Template for multi-pitch detection TP

*(reference: Klapuri) but with pitch detection with spectral sum

From G. Richard (with help from P. Vernhet), MAJ:2019

python version : 3.6

In [1]:

```
import os, sys, wave, struct

import numpy as np
import pyaudio
import pandas as pd
import matplotlib.pyplot as plt

from copy import deepcopy
from math import ceil
```

Functions

In [2]:

```
def load_music(file):
    return wave.open(file, 'rb')


def play_music(file, chunk = 1024):
    """
    Script from PyAudio doc
    """
    wf = load_music(file)
    p = pyaudio.PyAudio()
    stream = p.open(format=p.get_format_from_width(wf.getsampwidth()),
                    channels=wf.getnchannels(),
                    rate=wf.getframerate(),
                    output=True)
    data = wf.readframes(chunk)

    while data:
        stream.write(data)
        data = wf.readframes(chunk )

    stream.stop_stream()
    stream.close()
    p.terminate()


def plot_sound(data, times, name='default_name', save=False):
    plt.figure(figsize=(30, 4))
    plt.fill_between(times, data)
    plt.xlim(times[0], times[-1])
    plt.xlabel('time (s)')
    plt.ylabel('amplitude')
    if save:
        plt.savefig(name+'.png', dpi=100)
    plt.show()


def nextpow2(x):
    assert x>0
    p = ceil(np.log2(x))
    x_ = 2**p
    assert 2**(p-1) < x <= x_
    return p, x_


def f2idx(F, df):
    """
    Convert frequency to corresponding index in "frequencies" array
    """
    return ceil(F/df)
```

0 - Reading and playing .wav file

Choose the name of music for the rest of the notebook. Sounds are assumed to be set in a folder named 'sons_mutltipitch' (same directory as notebook).

In [3]:

```
current_path = os.getcwd()
data_path = os.path.join(current_path, 'sons_multipitch')
filename = 'A4_piano.wav'
music = os.path.join(data_path, filename)
```

Using wave

In [4]:

```
wavefile = load_music(music)
print(wavefile.getparams())
```

```
_wave_params(nchannels=1, sampwidth=2, framerate=32000, nframes=31994, compt
ype='NONE', compname='not compressed')
```

In [5]:

```
play = True
if play :
    play_music(music)
```

In [6]:

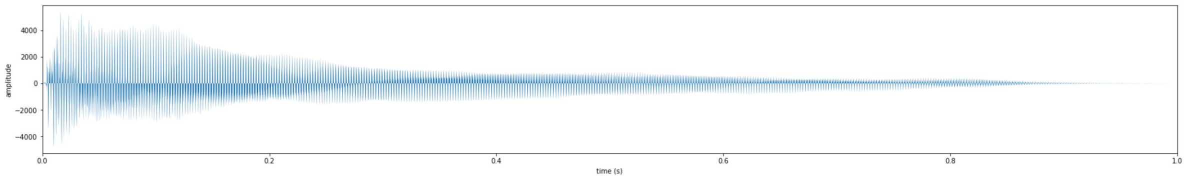
```
Fs = int(wavefile.getframerate())
num_samples = int(wavefile.getnframes())
data = wavefile.readframes(num_samples)
data = struct.unpack('{n}h'.format(n=num_samples), data)
x = np.array(data)
```

In [7]:

```
timestep = 1/float(Fs)
times = np.arange(len(x))*timestep
```

In [8]:

```
plot_sound(x, times)
```



I - Window and Fast Fourier Transform

1. Window size : A Hamming window is used, its length covering 700 ms of the entire signal

2. Offset : The offset is chosen to be about 100 ms,

3. Spectral precision after the FFT : The frequency precision is given by $dF_{\min} = \frac{F_s}{Nfft}$, where $Nfft$ is the size of the FFT window.

