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Dissertation

Master in Computer Engineering – Mobile Computing

Automatic Transcription of Music using Deep Learning Techniques

André Ferreira Gil

Leiria, 31st of March 2019

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Master in Computer Engineering – Mobile Computing

Automatic Transcription of Music using Deep Learning Techniques

André Ferreira Gil

Dissertation developed under the supervision of Professor Carlos Fernando Almeida Grilo, Professor Gustavo Miguel Jorge Reis and Professor Patrício Rodrigues Domingues, from the School of Technology and Management of the Polytechnic Institute of Leiria.

Leiria, 31st of March 2019

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Previous note

The following publication has resulted from this dissertation: (Gil et al., 2018d)

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Resumo

A transcrição de música consiste em identificar as notas musicais ao longo duma música. Esta é uma tarefa árdua que geralmente requer pessoas com muitos anos de treino. Devido à sua enorme dificuldade, tem havido um grande interesse em automatizar esta tarefa. No entanto, a transcrição automática de música engloba vários campos de pesquisa, tais como o processamento sinal, aprendizagem de máquina, teoria musical e cognição e percepção de pitch e de psicoacústica. Deste modo uma possível solução ao problema torna-se difícil de encontrar.

Neste trabalho é apresentado uma nova abordagem de transcrição automática de música de piano usando técnicas de aprendizagem profunda. Tiramos proveito deste tipo de técnicas para criar vários classificadores, sendo cada um deles responsável por identificar uma única nota musical. Em teoria, esta técnica de *divide to conquer* pode permitir melhorar a capacidade de transcrição de cada classificador.

É de realçar que também são aplicadas duas etapas adicionais denominadas por, pré-processamento e pós-processamento, com o intuito de aperfeiçoar a eficiência do nosso sistema. A fase de pré-processamento visa aumentar a qualidade dos dados de entrada antes de iniciar o processo de classificação, enquanto que a fase de pós-processamento visa em corrigir erros originados durante a fase de classificação.

Inicialmente, foram realizadas experiências preliminares de modo a otimizar o nosso modelo final ao longo das três etapas: pré-processamento, classificação e pós-processamento. O modelo resultante é finalmente comparado com outros dois trabalhos recentes que utilizam tanto a mesma técnica de inteligência artificial como também o mesmo conjunto de dados de treino e teste, mas com outro tipo de abordagem. A abordagem utilizada por estes trabalhos consiste em criar uma única rede neuronal responsável em identificar todas a notas musicais, em vez de uma rede neuronal por cada nota. No fim, é demonstrado que a nossa abordagem é capaz de superar os dois outros trabalhos em métricas de *frame-based* e ao mesmo tempo, alcançar resultados similares em métricas de *onset only*, demonstrando assim a viabilidade da abordagem.

Palavras-chave: *Transcrição Automática de Música, processamento de sinal digital, redes neuronais artificiais, aprendizagem computacional e aprendizagem profunda.*

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Abstract

Music transcription is the problem of detecting notes that are being played in a musical piece. This is a difficult task that only trained people are capable of doing. Due to its difficulty, there have been a high interest in automate it. However, automatic music transcription encompasses several fields of research such as, digital signal processing, machine learning, music theory and cognition, pitch perception and psychoacoustics. All of this, makes automatic music transcription an hard problem to solve.

In this work we present a novel approach of automatically transcribing piano musical pieces using deep learning techniques. We take advantage of deep learning techniques to build several *classifiers*, each one responsible for detecting only one musical note. In theory, this division of work would enhance the ability of each classifier to transcribe. Apart from that, we also apply two additional stages, pre-processing and post-processing, to improve the efficiency of our system. The pre-processing stage aims at improving the *quality of the input data* before the classification/transcription stage, while the post-processing aims at fixing errors originated during the classification stage.

In the initial steps, preliminary experiments have been performed to fine tune our model, in both three stages: pre-processing, classification and post-processing. The experimental setup, using those optimized techniques and parameters, is shown and a comparison is given with other two state-of-the-art works that apply the same dataset as well as the same deep learning technique but using a different approach. By different approach we mean that a single neural network is used to detect all the musical notes rather than one neural network per each note. Our approach was able to surpass in frame-based metrics these works, while reaching close results in onset-based metrics, demonstrating the feasability of our approach.

Keywords*: Automatic Music Transcription, multi-pitch estimation, digital signal processing, artificial neural networks, machine learning and deep learning.*

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List of acronyms

AI	- Artificial intelligence.
AMT	- Automatic music transcription.
ANN	- Artifical neural network.
CGP	- Cartesian genetic programming.
CNN	- Convolutional neural network.
CSV	- Comma Separated Values.
DFT	- Discrete Fourier Transform.
DSP	- Digital signal processing.
F0	- Fundamental frequency.
FFT	- Fast Fourier Transform.
GA	- Genetic algorithm.
HMM	- Hidden Markov Model.
Hz	- Hertz.
JPEG	- Joint Photographic Expercts Group.
KHz	- Kilohertz.
MIDI	- Musical Instrument Digital Interface.
NMF	- Non-negative matrix factorization.
RNN	- Recurrent neural network.
STD	- Standard deviation.
STFT	- Short-Time Fourier Transform.
SVM	- Support vector machine.
URL	- Uniform Resource Locator.

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1. Introduction

Music transcription is the process of discovering the musical notes that are present in a musical piece. This process is usually done by experts by hear and it takes several years of training until they are able to do it reasonably well.

Automatic music transcription (AMT) consists in the same process done by a machine. According to Reis (Reis, 2012), the process of transcription is composed by two main tasks (see Figure 1.1): 1) extraction of the piano-roll notation and; 2) the conversion of the actual piano-roll into a score.

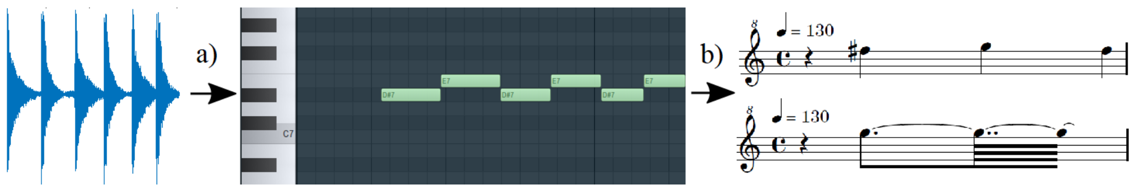


Figure 1.1 - The two main tasks of the transcription process. a) Extraction of the piano-roll notation taken from the music. b) Conversion of the piano-roll into a score.

It is worth mentioning, however, that AMT is mainly addressed as the extraction of the piano-roll notation. The conversion of the piano-roll into a score is, in fact, considered a different problem (Cemgil et al., 2006).

AMT can be decomposed into several sub-problems: pitch estimation, note onset/offset detection, loudness estimation and quantization, instrument recognition, extraction of rhythmic information and time quantization (Benetos et al., 2013). In this work, we mainly focus on one sub-problem called pitch estimation, or more specifically multi-pitch estimation. *Pitch estimation* consists in extracting the pitch of each musical note. In general, this transcription is done by splitting a musical piece into smaller chunks, called *frames* and then, afterwards, transcribe each one (see Figure 1.2).

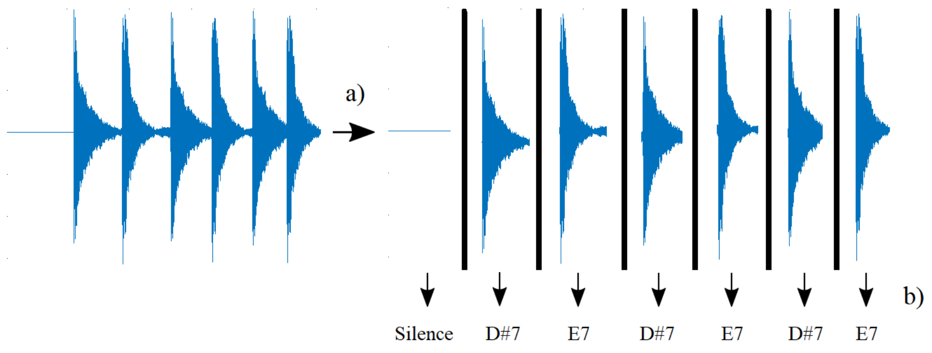


Figure 1.2 - Common approach for pitch estimation process. a) Splitting the music in frames. b) Transcribing each frame.

On the other hand, *multi-pitch estimation* consists in the same process as pitch estimation but applied to polyphonic music. This process is much harder because there are much more factors that influence the quality of the signal, like, the overlapping of multiple notes and the characteristics of each instrument used. We can think of multi-pitch estimation as the process of discovering the ingredients of a given soup. Dominant ingredients can be easier to distinguish among all the flavors but secondary ones can be missed.

Many research works have been done focusing on the AMT problem. Some of these works are even in the market, as, it is the case of the *AnthemScore* (Lunaverus, n.d.). However, so far, none of these works has been able to reach, let alone surpass the human level in music transcription (Klapuri and Davy, 2007), (Sigtia et al., 2016a), (Bereket and Shi, 2017) and (Hawthorne et al., 2018), making this area still a very active research area.

1.1. Motivation

As mentioned above, AMT is the process[1] of transcribing music automatically for which no suitable solution has been found so far. In general, this process is commonly though as a monolithic process where only one system is responsible for transcribing all the musical notes in a tune (see Figure 1.3). However, we can also think of it as a main process that contains multiple sub-processes, each one being responsible for detecting only one musical note (see Figure 1.4). This last point of view, is the one taken in this work. This approach that is also technically referred as *divide to conquer* technique is a common approach to be applied when dealing with hard problems. This is due to the fact that each sub-problem should be easier to solve. In this case, we refer to sub-processes as *classifiers*.

[1] When we refer to AMT as a process we are talking about the actual mechanical process of transcribing music.

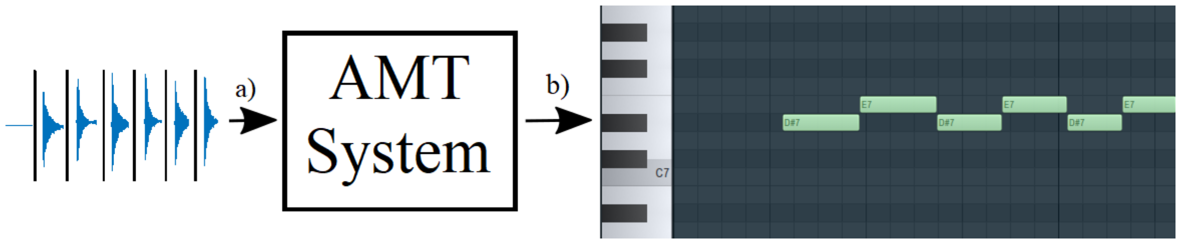


Figure 1.3 - Monolithic process for transcribing musical notes. a) Insertion of frames into the AMT system. b) Notes that the AMT system can detect. c) Transcription result.

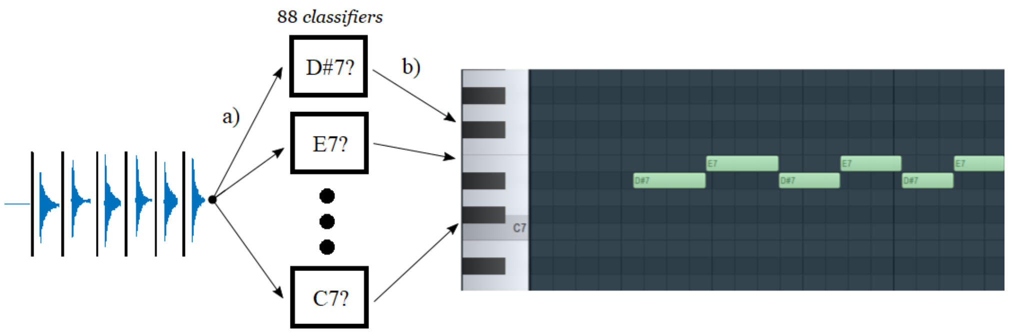


Figure 1.4 - Multiple classifiers, each one responsible for detecting a specific musical note. a) Insertion of the frames into each classifier. b) Transcription result from each classifier.

For this purpose, we built 88 classifiers, each one responsible for detecting a specific note. Please, keep in mind that, from now on we refer to this “new” approach as the *one-classifier-per-note* approach and the previous one (monolithic process) as the traditional approach.

Some previous research works in AMT, have already adopted the one-classifier-per-note approach, as for example in (Marolt, 2004), (Poliner and Ellis, 2007), (Zalani and Mittal, 2014) and (Leite et al., 2016). However, in none of these works, it is possible to fully compare both approaches, due to the usage of a different technique to detect notes and/or due to a different dataset. As a result, a comparison between both approaches is presented in this work.

1.2. Goals and contributions

The main goal of this project is to present the one-classifier-per-note approach based on machine learning techniques. As mentioned above, this approach consists on having *n* classifiers, where each one is responsible for transcribing one note, instead of the traditional approach, of having one classifier responsible for transcribing all the notes. Additionally, it is also presented some post-processing steps to improve the final results.

The contributions of this project are as follows:

- To update the current state-of-the-art.
- To present a comparison between the one-classifier-per-note approach and the traditional one.
- To present different types of post-processing steps.
- To collaborate by opening the source code of both *scripts* for creating the datasets and also for training the classifiers and the post-processing units.
- To publish a paper in the Portuguese Conference on Pattern Recognition.

1.3. Dissertation structure

The structure of the rest of this document is as follows:

- Chapter 2, Background – This chapter contains the concepts and terminologies needed to understand this work;
- Chapter 3, Related work – In this chapter a summary of works related to our project of the AMT field are described;
- Chapter 4, Proposed model – In this chapter our approach for the AMT problem is presented;
- Chapter 5, Preliminary experiments – In this chapter an overview of the preliminary experiments accomplished in order to achieve our final model are present;
- Chapter 6, Results – This chapter comprises the results achieved from our model as well as a comparison with other state-of-the-art works;
- Chapter 7, Conclusion and future work – In this chapter some final thoughts and conclusions are presented, as well as future work.

2. Background

The problem of automatic music transcription is a vast problem that combines different fields, from sound concepts and music theory to different types of digital processing methods. As a result, in this chapter we present the terminology and concepts that are necessary in order to understand the meaning of this work.

This chapter is divided into four main sections: general concepts, digital signal processing, multi-pitch estimation and aritificial neural networks.

In the general concepts section, an overview of the terminology and basic concepts is given. In the digital signal processing section, more advanced topics regarding signal processing are introduced. The multi-pitch estimation section compares single with multi pitch estimation. It also presents the main problems that can arise with pitch estimation problems. To finish, in the artificial neural networks section, an explanation about the artificial neural networks technique and its several variations are presented.

2.1. General concepts

Music is a form of art that is transmitted through sound. Thus, when dealing with music transcription, concepts regarding sound are also very important in order to achieve a good transcription.

In this section, basic concepts and terminologies such as what is referred as sound, the differences between digital and real-world sound, how a digital sound can have good quality, how a sound can be categorized and the main characteristics of the music, will be addressed.

2.1.1. Sound waves

We refer to sound as vibrations in some medium. Those vibrations, also called cycles, occur when the air is compressed (high pressure), rarefacted (low pressure) and finally returns to its original state. In general, human beings are able to hear vibrations from 20 to 20 000 times per second or, more technically, from 20 Hertz (Hz) to 20 Kilohertz (KHz), approximately. Any sound with a frequency bellow 20Hz is refered to as infrasound and above 20KHz as ultrasound.

In general, we visualize those vibrations in a digital format as, for example, in an oscillogram or in a computer program. These are represented as a function of time (see Figure 2.1), where time is represented horizontally (*x* axis) and pressures values (amplitude) are represented vertically (*y* axis).

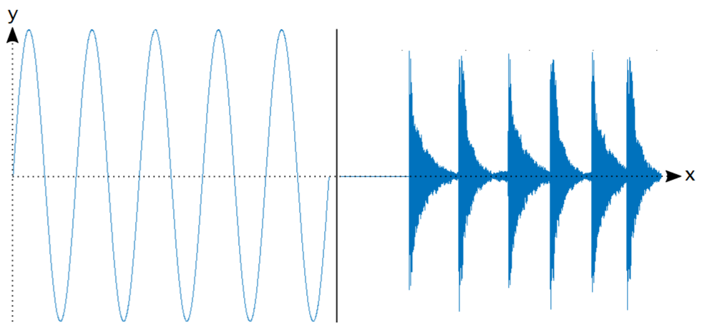


Figure 2.1 - Representation of the oscillations generated by a sound. The picture in the left side represents a sound generated mathematically and the picture in the right side shows a piano recording sound.

High levels of pressure (compression stage) are represented in the top part of the *y* axis, and low levels of pressure (rarefactor stage) in the bottom part of the *y* axis.

2.1.2. Digital audio recording

In the real world, the sound is continuous, or technically, it is referred as an analog signal. On the other side, in the digital world, the sound is discrete corresponding to an approximation of the reality (see Figure 2.2).

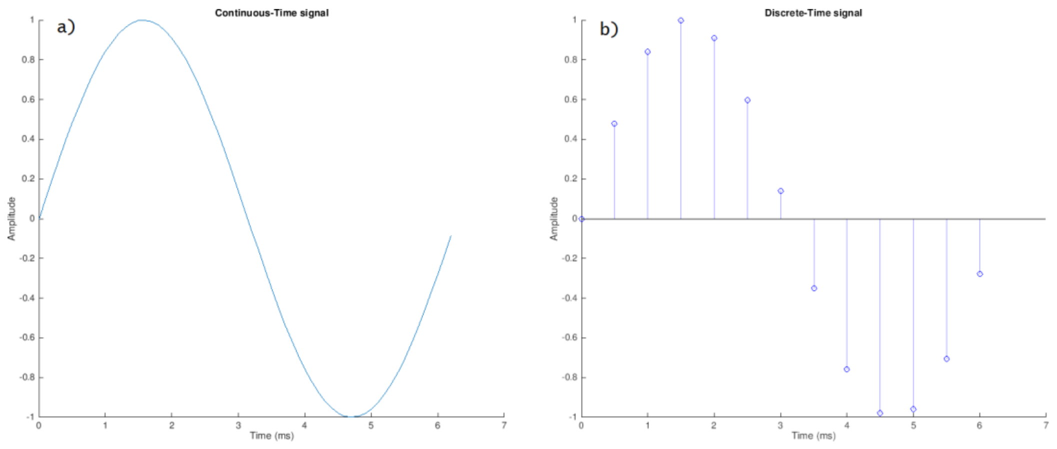


Figure 2.2 - Comparison of a continuous and a discrete signal. a) Continuous-time signal. b) Discrete-time signal.

Being the digital sound just an approximation, two main properties of it should be taken into account in order to have a good quality sound (close to the original sound): the *sampling rate* and the *sampling resolution*.

Sampling rate

The *sampling rate* consists of the number of times an analog signal is measured (sampled) per second. The higher the number of samples per second, the more similar the digital audio is to the analog signal. If the sampling rate is too low, the digital signal may have not enough resolution and it can be considerably different from the corresponding analog version (see Figure 2.3).

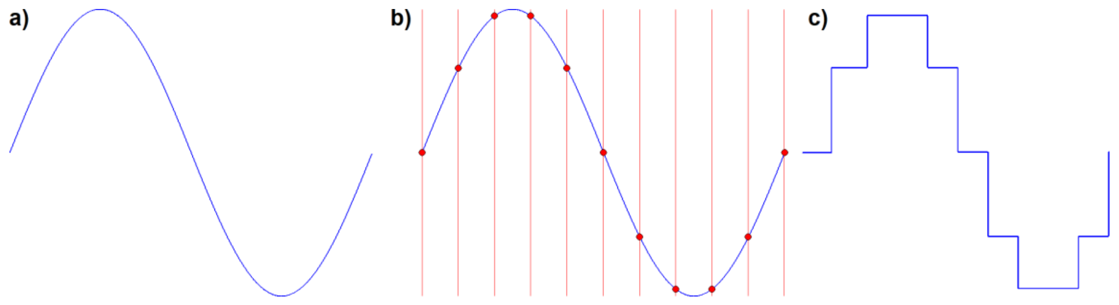


Figure 2.3 - Low sampling rate problem. a) Sine wave. b) Low sampled sine wave. c) Resulting sampled version of the low sampled wave.

To avoid the problem above, the *Nyquist theorem* can be applied to determine the minimum sampling rate (see Figure 2.4). This theorem specifies that, the sampling rate must be at least twice the highest analog frequency component. Mathematically, this can be expressed as the following:

$$Fs \geq 2 * Fmax, \tag{24.1}$$

where *Fs* represents the sampling rate and *Fmax* represents the highest frequency contained in the analog signal.

