PITCHER
Recognizing music notes exploiting ALSA and neural networks[*]

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[*] Developed for Computer Based Software Design

1 Abstract

This project deploys a recognizer of musical pitches, played both by instruments and voice. Commercial and free-ware tuners commonly compare the Fourier Transform (frequency plot) of signals coming into the input device with the one of other known signals. The quality of these applications usually depend on how they manage filters, how they reject noise and on the quality of the recorder and its drivers.

In the field of audio processing and computing, the use of neural networks has become very popular. Both in academic and commercial context, recurrent networks are nowadays the most employed for recognizing speech and music in real-time. Simpler categorization problems can be addressed by other neural architectures too.

We address the realization of a tuner that avoids FFT comparison but exploits the simplest neural architecture, the *perceptron*, for solving the problem of pitch recognition, which is a categorization task.

2 Outline

2.1 ALSA

The Advanced Linux Sound Architecture (ALSA) is an open-source framework embedded in Linux Kernel [1]. It provides a kernel API and a library API; its functionalities are exploited by other frameworks on a higher level, such as PulseAudio and the JACK audio connection kit.

ALSA cards correspond one-to-one to hardware sound cards. In this way, we can list the devices on each card with a string ID or a numerical index. Most of the hardware access done by ALSA is applied on devices, that can be opened and used independently.

ALSA arranges hardware audio devices and their components into a hierarchy of *cards*, *devices* and *subdevices*. This offers a map of the hardware through drivers that manage them. Subdevices are the most fine-grained objects ALSA can distinguish and are enumerated as devices are. An example is about channels of a device: in this case, the use of more subdevices (say multi-channel signals) implies that all of them need to block for playing.

Digitized sound has a number of parameters such as the sampling rate, the number of channels and the format in which sample values are stored. These parameters have to be set when recording or playing an audio file: the process is called *configuration*. ALSA distinguish between *hardware* and *software* configuration: parameters are not independent and cards can have limited possibilities (not all sampling rates can be applied, for example). ALSA accounts for this fact by arranging sets of parameters in an n-dimensional space, the *configuration space*. One of these dimensions corresponds to the sampling rate, one to the sample format, and so on. If the parameters of one specific sound card are all independent, all legal configurations lie in one big n-dimensional box and we

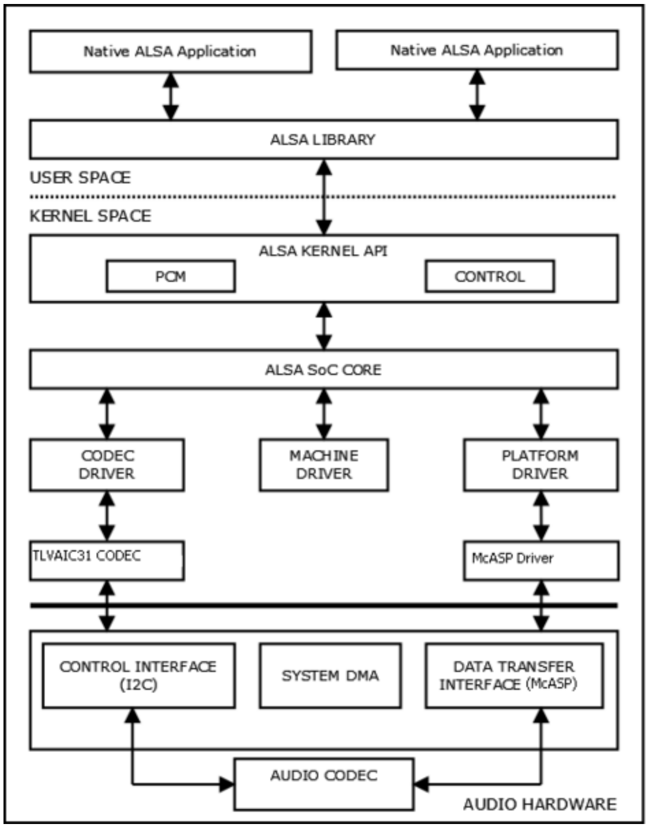


Figure 1: Software support for audio on various hardware devices can be achieved through ALSA. Here is a map of ALSA interface between user, kernel and hardware cards as it is designed for embedded processors and codecs [3].

could describe them by giving separate ranges for all parameters. On the contrary, if the parameters are not independent, the architecture varies acquiring complexity.

