a multi-output signal process individually, for instance the channels of a stereo signal or the lowpass, bandpass, highpass components of a state variable filter. E.g. for delaying the right channel of a stereo signal we have to write:

\[
\text{mix} \ (\text{delay} \ (\text{right} \ x))\]

and we run into the sharing problem, again.

We see two ways out: The first one is relying on LLVM’s optimiser to remove the duplicate code. However this may fail since LLVM cannot remove duplicate code if it relies on seemingly independent states, on interaction with memory or even on interaction with the outside world. Another drawback is that the temporally generated code may grow exponentially compared to the code written by the user. E.g. in

\[
\text{let } y = \text{mix} \ x \ x \\
\text{z} = \text{mix} \ y \ y \\
\text{in } \text{mix} \ z \ z
\]

the generator \( x \) is run eight times.

The second way out is to store the results of a generator and share the storage amongst all users of the generator. We can do this by rendering the signal to a lazy list, or preferably to a lazily singly linked list and even

\[
\text{take n =} \\
\text{\{valueOf n,} \\
\text{\( \backslash(a,\text{ToDo}) \rightarrow \text{do} \) \\
\text{cont \leftarrow icmp IntULT (valueOf 0) \text{ToDo} \\
\text{stillToDo \leftarrow sub \text{ToDo (valueOf 1) \return (cont, (a, stillToDo))} \}
\]

The function apply for applying a causal process to a signal generator has the signature

\[
\text{apply :: Generator a \rightarrow Generator b}
\]

and its implementation is straightforward. The function is necessary to do something useful with causal processes, but it loses the causality property. For sharing we want to make use of facts like that the serial composition of causal processes is causal, too, but if we have to express the serial composition of processes \( f \) and \( g \) by apply \( f \) (apply \( g \)), then we cannot make use of such laws. The solution is to combine processes with processes rather than transformations with signals. E.g. with \( >> \) denoting the serial composition we can state that \( g >> f \) is a causal process.

In the base Haskell libraries there is already the Arrow abstraction that was developed for the design of integrated circuits in the Lava project, but it proved to be useful for many other applications. The Arrow type class provides a generalisation of plain Haskell functions. For making Causal an instance of Arrow we must provide the following minimal set of methods and warrant the validity of the arrow laws [15].
The function loop :: \( \text{c} \to \text{Causal}(\text{a},\text{c}) \to \text{Causal}(\text{b},\text{c}) \to \text{Causal}\ \text{a}\ \text{b} \)

is its solution. For instance if we want

\[
\text{let } y = x + \text{delay}\ y \text{ in } x + \text{delay}\ (x + \text{delay}\ (x + \text{delay}\ y)) \ldots
\]

With loop however we can share the output signal \( y \) with its occurrences on the right hand side. Therefore, the code would be

\[
y = \text{apply}\ (\text{arr}\ \text{mixFanout} \gg\gg \text{second}\ \text{delay})\ x
\]

Since the use of arrow combinators is somehow less intuitive than regular function application and Haskell's recursive let syntax, there is a preprocessor that translates a special arrow syntax into the above combinators. Further on there is a nice abstraction of causal processes, namely commutative causal arrows [15].

We like to note that we can even express signal processes that are causal with respect to one input and non-causal with respect to another one. E.g. frequency modulation is causal with respect to the frequency control but non-causal with respect to the input signal. This can be expressed by the type

\[
\text{freqMod :: Generator}\ (\text{Value}\ \text{a}) \to \text{Causal}\ (\text{Value}\ \text{a})\ (\text{Value}\ \text{a})
\]

In retrospect, our causal process data type looks very much like the signal generator type. It just adds a parameter to the transition function. Vice versa the signal generator data type could be replaced by a causal process with no input channel. We could express this by

\[
\text{type Generator}\ \text{a} = \text{Causal}\ ()\ \text{a}
\]

where () is a nullary tuple. However for clarity reasons we keep Generator and Causal apart.

3.3. Internal parameters

It is a common problem in signal processing that recursive filters are cheap in execution but computation of their internal parameters (mainly feedback coefficients) is expensive. A popular solution to this problem is to compute the filter parameters at a lower sampling rate [18][19]. Usually, the filter implementations hide the existence of internal parameters and thus they have to cope with the different sampling rates themselves.

In this project we choose a more modular way. We make the filter parameters explicit but opaque and split the filtering process into generation of filter parameters, filter parameter resampling and actual filtering. Static typing asserts that filter parameters can only be used with the respective filters.