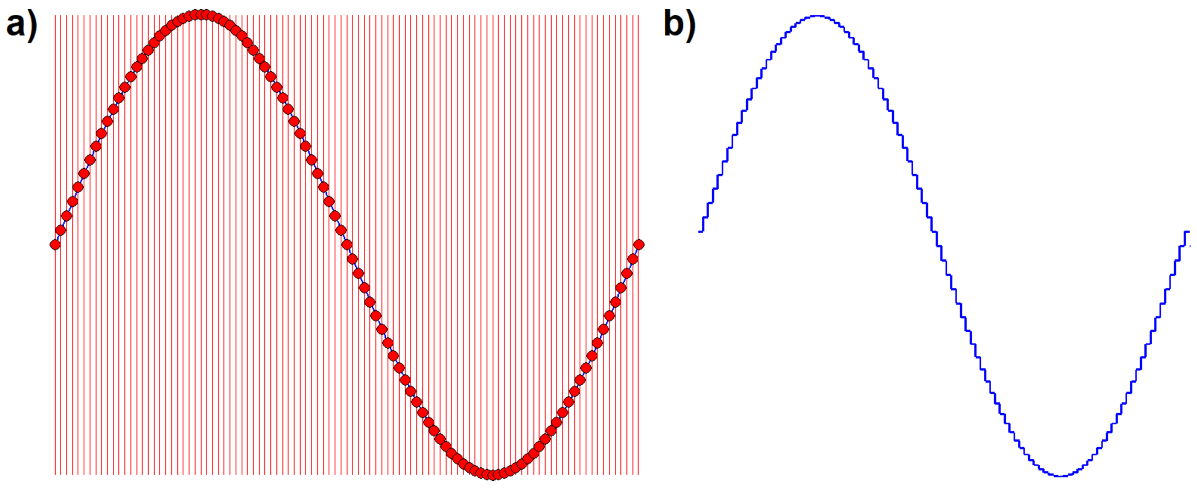


Figure 2.4 - An example of a digital sound that follows the Nyquist theorem. a) High sampled sine wave. b) Resulting digital version of the sampled sine wave.

Sampling resolution

In the process of converting an analog signal to digital, the samples are stored as the closest amplitude value from the real one, within a set of possible values, technically refered to as *levels*. These levels depend on the *bit depth* used. The bit depth corresponds to the amount of bits available to characterize one sample (Figure 2.5). One bit of resolution contains two different values (0 or 1), a two bit resolution could store four different values (00, 01, 10, 11), a four bit could store 16 different values, a eight bit could store 256 different values, sixteen bit could store 65536 values, and so on. In the industry, 16-bit is the sampling resolution adopted for the *Compact Disc* (CD) to reproduce high quality music.

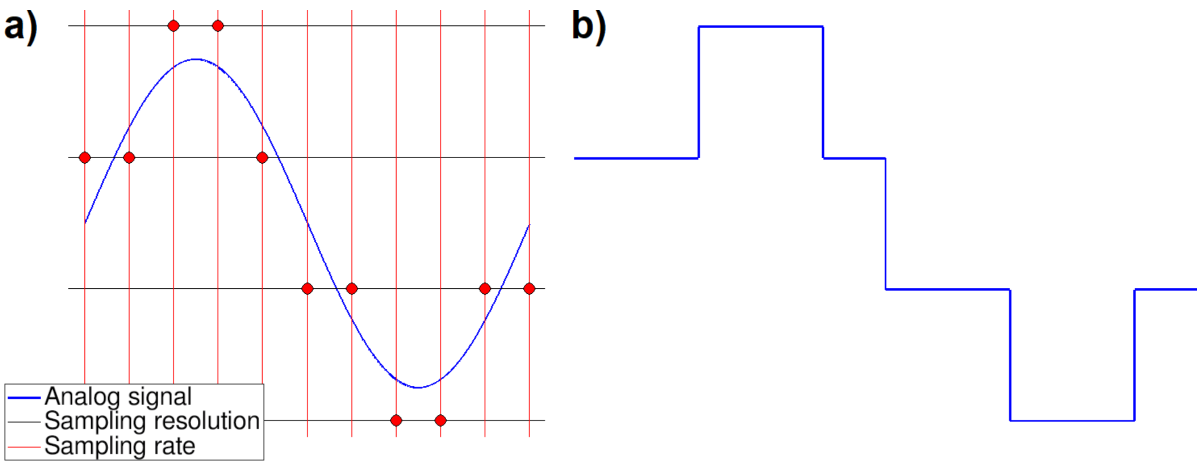


Figure 2.5 - Digital signal with a bit depth of 2. a) Sampled signal. b) Resulting digital signal with bit depth of 2.

2.1.3. Types of signal

Until now, we presented two types of signals, continuous-time signals and discrete-time signals. However, a signal can also be categorized into two categories: *non-periodic* or *periodic*.

A signal is denominated as periodic, when it repeats itself in another point of time (see Figure 2.6), while non-periodic the opposite scenario. Mathematically speaking, a periodic signal must follow the following equation:

$$\tilde{x}(t) = \tilde{x}(t + mT), m \in \mathbb{Z}, \qquad (24.2)$$

where T is a real number. The lowest positive value of T where the equation above is still true, it is referred to as the period of the fundamental component and it is represented as T_0.

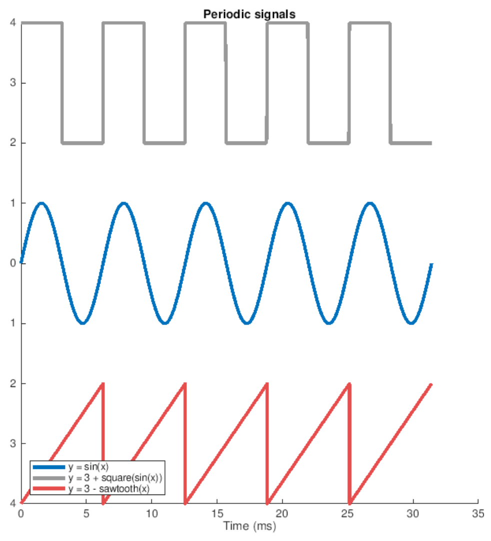


Figure 2.6 - Three examples of periodic signals.

Also, a signal can be considered quasi-periodic when some discrete amplitude values are almost periodic (Figure 2.7), being the wave shape very similar in each repetition cycle but not exactly the same.

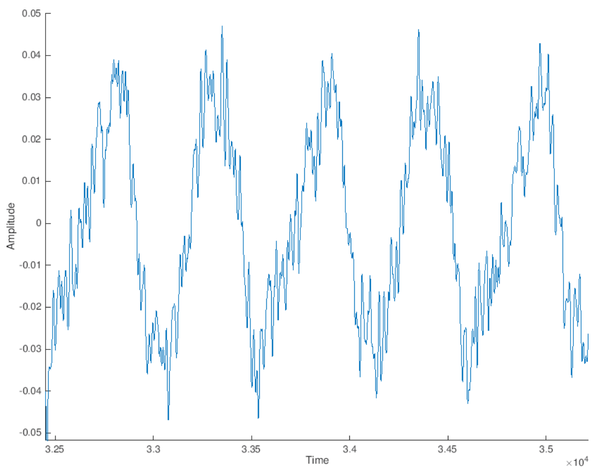


Figure 2.7 - Representation of a quasi-periodic signal. This sound was generated by a virtual piano software, playing the note E1.

2.1.4. Music characteristics

As mentioned previously, music is a form of art in which feelings, values and ideas are transmited through sound. Each played musical note has four fundamental characteristics: *dynamics*, *duration*, *timbre* and *pitch*.

Dynamics or note velocity in *Musical Instrument Digital Interface* (MIDI) terminology (Association, 1999) is the characteristic that refers to the volume or loudness of a sound. The most common dynamic indications are known as *pianissimo* (very soft), *piano* (soft), *forte* (loud) or *fortissimo* (very loud).

Duration is the time interval during which the musical note lasts. The moments in which the sound starts and ends are designated by *onset* and *offset*, respectively.

Timbre represents the type of the sound. It is the shape of the sound wave. This characteristic is what makes us differentiate a piano sound from a person singing.

Pitch is the tonal height of a sound. It represents how low or high a note sounds and it is closely related to the frequency: the physical property. In addition to that, it is the characteristic responsible for distinguishing different notes of the same instrument.

2.2. Digital signal processing

Digital signal processing (DSP), a sub-field of signal processing, consists in the application of computational methods on digital signals in order to extract features, which are used in analysis, classification, recognition or transformation problems.

The file format, *Joint Photographic Expercts Group* (JPEG), is a good example of where these techniques are applied in order to compress the size of images (Bako, 2004). Additionally, DSP techniques are commonly applied in order to estimate the velocity or the distance travelled of an object, by detecting the shift on the frequency signal received from a radar (Giordano, 2009).

In this work, DSP techniques are also applied in order to reach our goal, that is, transcribe piano music. Thus, basic terminologies like the frequency unit and more advanced ones such as how a signal can be decomposed into frequencies and a deeper understanding of some DSP methods, with a special focus to the set of methods from the family of the *Fourier Transform*, are introduced. At the end, problems and possible solutions, if any, regarding these methods will also be presented.

2.2.1. Fourier analysis

As stated before, sound consists in cycles (back and forth) in a medium. The number of cycles per unit of time of a sound wave is named as *frequency*. A sound with a high frequency contains a large number of cycles and small wavelength (*period*). On the contrary, a sound with low frequency has less number of cycles and a larger wavelength (Figure 2.8).

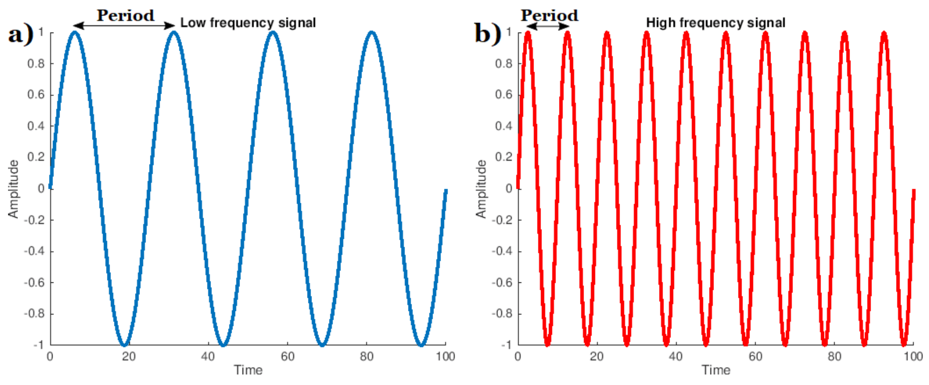


Figure 2.8 - Low and high frequency representation. a) Represents a low frequency sound wave. b) Represents a high frequency sound wave.

Jean-Baptiste Joseph Fourier was the first to have the vision that any continuous function could be represented as an infinite sum of simple sinusoids. That was later demonstrated to be true (Oppenheim et al., 1997). These sinusoids are simple waves mathematically represented by sines and cosines or complex exponentials. Due to the properties of those sound waves (sinusoids), it is possible to recover their frequency. It is important to point out that in a polyphonic signal, the sinusoid with the lowest frequency from all the sinusoids is considered as the *fundamental frequency* (F0). The F0, in music, is the main frequency closely related to the perceived musical pitch. Remember that the musical pitch is what makes us able to distinguish between different notes.

The process of decomposing a periodic signal into the sum of harmonics is known as *Fourier analysis* (Figure 2.9 a). The opposite process, of rebuilding a periodic function from those simple waves is denominated as *Fourier synthesis* (Figure 2.9 b).

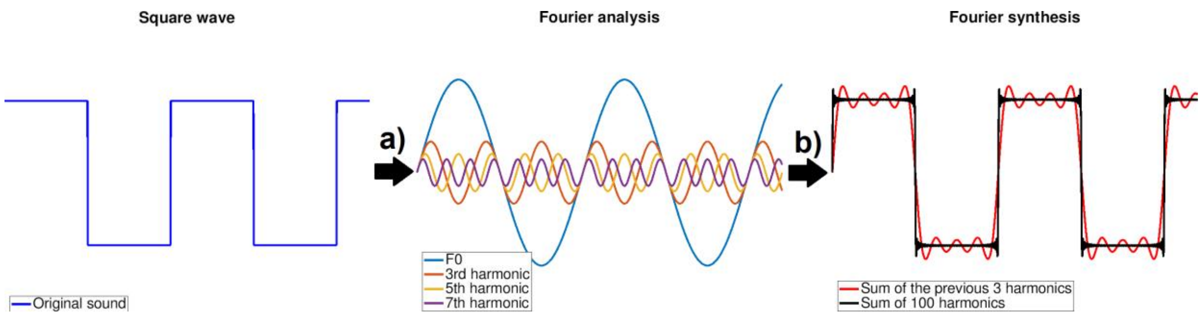


Figure 2.9 - Example of both the Fourier analysis and the Fourier synthesis processes. a) Decomposing signal into simple waves (Fourier analysis). b) Rebuilding a signal with simple waves (Fourier synthesis).

There are several known techniques to decompose a signal, depending on its characteristics: discrete or continuous and periodic or non-periodic. Within the scope of this work, the most important techniques are the *Fourier Series* and the *Discrete Fourier Transform (DFT)*.

Fourier Series can be applied to periodic and continous signals, and the Discrete Fourier Transform can be applied to quasi-periodic and discrete signals. As mentioned before, digital sound signals are discrete, hence it is important to keep in mind that only the DFT technique can be applied in this work.

Fourier series

Mathematically, the process of *Fourier synthesis* where the sum of infinite harmonics occurs, can be represented as follows:

$$\tilde{x} = \sum_{k=-\infty}^{+\infty} a_k e^{jk\omega_0 t}, k \in \mathbb{Z}, \tag{24.3}$$

where $\omega_0 = 2\pi F0 = \frac{2\pi}{T_0}$. An important point to consider in the Fourier series representation is that the harmonics forms an orthonormal set. This is relevant because the resulting integral and product will be zero. Hence, the process of *Fourier analysis* can be efficiently computed as follows:

$$a_k = \frac{1}{T_0}\int_{T_0} \tilde{x}(t) e^{-jk\omega_0 t}\, dt. \tag{24.4}$$

By readjusting the previous equation, of the *fourier synthesis* process, we have:

$$\tilde{x}(t) = a_0 + \sum_{k=1}^{+\infty}(a_k e^{jk\omega_0 t} + a_{-k}e^{-jk\omega_0 t}) = a_0 + \sum_{k=1}^{+\infty}(a_k e^{jk\omega_0 t} + a_k^* e^{-jk\omega_0 t}), \tag{24.5}$$

where $a_k^* = a_{-k}$. Finally, by considering a_k in the polar form as $a_k = \frac{A_k}{2} e^{j\phi k}$, we have a trigonometric equation as follows:

$$\tilde{x}(t) = a_0 + \sum_{k=1}^{+\infty} A_k \cos(k\omega_0 t + \phi_k). \tag{24.6}$$

This resulting equation (Equation 24.6) is frequently used for representing periodic signals in the Fourier series. If a sound can be represented using this last equation, it is called a *harmonic sound*. Since quasi-periodic signals have slightly different frequencies per each wave cycle, they are often cited as *partials*. Hence, an approximation of quasi-periodic signals is commonly used, with a finite number of harmonic components *H*:

$$\tilde{x}(t) \approx a_0 + \sum_{k=1}^{H} A_k \cos(k\omega_0 t + \phi_k). \tag{24.7}$$

Fourier Transform

Fourier transform and all its variations are techniques used to convert signals from the time domain (*time-amplitude*) into the frequency domain. These methods are commonly used by AMT systems because, as mentioned previouslly, pitch is a characteristic from music that gives us the possibility to distinguish notes from the same instrument and this characteristic is closely related to the frequency, making these methods highly relevant for the AMT problem.

The Fourier transform decomposes the signal into a sum of simple waves (fourier analysis) resulting in the frequencies of the signal. This technique is used for periodic continuous signals with infinite length as follows:

$$FT_{\tilde{x}}(f) = \tilde{X}(f) = \int_{-\infty}^{+\infty} \tilde{x}(t) e^{-j2\pi f t} dt. \tag{24.8}$$

Discrete Fourier Transform

As mentioned above, the Fourier Transform technique can only be applied to periodic continuous signals. However, a digital signal is discrete. Hence, another technique called *Discrete Fourier Transform* (DFT) is applied. The DFT can be calculated as follows:

$$DFT_{\tilde{x}}[k] = \tilde{X}[k] = \sum_{n=-\infty}^{+\infty} \tilde{x}[n]\, e^{-j2\pi k n}, \tag{24.9}$$

where *k* is the spectral bin corresponding to each frequency. In Equation 24.9, infinite discrete signals are targeted. However, infinite signals create computational problems. Thus, Equation 24.10 is defined to tackle this problem:

$$DFT_{\tilde{x}}[k] = \tilde{X}[k] = \sum_{n=0}^{N-1} \tilde{x}[n]\, e^{-j\frac{2\pi}{N}kn}, k = 0, \dots, N-1, \tag{24.10}$$

where *N* represents the length of the waveform (number of samples).

There are two main points that are necessary to be clarified here before we proceed. The first one, is that according to Shannon (1998), only the first half of the samples (until the *Nyquist* frequency) are relevant because the second half is just a mirror of the first half (Figure 2.10). The second point is that each value on the frequency domain represents a spectral bin, more specifically, it represents a range of frequencies and not just one frequency. For example, if a signal has 4096 samples and its sampling rate is 44100 Hz, each bin is linearly separated by $\Delta f = \frac{Fs}{N} = \frac{44100}{4096} \cong 10.77Hz$. Thus, each spectral bin k will contain a range of frequencies between $f_k = k * 10.77Hz \pm 10.77Hz$. As a result, some piano notes correspond to the same spectral bin, making the process of detecting notes harder.

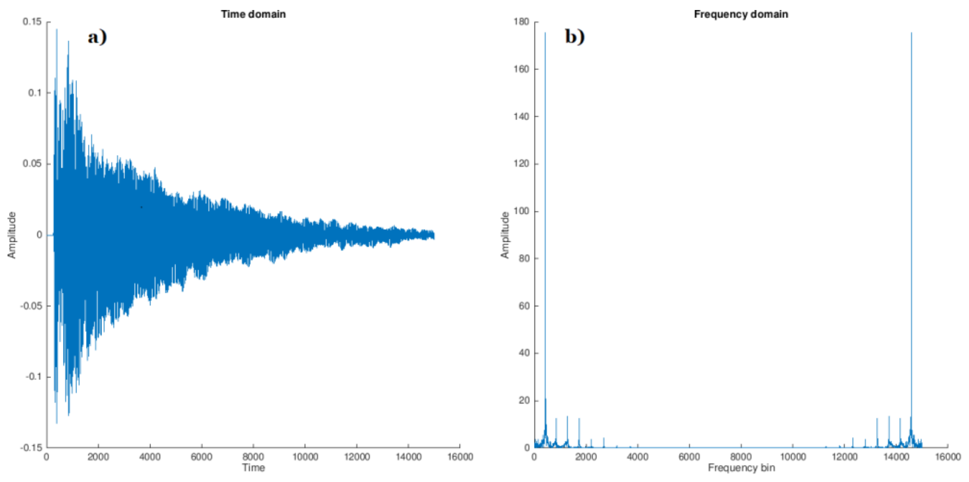


Figure 2.10 - A comparison of the same sound in two different domains. a) Sound in the time domain. b) Sound in the frequency domain.

Fast Fourier Transform

DFT is a common technique used for periodic discrete signals. However, this technique can be computationally expensive for real time applications, such as AMT systems. Thus, in order to fulfill this necessity, another technique called *fast Fourier Transform* (FFT) is used. This is the DSP technique applied in our work.

FFT is a fast algorithm which applies efficiently the DFT in a signal that contains a structured number of samples such as the power of two. This technique reduces the number of operations from $O(N^2)$, where N represents the number of samples, to $O(N * log_2 N)$ (Cooley et al., 1967).

2.2.2. Spectral leakage

The DFT and its variations assume that a signal is periodic. However, if the number of samples does not match with the whole number of periods, discontinuities will occur, leading to a distorted frequency representation. This event, known as *spectral leakage*, leads to frequencies being leaked or spread across adjacent frequency bins (see Figure 2.11).