When a hardware device is accessed with ALSA, parameters are not fixed independently of each other, but the legal configuration space for a device is narrowed down successively by restricting specific parameters. This makes it possible to set some minimal values rather than exact ones. In order to avoid these problems and to manage devices more efficiently, ALSA comes with a large set of *plugins*, enlisted in the official documentation [2]. Each plugin is a minimal component that is used to work with ALSA's basic and complex services, making a virtualization of real cards. One of the most important is `hw`, used for merely access an hardware driver.

2.2 Neural networks: perceptrons

The evolution of biology research in last century has led to the creation of systems that can emulate the behavior of human brain in very different ways. The brain has many special abilities that make it interesting to be applied also to artificial machines:

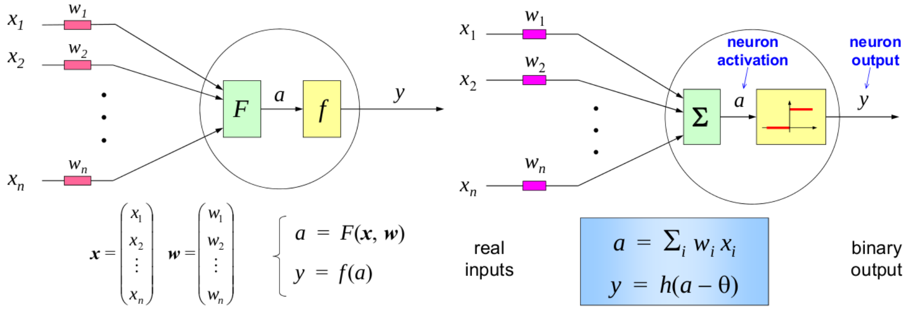
- efficiency
- fault tolerance
- graceful degradation

In last three decades neural networks have become more and more popular, mainly thanks to the fact that, after a long and hard time of research on how to overcome mathematical difficulties, the computational power and the huge amount of accessible data has literally exploded.

Artificial neural networks are not all the same, but they are divided in many categories depending on the problem they solve and the requirements they fulfill. We can use *supervised* training (learning by examples) or *unsupervised* one (called *reinforcement learning*) and we can apply a variety of designs, for instance perceptrons, self-organizing maps, Boltzman machines, convolutional nets and so on.

Since in this work we focus on categorization, that is the problem to assign a seen example to a defined category, we decided to follow the very simple approach of *perceptrons*. This model has been proposed by Rosemblatt in 1957 and its hardware implementation was one of the first and famous achievements in technology before strong limitations were demonstrated in 1969, causing the so called "AI winter". Thanks to a great algorithm improvement called Backpropagation (Rumelhart, Hinton and Williams, 1986) the research over artificial neural networks spread again until the progress seen nowadays.

The *perceptron* in a specialization of the binary-threshold neuron presented some years before, as visible in **Figure 2**.



(a) *Generic neuron* (b) *Perceptron*

Figure 2: Basic schema of artificial neurons under consideration.

N weights are associated to inputs and are processed with $F(w, x) = a$. A final activation function $f(a) = y$ determines the actual output of the neuron. The perceptron applies summation as F, while multiple choices of activation function can be made: sigmoid, hyperbolic tangent, signum and Rectified Linear Unit (ReLU) functions are of common use.

3 Developement

We design a modular component-based software that relies on:

- ALSA management of sound cards for reading files and input device
- a library for building, training, saving and loading a networks that can make predictions on properly adapted audio samples
- thread based programs for the realization of a soft real-time tuner

Our tuner is capable of recognizing both instrumental and voice, though the training of the network demonstrated to be affected by difficulties that we are going to explain in detail.

The project is maintained on GitHub [4].