This approach has several advantages:

- A filter only has to treat inputs of the same sampling rate. We do not have to duplicate the code for coping with input at rates different from the sample rate.
- We can provide different ways of specifying filter parameters, e.g. the resonance of a lowpass filter can be controlled either by the slope or by the amplification of the resonant frequency.
- We can use different control rates in the same program.
- We can even adapt the speed of filter parameter generation to the speed of changes in the control signal.
- For a sinusoidal controlled filter sweep we can setup a table of filter parameters for logarithmically equally spaced cutoff frequencies and ship this table at varying rates according to arcsin.

Classical handling of control rate filter parameter computation can be considered as resampling of filter parameters with constant interpolation. If there is only a small number of internal filter parameters then we can resample with linear interpolation of the filter parameters.

The disadvantage of our approach is that we cannot write something simple like

\[
\text{lowpass}\ (\text{sine}\ \text{controlRate})\ \text{(input}\ \text{sampleRate)}
\]

anymore, but with Haskell’s type class mechanism we let the Haskell compiler choose the right filter for a filter parameter type and thus come close to the above concise expression.

3.4. Vectorisation

Modern processors have vector units like AltiVec in PowerPC, SSE and MMX in X86 processors and Neon in ARM. These vector units are capable of performing an operation on multiple numbers at once. E.g. a processor equipped with the SSE1 extension can perform 4 single precision floating point multiplications with one instruction. In contrast to pure single-instruction-multiple-data (SIMD) architectures like todays GPUs these vector units also support rearrangement of the vector components. Fortunately

supports vector units through a uniform interface and moreover it allows us to directly call processor specific instructions. This way we have implemented various optimisations for SSE.

We have checked the use of vector units in four ways:

- for parallel processing like filter banks, processing of stereo signals or in multi-oscillators generating a chorus effect, a mixture of harmonics or a chord,
- for serial processing by dividing a signal into chunks of the length of the native vector size,
- for pipeline processing like in an allpass cascade or an implementation of BUTTERWORTH or CHEBYSHEV filters by a cascade of second order filters [17],
- for internal repetitive operations like dot products in filters.

We prefer to choose one way for all involved processes in order to avoid expensive rearrangement of the data. Our experiments show that the possibility for pipelining is rare and moreover pipelining introduces a delay. This is especially a problem for our model of causal processes. The optimisation of internal operations is mostly restricted to filters. Parallel vectorisation is possible only in cases where we do the same operations in parallel and the maximum possible speedup can only be achieved if the number of parallel channels is a multiple of the native vector size. Serial vectorisation is almost always possible due to the nature of most basic signal processes. However it requires that the user accepts a reduction of the time resolution in cutting operations by the factor of the size of a native vector. It turns out that even recursive processes can be vectorised but we may reduce the number of computations from $n$ to $\log_2 n$ only.

Coincidentally the loops for scalar computation are often the same as the ones for parallel vectorisation and serial vectorisation. Only the parameters are different. The serially vectorised counterpart of an oscillator with initial phase $p$ and frequency $f$ for vectors of size 4 is an oscillator with initial phases $(p, \text{frac}(p+f), \text{frac}(p+2f), \text{frac}(p+3f))$ and frequencies $(4f, 4f, 4f, 4f)$. In both cases the computation of the next phases consists of an addition and the projection into the interval $[0, 1)$. Thus serial vectorisation is just parallel vectorisation of processes that run at the same lower rate but at interleaved phases. We like to refer to Figure 4 again that shows real assembly code for a serial vectorisation.

Many generators (linear ramps, exponential curves, polynomial curves implemented by difference schemes or in a direct way, noise by linear congruences) and stateless causal processes (mixing, ring modulation, convolution ("non-recursive filters"), phase modulation in oscillators, mapping from oscillator phase to wave function, distortion) can be vectorised in this style.