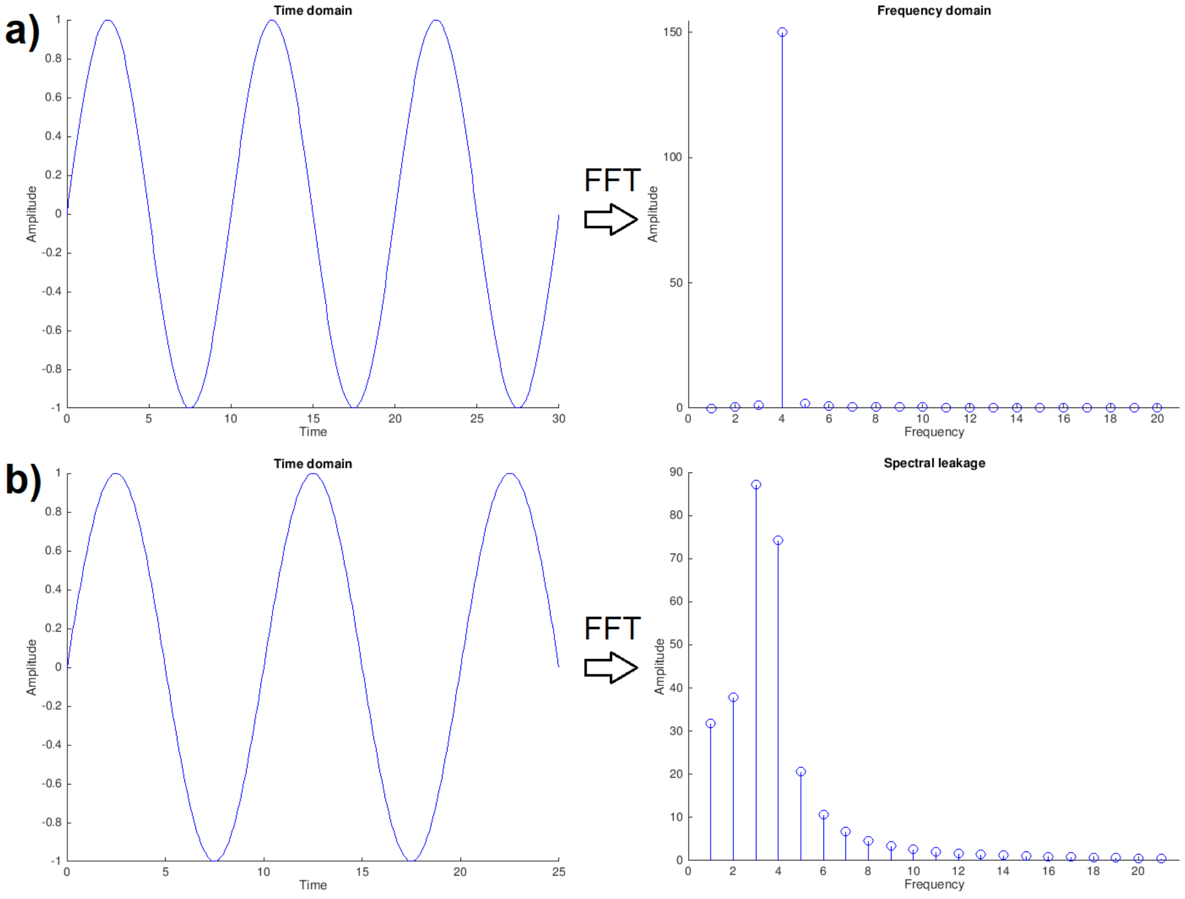


Figure 2.11 - Representation of the spectral leakage event. a) Signal with 30 samples, which corresponds to the whole number of periods. b) Signal with 25 samples causing the spectral leakage event, that can be viewed in the zoomed frequency spectrum on the right.

2.2.3. Windowing

In order to minimize the spectral leakage, a technique called *windowing* can be used, where the input signal is, firstly, multiplied by a smooth window, and only then the DFT is calculated. Resulting in a smoother frequency signal. There are several types of windows: rectangular, triangular, Hanning, Hamming, Blackman and Blackman-Harris. All of them have their pros and cons. A comparison can be found in (Harris, 1978). This technique can be calculated as follows:

$$Y_k = \sum_{n=0}^{N-1} a_n \tilde{x}_n W_N^{nk}, W = e^{-j2\pi}, \qquad (24.11)$$

where a_n is the the type of window.

2.2.4. Missing fundamentals

As mentioned previously, pitch is a characteristic that can be found in music and is closely related to a physical property called frequency. However, the pitch characteristic is also related to the spectral content and the loudness of a sound. This means that the frequency is not considered as a clear representation of the pitch characteristic. Therefore, when analysing the frequency of complex sounds, a phenomenum called *missing fundamental* commonly arises. For instance, when an audio signal is composed of two pure tones, one of them with 1000 Hz and another one with 1300 Hz, an additional tone would be perceived at 300 Hz (Figure 2.12).

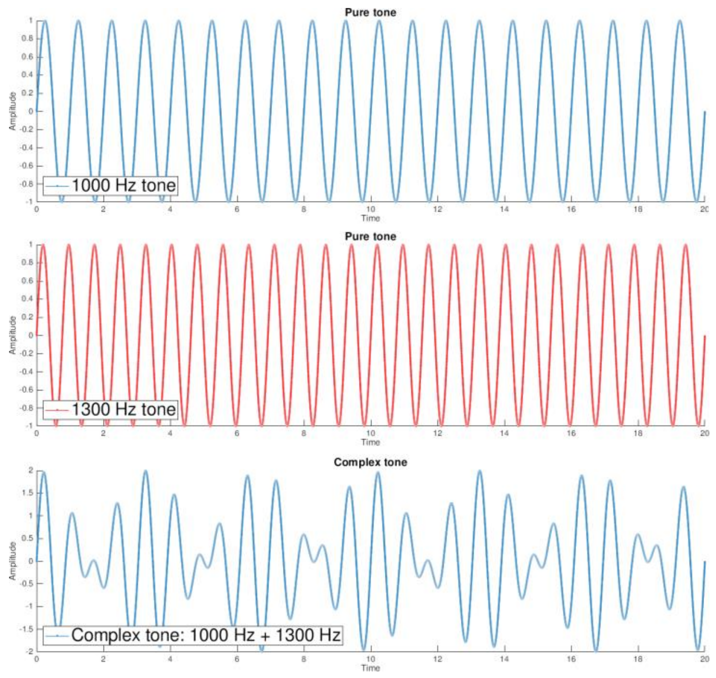


Figure 2.12 - An example of missing fundamental resulting at 300 Hz. a) 1000 Hz pure tone. b) 1300 Hz pure tone. c) complex tone: 1000 Hz + 1300 Hz pure tones.

Regardless, so far there are not any suitable solution to address this problem.

2.2.5. Pitch vs Fundamental frequency

Regarding the frequency of a given sound, a common error is made:

What is the frequency of the piano MIDI note number 55?

The sentence above is not completely correct because a piano note (like most of the sounds) do not contain a single frequency, but instead it is composed by several frequencies (harmonics). A better question would be the following one:

*What is the **fundamental** frequency of the piano MIDI note number 55?*

The *fundamental frequency* (F0), as mentioned previously, is the lowest frequency on an harmonic series and is the essential one in order to distinguish a pitch in a given signal. For instance, if a piano note sound has an F0 around 260Hz, our brain should be able to map it as a C4 pitch (see Table 2.1).

Table 2.1 - Corresponding frequency of each pitch, from C0 to B8.

Note	**Octave**								
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
C	16	33	65	131	262	523	1047	2093	4186
C#	17	35	69	139	278	554	1109	2218	4435
D	18	37	73	147	294	587	1175	2349	4699
D#	20	39	78	156	311	622	1245	2489	4978
E	21	41	82	165	330	659	1319	2637	5274
F	22	44	87	175	349	699	1397	2794	5588
F#	23	46	93	185	370	740	1475	2960	5920
G	25	49	98	196	392	784	1568	3136	6272
G#	26	52	104	208	415	831	1661	3322	6645
A	28	55	110	220	440	880	1760	3520	7040
A#	29	58	117	233	466	932	1865	3729	7459
B	31	62	124	247	494	988	1976	3951	7902

In the field of AMT two different terms are commonly confused: *F0 estimation* and *pitch estimation*. F0 estimation consists in the extraction of the exact frequency components of a signal and then match them to the pitches of the notes. The second process, pitch estimation, consists on determining the pitch from a given signal even without knowing exactly the F0 of the sound. This last process is the one applied in this dissertation.

2.3. Multi-pitch estimation

Multi-pitch estimation algorithms commonly assume that there can be two or more harmonic sources in the same short-time signal. According to Yeh et al. (2010), a signal can be expressed as a sum of harmonic signals plus the residual part:

$$y[n] = \sum_{m=1}^{M} y_m[n] + z[n]\,, \quad M > 0 \quad \text{with } y_m[n] \approx y_m[n + N_m], \qquad (24.12)$$

where n represents the discrete time index, M is the number of harmonic signals, $y_m[n]$ the quasi-periodic part of the mth source, N_m the period of the mth source and *z[n]* the residual part.

This combination of harmonic sources makes the process of estimating the pitches even harder. In a monophonic signal the notes are played separately and therefore, it does not suffer any type of distortion from other harmonic sources, which is not the case in a polyphonic signal (see Figure 2.13 and Figure 2.14).

Figure 2.13 - Representation of a monophonic signal, where each note (C#, C, D# and F#) are played separately.

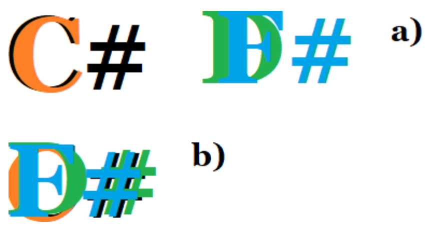


Figure 2.14 - Representation of a polyphonic signal. a) A chord of 2 notes (C# and C), been played simultaneously. b) A chord of 4 notes (C#, C, D# and F#) played simultaneously.

As it is possible to notice, the more harmonic sources a signal has, the harder the process of estimating the pitches.

In addition to that, other types of problems, can also occur, such as the distortion of a signal because of its residual components. The residual components are all the components that cannot be explained by simple waves (sinusoids), as for example the background noise, non-harmonic partials or spurious components.

In the following sections, several common problems regarding the multi-pitch estimation problem are presented.

2.3.1. Overlapping partials

As mentioned above, in polyphonic signals, different sources may overlap or interfere with each other. Those different sources can be considered in harmony if their fundamental frequencies (F_a and F_b) can be represented as follows:

$$F_a = \frac{m}{n} F_b, \qquad n, m \in \mathbb{N}, \tag{24.13}$$

in which every n^{th} partial of the source a overlaps every m^{th} partial of source b, as proved by Klapuri in (Klapuri, 1998). This augments the probability of partial collisions. Another issue demonstrated in (Yeh, 2008) occurs when the F0 of a note is multiple of another note's F0. In this case, the higher note can hide the lower one.

Interference and overlaping of different sources can disturb a signal in several ways, as its frequencies, amplitudes and phases. For instance, when two sources are superposed, the resulting sound wave would be a sum of those two sources. On the contrary, when there is a harmonic overlap, the resulting wave would have two simple harmonic motions with the same frequency but with different amplitude and phases.

There are several works in which the authors tried to detect those overlaping partials, which in the case of being successful could help in the process of multi-pitch estimation. In (Parsons, 1976) the author tried to detect those overlapping components based on three tests: spectral peak symmetry, distance and well-behaved phase. However, even with only two different sources, that is actually a very restrictive number of sources, the results were not good. Later on, several authors (Viste and Evangelista, 2002), (Virtanen, 2003), (Every and Szymanski, 2004) and (Yeh and Roebel, 2009) tried to address the problem by knowing in advance how many different sources existed in a given signal but unfortunatelly the results were poor. Thus, this problem remains a challenge.

2.3.2. Spectral characteristics

In a musical piece, it is common that several types of instruments are played simultaneously. This adds even more complexity to the transcription problem.

In the following three sub-sections, different types of instrument characteristics are present, such as: the spectral envelope, inharmonic partials and spurious components.

Spectral envelope

We refer to the spectral envelope, as the contour of the prominent peaks of a given signal, in which most of them are partials (see Figure 2.15). Each musical instrument has a different spectral envelope, as for example pianos and trumpets. Even instruments of the same family, as for instance two pianos, have slightly different spectral envelopes. According to Jensen (Jensen, 1999), Loureiro et al. (Loureiro et al., 2004) and Burred et al. (Burred et al., 2006), still an universal model that generalizes different types of instruments needs to be developed.

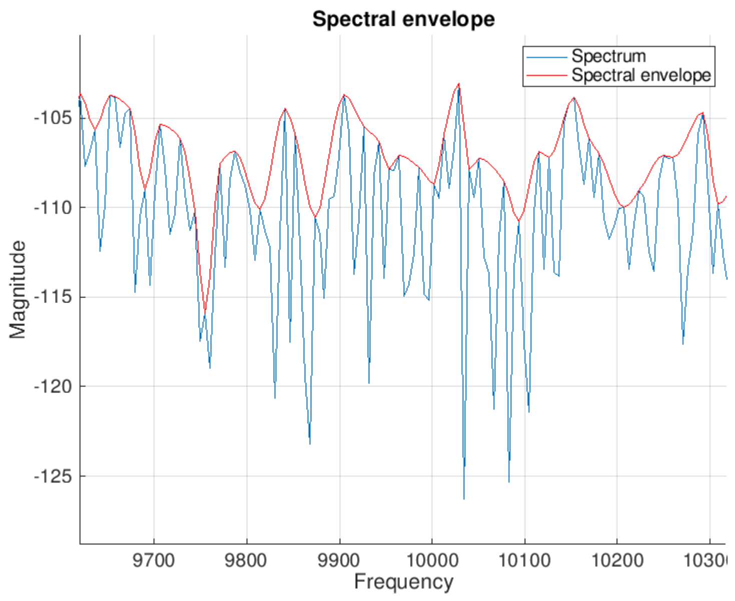


Figure 2.15 - An example of the spectral envelope.

Inharmonic partials

In an ideal harmonic sound, the frequencies of the harmonics are integer multiples of the fundamental frequency. However, in real musical instruments this does not occur. Those deviated harmonics (from the ideal F0) are called *inharmonic* partials, and it is a common phenomenum in string instruments.

Spurious components

Another type of influent characteristic that can be also observed in string instruments is the one called *phantom partials*. According to Conklin (Conklin, 1999), these phantom partials, in string instruments are related to the tension variation on the plucked strings, and are close to the frequencies of the normal partials. Nevertheless, recent works (Moore et al., 2017) and (Moore et al., 2018) also suggest that non-string components, like the mechanical parts or the wooden components of a piano, could also contribute to the appearance of those phantom partials. These kind of partials are sometimes fairly dominant compared to the normal partials, which in turn can lead to a bad transcription.

2.3.3. Transients

In music, it is quite common, specially in some types of musical pieces, that the notes are played roughly, resulting in abrupt variations in the sound signal. According to Rodet and Jaillet (Rodet and Jaillet, 2001), these fast variations are denominated as *transients*. The transients usually refer to note onsets (fast attacks) or to note offsets (fast releases). Due to those abrupt variations and also that most of the variations have high levels of energy, the sound signal will contain several spurious components, making the process of estimating the pitch in those areas very hard. Recent research works tend to consider the transient as a specific signal component, where it is detected by either a parametric approach (Daudet, 2004) and (Molla and Torrésani, 2004), or a non-parametric approach (Rodet and Jaillet, 2001), (öbel, 2003) and (Bello et al., 2005).

2.3.4. Reverberation

When a note is played and then released, the sound produced does not disappear suddenly. It usually takes time in order to be not earable anymore. This process, the prolongation of a preceding sound is called *reverberation*. Thus, a recorded signal can be considered as a mixture of multiple sounds, which are direct sounds, reflected sounds and reverberated sounds. According to Yeh et al. (Yeh et al., 2006), Beauchamp et al. (Beauchamp et al., 1992) and Baskind et al. (2012), depending on the recording environment, a monophonic sound can also become a polyphonic sound, because the reverberated and reflected sounds add complexity to the analysis of the recorded signal.

2.4. Artificial neural networks

Artifical neural networks (ANNs) or simply *neural networks* are an *artificial intelligence* (AI) technique based on biological brains. This technique has been used successfully in many complex problems, such as: autonomous vehicles (Bojarski et al., 2016), autonomous farm (Pearlstein et al., 2016), (Luo et al., 2010) and (Stentz et al., 2002), anomaly detection in internet traffic (Pradhan et al., 2012), cancer detection in medical images (Singh et al., 2015) and also music transcription (Sigtia et al., 2016a) and (Kelz et al., 2016). This is one of the reasons whereby we have applied ANNs in this work, because they are good at tackling difficult problems and, apart from that, it's a technique already applied in the AMT problem, and thus, a more closer comparison with other works can be made.

This section is divided into five topics: neuron model, ANN architecture, learning method, types of activation functions and types of ANNs. Initially, a comparison between the biological neuron and an artificial neuron is presented. Then, an overview of the main components of an ANN is introduced. Continuing, an explanation of how the ANNs learn is presented. To conclude, a deeper explanation regarding activation functions, following by an introduction of several types of ANNs are presented.

2.4.1. Neuron model

As mentioned above, ANNs were inspired by biological brains. The human brain has roughly $86 * 10^9$ of connected elements, called neurons. Each neuron, is composed by three main components (see Figure 2.16, bellow): the *dentrites*, the *cell body* and the *axon*. The dentrites are *tree-like* connections that receive and transport incoming signals to the cell body. Hence, the cell body is the component responsible for processing the incoming signals, by summing and thresholding. However, sometimes, the dentrites also process those informations before it arrives to the cell body. The last main component, the axon, is in charge of transporting and transmiting the output signal from the cell to other neurons. The transmition, is done in the edge of the axon in a zone called synapse. Synapses transform the electrical signal into a chemical one and, then, send it to the dentrites of other neurons.

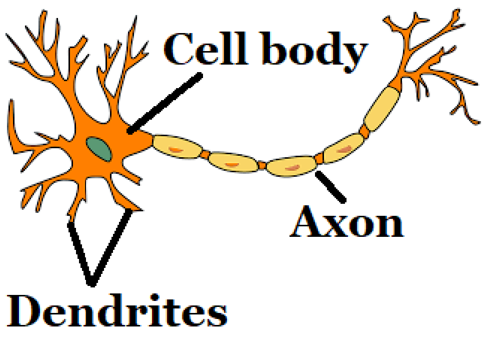


Figure 2.16 - Representation of a biological neuron. Adapted from (Pixabay).

On the other side, a neuron of an ANN is composed by three main elements (see Figure 2.17, bellow): the *connection weights* or simply the weights, a *bias weight* and an *activation/transfer function*. Each connection weight, represents the relevance of the connection that the neuron is attached to. The bias weight, or just bias, is a special weight attached to a special connection with a constant input that helps the artificial neuron to adapt itself better to the data received. The activation function is a linear or non-linear function that is used in order to modulate the output result. It receives as input the weighted sum of the inputs.

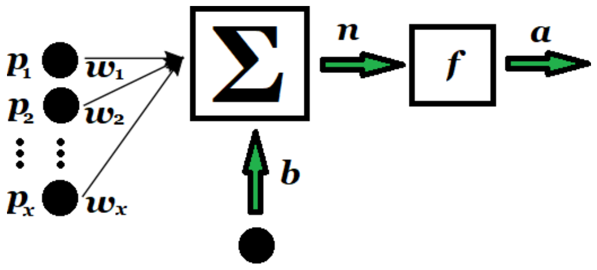


Figure 2.17 - Representation of an artificial neuron. ***p*** *represents the inputs vector,* ***w*** *the weights vector,* ***b*** *the bias,* ***n*** *the weighted sum of the inputs,* ***f*** *the activation function and* ***a*** *the output result of the neuron.*

If we relate the artificial neuron with the biological neuron seen above, we can consider each weight (w_x) as the strength of the respective synapse, the summation and the activation function (*f*) as the cell body and the output result of the neuron (a) as the signal on the axon.

Mathematically, the output result of a multiple-input neuron can be calculated as follows:

$$a = f(\boldsymbol{wp} + b), \qquad (24.14)$$

where ***w*** represents a vector of weights and ***p*** the inputs vector, *b* the bias and *f* the activation function. For a given ***w*** and ***p*** of size *n*, the calculus would be as follows:

$$a = f\left(w_{1,1} * \ p_1 + \ w_{1,2} * p_2 + \cdots + w_{1,n} * p_n + b\right), \qquad n \ \in \mathbb{Z}^{+}. \qquad (24.15)$$

2.4.2. ANN architecture

In general, a single artificial neuron is not enough to extract meaning from the data itself, even if that neuron has multiple inputs. It is more common to use a group of neurons, called *layer*, which works in a parallel way. In an ANN, there are three types of layers (see Figure 2.18): the *input layer*, that is basically the input data; the *hidden layer*, which are all the layers placed between the input and the output layer and where most of the extraction of meaning is done; finally, there is the *output layer*, which is the last layer of the network and which in turn is responsible to output a final result based on the features extracted by the hidden layers.