3.1 ALSA utilities

As mentioned in **Chapter 2.1**, while using drivers with ALSA we must take care of parameters. After that, we can use devices in a way that remembers the one we follow with files: we open a so called *handler* on a specified device (for our purposes, `default` is sufficient); we allocate, set and apply hardware parameters; we use the device for reading or writing until we close the handler. See **Figure 3** for a summary.

The parameters of our interest are:

- **access**: the way frames are managed into the buffer, dealing with channels. If we have a single channel, frames are simply subsequent, whereas with more channels we can *interleave* them, namely put samples of more channels one after another, or *non-interleave* them, namely put samples of the same channel in series until the end of frames, then begin again with other channels. The type we chose is `INTERLEAVED`
- **sampling format**: the kind of datum we are going to extract or put into the buffer submitted to the sound card. It is not only related to the size (`short int`, `int`, `float` etc.) but also to the *endianess*. The format we chose is 32-bit `float` Little Endian
- **sample rate**: this parameter is usually rounded down by ALSA, depending on the capability of the soundcard. If the rounded value is not acceptable for the user, he can decide to treat is as an error. We always work with the basic 44100 Hz frequency

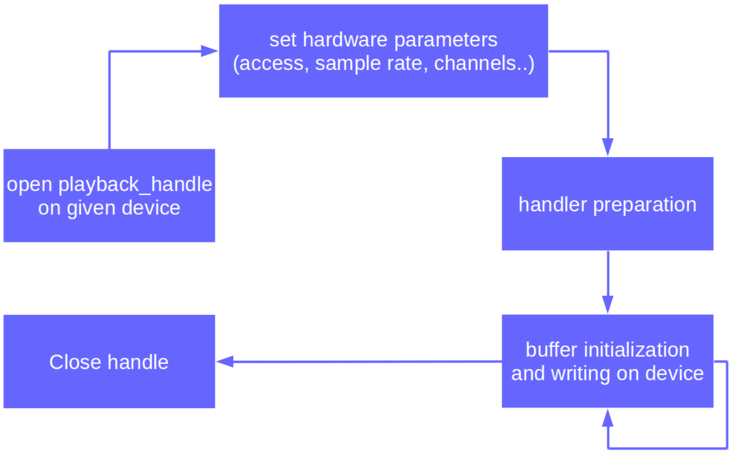


Figure 3: Brief summary of passages to follow while preparing an example app for playback.

- **channel count**: number of channels requested to read or write. We have to remember to prepare the read/write buffer in the proper way, according to the number of channels and the access type just set

The `autil` library provides similar functions to read and write buffer using the ALSA API. They follow the same paradigm followed by the ALSA project and other libraries available on the web: for each format, a proper function can be called.

For further details, refer to `autil.h/autil.c`

3.2 Reading `.wav` files

We trained our networks using two kinds of elements: artificially generated sinusoidals of known frequency, from which we take the FFT, and `.wav` files. Some of these files have been recorded from an electric piano, while others have been downloaded and properly formatted.

The files `wav.h/wav.c` exploit services delivered by the `libsndfile` [5] library, which is designed to deal with a variety of audio files and formats. The process to follow for extracting samples is pretty similar to what ALSA requires, except of course doing specific parameter setting before the start. After a `.wav` file is open, characteristics can be stored and easily used for playback or recording, if needed. Our `wav` library focuses of opening and reading chunks of files of a certain number of frames. In particular, each chunk is usually not greater than 2205 frames, which is the amount of frames read in 50 milliseconds while capturing audio at 44.100 KHz. Also in this case, functions are organized following the type of datum we need to read, be it `short`, `int` or `float`.

There is also an additional “complete” method to read a `.wav` entirely and play back it out. This can be useful to roughly check the quality and the correctness of the files we upload.

3.3 Library for perceptron-based networks

This is the backbone of the application. There are two distinguished modules about networks: the `pnet` and the `pnetlib` library. We discuss each of them separately.

pnet Contains the definition of perceptron, layer of perceptrons and network of perceptrons, alongside with methods for dynamically instantiate, initialize and destroy every part of them.