In [9]:

```
N=ceil(0.7*Fs)       # Window size of analysed signal (only one window of signal is analyse
dF_min=Fs/N   # Minimal frequency resolution
print('The minimal frequency resolution is of {:.2f} Hz'.format(dF_min))
```

```
The minimal frequency resolution is of 1.43 Hz
```

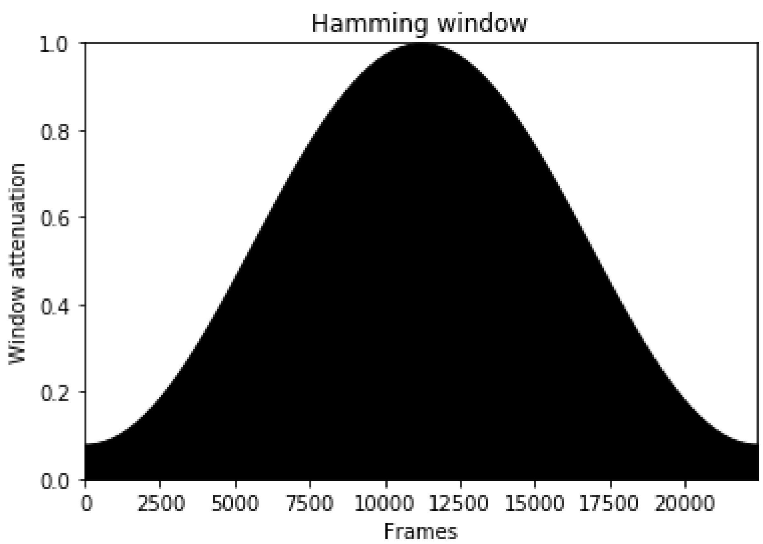
> The size used is N. It seems relevant since the narrowest windows in the time domain give the largest main lobes in the frequency domain, and vice versa and N is adapted appropriately.

In [10]:

```
w=np.hamming(N)  # Window
width = 4*dF_min # largeur du pic spectral (en Hz) 4*dF_min
eps=float(1e-20)   #precision
```

In [11]:

```
plt.fill_between(np.arange(len(w)), w, color='k')
plt.title('Hamming window')
plt.xlabel('Frames')
plt.ylabel('Window attenuation')
plt.xlim(0, len(w))
plt.ylim(0, 1)
plt.show()
```



Discarding the attack of the sound

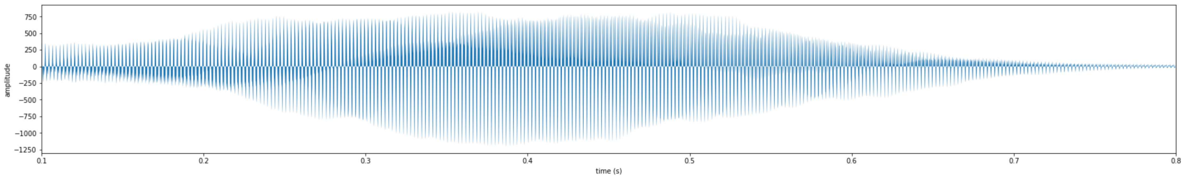
In [12]:

```
offset=ceil(0.1*Fs)
xw=x[offset:offset+N]*w    # xw is the analysed signal frame
n_xw = xw.size
```

> The offset parameter is used to reject the first attack of the sound.

In [13]:

```
plot_sound(xw, times[offset:offset+N])
```



This is the temporal visualization of the sound we will be working on.

Processing for efficient FFT (*by truncating to powers of 2*)

In [14]:

```
#Minimal number of data points to satisfy the minimal frequency resolution
Nfft_min=Fs/dF_min

#compute the smallest power of two that satisfies the minimal frequency resolution for FFT
p, Nfft = nextpow2(Nfft_min)
x_fft = np.fft.fft(xw, n=Nfft) #calcul FFT
x_fft /= np.max(np.abs(x_fft))+eps # Normalization

df=Fs/Nfft # frequency virtual resolution of FFT
print('Frequency virtual resolution of FFT {:.2} Hz'.format(df))
```

```
Frequency virtual resolution of FFT 0.98 Hz
```

> The precision is df=0.98 Hz

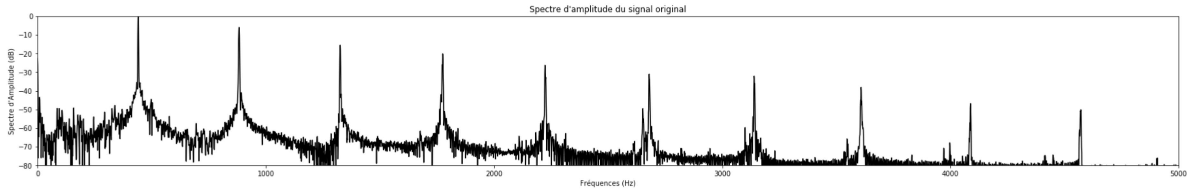
In [15]:

```
frequencies = np.arange(Nfft)*df  # equivalent to np.fft.fftfreq(n=Nfft, d=timestep)
X_fft = np.abs(x_fft) # absolute value of FFT (phase doesn't play a role)
```