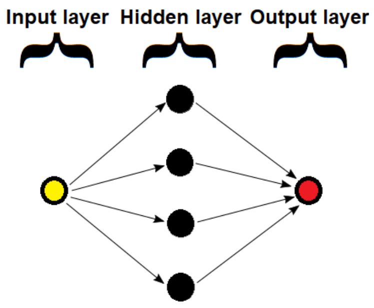


Figure 2.18 - Representation of an ANN with a single hidden layer, where it is possible to distinguish between the three different types of layers.

During several years, ANNs had no hidden layers. The reason of that was because no one knew how to “teach” an ANN with multiple layers. Only after the proof of work in (Rumelhart et al., 1986), of an algorithm called *backpropagation*, was when ANNs started to include hidden layers (see Figure 2.19). In general, ANNs with multiple hidden layers perform much better than a single layer neural network. Nevertheless, the more layers an ANN has, the more parameters the ANN needs to learn which in turn increases the difficulty of the *learning*/*training* process. Thus, for each problem a study of different number of layers and neurons is commonly done.

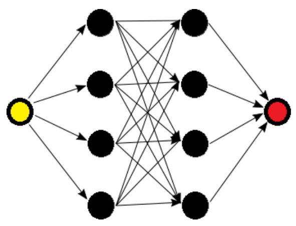


Figure 2.19 - Representation of a multi-layer neural network.

2.4.3. Learning method

The way an ANN learns, also called *training* process, can be divided into two main steps: *forward propagation* and *backpropagation*. The forward propagation is the step where the neural network outputs a result from the given input data. This result is calculated by applying equation 24.14 (see above), to each neuron, starting from the first layers up to the last one, until an output result from the network is given. Note that all the outputs from a layer are used as input of the following one (see Figure 2.19, above).

This final output of the network, technically called *prediction*, is then used for the next step, called backpropagation. In the backpropagation step, a readjustment of the weights of the network is done, according to how close the prediction is to the reality (*label*). The idea consists in doing changes to the weights proportional to the negative derivative of the error. This type of learning, where a reality is known is called *supervised learning*. Nevertheless, there are other types of learning, like *unsupervised learning*, where no label is known in advance and the algorithm learns by identifying commonalities from the data, or even *reinforcement learning*, where the algorithm learns by receiving rewards from the actions (predictions) taken in a given enviroment, like a game.

Backpropagation can be divided in two main steps: the calculation of the error and the update of the weights. In the process of calculating the error, an error is calculated for each layer, starting from the output layer and then backpropagating it down to the input layer, layer by layer. In the end, each neuron has an error associated. These errors are then used to adjust the weights. The adjustement of each weight is called *gradient*.

2.4.4. Types of activation functions

As mentioned in the beginning of this chapter, ANNs are applied in almost any kind of problem. The peculiarity of this technique, is that a suitable solution can be found for almost any type of non-linear problem (see Figure 2.20). However, this peculiarity, as we mentioned, it is only possible if a non-linear activation function is applied. Thus, most of the time a non-linear activation function is used.

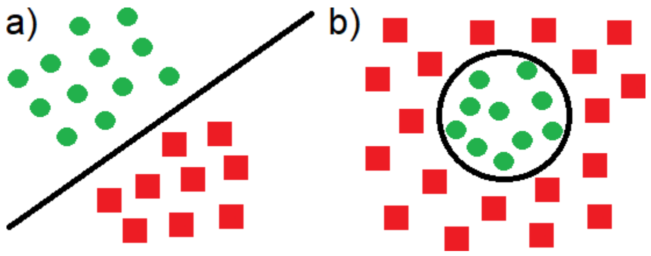


Figure 2.20 - Example of a linear and a non-linear problem. a) linear problem where a simple straight line is able to separate the circles from the squares. b) non-linear problem where a straight line is not able to separate the circles from the squares, thus, as an alternative, a circular line is applied.

There are several types of non-linear activation functions, like: the *sigmoid*, the *hyperbolic tangent* (tanh), the *softmax*, the *softplus* (Dugas et al., 2000), the *swish* (Ramachandran et al., 2017) and the *rectified linear units* (relu) and also its variations like the *leaky relu* and the *scaled exponential linear unit* (selu) (Klambauer et al., 2017). Commonly, activation functions like the softplus, rectified linear units or the swish are used for the hidden layers. On the other side, the sigmoid, the softmax and the tanh are used in the output layer, as can be seen in the following works: (Nair and Hinton, 2010), (Zeiler et al., 2013), (Senior and Lei, 2014), (He et al., 2015), (Ioffe and Szegedy, 2015) and (Ramachandran et al., 2017). There are several reasons for this common approach, like the computation time (relu and most of its variations), ideal output for classification (sigmoid, tanh or softmax) and problems like the *vanishing gradient*[2] or *not being zero centered*[3] (these last two problems can make the training process longer). In the following figures, a representation of all the previously mentioned activation functions, except the softmax (due to being a multi-class[4] activation function), are presented. Nevertheless, according to Rennie the softmax is convex (Rennie, 2005).

[2] The vanishing problem consists on small updates of the weights due to an almost zeroed derivative.

[3] A not zero centered function can introduce undesirable zig-zagging in the gradient updates (all positive or all negative gradients).

[4] A multi-class activation function is a function that has two or more possible outputs. However, it is more commonly applied in problems that have three or more.

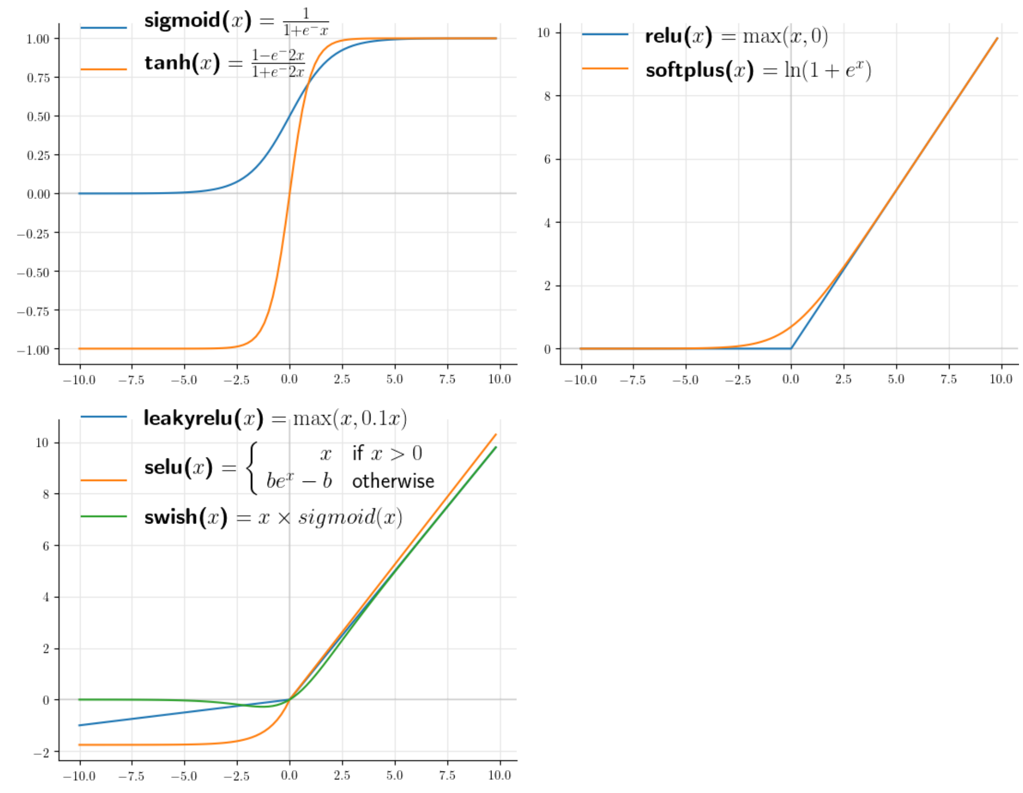


Figure 2.21 - Representation of several activation functions.

2.4.5. Types of neural networks

One of the drawbacks of the artificial neural networks technique is that it is computationally expensive. However, due to the computer power being growing almost exponentially and its price being decreasing, this drawback has almost vanished, whereby today its one of the most popular techniques to be applied in several types of problems. As a result, several types of artificial neural networks have been created: the traditional feedforward neural network, simply refered to ANN, *recurrent neural networks* (RNNs) and *convolutional neural networks* (CNNs), to name just a few.

An ANN is a type of neural network where the information of the input data moves only in one direction and where time is not taken into account. On the other side, an RNN, is an ANN that tries to take advantage of sequential information from the input data. This can be a major advantage when dealing with problems such as language translation or even music transcription. However, this type of network can be very hard to train. Another type of ANNs that have been responsible for major breakthroughs, specially in problems such as vision, are CNNs. This type of technique has been developed mainly because simple ANNs perform poorly when applied to problems with images and also because the input data of an ANN must have a strict size, which is not usual, in the case of images. However, CNNs also use simple ANNs, but they are only applied after the input data is “parsed/filtered” by *convolutional* and (commonly) *pooling* layers. We can think of both these layers as a way of extracting the main features of an image. In addition to that, also the pooling layer is responsible for transforming the input data into a strict size.

2.5. Summary

This chapter presented several important topics of the dissertation. The topics range from general basics such as sound and music characteristics to more specific concepts such as deeper analysis of digital signal processing. The chapter also touched on artificial neural networks.

Remember that, most AMT systems commonly apply methods such as the FFT, referred above, to a sound signal to be easier in detecting pitches on it. However, these methods have their own set of problems, namely: missing fundamentals and spectral leakage. Regarding spectral leakage, a possible solution called windowing could be applied in order to attenuate the problem. For missing fundamentals, to the best of our knowledge, currently, there is no known solution. Another important point is that, ANNs are good problem-solvers for almost any type of complex problem, including automatic music transcription. As a result, we have applied in this work the FFT and the ANN technique.

In the following chapter, a review of other research works related to single and multi estimation problems are presented, in order to understand how other authors tackled them.

3. Related work

This chapter reviews related works of the AMT field. The review has three main sections: 1) general overview; 2) artificial neural networks and 3) genetic algorithms.

3.1. General overview

The problem of transcribing monophonic music automatically can be considered solved. However, automatic transcription of polyphonic music is still being researched.

Since the first polyphonic music transcription system (Moorer, 1975), several posterior related works have been presented. These works have originated the appearance of several different approaches to the AMT problem. According to Yeh (Yeh, 2008), those approaches can be classified into two groups: *iterative estimation* approaches and *joint estimation* approaches.

3.1.1. Iterative estimation

An iterative estimation approach consists in finding the most predominant-F0 estimation, apply the respective cancelation or surpression technique and repeat this process until the termination condition is met. This approach assumes that per each iteration a dominant source exists. When this assumption is not met, the iteration process can lead to an accumulation of errors.

There are two types of cancelation techniques, direct cancellation and cancellation by spectral models.

Direct cancellation

Direct cancellation applies a single-F0 estimation algorithm to extract the predominant-F0 and then removes all harmonics of the extracted source from the observed input signal. This technique assumes that the complete removal of the dominant source does not affect the following estimations. The term “direct” cancellation denotes that the source interaction, as for example, overlapping partials, are not taken into account.

In (Parsons, 1976) the author applied the Schoroeder’s histogram in order to extract the predominant-F0s in a two-speaker separation problem. After the first F0 estimation, the spectral peaks corresponding to its harmonics were excluded before the calculation of the next histogram. In (Lea, 1992) the author used a method that iteratively extracts the predominant peak in the *summary autocorrelation* as an F0 and cancels the estimate in the *autocorrelation* array. In 1993, in the work (Cheveigné, 1993), the author proposed a time-domain cancellation model where both iterative and joint approaches were studied. The iterative cancellation approach was responsible for estimating the predominant F0 by *average magnitude difference function* and cancel it by comb filtering. Direct cancellation was also used on the spectral domain. In (Ortiz-Berenguer et al., 2005), the authors used spectral patterns trained from previously recorded piano sounds to perform harmonic matching. The predominant-F0s found were removed iterativelly by means of binary masks around the matched harmonics in the observed spectrum.

Cancellation by spectral models

In (Klapuri, 2003) the author introduced an algorithm based on harmonicity and spectral smoothness. In the preprocessing stage a RASTA-like technique (Hermansky and Morgan, 1994) a logarithmic frequency scale is used, to compress the spectral magnitudes and remove the additive noise. The resulting spectrum is then splitted into multiple frequency bands. F0 weights are calculated on each band by normalizing the sum of their partial amplitudes and by taking into account the inharmonicity. The predominant weights, from those resulting F0 weights, are then smoothed using an algorithm described in (Klapuri, 2001) and finally subtracted from the signal spectrum to avoid its corruption after several iterations of direct cancellation. This way, the overlapping partials still contain energy for the following sources. This method, which is denominated by *bandwise smooth model*, uses the moving average over the amplitudes within one octave band in order to smooth the envelope of an extracted source. This process is repeated until the maximum weight related to the *signal-to-noise ratio* is lower than a certain threshold.

Later on, in (Klapuri, 2005) a perceptually motivated multiple-F0 estimation method is presented. Initially, subband signals were compressed and an half-wave rectifier was applied. Harmonic matching is then applied on the summary spectrum. This way, the predominant F0 is extracted. Then, a *1/k smooth*[5] is used to smoothen the predominant source while retaining energy of higher partials for the next iteration. Later on, in (Klapuri, 2006), the author proposed a spectral model, similar to the previous mentioned 1/k smooth model, which attempts to generalize a variety of musical instrument sounds.

In (Santoro and Cheng, 2009) the authors presented an algorithm based on Klapuri's work, for multiple F0 estimation using the *modified discrete cosine transform* domain.

[5] Partial amplitudes are inversely proportional to the partial index.

3.1.2. Joint estimation

Nowadays, joint estimation approaches are the most common used approaches for automatic music transcription systems. According to Benetos et al. (Benetos et al., 2013), those approaches can be categorized as: *feature-based, statistical model-based* and *spectrogram factorisation-based*.

Feature-based

From all the types of joint approaches, feature-based approaches, are the most currently used for AMT systems. This can be due to the fact that since the last few years, the field of AI have grown up significantly.

Regarding AMT, several types of feature-based approaches have been proposed.

In (Yeh, 2008) and (Yeh et al., 2010) the author(s) proposed a frame-based system for estimating multiple fundamental frequencies (F0s) of polyphonic music signals. This system is composed of five main tasks: *FFT analysis* – in this step, each frame is converted to the time-frequency domain; *Noise level estimation* – step responsible to detect sinusoids and noise from the previous analysed data representation; *F0 candidate selection* – step responsible for selecting the possible F0s candidates; *Jointly F0 evaluation* – step responsible for jointly evaluate the possible combinations from the previously selected F0s; *Polyphony inference* – step responsible for estimating the existent notes.

In (Lunaverus, n.d.) the author presents a music transcription system using convolutional neural networks (CNNs). This system uses what they call *Dynamic Q*, which, according to them, is an improved version of the constant-Q transform. Focusing on the AMT problem, using the constant-Q transform instead of the Short-Time Fourier Transform (STFT) as data representation should perform better because in the constant-Q transform the frequencies are spaced with a similar distance to the way that the notes are spaced (in terms of frequency) in a piano.

In (Bello and Sandler, 2000), the authors proposed a simple polyphonic music transcription system using a *blackboard system* with the top-down approach. A blackboard system is designed to handle complex problems. This technique works as a group of experts trying to solve a problem in a blackboard in which they only take action when it is related to their area of expertise. The blackboard system presented contains a hypotheses database, a scheduler and knowledge sources. One of the knowledge sources is a neural network that is able to recognize chords in order to adapt the number of notes that the system needs to detect.

In (Reis et al., 2008b), the authors proposed an hybrid approach in which it sits between classical *genetic algorithms* (GAs) and traditional *memetic algorithms*. As the authors explain, genetic algorithms are good for exploring the space but, on the other side, they are not good enough to refine an already found solution, and that is the reason why they combine with memetic algorithms.

Statistical model-based

In (Duan et al., 2010), the authors present a multi-F0 estimation system in which a maximum likelihood approach is used. In this system spectral peaks are detected using a peak detector described in (Duan et al., 2008). Those peaks are then used to generate F0s candidates. Then, a greedy search strategy is applied in order to reduce the number of generated F0s candidates. To finish, an interation process is done in which newly estimated F0s are added, until the maximum allowed polyphony is reached.

In (Davy et al., 2006) the authors extended the previous work done in (Walmsley et al., 1998), (Walmsley et al., 1999), (Davy and Godsill, 2002b) and (Davy and Godsill, 2002a) named in their work, Bayesian harmonic model. Here, the authors assumed the noise as white, as opposed to one of the previous works, and the inharmonicity parameter took a multiplicative form. Also a re-design of the *Markov Chain Monte Carlo* was done. All these modifications have originated a more robust and efficient (in computational terms) model.

In (Emiya et al., 2010), a multipitch estimator based on the likelihood maximization principle is presented. This system decomposes the audio signals into a sum of sinusoidal components and a colored noise. Then, a moving average process is applied to the noise and the spectral envelope of the partials is modeled by an autoregressive model. The F0 is then calculated using the *Weighted Maximum Likelihood* principle. Finally the F0s are jointly evaluated.

Spectrogram factorisation-based

In (Smaragdis and Brown, 2003), the *non-negative matrix factorization* (NMF) technique was introduced for the first time in the AMT problem. This technique aims at decomposing the input signal (into *x* frequency bins and *n* frames). Later on, in the work (Cont, 2006), new rules were added into the NMF update rules as an attempt to improve the performance of the algorithm. In (Vincent et al., 2010), harmonicity and spectral smoothness constraints were added in order to reduce octave errors. In (Bertin et al., 2010) a Bayesian framework for NMF was proposed by the authors. This framework considered each pitch as a model of Gaussian components in harmonic positions. In (O'Brien and Plumbley, 2017), a refinement of *non-negative matrix decomposition* is presented. This model assumed that the transcription itself was approximately low rank. The idea behind this, as they mention, is that:*"the total number of distinct activation patterns should be relatively small since the pitch content between adjacent frames shoud be similar"*.

3.2. Artificial Neural Networks

In this section several related works that apply ANNs to the AMT field are described. These works are essential in order to understand the way taken to achieve our final solution. Additionally, two current state-of-the-art works which are used as a reference, in a following chapter, to compare our work are also described.

3.2.1. How the training data affects music transcription systems

The goal of the project undertaken by Kelz and Widmer (Kelz and Widmer, 2017) was to analyze how a dataset used for training a music transcription system, based on ANNs, can affect their performance. For that purpose, the authors created three different datasets, based on the MAPS dataset (Emiya, 2008), denominated by FLUID-ISOL, FLUID-COMBI and MAPS-MUS.

The FLUID-ISOL dataset contains only isolated notes, in the training set, and chords in the testing set that were created with a synthesizer, using isolated notes and two-note combinations. The FLUID-COMBI dataset contains chords in the training set, that were previously created by the authors for the FLUID-ISOL, and isolated notes in the testing set. The MAPS-MUS dataset, contains pieces of music in both the training set and testing set (the configuration used is similar to the *Configuration 2*, described in section 3.2.3).

For the experiments, the authors used three different types of ANNs: *ConvNet* which has the same architecture as the one used in (Kelz et al., 2016); *SmallConvNet*, similar to the *ConvNet* but smaller; *AUNet*, based on (Ronneberger et al., 2015).

The experiments carried out were as follows: *SmallConvNet* with FLUID-ISOL, SmallConvNet with FLUID-COMBI and *ConvNet* and *AUNet* with MAPS-MUS.

In the experiment with *SmallConvNet/*FLUID-COMBI the results were positive, in sense that the ANN was able to transcribe most of the piano midi notes with an accuracy higher than 80% (the accuracy is calculated according to MIREX). On the other side, in *SmallConvNet*/FLUID-ISOL, as the authors mention, the ANN could not generalize the features learnt from the isolated notes in order to be able to identify chords. Most of the piano midi notes had an accuracy bellow 20%. In the last experiments, the *ConvNet*/MAPS-MUS and *AUNET*/MAPS-MUS, the authors compared their performance in two different case scenarios: *shared notes* and *unshared notes*.

The first scenario, *shared notes*, contains notes and chords that appear in both the training set and the testing set. On the second scenario, the *unshared notes*, the *testing set* contains different notes and chords from the training set.