An instance of `perceptron` contains:

- `int nweights`: number of weights (bias excluded)
- `float* weights`: dinamically allocated array of weights
- `float bias`: trained as an additional constant, whose input is set to -1. It's influence varies with the objective function chosen
- `float a`: sum of all `weights*inputs - bias`
- `float y`: actual output given from objective function evaluated on the previous sum, $f(a)$
- `float d`: δ stored during a backpropagation step (see later)
- `float (*fx) (float x)`: pointer to the objective function
- `float (*dfx)(float x)`: derivative of $f(a)$, needed in backpropagation

A `p_layer` and a `p_net` are simply dynamic arrays to build up the entire structure.

We implement here the *backpropagation algorithm*, to be applied both for weights and for bias. Given a network and an example, returns the amount of updates needed for each weight and bias of each perceptron: this object is called *delta rule*. Specifically, in a network of L layers, where w_{ji} is the i-th weight of neuron j in layer l, we get Δw_{ji} as the delta rule applied for w_{ji} (**Figure 4**).

The delta rule is computed as follows. The generalized formula is:

$$\Delta w_{ji} = \eta \delta_j x_i$$

where η is the *learning rate*, x_i is the i-th input (associated to w_{ji}) and δ_j is defined as:

$$\delta_j := -\frac{\partial E_k}{\partial a_j}$$

being E_k the error en example k.

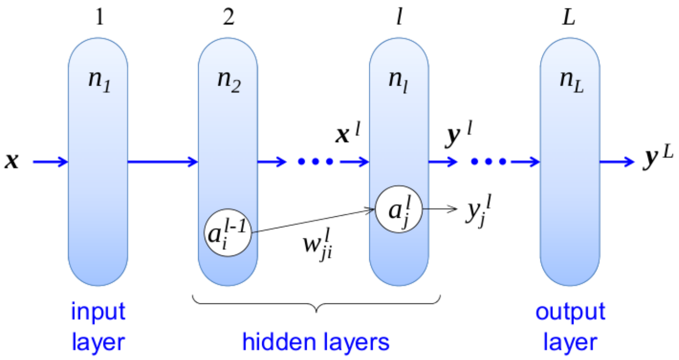


Figure 4: Definitions needed by the algorithm

By first, we present an example so that the network stores a prediction for any of its neurons. Given L layers (enumerated from 1 to L), and assuming to use as error $E_k = (target_j - y_j)^2$ we start from the output layer computing for each example k:

$$\delta_j^L = (target_j - y_j)f'(a_j)$$

For any other other layers $l < L$, going from the top to the bottom, being n_l the number of weights incoming on any neuron of layer l, we evaluate:

$$\delta_i^l = f'(a_j^{l-1}) \sum_{j=1}^{n_l} w_{ji}^l \delta_j^l$$

Normally, the delta rule is not applied immediately, but an average is taken over subsets of the training set, called *batches*. This helps minimizing the error fluctuations and also to limit the *gradient vanishing* phenomenon. We followed this technique too in the actual training algorithm implemented in `pnetlib.h/pnetlib.c`

pnelib This library defines a generalization of examples that can be provided to a perceptron network freely created. A `struct example` is formed by:

- `float* samples, *label`: dynamic arrays for samples of the example, and relative label. The label can vary depending on how we address categorization: for instance, label could be binary or a list of n categories. An object belongs to category i if the i-th element is 1
- `int ns, int nl`: size of the mentioned arrays

Some methods help to build up a list of this examples in order to create the training set required for the network.

Examples can be *normalized* and/or *standardized*, which are common practices used to get a better training set to issue. In fact, with normalized data, the error function tends to be symmetric and the minimum can be reached more quickly. Otherwise, the error function squeezes and a small Δw can cause the error to oscillate. The formula we used for *normalization* (taking all values in the range $[0, 1]$) is:

$$x_i^{new} = \frac{x^{old} - x_{min}}{x_{max} - x_{min}}$$

The *standardization* formula, given M examples of n_s samples, and being μ_i and σ_i^2 the *mean* and *std variation* respectively of example $i = 0...n_s$:

$$\begin{aligned} \mu_i &= \frac{1}{M}\sum_{k=1}^{M} x_i(k) \\ \sigma_i^2 &= \frac{1}{M}\sum_{k=1}^{M}(x_i(k) - \mu_i)^2 \\ x_i^{new} &= \frac{x^{old} - \mu_i}{\sigma_i} \end{aligned}$$

This stated, `pnetlib` is used to perform the training itself. We apply the *mini-batch* approach: we split the training set into batches and we accumulate the delta rule over each example of the batch. At the end of the batch, we average the delta rule and then we apply it. Hence, we can monitor a “local” error averaged over the batch and a “global” error averaged over the entire training set.