Plot FFT spectrum

In [16]:

```
plt.figure(figsize=(30, 4))
plt.plot(frequencies[:int(Nfft/2)], 20*np.log10(X_fft[:int(Nfft/2)]), color='k')
plt.xlim(0, 5000)
plt.ylim(-80, 0)
plt.xlabel('Fréquences (Hz)')
plt.ylabel('Spectre d\'Amplitude (dB)')
plt.title('Spectre d\'amplitude du signal original')
plt.show()
```



For **A4_piano.wav**, we clearly see the harmonic around ~ 440 Hz and partials (multiples of the fundamental frequency peak).

II - Fundamental frequency estimation by spectral product/sum method

The different steps include :

#loop on the number of pitches

```
- example criterion could use an energy ratio "while criterion > seuil_F0"
```

#Detection of main F0

```
    -Compute spectral sum
    -locate maximum
    -store value of estimated F0
```

#Subtraction of main note (Main F0 with its harmonics)

```
    -localisation of harmonics around theoretical values (with or without inharmon
icy coefficient)
    - beta: harmonicity coefficient ;  alpha: coefficient of tolerance

    - Harmonic suppression (wideness of an harmonic to be suppressed depends on th
e main lob of the TF of the analysis window); suppression of harmonics is done on
 abs(Xk) on forcing all values of a harmonic peak to the minimum value of the peak
 (e.g. the level of noise).
```

#end of loop

In [17]:

```
Fmin=100             # Minimal F0 frequency that can be detected
Fmax=900             # Maximal F0 frequency that can be detected
H=4                  # H = nombre de versions compressées
Rmax = ceil((Nfft-1)/(2*H)) # fréquence maximale
```

In [18]:

```
Nmin = f2idx(Fmin,df)-1
Nmax = f2idx(Fmax,df)
assert Nmax <= Rmax and Nmin >= 0
```

Functions sum and product

In [19]:

```
def spectral_prod(x, R, H):
    """
    Spectral Product
    """
    prod=[]
    i=1
    while(i<R):
        s=1
        for h in range(H):
            s*=x[h*i]
        prod.append(s)
        i+=1
    return np.array(prod)


def spectral_sum(x, R, H):
    """
    Spectral sum
    """

    summ=[]
    i=1
    while(i<R):
        s=0
        for h in range(H):
            s+=x[h*i]
        summ.append(s)
        i+=1
    return np.array(summ)


def spectral_method(x, R, H, method='product'):
    """
    Factorization of previous methods
    """
    assert method in ['sum', 'product']
    if method == 'sum':
        return spectral_sum(x, R, H)
    else:
        return spectral_prod(x, R, H)
```

Maximum Search

In [20]:

```
method = 'product'
P = spectral_method(X_fft, Rmax, H, method)
```

In [21]:

```
(np.argmax(P)+1)*df
```

Out[21]:

```
441.40625
```

In [22]:

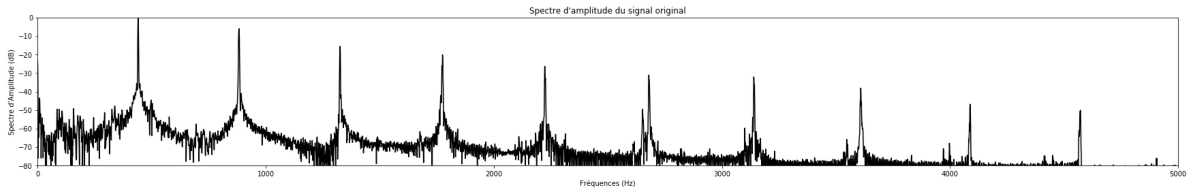
```
def spectral_energy(x, R):
    s=0
    i=0
    while(i<R):
        s+=x[i]**2
        i+=1
    return s
seuil=spectral_energy(X_fft,Rmax)
```