The results on the first scenario, *shared notes*, were positive. Both ANNs were able to surpass 60% of accuracy in most piano notes. However in the second scenario, *unshared notes*, the accuracy in both ANNs dropped significantly, and most of the notes had an accuracy bellow 20%, some even got an accuracy of 0%.

Based in these results, the authors concluded that certain neural networks have difficulty to generalize the leaned features, leading to poor results when it consists in transcribing unseen notes or chords.

To conclude, the authors suggest that a possible solution could be the use of *source separation* to decompose the input signal into its constituent parts but, as they mention, source separation, is still an ongoing research field. The purpose of this technique is to decompose a mixture of sounds. An example of that could be when we are in a noisy environment, as a disco, and we focus on a desirable conversation, ignoring the surrounding noise.

3.2.2. Feature learning and 88 classifiers

In (Zalani and Mittal, 2014), the authors implemented a polyphonic music transcription system based on deep learning techniques. Their chosen dataset is the MAPS, where they used six pieces of music of nearly 30 minutes each for the training set and four different pieces of music of around 15 minutes for the testing set. These authors used the following two techniques in succession: feature learning, which is like a recursive restricted Boltzmann machine and 88 support vector machines (SVMs).

The first technique, feature learning, is an unsupervised system that is in charge of extracting features coming from the music, like temporal dependencies among different notes, whose purpose is to help the SVMs afterwards.

The second technique, the 88 SVMs, are supervised systems, in which each one is responsible for transcribing only one note. These SVMs were trained with the STFT coming from the music and with the data extracted from the feature learning step.

The authors also mention that a smoothing algorithm, called Hidden Markov Model (HMM), was applied to improve their accuracy results from 52,07% to 63,10%.

3.2.3. Comparison of different types of Neural Networks

In (Sigtia et al., 2016a), the authors have created a supervised neural network model for polyphonic piano music transcription. As they mention, the architecture of their model is a combination of an *acoustic model* and a *music language model*. This type of architecture is a common one in another field, called speech recognition. The *acoustic model* is responsible for detecting the notes in each frame of the piece of music and the *music language model* is the one responsible for making correlations between the output of the previous model over time.

For the *acoustic model*, three different neural networks were experimented by the authors: an artificial neural network, a recurrent neural network and a convolutional neural network (CNN). All those neural networks were trained using the constant-Q transform.

For the *music language model*, the authors also experimented three different types of neural networks: the generative RNN, the Neural Autoregressive Distribution Estimator (NADE) (Larochelle and Murray, 2011) and the RNN-NADE.

The experiments were done with two different datasets, both of them based on MAPS called *Configuration 1* and *Configuration 2*.

The *Configuration 1*, dataset is a group of four folds of different pieces of music, each one with 216 pieces of music in the *training set* and 54 pieces of music in the *testing set* (more information can be found in (Sigtia et al., 2016b)).

The *Configuration 2* dataset contains 210 pieces in the training set (180 were used for training and 30 for evaluation) and 60 pieces in the testing set. This last dataset can be considered more realistic, as the authors mention, because the pieces of music in the testing set have been recorded from a different piano.

In order to improve their results, the authors applied three different post processing methods, a thresholding method, a HMM and a hybrid architecture.

The results obtained using both datasets, *Configuration 1* and *Configuration 2* show that, CNNs yields the best performance in all evaluation metrics (*f-measure*). In *Configuration 1* the CNN reached between 73,57%-74,45% in f-measure frame-based and 65,35%-67% in f-measure onset only (further details regarding the evaluation metrics can be seen in section 6.2) . The ANN, on the other side, reached between 67,54%-68,32% in frame-based and 60,02-63,18%. In *Configuration 2*, the CNN reached 64,14% in frame-based and 54,89% in onset only. The DNN reached 59,91% in frame-based and 49,43% in onset only.

3.2.4. Exploring the limits of simple architectures

There are some transcription systems whose architecture is composed by two main parts: *acoustic model* and the *music language model*. An example of this can be found in the work mentioned above, in section 3.2.3. However, in (Kelz et al., 2016) the authors focus only on the *acoustic model*, in order to explore the limitations of simple architectures for music transcription systems. They compared three different types of ANNs for the *acoustic model*: ANN, CNN and a fully convolutional neural network which is called *AllConv*.

The datasets chosen by the authors are the *Configuration 1* and a similar dataset to *Configuration 2*, from the work referred above (Section 3.2.3).

In order to get the best possible results, the authors have focused their efforts in two sets of preliminary experiments, *types of representation* and *hyperparameters*[6] *search and optimization techniques*. In the first set, the one that the authors called *types of representation*, they did several experiments in order to determine what should be the best data representation for training the ANNs. For these experiments, the authors used two

[6] Hyperparameters are parameters that need to be predefined before the training phase of the ANNs.

different types of ANNs: a perceptrons network and a shallow net. In addition to that, the authors experimented four different types of data representation: spectrograms with linearly spaced bins (S), spectrograms with logarithmically spaced bins (LS), spectrograms with logarithmically spaced bins and logarithmically scalled magnitude (LM) and constant-Q-transform. After analyzing the results, they concluded that, for the perceptrons network, the best type of data representation was the S type and that, for the shallow net, the best was the LM type.

In the second set of experiments, the authors conducted several experiments in order to understand which type of hyperparameters or technique have more influence in the results so that the authors could know where to focus. With the obtained results, the authors concludes that the most influential hyperparameter is the *learning rate*. The learning rate is the parameter that determines how much the weights are updated each iteration.

To finish the study, after studying several preliminary experiments, mentioned above, they conducted their final setup experiment. The results were positive. In *Configuration 1* the CNN was able to reach a f-measure of 79,33% and the ANN 73,11%. In the second dataset, *Configuration 2,* the CNN reached a f-measure of 70,60% and the ANN 65,15%.

As the authors mention, simpler arquitecture approaches, that is to say, those that use only an *acoustic model*, are able to reach or surpass more complex arquitectures in frame transcription, those with an *acoustic model* and a *music language model*.

3.3. Genetic algorithms

So far, we have seen multiple works, regarding AMT, using mainly artificial neural networks. In this section, another type of technique of the AI field is discussed, *genetic algorithms* (GAs), which promise positive and efficient results to the AMT problem.

The following research works have applied this technique to this problem, (Reis et al., 2008a) in which the authors evolved a harmonic structure using genetic algorithms; (Reis et al., 2012) where the authors used genetic algorithms in combination with an onset detection algorithm; and (Leite et al., 2016), in which the authors applied for the first time cartesian genetic programming to the AMT problem.

Genetic algorithms are a different technique from neural networks. This technique is based on the theory of evolution, consisting in evolving a population of individuals. Each individual is a potential solution for the problem. The process of evolving a population consists in applying two types of operators, called *recombination* and *mutation*, to the population in order to find the best individual for the problem. The recombination operator consists in combining characteristics from different individuals. Mutation consist in randomly changing characteristics from the individuals.

To be able to find the best solution, it is also important to specify two main components: a fitness function, used to assess the quality of each individual, and a selection method, used to stochastically select the best individuals.

A description of several works that apply genetic algorithms and as well had a major influence on our work, are explained in the following topics.

3.3.1. Reducing the search space by using a better initialization method

GAs can find effective solutions for almost any kind of problem. However, often, a considerable amount of time is needed to find a good solution, be it because the search space is extremely vast or because the evaluation step is computationally demanding.

In AMT, the search space is extremely vast, which makes the application of GAs in this problem very tough. However, if we could be able to "reduce" the search space, of the AMT problem, that disadvantage would be alleviated. And that was the focus in (Reis et al., 2007).

Of course, reducing the search space is not possible. However, it is possible to give a starting point closer to the target solution, which in turn reduces the number of generations necessary to find the target solution.

In order to give a better starting point that could be closer to the target solution, the authors have initialized the first population of the GAs with the most likely notes in a given song. Those likely notes were discovered by analyzing the frequencies of a signal. In the end, the frequencies with the highest picks in the signal are matched each one with the corresponding note(s), giving as a result the likely notes.

Another relevant point that must be mentioned about this work, is the way of evaluating an individual. The authors created a synthesizer that was responsible to generate an audio from each individual. Then, the resulted audios, were compared with the original sound in the fitness function, whereas the more similar the generated audio were to the original one, the better the individual was considered.

3.3.2. Combining genetic algorithms with an onset detection algorithm

In (Reis, 2012), the author has proven that genetic algorithms can reach state-of-the-art results in the AMT problem, by overcoming all the current obstacles regarding this technique. In order to overcome those problems, the author has elaborated a transcription system in which three different steps must be taken into account in order to complete the process: audio segmentation, transcription step and adjust note duration.

The first step, audio segmentation, consists in a note onset detection algorithm (Martins, 2008), which is fundamental because the detected onsets are used, afterwards, to split the song in several segments. Those resulting segments of the song, are then used in the transcription step.

The transcription step is in charge of transcribing each segment of the song. As mentioned in the work above, an ideal initialization of the population has a positive impact on the results. Taking that into consideration, the authors used a similar process of initializing the population with the likely notes in a given song (based on the most relevant frequencies contained on it).

To finish, in the third step, to adjust note duration, a *Hill-Climber* algorithm is used. This algorithm is responsible for transversing all musical notes and, then, the duration of each note is augmented 50 miliseconds. From all those notes, if some note overlaps another one, both notes are merged (this process can be repeated if the quality of the individual gets improved).

3.3.3. Using cartesian genetic programming to evolve several classifiers

Cartesian genetic programming (CGP) is a recent variation of genetic algorithms proposed by Julian Miller in (Miller and Thomson, 2000). Generally speaking this technique is a simple integer representation of a program in the form of directed graph. In non technical terms, we can describe this as a lookup table.

The genotypes in CGP are just a list of integers where their primitives and their connections are represented. As for example, for a genotype as follows "*3 1 4 -> 6*": *3* represents a reference to the function that will be applied to the input data; *1* and *4* represents both a reference to the input data of that function; *6* represents the output result of that function, which can afterwards be used as input data for other genotypes.

For the first time, in (Leite et al., 2016) the authors applied CGP to the AMT problem. They have taken the advantage of CGP in order to explore and evolve complex mathematical functions, as classifiers, being each classifier responsible for transcribing one note. This approach of creating a classifier per note is the approach taken in this work. However, in our work we extend it by being able to compare this last approach with the traditional one.

In automatic music transcription systems, one of the most important steps is to choose the type of data representation to be used in order to evolve the system. In a traditional system, only one type of data representation is used. However in this work, the authors used four different types of data representations derived from the DFT. This way, as they mention, the classifiers would have the possibility to choose, by themselves, the best suitable type of data representation for the problem.

In CGP, as mentioned above, each genotype contains a reference to a function in a lookup table (*function set*). In order to have a big variety of heterogeneous solutions, the authors implemented a function set with 24 functions. This function set is basically composed by filtering and arithmetic operations.

3.4. Summary

This chapter presented a brief description of several works that are related to the AMT field. Different proposals have been seen. Some authors suggest the extraction of features from the data using Restricted Boltzmann machines to help the classifiers in the transcription process. Others, propose a combination of an onset algorithm to improve the detection of note onsets, or even the use of a language model in order to detect patterns in note sequences and chords combinations, or just the use of *simpler* approaches, where only a fine-tuned system was designed. In the coming chapter, our own proposed model is described.

4. Proposed model

As already mentioned, the aim of this project is to verify the viability of the one-classifier-per-note approach. Again, this approach consists on having one classifier responsible for transcribing a single note (see chapter 0), instead of the traditional approach, of having a single classifier that is responsible for transcribing all the notes.

In this chapter, the overall architecture of the proposed model is presented, followed by a deeper explanation of each component.

4.1. Architecture

The proposed model consists in a supervised learning system based on several Artificial Neural Networks, each one responsible for transcribing one musical note, resulting in a total of 88 ANNs per dataset. In this case, we used classic Multi-Layer Perceptron Neural Networks, instead of more recent techniques as the ones used in Deep Learning, in order to get baseline results.

Figure 4.1 shows the overall system architecture. Besides the classification stage, two additional stages should also be taken into account in order to improve the performance of the whole system: the *pre-processing stage* and the *post-processing stage*. This results in a system with three main stages: 1) pre-processing, 2) classification and 3) post-processing.

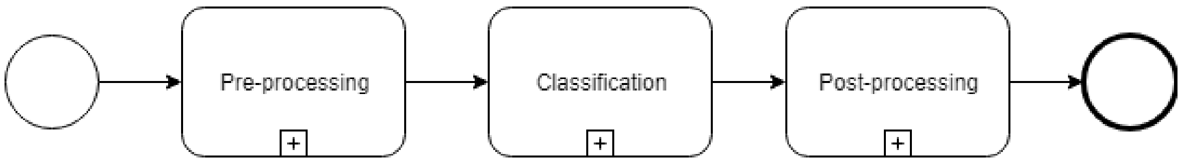


Figure 4.1 - Overall architecture of the proposed model.

In the following sections, a deeper explanation of each stage is presented.

4.2. Pre-processing

The pre-processing stage, is the first stage from the chain of stages. This stage is responsible for transforming the given data, in this case, the piano musical pieces and their correspondent transcription sheet, into a more readable file format, *Comma Separated Values* (CSV). Apart from that, it is also an elemental step, specially during the training phase of the classifiers, because it is the step responsible for transforming the input data into good quality data. We refer as good quality data to the type of data that optimizes the learning process of the classifiers. In other words, the type of data that makes the classifiers achieve better transcription results. However, the expression *good quality data* can be quite abstract and, actually, it commonly changes from problem to problem. A study has been done in order to better understand what is the “real” meaning of good quality data. Therefore, with the collected information from the study, data transformations and methods were tested in order to improve the quality of the data. The final structure of the main steps contained during the pre-processing stage are as follows:

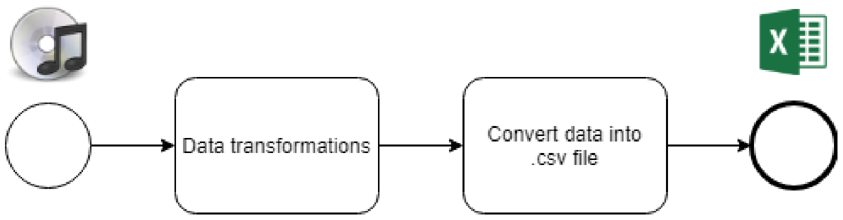


Figure 4.2 - Representation of the main steps during the pre-processing stage.

The data transformations step, is where the input data, as the proper name says, is transformed. Initially, each musical piece is splitted into frames (smaller chunks of the musical piece) of 4096 samples (see Figure 4.3 a). Each frame represents ≈93 miliseconds (ms) of a musical piece. Then, all the frames are converted into the frequency domain, using the Fast Fourier Transform (FFT) method, described in Chapter 1 (see Figure 4.3 b). Given that the second half of this resultant frequency signal, mirrors the first half, only the first 2048 values are taken into account.

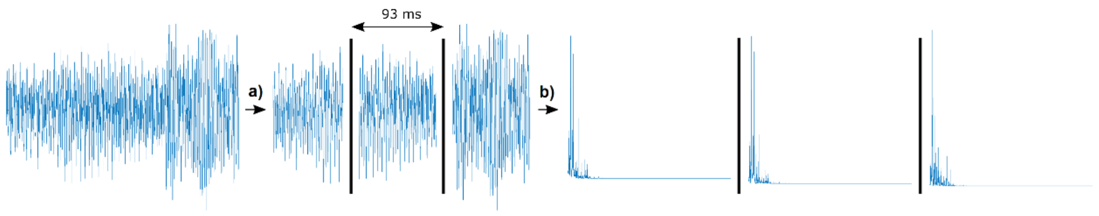


Figure 4.3 - Representation of the initial steps of the data transformation step. a) split the musical piece into frames. b) transform each frame into the frequency domain and ignore the second half of the resultant frequency signal.

For the generation of the training set, additional transformations are also applied. These transformations consist in the removal of meaningless data, like frames with silence, and also to pick the best ratio between frames with and without a specific musical note, referred to as *positive* and *negative* frames, respectively (see Figure 4.4). Please, note that each classifier may have its own training set. As a result, a training set has been generated for each classifier, where the *20/80* rule is applied, with 20% of the frames corresponding to positive frames and the remaining 80% corresponding to negative frames (see Figure 4.5).

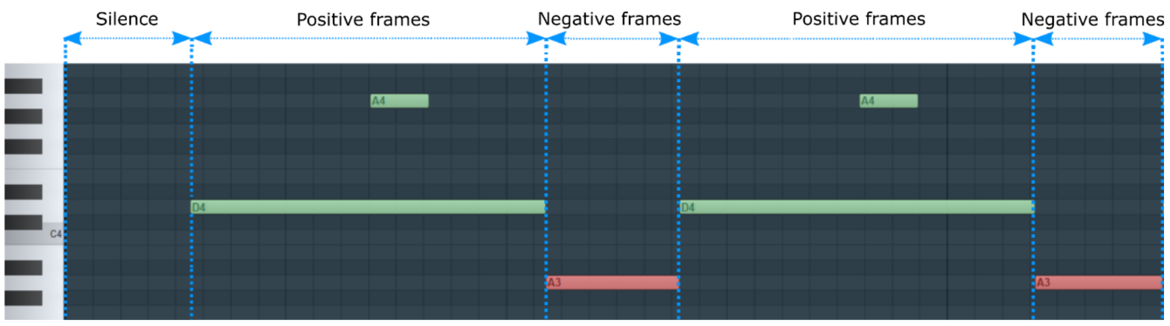


Figure 4.4 - Example of positive, negative or silence frames, regarding the musical note D4. This figure was originally created using (FL Studio 20).

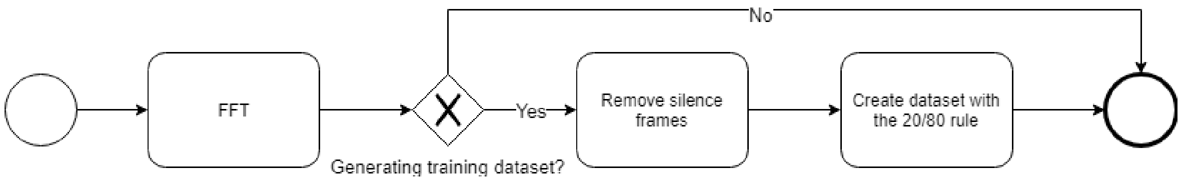

FFT
No
Yes
Generating training dataset?
Remove silence frames
Create dataset with the 20/80 rule

Figure 4.5 - Representation of all the transformations that occurs during the data transformation step in the pre-processing stage.

4.3. Classification

The classification stage is where the actual transcription process begins. The data given from the previous stage, the pre-processing stage, is therefore inserted into this stage in order to detect pitched notes. In this case, we apply the one-classifier-per-note approach. We believe that this approach could lead to the improvement of the final transcription, due to the common reasoning of “its easier to be an expert in one field than to be an expert in several fields”. In this case, we could take *field* as a single note and several *fields* as multiple notes. In other words, it should be easier to be an expert in detecting a single note than several notes (see Figure 4.6).

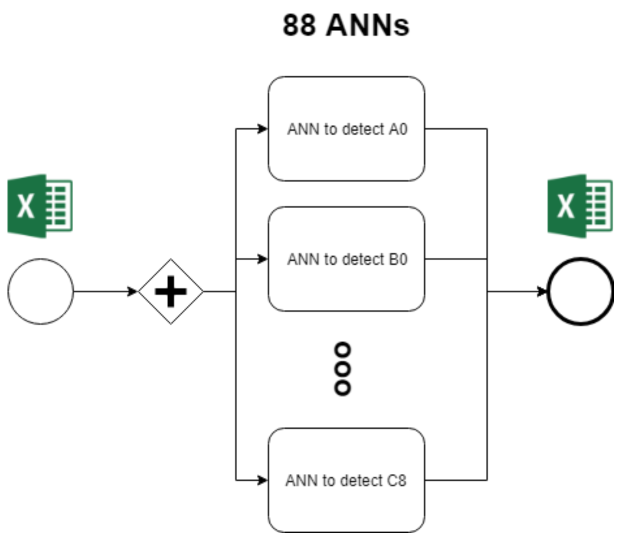


Figure 4.6 - Representation of the main steps that happen during the classification stage.

During the transcription process, each classifier, receives as input a frame at a time, each one containing 2048 samples, and it outputs a *yes* or *no* answer. *Yes* means that classifier believes that the specific note is contained in the given frame and *no* means the opposite scenario. In the end, a CSV file is created with all the outputs of all the classifiers. This CSV file is used afterwards in the following stage.