The batch dimension can be set at run time. If this dimension does not divide the set in equal parts, the surplus is managed in the same way as well, considering the actual dimension of the residual.

This approach is called *mini-batch Stochastic Gradient Descent* algorithm, whose pseudo-code is described in **Figure 5**.

In order to contrast error’s fluctuation, two methods are commonly used:

1. dynamic variation of the learning rate η, as a function of th error

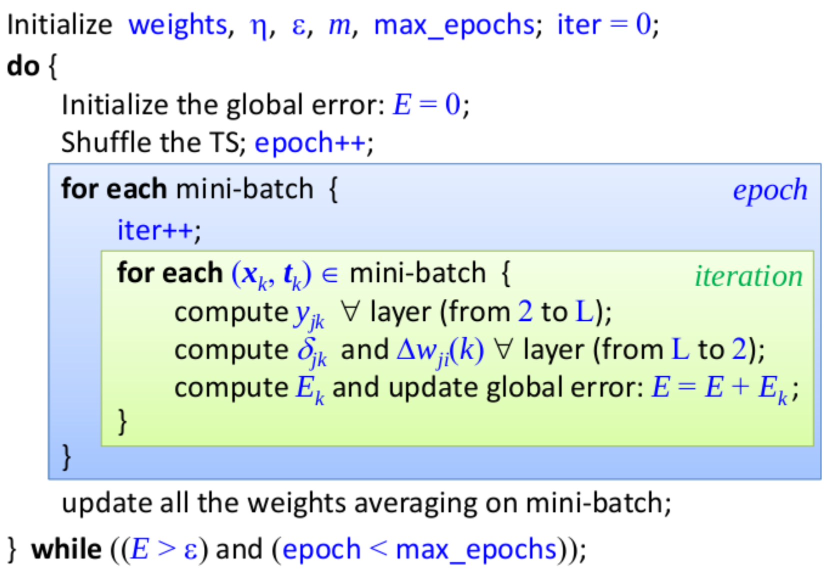
2. use of *momentum* m

We implemented the second approach with a *momentum* m that can be set at run-time. At the end of the batch, we apply:

$$\Delta w_{ji}(t) = \Delta w_{ji}^{avg} + m\Delta w_{ji}(t-1)$$

3.4 A closer look to `ftrain` and `fpitcher`

Since we are using a neural network, the use of Fourier Transforms, filters and other signal processing techniques should be negligible. In fact, by definition, a neural network builds itself according to shown examples and to the way it is programmed for learning. This means, for example, that a network could learn to recognize a pattern even in presence of errors, if it categorizes them through



```
Initialize weights, $\eta$, $\varepsilon$, $m$, max_epochs; iter $= 0$;
do {
    Initialize the global error: $E = 0$;
    Shuffle the TS; epoch++;
    for each mini-batch {                                              epoch
        iter++;
        for each $(\mathbf{x}_k, \mathbf{t}_k) \in$ mini-batch {                  iteration
            compute $y_{jk}$ $\forall$ layer (from $2$ to $\mathrm{L}$);
            compute $\delta_{jk}$ and $\Delta w_{ji}(k)$ $\forall$ layer (from $\mathrm{L}$ to $2$);
            compute $E_k$ and update global error: $E = E + E_k$;
        }
    }
    update all the weights averaging on mini-batch;
} while (($E > \varepsilon$) and (epoch $<$ max_epochs));
```

Figure 5: Mini-batch concept flow for backpropagation

examples. For this reason, we designed the training and the "pitcher" to work directly with raw audio samples. Nevertheless, to make the debugging much easier, we shifted to the use of Fast Fourier Transforms: libraries as FFTW3 are widely available and stable [6]. Using FFT, it possible to clearly see the spectrum of a signal together with the frequencies on which a potential noise accumulates (**Figure 6**).