The vectorisation of stateful causal processes is different, if it is possible at all. Consider an oscillator with a frequency modulated at sample rate. Computing the phases means computing the cumulative sum followed by a parallel computation of the fraction of all interim sums. E.g. the cumulative sum $d$ of an 8-element vector $a$ can be computed by

\begin{align*}
  b &= a + a \gg 1 \quad (1) \\
  c &= b + b \gg 2 \quad (2) \\
  d &= c + c \gg 4 \quad (3)
\end{align*}

where $x \gg n$ denotes shifting the vector $x$ by $n$ components upwards, filling the least components with zeros. The same way we can write a first order filter with feedback factor $k$.

\begin{align*}
  b &= a + k \cdot a \gg 1 \quad (4) \\
  c &= b + k^2 \cdot b \gg 2 \quad (5) \\
  d &= c + k^4 \cdot c \gg 4 \quad (6)
\end{align*}

We can express this by the $z$-transformation of that filter:

\[
\frac{1}{1-k \cdot z^{-1}} = \frac{1 + k \cdot z^{-1}}{1 - k^2 \cdot z^{-2}} = \frac{(1 + k \cdot z^{-1}) \cdot (1 + k^2 \cdot z^{-2})}{1 - k^4 \cdot z^{-4}}
\]

Generally by extending a polynomial fraction with the alternating polynomial of the denominator we eliminate all monomials with odd exponent in the denominator. This way we can decompose a purely recursive filter of any order into a short-term non-recursive filter and a long-term recursive filter. For a second order filter we obtain

\[
\frac{1}{1 - a \cdot z^{-1} + b \cdot z^{-2}} = \frac{1 + a \cdot z^{-1} + b \cdot z^{-2}}{1 - (a^2 - 2 \cdot b) \cdot z^{-2} + b^2 \cdot z^{-4}}
\]

and we repeat that extension until the non-recursive filter mask reaches the native vector size, that is usually a power of two. In a real application we must cope with varying filter parameters. To this end we had to adjust the general principle in order to get the same results for scalar and vector implementations that are controlled at “vector rate” (sample rate divided by native vector size).

3.5. Parameters at Runtime

So far we have only considered signal generators with parameters that are hard-wired into the machine loop. This means however that when rendering a song we need to recompile the signal generator for every tone according to its pitch, its velocity and the gate signal. In order to overcome this we let the user define a record type $p$ that contains all parameters he wishes to control. The generator type becomes Generator $p$ a and e.g. the type of an exponential curve generator becomes

\[
\text{exponential ::} \\
(p \rightarrow \text{Float}) \rightarrow (p \rightarrow \text{Float}) \rightarrow \text{Generator } p \text{ (Value Float)}
\]

where the parameters are functions that get a value from the record ($\text{record field selectors}$). The function

\[
\text{compile ::} \\
\text{Generator } p \text{ (Value a)} \rightarrow \text{IO (p \rightarrow StorableVector a)}
\]

compiles the generator via [LLVM] and returns a function that depends on the parameter set of type $p$. In our implementation we distinguish between constant parameters and open parameters and hard-wire constant parameters into the machine loop.

4. RELATED WORK

Our goal is to make use of the elegance of Haskell programming for signal processing. Our work is driven by the experience that today compiled Haskell code cannot compete with traditional signal processing packages written in C. There has been a lot of progress in recent years, most notably the improved support for arrays without overhead, the elimination of temporary arrays
In Section 2 we gave some general thoughts about possible designs of signal processing languages. Actually for many combinations of features we find instances: The two well-established packages CSound \[18\] and SuperCollider \[19\] are domain specific untyped languages that process data in a chunky manner. This implies that they have no problem with sharing signals between signal processors but they support feedback with short delay only by small buffers (slow) or by custom plugins (more development effort). Both packages support three rates: note rate, control rate and sample rate in order to reduce expensive computations of internal (filter) parameters. With the Haskell wrappers \[7, 8\] it is already possible to control these programs as if they were part of Haskell, but it is not possible to exchange audio streams with them in real-time. This shortcoming is resolved with our approach.

Another special purpose language is ChucK \[21\]. Distinguishing features of ChucK are the generalisation to many different rates and the possibility of programming while the program is running, that is while the sound is playing. As explained in Section 3.3 we can already cope with control signals at different rates, however the management of sample rates at all could be better if it was integrated in our framework for physical dimensions. Since the Haskell systems Hugs and GHC both have a fine interactive mode, Haskell can in principle also be used for live coding. However it still requires better support by LLVM (shared libraries) and by our implementation.

Efficient short-delay feedback written in a declarative manner can probably only be achieved by compiling signal processes to a machine loop. This is the approach implemented by the Structured Audio Orchestra Language of MPEG-4 \[22\] and Faust \[23\]. Faust started as compiler to the C++ programming language, but it does now also support LLVM. Its block diagram model very much resembles Haskell's arrows (Section 7.2). A difference is that Faust's combinators contain more automatisms which on the one hand simplifies binding of signal processors and on the other hand means that errors in connections cannot be spotted locally.