Each classifier consists in a Multi-Layer Perceptron Neural Network, that is composed of an input layer with 2048 units, 5 hidden layers (with 256 units, 128, 64, 32 and 16, respectively) and an output layer with a single unit (*yes* or *no*). The hidden layers apply the common activation function *leaky relu* and the output layer the *sigmoid* function (see Figure 2.21, in Chapter 1). Apart from that, during the training phase of these classifiers, the optimizer of choice was the *Adam* (Kingma and Ba, 2014), with a *learning rate* of 1^{-6} and the *cross entropy* as the loss function. Apart from that, also optimization techniques such as the *dropout* (Srivastava et al., 2014), noisy gradients (Neelakantan et al., 2017) and data shuffling (Montavon et al., 1998) were used. In the following chapter, a description of each optimization technique will be given but, for now, think of each one as a way of improving the learning process.

4.4. Post-processing

After the classification process, some errors in the final transcription are common. This means that notes that are not present in the musical piece are identified as being there and/or notes that are in the musical piece are not identified. Also, it may happen that, the starting time and/or the duration of a note being played is not correctly transcribed. This can be due to several factors, such as the ones mentioned in Chapter 1 (overlapping partials, spectral characteristics, transients and/or reverberation). Post-processing techniques can be applied in this case, in order to attenuate some of those transcription errors.

In this stage, several post-processing steps are applied, which also use the same concept of the one-classifier-per-note approach. This means that a single post-processing unit is responsible for correcting the mistakes of only one transcribed note. These results in 88 post-processing units per each step. This choice, was due to the same reasoning as the previous stage: "it is easier to be an expert in one field than to be an expert in several fields" (see Figure 4.7).

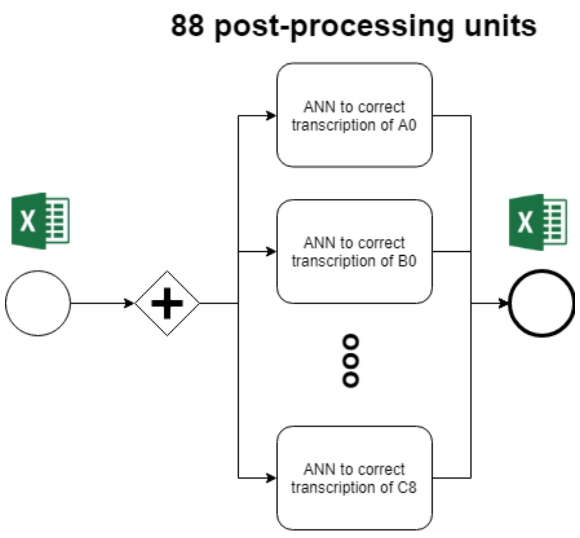

88 post-processing units
ANN to correct transcription of A0
ANN to correct transcription of B0
ANN to correct transcription of C8

Figure 4.7 - Representation of the structure of a single step in the post-processing stage.

On one hand, we can think of this approach as not viable due to the overhead generated. On the other hand, it is important to recall that the heavy computational effort is done during the training phase, which is done offline.

In this work, three post-processing steps have been created (see Figure 4.8, bellow). Each step generates 88 ANNs, resulting in a total of 264 ANNs, during all the post-processing stage. In the end, the whole system is composed of 352 ANNs for both the classification and post-processing stages. Of course, this is an enourmous system but the goal of this stage was to push the boundaries of applying several post-processing steps until its breaking point. This would encourage or discourage future researchers when choosing possible post-processing steps.

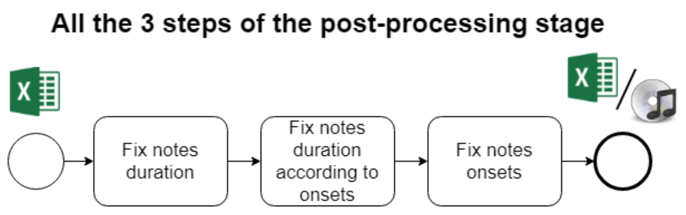

All the 3 steps of the post-processing stage
Fix notes duration
Fix notes duration according to onsets
Fix notes onsets

Figure 4.8 - Representation of the all three steps that are taken during the post-processing stage.

An important point to clarify here is that during the training phase of each ANN of the post-processing stage, a pre-processed training dataset has been given. Transformations like the removal of meaningless data and the 20/80 rule, applied in the previous pre-processing stage, were also used. This has improved the performance of those post-processing units. Apart from that, each ANN has used identical hyperparameters as the ones applied in the classifiers, except the model architecture and the learning rate. The model architecture used was the one labelled as *Tiny Linear shape model* (further details in Table C.0.6, in the Appendix), which is composed of three hidden layers with five neurons each. The learning rate applied was with a value of 1^{-5} for the initial two steps and a value of 1^{-3} in the last one. Apart from that, in the last step (step 3) a different activation function and loss function was used, which will be later clarified.

In the following sections, a description of each step from the post-processing stage is given.

4.4.1. Fix notes duration (step 1)

The first step, called *correct notes duration*, as the name describes, was the first step responsible for fixing errors related to the duration of the transcribed musical notes. This is an important step, specially in pitch or multi-pitch estimation problems where the transcription process is done by only taking into account a single frame at a time. This way, the transcription of a given frame is independent of previous or following frames, losing the sense of time. Possibly resulting in a poor transcription because music is a time-series problem[7]. As a result, in this step we tried to incorporate that sense of time by creating an ANN that receives as input the output of the corresponding note classifier (previous stage) with some preceding and following frames and gives as output a *yes* or *no* answer in order to determine if the frame in the middle of that sequence really contains the specific note or not. For instance, in the following example, the resultant transcription of a given classifier is:

[7] Problem that is time dependent. In other words, a current state is closely related to the previous and following ones.

0,0,0,0,0,1,1,0,1,0,1,0,0,0,1,0,0,0,0

and the expected transcription is:

0,0,0,0,1,1,1,1,1,1,1,1,0,0,0,0,0,0,0,

where the red numbers represent the wrongly transcribed frames, the *1s* represent frames that contain the specific musical note and the *0s* the opposite scenario. Then, this post-processing unit receives per each frame its current transcription/prediction plus its preceding and following four frames and predicts if that given frame contains the specific musical note or not (see Figure 4.9, bellow).

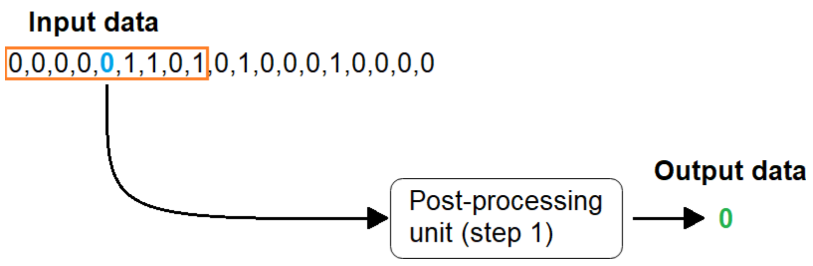
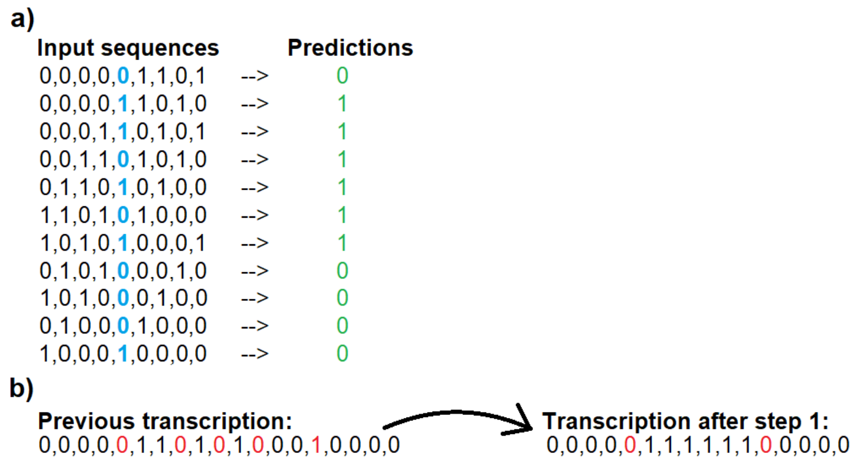


Figure 4.9 - Example of how the step 1 from the post-processing stage works. The number in blue, represents the frame that the post-processing unit is trying to predict. The orange square (window), represents the sequence that is given to the post-processing unit, related to the blue number. Finally, the green number represents the prediction of the post-processing unit.

Please note, that during the post-processing process, the orange window represented in the Figure 4.9, above, will slide one frame at a time, to the right, until the end (the fifth to last frame). Each sequence, contained on that window, is then given to the post-processing unit, which will predict the possible transcription for the frame in the middle of that given sequence (see Figure 4.10 a). In the end, the previous transcription result is updated with the new predicted values from this post-processing step (see Figure 4.10 b).



a)

Input sequences		Predictions
0,0,0,0,0,1,1,0,1	-->	0
0,0,0,0,1,1,0,1,0	-->	1
0,0,0,1,1,0,1,0,1	-->	1
0,0,1,1,0,1,0,1,0	-->	1
0,1,1,0,1,0,1,0,0	-->	1
1,1,0,1,0,1,0,0,0	-->	1
1,0,1,0,1,0,0,0,1	-->	1
0,1,0,1,0,0,0,1,0	-->	0
1,0,1,0,0,0,1,0,0	-->	0
0,1,0,0,0,1,0,0,0	-->	0
1,0,0,0,1,0,0,0,0	-->	0

b)

Previous transcription:
0,0,0,0,0,1,1,0,1,0,1,0,0,0,1,0,0,0,0

Transcription after step 1:
0,0,0,0,0,1,1,1,1,1,1,0,0,0,0,0

Figure 4.10 - Representation of all the sequences given to the post-processing step 1 and its resultant transcription, regarding the previous mentioned example. a) illustration of all the given input sequences and its predictions. b) representation of the previous transcription and the resultant/post-processed transcription.

As the reader can notice from Figure 4.10 b), this post-processing unit is able to successfully fix most of the errors like “holes” in the middle of a transcription or errors such as lonely false positive transcribed frames. However, regarding errors like note *onsets*[8] and *offsets*[9], there is still space for improvement. This is the main reason why additional post-processing steps have been proposed.

An important point regarding this type of post-processing unit is that it only starts to fix errors from the fifth frame until the fifth to last frame, due to the necessity of preceding and following four frames. As a result, the first and last four frames of any musical piece have not been post-processed. Instead, they have been zeroed. We could have also assumed a padding of 0s, instead of zeroing, but because none of the musical pieces has any musical note during those time intervals, those frames can be considered as unrelevant data for the post-processing units. Thus, the zeroing instead of the padding.

Also, it is important to point out, that in reality the sequences given to this type of post-processing unit do not contain binary data (only values with zeros or ones) but instead values between 0 and 1, inclusive. However, in order to ease understanding, in all the examples of this and following two sections, those values are represented as binary data.

[8] Please remember that an onset consists in the exact time on which a musical note starts.
[9] An offset consists on the exact time on which a musical note is released.

4.4.2. Fix notes duration according to onsets (step 2)

In order to improve the current transcription, regarding problems like note onsets and offsets, an additional post-processing step has been created. This new step is similar to the previous one since it receives as input a sequence of transcribed frames from the previous post-processing step (step 1). However, in this step, two additional sequences are also given as input. One sequence, with the initial transcription created by the classifiers and a second one, based on the output of an onset algorithm *(Martins, 2008)* (see Figure 4.11, bellow).

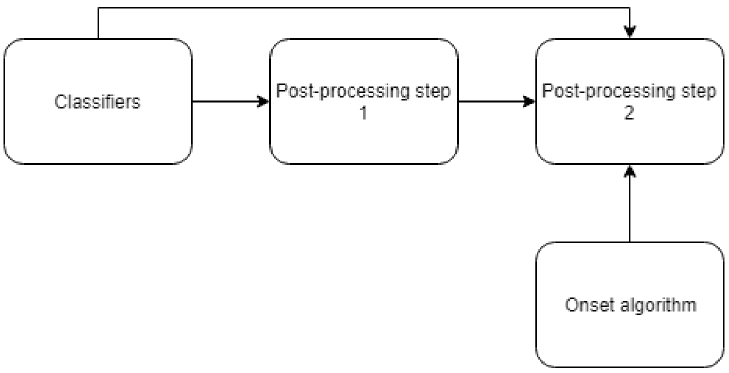


Figure 4.11 - Representation of the three types of sequences, received by the post-processing step 2.

The idea behind the concept of receiving both sequences of previous transcribed frames of step 1 and the initial transcription from the classifiers was figured out based on the article (Zhang et al., 2016). In this article, the authors have proposed a system for creating new images based on two stages, instead of just one, which was the common approach at that time. This second stage would receives the original input given to the first stage plus the predicted outcome from that initial stage. In the end, they were able to improve their results. In this case, we considered the original input as the first input received from the post-processing stage, the one created by the classifiers, and the predicted output as the predicted transcription from the previous post-processing step (step 1).

In addition to that, a sequence of the output of an onset algorithm was also given. This algorithm has the main goal of detecting musical note onsets contained in a musical piece. Of course, this algorithm is not 100% accurate, but its performance is good (around ~78% of f-measure value). However, this algorithm is not able to distinguish between onsets of different musical notes (see Figure 4.12, for an example).

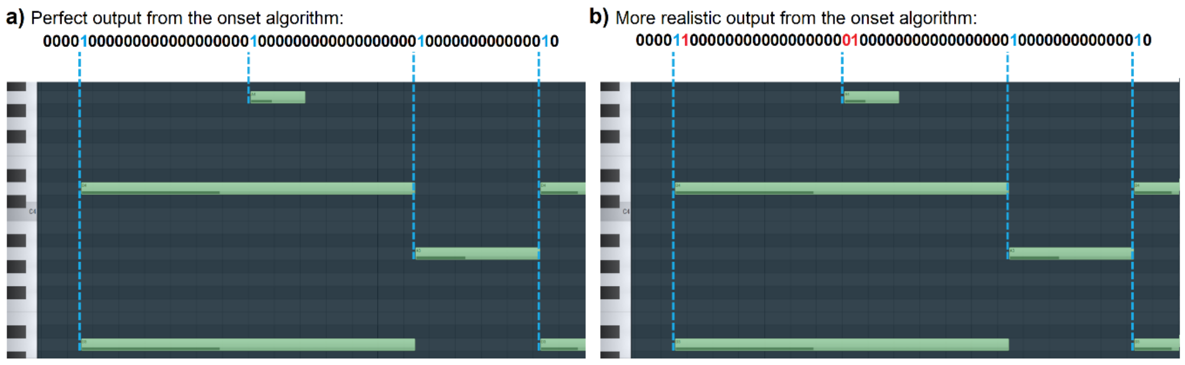


Figure 4.12 - Representation of a perfect onset detection and a more likely output from our onset algorithm. The 1s mean that an onset was detected in the given frame and 0s the opposite scenario. The blue numbers represent the correctly detected onsets and the red numbers the missing or the wrongly detected note onsets.

As can be seen in the figure above, the algorithm is only able to predict if an onset is contained in a given frame or not. Thus, this post-processing unit needs to deal with problems like: (1) falsely and missing detected onsets and (2) onsets of other musical notes.

In the end, this post-processing step was able to fix additional transcription errors, like musical notes duration and note onsets. However, after a deeper analysis of the resultant transcription, we noticed that most of the still remaining note onset errors were by a difference of only one frame. That is, if the expected transcription was:

00000111110000,

two common note onset errors that occur are:

000000011110000 or *00001111110000*

This basically means that the note onset is wrong by a difference of ~93ms, which corresponds to the time contained in each frame. As a result, an additional type of post-processing step was also added to target these types of problems.

4.4.3. Fix notes onsets (step 3)

As mentioned previouslly, after step 2 of the post-processing stage, an important percentage, ~50% to be more specific, of the total amount of note onset errors (40% of errors), are wrong by a small difference of ~93 milliseconds (ms) of the real onset. With that in mind, a new type of post-processing step is proposed.

In the previous steps (1 and 2), all the frames of all the musical pieces were targetted for post-processing, except the initial and last four frames of each musical piece. However, in this third step, only the frames predicted as note onsets are targetted. Thus, for each predicted note onset, this post-processing unit predicts if that note onset needs to be readjusted/shifted or not. For instance, by taking the previous example into account, where the expected transcription is 00000111110000, and the outputted transcription from step 2 of the post-processing stage was 00000011110000, then this post-processing unit should predict the readjustment of the onset to one frame before, resulting in the expected transcription (see Figure 4.13 a). On the other side, if the outputted transcription from the step 2 was 00001111110000 then, this post-processing unit should predict the readjustment of the onset to be one frame later (see Figure 4.13 c). However, in case that the predicted note onset is correct, the post-processing unit should predict it as already correct, and no readjustment is necessary (see Figure 4.13 b).

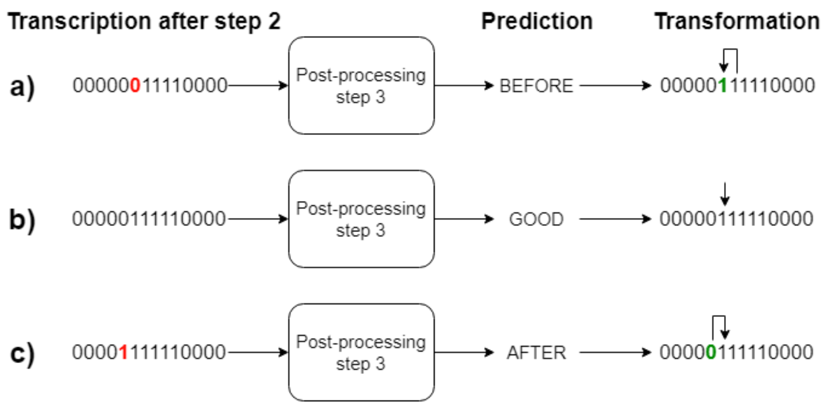


Figure 4.13 - Representation of the three possible transformations that could occur in this post-processing step. a) an example of when the note onset should be readjusted to one frame before. b) example of when the note onset should be kept in the same place. c) example of when the note onset should be readjusted to one frame later/after.

In order to predict, if a note onset should be readjusted or not, two types of sequences are given as input to this post-processing unit. One with the correspondent transcription of the note onset and nearby frames (previous and following four frames), and a second sequence, with the ouput of the onsets algorithm (same algorithm as the one used in the previous step). Thus, in the case of the three examples represented in Figure 4.13, the input data received by this post-processing unit could be as follows:

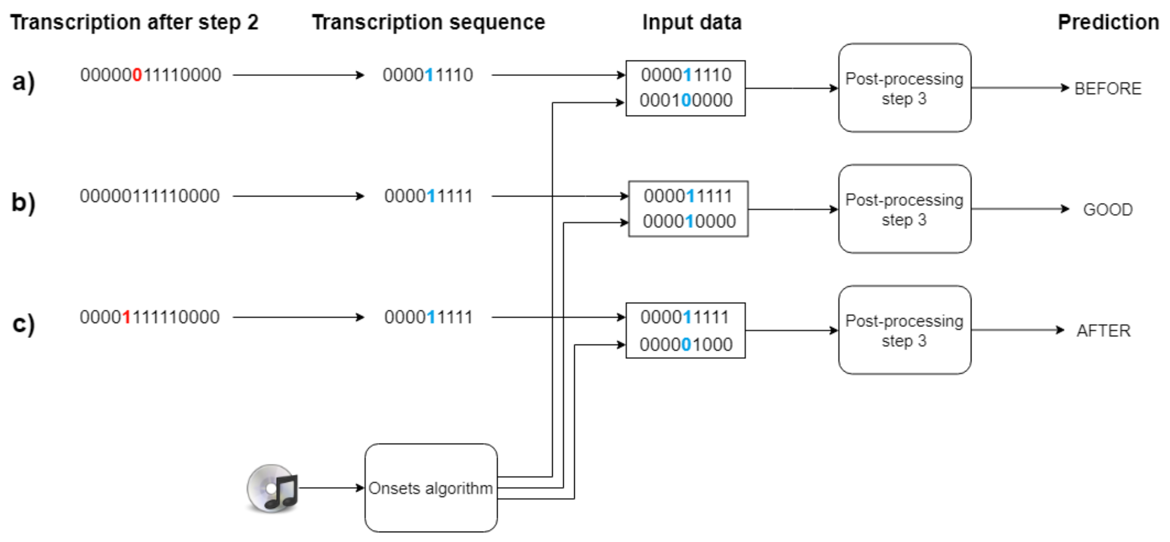


Figure 4.14 - Illustration of the given input data in an ideal scenario, with all the three types of possible predictions. a) scenario where the predicted onset needs to be readjusted to the left. b) scenario where the predicted onset is correct. c) scenario where the onset needs to be shifted to one frame to the right.