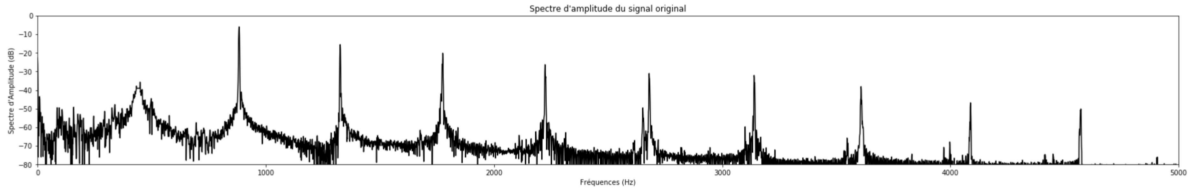
> About inharmonicity : In the lower half of the piano compass, a variation range of 0<beta<0.0007 would be reasonbale. We can determine beta by : *the analysis of synthesized tones with known inharmonicity and comparison between the measured width of pitch peaks with predictions* optimizing method : find the maximum amplitude of the pitch peak by variation in a parameter (like MLE maximum likelihhod estimation), this is done by introducing n inharmonicity scaling factor in the spectral product

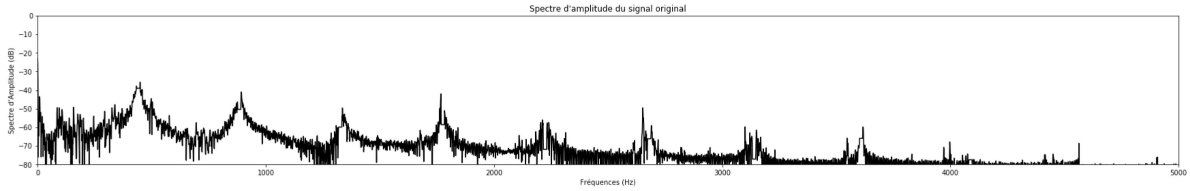
with spectral sum

In [23]:

```
from math import sqrt
plt.figure(figsize=(30, 4))
plt.plot(frequencies[:int(Nfft/2)], 20*np.log10(X_fft[:int(Nfft/2)]), color='k')
plt.xlim(0, 5000)
plt.ylim(-80, 0)
plt.xlabel('Fréquences (Hz)')
plt.ylabel('Spectre d\'Amplitude (dB)')
plt.title('Spectre d\'amplitude du signal original')
plt.show()
xtemp=deepcopy(X_fft)

method='sum'
while(spectral_energy(xtemp,Rmax)>seuil/100):

    P = spectral_method(xtemp, Rmax, H, method)
    indmax=np.argmax(P)+1

    f0=indmax*df
    k=1

    while k*f0<frequencies[-1] :

        beta=0.00030 # or 0 if without inharmonicy coefficient, Here we are dealing with an
        finhar=k*f0*sqrt(1+k*k*beta)
        alpha=df/(finhar) # or df\f0, there are many choices to alpha whether constant ( th
        # it shoud verify  (1+alpha)fk-(1-alpha)>=2df ie alpha>=df/fk

        kmin=ceil(min(((1-alpha)*finhar),frequencies[-1] )/df)

        kmax=ceil(max(((1+alpha)*finhar),frequencies[-1] )/df)

        ind_fk=np.argmax(xtemp[kmin:kmax+1])+kmin
        fk=ind_fk*df

        eps=1
        wind=(4+eps)/0.7
        k1=ceil((fk-wind)/df)
        k2=ceil((fk+wind)/df)

        xtemp[k1:k2]=min(xtemp[k1:k2])
        k+=1

    plt.figure(figsize=(30, 4))
    plt.plot(frequencies[:int(Nfft/2)], 20*np.log10(xtemp[:int(Nfft/2)]), color='k')
    plt.xlim(0, 5000)
    plt.ylim(-80, 0)
    plt.xlabel('Fréquences (Hz)')
    plt.ylabel('Spectre d\'Amplitude (dB)')
    plt.title('Spectre d\'amplitude du signal original')
    plt.show()
```