Before our project the compiling approach embedded in a general purpose language was chosen by Common Lisp Music \[24\], Lua-AV \[25\], and Feldspar (Haskell) \[26\].

Of all listed languages only ChucK and Haskell are strongly and statically typed, and thus provide an extra layer of safety. We like to count Faust as being weakly typed since it provides only one integer and one floating point type.

5. BENCHMARKS

We like to put the performance of our implementation in the context of existing signal processing packages. To this end we compare it with the well-established packages CSound 5.10 and SuperCollider 3 on an X86 machine with SSSE3 in Table 1. The code for the examples can be found in the dafx2010 directory of our repository \[12\]. SuperCollider is designed as real-time server, but we run it in non-real-time mode. In order to increase relative time measuring precision we chose a large number of generated samples, namely 200 · 44100 that is about 10 million samples. We generate single precision float samples since this is the native format of both packages. We measure the “user time” with UNIX's time, thus the time for writing to the disk is ignored.

The columns “scalar” and “vector” refer to our implementation with scalar and vector operations up to SSSE3, respectively. As far as we know both CSound and SuperCollider do not use the X86 vector unit in the tested versions. Compilation and optimisation by LLVM-2.6 is part of the execution time for our implementation, but it is really not noticeable.

“Saw” denotes a sawtooth oscillator with constant frequency and no anti-aliasing. That is, for SuperCollider we use \textbf{lfsaw} instead of the band-limited \texttt{saw}. It is certainly the most simple waveform we can generate. In CSound the particular waveform does not matter since the oscillator reads it from a table. “Ping” is the same sawtooth enveloped in an exponential curve and shall check whether it helps to fuse different signal generators into one loop. We have chosen the half-life large enough in order to not run into denormalised numbers. Their handling is expensive, but it may also be avoided by the round-denormalised-to-zero mode.

“Chord” is a mixture of four sawtooth tones at different frequencies and shall demonstrate whether parallel vectorisation pays off. The number of tones is small enough to hold all loop variables in SSE registers. “Chordchorus” is a mixture of four chorus oscillators, each consisting of four plain sawtooth oscillators, that is a total of 16 oscillators. Here the number of SSE registers is exceeded. “Butterworth” is a filter sweep of a 10th order \texttt{BUTTERWORTH} lowpass filter applied to white noise where the control rate is a 100th of the sample rate. Since SuperCollider does not provide a higher order \texttt{BUTTERWORTH} filter we use a cascade of 5 second order \texttt{BUTTERWORTH} filters (\texttt{lpf}). The result is different but the speed should be comparable. This example shall demonstrate that our vectorised implementation of second order filters actually gives a little increase in performance. The noise however is vectorised, too. “Allpass” is a phaser implemented as causal process using an allpass cascade. It is applied to the expensive “Butterworth” generator in order to show the savings of sharing the original and the allpass filtered signal. However, for SuperCollider we have chosen a simple delay line because of the lack of a first order allpass. “Karplus-Strong” is a variant of the according algorithm using a feedback with delay of 100 samples and a first order lowpass.

6. CONCLUSIONS AND FURTHER WORK

The speed numbers of our implementation are excellent, yet the generating Haskell code looks idiomatic. The next step is the

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<th>SuperCollider</th>
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<td>0.60</td>
</tr>
<tr>
<td>allpass</td>
<td>1.54</td>
<td>0.58</td>
<td>1.07</td>
<td>0.84</td>
</tr>
<tr>
<td>karplus</td>
<td>1.64</td>
<td>0.34</td>
<td>0.08</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Table 1: Benchmarks for computing 8820000 (200 seconds at 44100 Hz) single precision floating point samples. Computing times are given in seconds.
integration of the current low-level implementation into our existing framework for signal processing that works with real physical quantities and statically checked physical dimensions. There is also a lot of room for automated optimisations by GHC rules, but it for vectorisation or for reduction of redundant computations of frac.

We hope that LLVM supports GPUs in the future and thus makes them accessible by our framework. However this will certainly need a concerted effort for the LLVM developers and it also requires an adapted design of our vectorisation, since GPUs have no notion of a vector and thus cannot shuffle vector elements. Actually LLVM can already generate C code, but we have not checked whether this is compatible with CUDA.

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8. REFERENCES