From the figure above, it is possible to notice that, the output of the onset algorithm can influence directly the prediction of the post-processing step. If the predicted note onset is misaligned with the detected onset from the onsets algorithm, probably a readjustment should be done. For instance, in the first and last example, Figure 4.14 a) and c), the output of the onset algorithm was misaligned by one frame to the left or right, respectively, which will influence the unit to predict a necessary readjustment in that direction. This did not occur in the example of Figure 4.14 b), where both note onsets were aligned.

However, remember that Figure 4.14 represents an ideal scenario. In reality, this step also needs to deal with problems, regarding the onset algorithm, as the ones mentioned previouslly: falsely and missing musical onsets and the mix of other onsets related to other musical notes.

As mentioned previouslly, a different activation function and a custom loss function was also used in this step. From Figure 4.13, the reader can notice that, per each input, a prediction is given, based on three possible transformations: BEFORE, GOOD, AFTER. In order to achieve that, forcing an ANN to predict only one transformation per input, the softmax activation function was applied in the output layer. This layer is composed of three units, each one representing a possible transformation. As mentioned in Chapter 1, the sum of all the output results from the softmax is always 1. This means that each unit always has a certain “percentage” associated to it. As a result, we have assumed that the unit with the highest percentage, is the prediction given by the ANN.

Nevertheless, a custom loss function was also necessary in order to better fulfill the goal of this post-processing step. Until now, during the classification stage or the previous steps of the post-processing stage, the error was calculated by comparing the prediction with the reality. In other words, if a given frame was correctly transcribed or not (if it does or does not contain a specific musical note). However, in this step, we are predicting if a note onset needs to be shifted or not. Thus, some wrong predictions can detiorate more the resultant transcription than others. For instance, if the ANN should shift the note onset to the right side, but instead, it predicted a shift to the left, then the error should be much higher than if the prediction was to not occur any shift at all (see Figure 4.15).

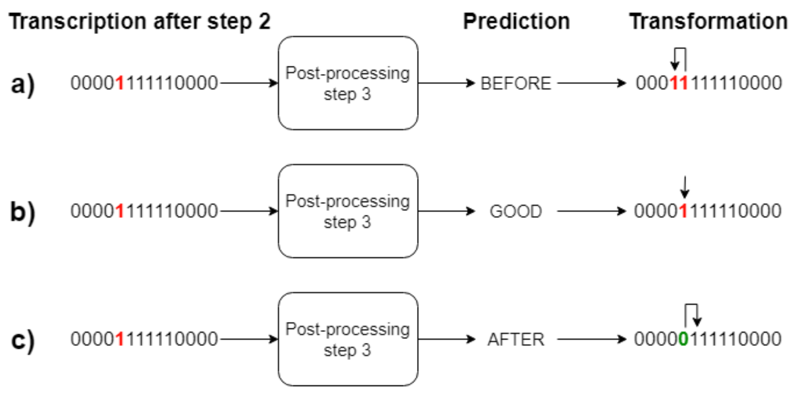
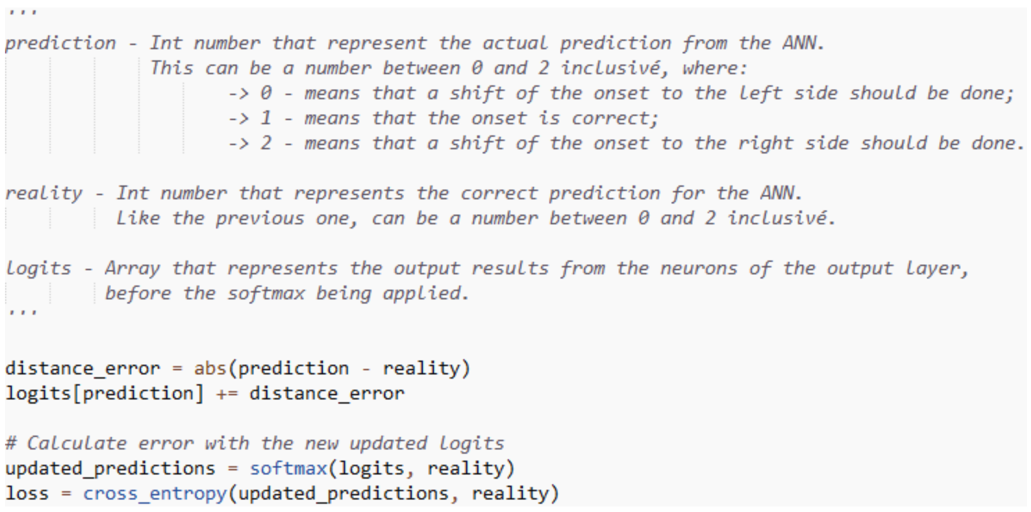


Figure 4.15 - Representation of the difference on how different predictions, from step 3, could affect the resultant transcription. a) an example of a prediction for shifting the onset to one frame before. b) an example of a prediction for not moving the onset. c) an example of a prediction for shifting the onset to one frame after.

In order to fix this problem, the loss function was adapted to take into account, not only if the prediction was correct or not but also how “far away” it is from the reality. The following figure describes the pseudo code of this adaptation.



```
'''
prediction - Int number that represent the actual prediction from the ANN.
             This can be a number between 0 and 2 inclusivé, where:
                   -> 0 - means that a shift of the onset to the left side should be done;
                   -> 1 - means that the onset is correct;
                   -> 2 - means that a shift of the onset to the right side should be done.

reality - Int number that represents the correct prediction for the ANN.
          Like the previous one, can be a number between 0 and 2 inclusivé.

logits - Array that represents the output results from the neurons of the output layer,
         before the softmax being applied.
'''

distance_error = abs(prediction - reality)
logits[prediction] += distance_error

# Calculate error with the new updated logits
updated_predictions = softmax(logits, reality)
loss = cross_entropy(updated_predictions, reality)
```

Figure 4.16 - Pseudo code of the adapted loss function applied in the step 3.

4.5. Summary

This chapter described our proposed model. Recall that the whole system consists of three main stages: pre-processing, classification and post-processing.

The first stage is where all the preparation and transformations steps happen, around the creation of both the dataset used for training and testing. This is an elementary stage, to improve the quality of the data.

The second stage is where the actual transcription process starts. In this case, the one-classifier-per-note approach is applied. In the end a total of 88 classifiers are created.

Finally, the third stage is where transcription errors, like note onsets and notes duration, are aimed to be fixed. Additionally, an external onset algorithm is used to help in this process.

In the following chapter a description of all the experiments done during the progress of this work is given. These experiments represent the way that we took to reach our final proposal.

5. Preliminary experiments

To fine tune the parameters for our model, we performed several preliminary experiments. For those experiments, we resorted to tools such as Matlab (The MathWorks inc, 2018) and Tensorflow (Google Brain Team, 2018). Matlab was used for the whole pre-processing stage. Tensorflow, a python *framework*[10] for machine learning, supported the classification and post-processing stages.

This chapter is split into four sections: dataset, pre-processing, classification and post-processing. The dataset section describes the dataset used in the preliminary experimens. The pre-processing section introduces the preliminary experiments performed for data transformations in order to improve the quality of the data. The classification section focuses on the search towards the best *hyperparameters* and *optimization techniques*. Finally, the last section presents the experiments regarding the different post-processing techniques and ways to improve their performance.

5.1. Dataset

Our dataset of choice is the MAPS (Emiya, 2008) dataset, which is widely used in works related to AMT (Reis, 2012), (Leite et al., 2016), (Kelz et al., 2016) and (Kelz and Widmer, 2017). As mentioned in Chapter 3, MAPS contains piano sounds with isolated notes, chords and musical pieces. However, in our study, we resorted to musical pieces only. This is motivated by the fact that current state-of-the-art studies, which we use to compare our own work, only deal with musical pieces (Sigtia et al., 2016a), (Kelz et al., 2016), (Hawthorne et al., 2018) and (Li et al., 2018).

When doing preliminary experiments, the ideal approach would be to use the same dataset as in the final setup experiments. However, due to the long time required per each experiment, a smaller dataset, referred as *70 musics*, has been created and used (further details can be found in (Gil et al., 2018c) and in (Gil et al., 2018b)). This smaller dataset significantly reduced the computational time needed per experiment, allowing to perform a wider range of experiments. Additionally, to further limit computational time demands, we focused our preliminary experiments on the musical note MIDI number 55. According to

[10] A framework is a structure designed for supporting or enclosing an entity in order to simplify the process of doing/create a given task.

our preliminary study (described in the following topic), MIDI number 55 is one of the most frequent musical notes in the dataset, and it is thus a good reference point.

The *70 musics* dataset comprises 68 musical pieces in the training set and eight pieces in the testing set. The musical pieces were carefully selected according to the following links: (Emiya et al., 2007) and (Reis, n.d.). Note that, there are no repeated musical pieces in both sets.

For the preliminary experiments of the post-processing stage, we used the second fold of *Configuration 1*. This fold is comprised of 216 musical pieces in the training set and 54 pieces in the testing set. The rationale for this option is twofold: i) experiments for the post-processing stage are much less computationally demanding and ii) this is one of the folds of the dataset selected for our final setup.

5.2. Pre-processing

When dealing with ANNs, a fundamental point to get good results is to have good quality data. However, the expression *good quality data* is quite abstract. Moreover, it depends on the problem itself. To get a better grasp of the data, an analysis was performed, resorting to several metrics such as i) the number of frames with each note, ii) number of frames without each note, iii) number of notes played simultaneously with also the correspondent number of frames associated with it, among many other fields. The full details are given in the Appendix, Section A.

Five main observations were revealed from the assessed metadata: (1) The musical note MIDI number 55 is one of the most frequent musical notes in the dataset and, therefore, it is a good reference point for our preliminary experiments; (2) Some musical notes, like the ones ranging from 21 to 29 or 100 to 108, are rarelly or never played during a musical piece, which can make the detection of those musical notes unfeasible, due to insufficient training data; (3) some frames of a musical piece, can contain up to 16 or more (played) simultaneous musical notes substantially hardening the transcription process; (4) all the musical pieces have frames that only contain silence/noise, which is nonrelevant data for the training phase of the classifiers and the post-processing units; (5) each musical note has a different balance of frames with and without that note, a situation that impairs the transcription when the unbalance is too large.

These five observations allowed us a better understanding of some possible transformations that could improve the transcription results. Nevertheless, and since tests are the best way of knowing whether the quality of the data has been improved or not, several tests were performed with a default classifier (further details can be found in Appendix, Section A).

The experimented data transformations can be categorized into three types: i) *data representation*, when the transformation aims at improving the quality of the data by transforming the input data into another type of representation; ii) *parsing,* to improve data by discarding (nonrelevant) frames; iii) *augmenting detection precision*, to improve the temporal resolution, enhancing the precision of note onsets and offsets. An important point is that the parsing-based transformations were solely applied to the training set, because they transform the data according to the ideal/expected transcription (labels), something impossible in a real scenario.

The tested transformations are listed in the table bellow.

Table 5.1 - Data transformations experimented. The transformations in bold represent the ones incorporated into our model.

Name	Type	Positive impact?
Frequency signal	Data representation	Yes
Removal of nonrelevant frames	Parsing	Yes
Ratio between positive and negative labels	Parsing	Yes
Normalization	Data representation	No
Silence classifier	Parsing	No
Overlapping	Augmenting detection precision	Yes
Frequency mean	Data representation	No

The first three data transformations, represented in the table above are the transformations proposed in our model (see previous chapter). All these three transformations positively impacted the results of the transcription system and were therefore incorporated them into our model. Furthermore, although the *overlapping* transformation allowed for improved results, a problem related to the application of the transformation forced us to drop it (we discuss this later). Next, we briefly review each of the transformation models.

The *Frequency signal* data transformation converts the input signal into the frequency domain, using the FFT. The *Removal of nonrelevant frames* transformation discards unrelevant frames such as frames with silence. The *Ratio between positive and negative labels* aims at balancing the training set with the *20/80* rule, where 20% of the frames have the specific musical note and the remaining 80% of the frames do not have it. Several different percentages were tested for this data transformation, namely: *10/90*, *20/80*, *30/70*, *40/60* and *50/50*. The 20/80 division delivered the best results. *Normalization* is a data transformation that aims at changing the range of the input values so that they fall within the range –1 to 1 (close to zero). This, in theory, should make the training process of the ANNs shorter and, it may lead to ANNs with better performance. However, this was not the case and, thus, this approach was excluded from our model. The *Silence classifier* is a type of transformation where an additional classifier, responsible for detecting frames with silence only, functions like a gate for the remaining classifiers (the ones responsible for detecting musical notes). Specifically, if a given frame is marked as silence only by the *Silence classifier*, then the remaining classifiers skip this frame. Conversely, if the given frame is considered to be non silent, then the frame is passed to the remaining classifiers for detecting the pitches contained on it (see Figure 5.1). However, the performance of detecting frames with silence only, by this classifier, was not good enough (~78% of *f-measure*), and thus this transformation was also dropped from our proposal.

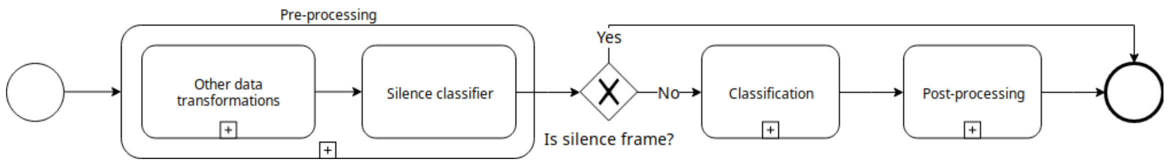


Figure 5.1 - Example of how the silence classifier works.

The *overlapping* transformation is a common transformation, applied in several works related to the AMT field (Ryynanen and Klapuri, 2005), (Emiya, 2008) and (Reis, 2012), to improve the temporal resolution (precision of the musical note onsets and offsets). Usually, when dealing with pitch or multi-pitch estimation problems, the samples contained on a musical piece are splitted into separate frames. However, if an overlap is used, some samples of a previous frame are also contained in the following frame (see Figure 5.2, bellow). This yields a “smoother” split of the musical piece. Within this dissertation, several different overlapping values, technically referred as *hop sizes*, have been tested: 256, 512, 1024, 2048 and 3072 samples. From all of this set of hop sizes, the 3072 hop-size yielded the best results.

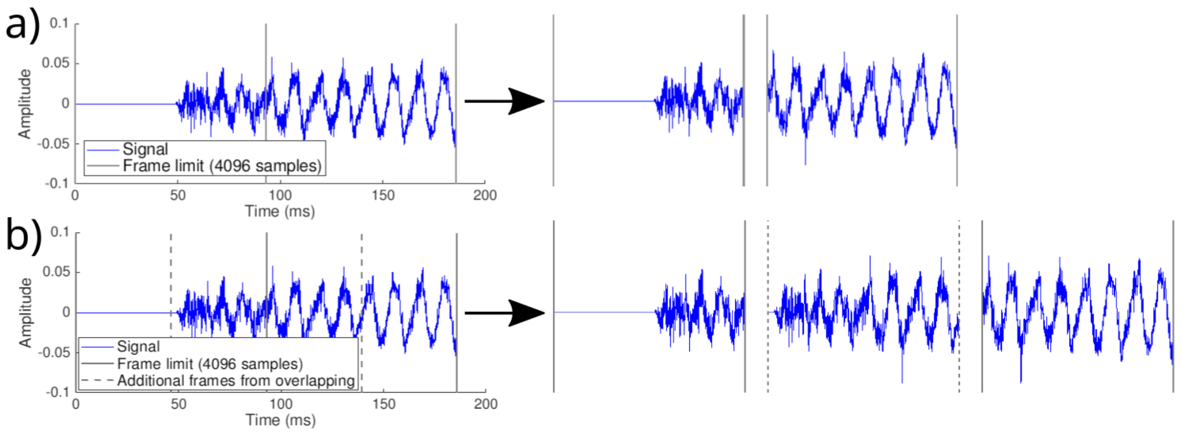


Figure 5.2 - Differences between the separation of the musical piece into frames with and without the overlapping technique. a) Separation of the musical piece into frames without overlapping; b) Separation of the musical into frames with a hop size of 2048.

The overlapping transformation has, however, one major drawback: it augments the size of the dataset, which in turn significantly augments the computational time needed per experiment. For this reason, it was not included in our proposal, despite its positive impact in the transcription process (1% to 2% of improvement in the experiments done).

Lastly, *Frequency mean* is a transformation to smoothen the resultant frequency spectrum. A moving-average of surrounded frequency bins is applied to the spectrum in order to attenuate the background noise (see Figure 5.3). We assessed the mean of 3 and of 5 frequency bins. Mean of 3 is computed with the respective bin plus the previous and following bins, while the 5-mean resorts to the given bin plus the previous and following two bins. However, since none of the tested means improved our results, this transformation was discarded from our proposal.

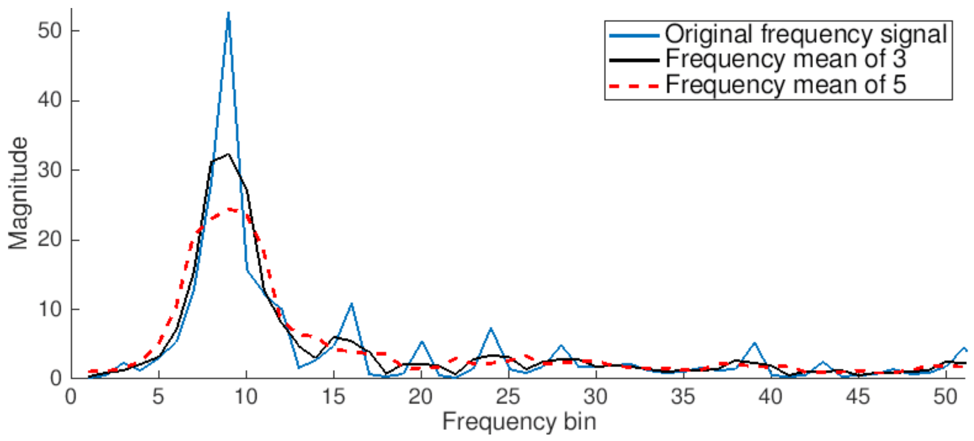


Figure 5.3 - Representation of the impact on the frequency spectrum when the frequency mean data transformation is applied.

To summarize, we experimented seven data transformations with the aim of improving the quality of the data. From the seven studied transformations, only three were retained for our main experiences: i) *Frequency signal,* that converts the signal into the frequency domain, ii) *Removal of nonrelevant frames*, that discards frames with silence, and iii) *Ratio between positive and negative frames*, that balances the data between positive and negative frame with the *20/80* rule. Note that the *Frequency signal* was applied to both the training and testing set, while the remaining ones were solely used on the training set.

5.3. Classifiers

After defining the data transformations, we pursued with the preliminary experiments regarding the classifiers. These experiments had the aim of knowing which hyperparameters and optimization techniques were best suited for this problem.

As mentioned previously, hyperparameters are variables that affect the training process, and that need to be specified ahead-of-time by the developer. The *learning rate* and the *activation function* applied are two good examples of hyperparameters.

In this work the tested hyperparameters and/or group of hyperparameters were the following ones:

Table 5.2 - Hyperparameters and/or group of hyperparameters tested. The values in bold represent the ones applied in our model.

Hyperparameter(s)	Values tested
Model architecture	**Cone shape**, Diamond shape and Linear shape
Weights initialization	**Random initialization** and **suggested initialization techniques**.
Optimizer	***Adam***, *Adagrad*, SGD and *RMSProp*.
Momentum	**Off**, 0.5, 0.7, 0.9, exponential decay starting with 0.5 and 0.8.
Learning rate	1×10^{-3}, 1×10^{-4}, 1×10^{-5} and $\mathbf{1 \times 10^{-6}}$
Activation function (hidden layers)	**Leaky relu**, Swish and Selu.
Activation function (output layer)	**Sigmoid** and Softmax.
Loss function	Log loss, mean squared and **cross entropy**.

Experiments called *Model architecture* were devised to search for the combination of layers and neurons that are better suited to the ANN. Specifically, two types of experiments were performed: 1) one to determine the best shape for the ANN and another one 2) to reduce or augment the dimensionality of the ANN. In the first type, three different shapes of the ANN were tested (see Figure 5.4). We designate as *shape* to the contour of the layers that the ANN is built of. The three tested shapes were the Cone, Diamond and the Linear (the last one was used in Sigtia et al., 2016a and Kelz et al., 2016). For further details see the Appendix, Section A.