The training set is built up using frequencies of the 4th octave (C4-B4) at different volumes. Each has been normalized before the FFT application. Frequencies are listed in the following table.

PITCH	FREQUENCY [Hz]
C	261.63
C#	277.18
D	293.66
D#	311.13
E	329.63
F	349.23
F#	369.99
G	392.00
G#	415.30
A	440.00
A#	466.17
B	493.86

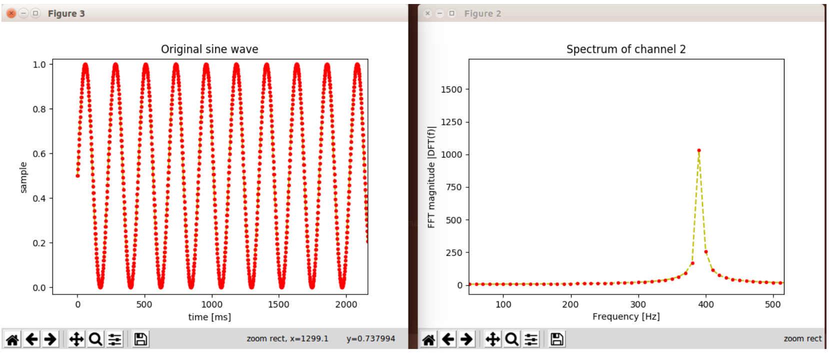


Figure 6: Example of auto-generated sine wave and FFT, using normalization on the initial samples: here, pitch is G at 392.00 Hz.

Then, the neural network is created with 2 layers. The first is the hidden layer (input layer is implicit) with `nhd` neurons, `NUM_INPUTS` weights and `sigmoid` as objective functions. Since we work with real numbers, the FFT of N values will have N complex numbers, whose the first $\frac{N}{2}+1$ are relevant, and the remaining are the conjugate of the first ones and then can be neglected [7].

The second layer is the top layer, hence it will have as many neurons as the number of pitches and a number of weights equal to the number of perceptrons of the previous layer. The code is going to be the following:

```
network = p_net_create();
p_net_init(network, 2);
// add hidden in front of input
add_layer(network, 0, nhd, NUM_INPUTS, sigmoid, ddx_sigmoid);
// add output layer
add_layer(network, 1, NPITCHES, nhd, sigmoid, ddx_sigmoid);
```

After normalization and a proper setting of the training parameters presented above, we call the function responsible to train our network. The error's evolution is saved on files.

```
p_net_train_SGD (network, max_epoch, batches,
  learning_rate, momentum, min_err,
  &training_set, train_size, lerr_file, gerr_file);
```

The scheme `fpitcher` follows is instead:

- create 2 threads called `capturer` (ALSA recorder) and `recognizer`
- `recognizer` loads the network prepared by the previous training, then waits for new samples coming from the `capturer`
- the 2 threads act in mutual exclusion according to reader/writer problem

The thread `capturer` *writes* on a shared buffer locking a mutex each time a new chunk is available on the device, after it has been activated (periodically every 50 ms). A variable max_overwrite counts how many times this happens without the recognizer has extracted the last written chunk. If the counter crosses a threshold of 5 seconds, this means the latency of the recognizer (then the latency of the neural network) is too long. Both threads stop in this situation.

The variable max_overwrite can be used also for delivering ALSA errors (which cause proper program termination too), throughout THREAD_EXIT_FLAG.

It's important to notice that, for every captured (or read from file) chunk, the power of the signal is checked before being issued to recognizer and then to the network. We computed a threshold as the average on the .wav files we recorded and we use it for discarding chunks that are not acceptable because too low: this approach has been also in **Section 3.5**. We also made use of the plugin alsamixer [8] to tune the capabilities of the embedded microphone of our sound card properly.

The thread recognizer *reads* the shared buffer and clears the counter as soon it has output the prediction of the network.