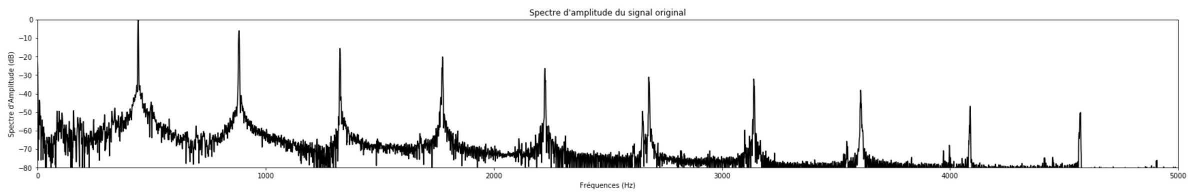


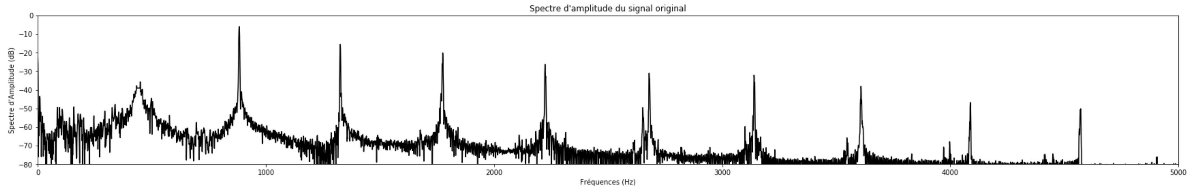


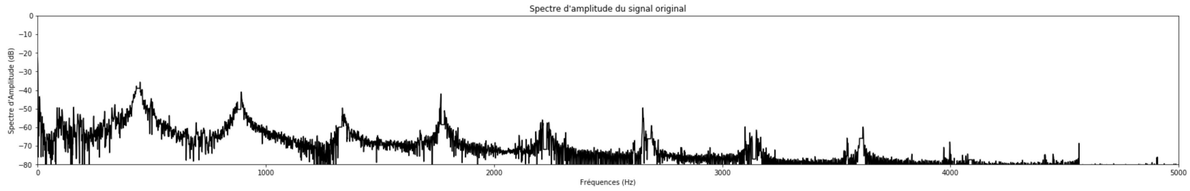
with spectral product

In [24]:

```
from math import sqrt
plt.figure(figsize=(30, 4))
plt.plot(frequencies[:int(Nfft/2)], 20*np.log10(X_fft[:int(Nfft/2)]), color='k')
plt.xlim(0, 5000)
plt.ylim(-80, 0)
plt.xlabel('Fréquences (Hz)')
plt.ylabel('Spectre d\'Amplitude (dB)')
plt.title('Spectre d\'amplitude du signal original')
plt.show()
xtemp=deepcopy(X_fft)

method='product'
while(spectral_energy(xtemp,Rmax)>seuil/100):

    P = spectral_method(xtemp, Rmax, H, method)
    indmax=np.argmax(P)+1

    f0=indmax*df
    k=1

    while k*f0<frequencies[-1] :

        beta=0.00030 # or 0 if without inharmonicy coefficient, Here we are dealing with an
        finhar=k*f0*sqrt(1+k*k*beta)
        alpha=df/(finhar) # or df\f0, there are many choices to alpha whether constant ( th
        # it shoud verify  (1+alpha)fk-(1-alpha)>=2df ie alpha>=df/fk

        kmin=ceil(min(((1-alpha)*finhar),frequencies[-1] )/df)

        kmax=ceil(max(((1+alpha)*finhar),frequencies[-1] )/df)

        ind_fk=np.argmax(xtemp[kmin:kmax+1])+kmin
        fk=ind_fk*df

        eps=1
        wind=(4+eps)/0.7
        k1=ceil((fk-wind)/df)
        k2=ceil((fk+wind)/df)

        xtemp[k1:k2]=min(xtemp[k1:k2])
        k+=1

    plt.figure(figsize=(30, 4))
    plt.plot(frequencies[:int(Nfft/2)], 20*np.log10(xtemp[:int(Nfft/2)]), color='k')
    plt.xlim(0, 5000)
    plt.ylim(-80, 0)
    plt.xlabel('Fréquences (Hz)')
    plt.ylabel('Spectre d\'Amplitude (dB)')
    plt.title('Spectre d\'amplitude du signal original')
    plt.show()
```







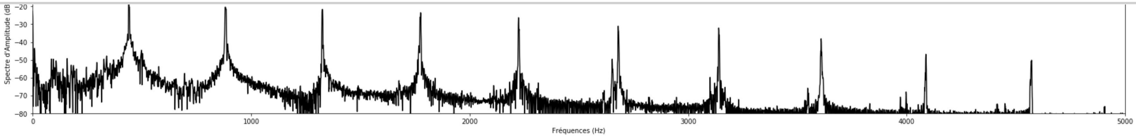
> We notice that the spectral product forces the harmonic to the level of noise better than the spectral product, (there are some small peaks remaining with the spectral sum). We notice also that the spectral product takes one more iteration than the spectral sum method.

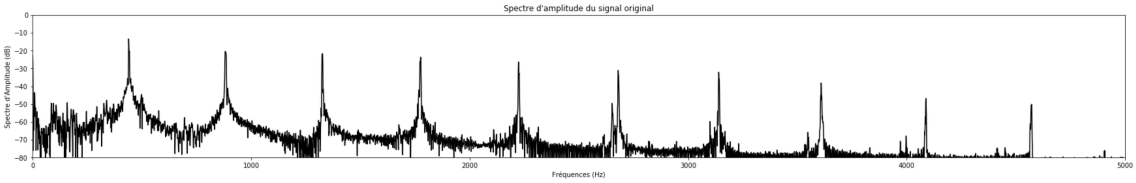
Harmonic suppression with spectral smoothness principle

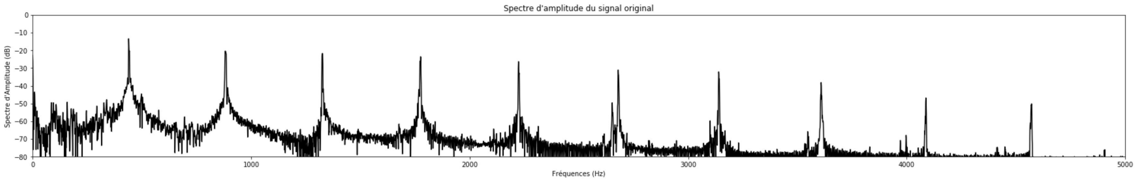
In [25]:

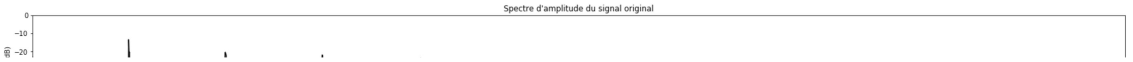
```
from math import sqrt
plt.figure(figsize=(30, 4))
plt.plot(frequencies[:int(Nfft/2)], 20*np.log10(X_fft[:int(Nfft/2)]), color='k')
plt.xlim(0, 5000)
plt.ylim(-80, 0)
plt.xlabel('Fréquences (Hz)')
plt.ylabel('Spectre d\'Amplitude (dB)')
plt.title('Spectre d\'amplitude du signal original')
plt.show()
xtemp=deepcopy(X_fft)

method='sum'
while(spectral_energy(xtemp,Rmax)>seuil/100):

    P = spectral_method(xtemp, Rmax, H, method)
    indmax=np.argmax(P)+1

    f0=indmax*df
    k=1
    harmonics=[indmax,indmax]

    while k*f0<frequencies[-1] :

        beta=0.00030 # or 0 if without inharmonicy coefficient, Here we are dealing with an
        finhar=k*f0*sqrt(1+k*k*beta)
        alpha=df/(finhar) # or df\f0, there are many choices to alpha whether constant ( th
        # it shoud verify  (1+alpha)fk-(1-alpha)>=2df ie alpha>=df/fk

        kmin=ceil(min(((1-alpha)*finhar),frequencies[-1] )/df)

        kmax=ceil(max(((1+alpha)*finhar),frequencies[-1] )/df)

        ind_fk=np.argmax(xtemp[kmin:kmax+1])+kmin
        fk=ind_fk*df
        harmonics.append(ind_fk)


        k+=1
    harmonics.append(ind_fk)

    for j in range(1, len(harmonics)-1):
        smoothspectrum=(xtemp[harmonics[j-1]]+xtemp[harmonics[j]]+xtemp[harmonics[j+1]])/3
        diff=xtemp[harmonics[j]]-smoothspectrum
        xtemp[harmonics[j]]=smoothspectrum
        eps=1
        wind=(4+eps)/0.7
        k1=ceil((fk-wind)/df)
        k2=ceil((fk+wind)/df)
        if diff<0 :
            xtemp[k1:k2]=min(xtemp[k1:k2])
        else:
            xtemp[k1:k2]= diff


    plt.figure(figsize=(30, 4))
    plt.plot(frequencies[:int(Nfft/2)], 20*np.log10(xtemp[:int(Nfft/2)]), color='k')
    plt.xlim(0, 5000)
    plt.ylim(-80, 0)
    plt.xlabel('Fréquences (Hz)')
```

```
    plt.ylabel('Spectre d\'Amplitude (dB)')
    plt.title('Spectre d\'amplitude du signal original')
    plt.show()
```









In [ ]:

```
```