3.5 Cross comparison between FFT

As a completion and comparison for the work done, we can exploit autil and wav to get a valuable training set that now will not be used for a network but for providing a base of comparison for raw signals coming from an ALSA device.

We developed fcross and fcross_wav programs that apply the schema shown in **Figure 7**. They follow these steps:

1. prepare the reference set
   - prepare N samples of sinusoidal waves or chunks read from .wav files
   - normalize the samples
   - store their FFT in a list
2. periodically (we exploit a single capturer thread again)
   - capture a 50 ms chunk of audio samples (namely, 2205 frames per channel)
   - compute the *minimum average squared error* with all the examples of the reference set
   - elect as winner the sample of the reference set corresponding to the minimum error, and print the result

Both fcross.c and fcross_wav.c exploit a reference of pitches from 3rd to 5th octave (from Low C to B under Soprano C). These programs demonstrate to work well with voice: they just show some error when changing pitch or while sliding between them. In the case of instruments, we noticed more uncertainty in recognizing the lower octave: played pitch can be switched to its respective fifth, or to the upper octave. Maybe this happens because digital pianos deliver more harmonic series than normal voice, causing a sort of interference.

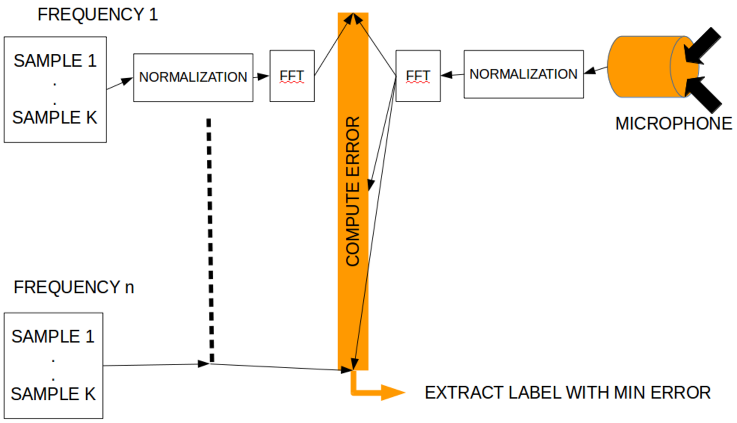


Figure 7: Schema of what's coded in `fcross.c`

4 Problems and future work

Even though the development has been linear and many successful tests have been performed on simple perceptron networks (see `hello_test_and.c`, `hello_testxor.c`, `hello_t estchar.c` and others), training the network for our purpose efficiently demonstrated to cause a real hard time.

The main discrepancy is that, even if the error seems to go quite small during training (always converging around 7.56%), after some epochs no further improvement is visible and a counter check on the training set itself causes a high failure rate (about 80%, meaning an accuracy of about only 20%). This seems to happen because the values of predictions are very small (much less than 0.1) but all similar on average. This means that, while we are seeking for a prediction near to "all 0s and a one 1" on the correct category, we are getting a prediction with values very similar one to each other and no strong winner. The training set has been verified accurately, using plots and synthesized samples, and labels too.

In general, increasing the number of neurons causes *overfitting* ("best" results have been obtained with very few neurons, even less than the number of categories of the output layer), while is good to maintain high momentum m (about 0.9). We would expect a small learning rate η to be a good choice (for example 10^{-3}) but in general making it bigger or smaller only changes speed in converging to the value said above. Changing objective function also does not give appreciable improvements.

The topic is intriguing, but for the scope of this exam the resolution is left to future work.

References

[1] https://www.alsa-project.org/wiki/Main_Page

[2] The official reference of PCM plugins can be found at: https://www.alsa-project.org/alsa-doc/alsa-lib/pcm_plugins.html

[3] Sitara Lunux Audio Driver http://processors.wiki.ti.com/index.php/Sitara_Linux_Audio_Driver_Overview#

[4] https://github.com/Ilancia/pitcher

[5] http://www.mega-nerd.com/libsndfile/

[6] http://www.fftw.org/fftw3_doc/

[7] http://www.fftw.org/fftw3_doc/One_002dDimensional-DFTs-of-Real-Data.html#One_002dDimensional-DFTs-of-Real-Data

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