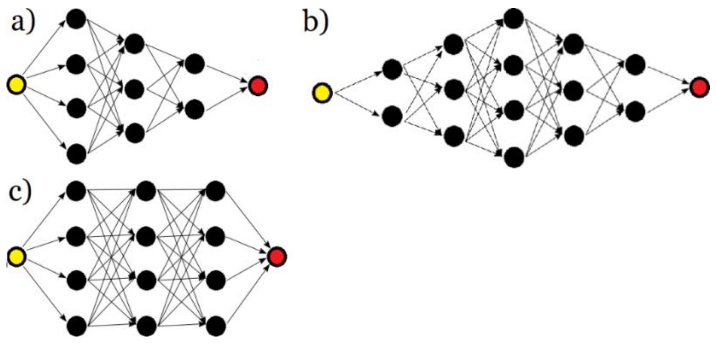


Figure 5.4 - Types of model shapes experimented. Note that the number of neurons and layers represented in this figure are only a mere representation of the reality. a) Cone shape. b) Diamond shape. c) Linear shape.

After some first experiments, the Cone and the Linear shapes achieved the best metrics with similar computational time and, thus, they were both used in the second type of experiments. In the second type of experiments, both shapes were reduced and augmented until a balance between computational time and metrics achieved was found. From the iterations, we determined that the best shape was a reduced model with a Cone shape (further details can be found in Table C.0.3 in the Appendix).

The *Weights initialization* experiments comprised a comparison between random initialization and suggested initialization (He et al., 2015) and (Glorot and Bengio, 2010) according to the used activation functions. This allowed us to determine that the suggested initialization favored the hidden layers, while the random initialization was more suited for the output layer and therefore, in the hidden layers the suggested initialization was used and in the output layer the random one.

The three set of experiments labeled as *Optimizer*, *Momentum* and *Learning rate* were jointly tested due to the fact that they are closely related to each other. Nevertheless, in order to reduce the number of experiments to a feasible number, we divided those combined experiments into two types. The first type of experiments aims at finding the three most performant optimizers combined with different values of momentum, while the second type pursues the goal of applying different learning rates to those three previous selected optimizers in order to discover the best combination of both. The learning rate is the hyperparameter that determines the amplitude of the changes when updating the weights. The *momentum* is a hyperparameter that works as a ”push” on the process of updating the weights based on the slope of the error surface derivative. The *momentum* was also tested with an exponential decay where for each 20 *epochs*[11] its value was reduced by 20%. In the end, the best combination was the *Adam optimizer* with ”no momentum” and a learning rate of 1×10^{-6}. By ”no momentum” we mean that we did not specify a momentum from the table above (50, 70 or 90), because the Adam optimizer already applies and adapts by itself the value of the momentum[12]. In the set of experiments denominated as *Activation functions*, commonly applied functions like the *sigmoid* and the *leaky relu* and other, more recent activation functions such as the *softmax*, the *swish* and the *selu*, were experimented. We found that a combination of both the leaky relu in the hidden layers and the sigmoid on the output layer was the most performant. Finally, three different loss functions were tested: *log loss*, *mean squared* and *cross entropy*. In this case the cross entropy was the most prominent.

After the hyperparameters being established, we focused on the optimization techniques to apply. These consist on techniques used during the training process to improve the performance of the ANN. Commonly, these techniques focus on improving at least one of the following points: i) computation time required for the training process and/or ii) results achieved.

In this dissertation six different optimization techniques have been experimented (see Table 5.3).

[11] An epoch represents a forward and backward pass of all the training examples.

[12] Actually, the Adam optimizer does not apply the momentum hyperparameter. Instead, it applies a closely related concept. However, for the sake of understanding, we refer to it as momentum.

Table 5.3 - Optimization techniques experimented. The ones in bold represent the techniques incorporated into our model.

Optimization technique	**Values tested**
Trainable optimizers	Adam
Dropout	5%, 10%, 15%, 20%, 30% and with exponential decay starting with 60%, 70% and 80%
Batch normalization	----
AlphaDropout + Selu + Weights initialization	SGD and Adam with both 5% and 10%
Noisy gradients	50%, 70% and 100% with a standard deviation of 0.05, 0.1 and 0.15
Shuffling	----

Adam is an optimizer that adapts both the learning rate and the “momentum” during the training phase. Nevertheless, to be able to adapt both variables, two additional hyperparameters need to be specified. According to the authors of Adam, those hyperparameters should be static. However, recently, other authors (Wichrowska et al., 2017) also propose dynamic hyperparameters that are learnt during the training phase, which should reduce the computation time of that phase. We experimented this *trainable Adam* optimizer, and even though the training time was reduced, the achieved results were worse (less ~3%) than the ones in the original Adam. Thus, this technique was discarded.

Dropout (Srivastava et al., 2014) is an optimization technique that consists on randomly disabling neurons during the training phase. This, in theory, should make them more independent of each other. For this event, randomly disable neurons, to occur, a probability must be specified. We experimented five different probability values: 5%, 10%, 15%, 20% and 30%. Apart from that, we also tested an exponential decay of this probability starting with three different percentages: 60%, 70% and 80%. The rationale for this intuition is that, in the early steps, each neuron would be almost forced to learn some features individually and then, in a later stage, they would apply and polish that acquired knowledge in collaboration with other neurons. In the end, exponential decay has significantly reduced the training time. The best results were achieved with a static probability of 15% and, thus, this value was applied in the final model.

Batch normalization (Ioffe and Szegedy, 2015) is an optimization technique that aims at reducing the time required during the training phase by tackling the so called *covariance* *shift* problem. Recall that, in a multi-layer neural network, the update of the weights is done from the last layer to the first one. According to the authors, when the initial layers are updated, the following ones should also be readapted according to that change. Otherwise, the problem of covariance shift will occur. This effect gets even stronger when deeper ANNs are used. Nevertheless, our proposed model has only five hidden layers and thus it is not strongly impacted by the covariance shift problem. Furthermore, this technique also implies additional calculations which in turn augments the computational time of each update of the weights. As a result, we did not include this technique into our model because, even though the number of epochs were slighly reduced, the computational time taken for the whole training process was almost the double.

The *AlphaDropout + Selu + Weights initialization* (Klambauer et al., 2017) is a recent optimization technique that also aims at reducing the time needed during the training phase like the previously mentioned technique, but without additional computationally expensive calculus. According to the authors, a combination of the AlphaDropout, which consists on a variation of the dropout technique, with the selu activation function and a suggestive way of initializing the weights should reduce significantly the training time. Although the authors only present experiments regarding the SGD optimizer, in this work we tried both the Adam and the SGD. Additionally, they also mention that a smaller value of dropout occurrence should be used, around 5% or 10%. Thus, in this work we have tested both the SGD and the Adam optimizer with 5% and 10%. In the end, we noticed that this technique has significantly reduced the training time, but at the cost of the achieved results, which were poorer (less ~5%), and thus it was discarded.

One way of improving the ANNs performance is by forcing them to broaden their search. Both the *noisy gradients* (Neelakantan et al., 2017) and the *shuffling* (Lecun et al., 1998) optimization techniques do that but in different ways. The noisy gradients technique aims at randomly adding a *gaussian distribution* of noise to the gradients of the network. The shuffling, on the other hand, aims at randomly shuffle the training sequence of the input data. Both techniques have helped to improve the robustness of our model, leading to better results, and through this way their implementation. Regarding the noisy gradients technique, we determined that a probability of 70% with a *standard deviation* (STD) of 0.05 resulted in the best achieved results. On the other hand, the shuffle was applied every time that was possible due to its positive results.

To recapitulate, we experimented several hyperparameters and optimization techniques in order to improve the transcription results during the classification stage. The most prominent hyperparameters and optimization techniques found are as follows:

Table 5.4 - Overview of the most prominent hyperparameters and optimization techniques found.

Hyperparameters	Reduced cone shape.
	Weights of the hidden layers initialized using (He et al., 2015).
	Weights of the output layer randomly initialized.
	Adam optimizer.
	Learning rate of 1×10^{-6}.
	Leaky relu on the hidden layers.
	Sigmoid on the output layer.
	Cross entropy as the loss function.
Optimization techniques	Dropout, noisy gradients and shuffling.

5.4. Post-processing

Multi-pitch estimation is a hard problem, where several factors like the overlapping of musical notes makes the transcription process harder and consequently errors are common. To attenuate those errors, some post-processing techniques can be applied. In this work we experimented five different types of post-processing techniques:

Table 5.5 - Post-processing techniques experimented. The ones in bold represent the post-processing techniques incorporated into our model.

Post-processing technique	Positive impact?
Fix notes duration	Yes
Fix notes duration according to onsets	Yes
Fix onsets	Yes
Fix offsets	No
Discard notes	No

As described before, the *fix notes duration* post-processing technique aims to add the sense of time into the transcription system by receiving as input data a sequence of previously transcribed frames (from the classifiers) and predicts the possible transcription for the frame in middle of that sequence. The *fix notes duration and notes onsets* is a similar post-processing technique as the previous one, but it also tries to improve the note onsets by also receiving the output from an onset algorithm (Martins, 2008). Apart from that, it also receives a sequence of the original transcription from the classifiers. The *fix onsets* is a technique that specifically targets improving the note onsets by readjusting a note onset, if needed, to one previous or posterior frame. It receives as input a sequence of previous transcribed frames and the output of the onset algorithm. The *fix offsets* is similar to the *fix onsets* but, instead, it targets note offsets. However, this technique only receives as input the sequence of previously transcribed frames. Finally, the *discard notes* is a post-processing technique that aims at discarding wrongly detected musical notes. It does that by receiving as input, informations such as: i) the number of frames within that musical note, ii) the sequence of previously transcribed frames, iii) the output of the onset algorithm and iv) the output of the *possible notes* algorithm (Reis, 2012), which consists on an algorithm for detecting notes by considering the most prominent spectral peaks.

In our experiments, only the first three post-processing techniques -- *fix notes duration, fix notes duration according to onsets* and *fix onsets* -- had a positive impact in the results, and thus were selected to integrate our model.

5.5. Summary

This chapter introduced the preliminary experiments done in order to reach our final model. For each main stage – pre-processing, classification and post-processing – preliminary experiments have been accomplished. These experiments were essential to fine tune our model in order to improve its final transcription.

In the next chapter the results achieved from our fine tuned model are presented.

6. Results

This chapter describes the results achieved with our model. Initially, a description of the dataset and the metrics used for evaluating the model are presented. The configurations applied on the model are also described. Finally, the achieved results and a comparison with two other state-of-the-art works, followed by a demonstration of the impact of the onset algorithm applied is given.

6.1. Dataset

As previously explained, one of the main motivations for this work is to compare both the one-classifier-per-note approach with the traditional one. For this purpose, we have used the *Configuration 1*[13] dataset based on the MAPS (Emiya, 2008), which is a popular dataset used in recent AMT works. Recall that this dataset is composed of four folds, each one containing a different combination of musical pieces, with 216 musical pieces in the training set and 54 pieces in the testing set. This means that, for each fold, a transcription system comprised of 88 ANNs for the classification stage and *88 * 3 (number of steps)* = 264 ANNs for the post-processing stage, must be created.

We consider *Configuration* 1 to be an appropriate dataset for the purpose of comparing both approaches, because it is composed of four folds instead of a single one. In the end, the difference of the results obtained, that is, the mean from all the folds, should highlight the difference of applying a distinct approach, instead of other complementary factors such as the use of different *hyperparameters*. This is due to the fact that fine tuned hyperparameters for a given fold may not be as optimal when applied to another fold.

6.2. Metrics

Regarding the AMT field, when comparing different approaches, two different types of metrics are commonly used: *frame-based* and *note-based* metrics (Bay et al., 2009). Frame-based metrics consists on evaluating frame-by-frame the resultant transcription whereas note-based consists on evaluating each transcribed musical note by considering its pitch, onset and, depending on the given metric, its offset. In this work, we use both types of metrics. The note-based metrics are based on MIREX (“MIREX”). We refer as *onset only* to the metrics that consider the pitch and the onset with a tolerance of $\pm 50ms$ (its assumed

[13] More details can be found in (Sigtia et al., 2016b).

a tolerance of 50ms because the human ear cannot perceive differences with such a small interval of time) and *onset/offset* to the note-based metrics that additionally consider the offset with a tolerance of: i) $\pm 50ms$ or ii) 20% of the musical note duration.

The results are presented using the *f-measure*, which is a harmonic mean (Kenney, 1962) between: i) the *precision*, percentage of correctly transcribed notes or frames, depending on the type of metric, note-based or frame-based respectively and ii) the *recall*, percentage of existent notes or frames that were correctly identified, also depending on the type of metric.

Mathematically, the metrics can be expressed as:

$$Precision\ (P)\ = \frac{TP}{TP + FP} \tag{6.1}$$

$$Recall\ (R)\ = \frac{TP}{TP + FN} \tag{6.2}$$

$$F - measure\ (F)\ = \frac{2 \times recall \times precision}{recall\ +\ precision}, \tag{6.3}$$

where *TP* represents true positives, which consists on correctly identified frames or notes, *FP* describes false positives, which consists on wrongly detected frames or notes and, finally, *FN* which illustrates false negatives that consists on missed detected frame or notes.

6.3. Experimental setup

As mentioned earlier, the most prominent pre-processing techniques, hyperparameters, optimization techniques and post-processing techniques were jointly applied in this final setup. In the following three tables a review of those techniques and their sequence order are presented.

Table 6.1 - Sequence order of the pre-processing techniques used.

Pre-processing techniques
1st *Frequency signal*
2nd Removal of nonrelevant frames
3rd Ratio between positive and negative labels – using the 20/80 rule.

Table 6.2 - Sequence order of the optimization techniques applied.

Optimization techniques (both used in the classification and post-processing stages)
1st *Shuffling*
2nd *Noisy gradients* – with 70% of probability and 0.05 STD
3rd *Dropout* – with 15% of probability

Table 6.3 - Sequence order of the post-processing techniques applied.

Post-processing techniques
1st Fix notes duration
2nd Fix notes duration according to onsets
3rd Fix onsets

Additionally, the hyperparameters used in both the classification stage and post-processing stage are described in the table bellow:

*Table 6.4 - Hyperparameters applied during both the classification and post-processing stage. *means that the given hyperparameter(s) was applied in the classification stage, **applied in the fix notes duration and fix notes duration according to onsets post-processing techniques and ***applied in the fix onsets post-processing technique.*

Hyperparameter(s)	**Values**
Model architecture	Reduced Cone shape
Weights initialization (hidden layers)	Suggested initialization technique
Weights initialization (output layer)	Random initialization
Optimizer	Adam
Momentum	Off
Learning rate	1×10^{-6}*, 1×10^{-4}** and 1×10^{-3}***
Activation function (hidden layers)	Leaky relu
Activation function (output layer)	Sigmoid
Loss function	Cross entropy

6.4. Achieved results and comparison

The achieved results were as follows:

*Table 6.5 - Achieved results. *Average of the four folds.*

Fold #	**Frame-based**			**Onset only**			**Onset/Offset**		
	P	***R***	***F***	***P***	***R***	***F***	***P***	***R***	***F***
1	87.67	76.99	81.98	64.4	68.17	66.23	45.29	47.94	46.58
2	85.22	77.84	81.36	62.8	62.16	62.47	45.81	45.34	45.57
3	84.33	73.04	78.28	56.74	56.82	56.78	41.21	41.27	41.24
4	82.54	78.06	80.24	63.29	59	61.07	39.27	36.61	37.89
Avg*	**84.94**	**76.48**	**80.47**	**61.81**	**61.54**	**61.64**	**42.90**	**42.79**	**42.82**

A deeper insight of the improvements gained through each post-processing step can be viewed in the following table:

Table 6.6 - Improvements through each post-processing step.

Stage/Step	**Frame-based (F)**	**Onset only (F)**	**Onset/Offset (F)**
Classifiers	66.89	33.08	24.91
Post-processing step 1 (*Fix notes duration*)	79.78 (+12.89)	51.61 (+18.53)	34.54 (+9.63)
Post-processing step 2 (*Fix notes duration according to onsets*)	80.23 (+0.45)	55.97 (+4.36)	39.07 (+4.53)
Post-processing step 3 (*Fix onsets*)	80.47 (+0.24)	61.64 (+5.67)	42.82 (+3.75)

From the table above, we may conclude that the post-processing stage plays an essential role in the improvement of the transcription results. The frame-based metrics were improved by an amount of 13.58%, the *onset only* metrics, by 28.56% and the *onset/offset* by 17.91%.

To better understand the impact of those steps, a portion of the resultant transcription and an audible version, per each step, from the musical piece *BMW 846 Prelude in C Major* from Johann Sebastian Bach, can be viewed and listened in the underneath figures (Figure 6.1 and Figure 6.2) and table (Table 6.7). Also, additional examples can be seen in the Uniform Resource Locator (URL) described in Appendix section A.

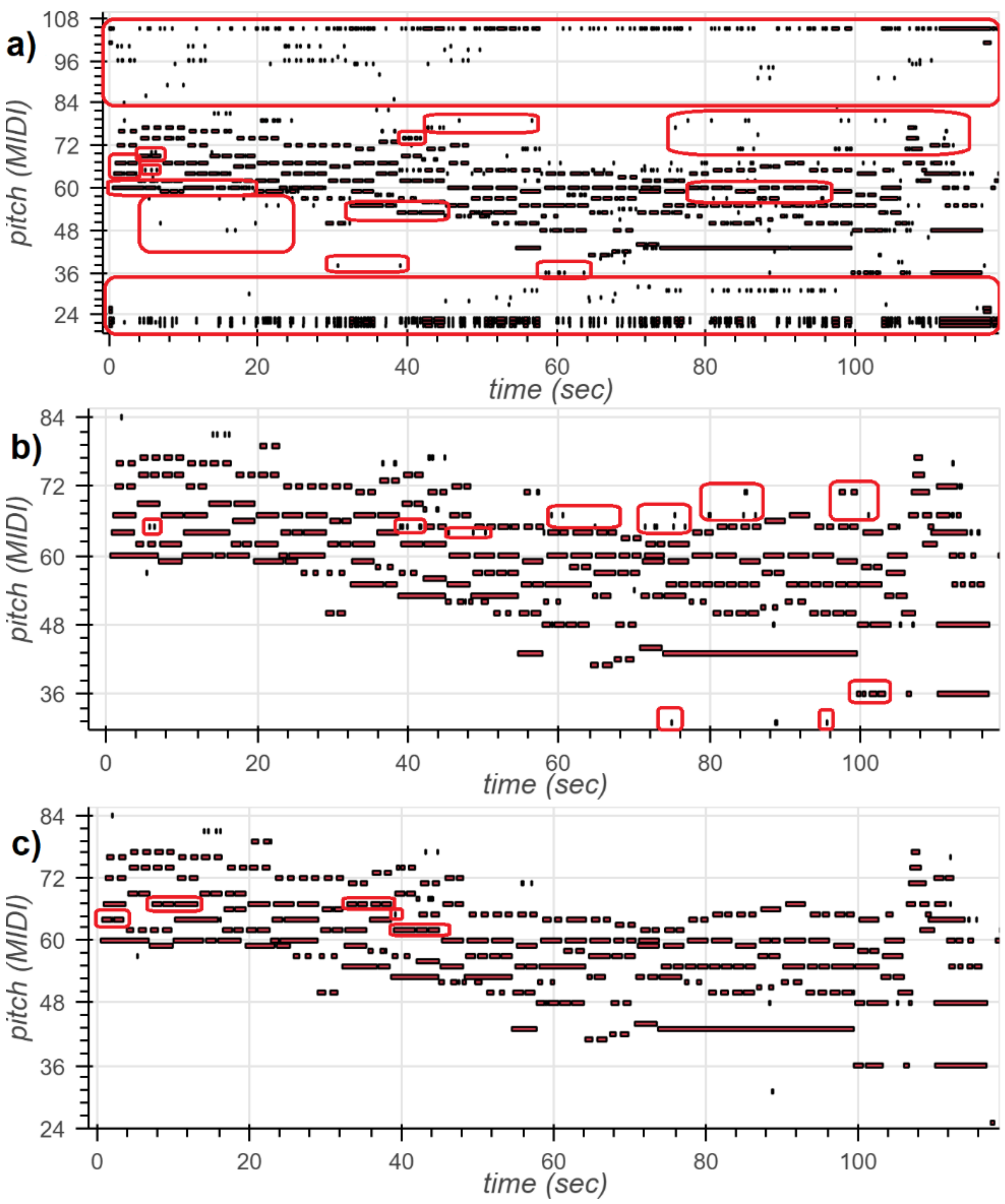


Figure 6.1 – Representation of the resultant transcription from the classification stage up to the post-processing step 2. The red squares denote the problems that are solved in the following step. a) Transcription from the classification stage. b) Transcription from the post-processing stage step 1. c) Transcription from the post-processing stage step 2.

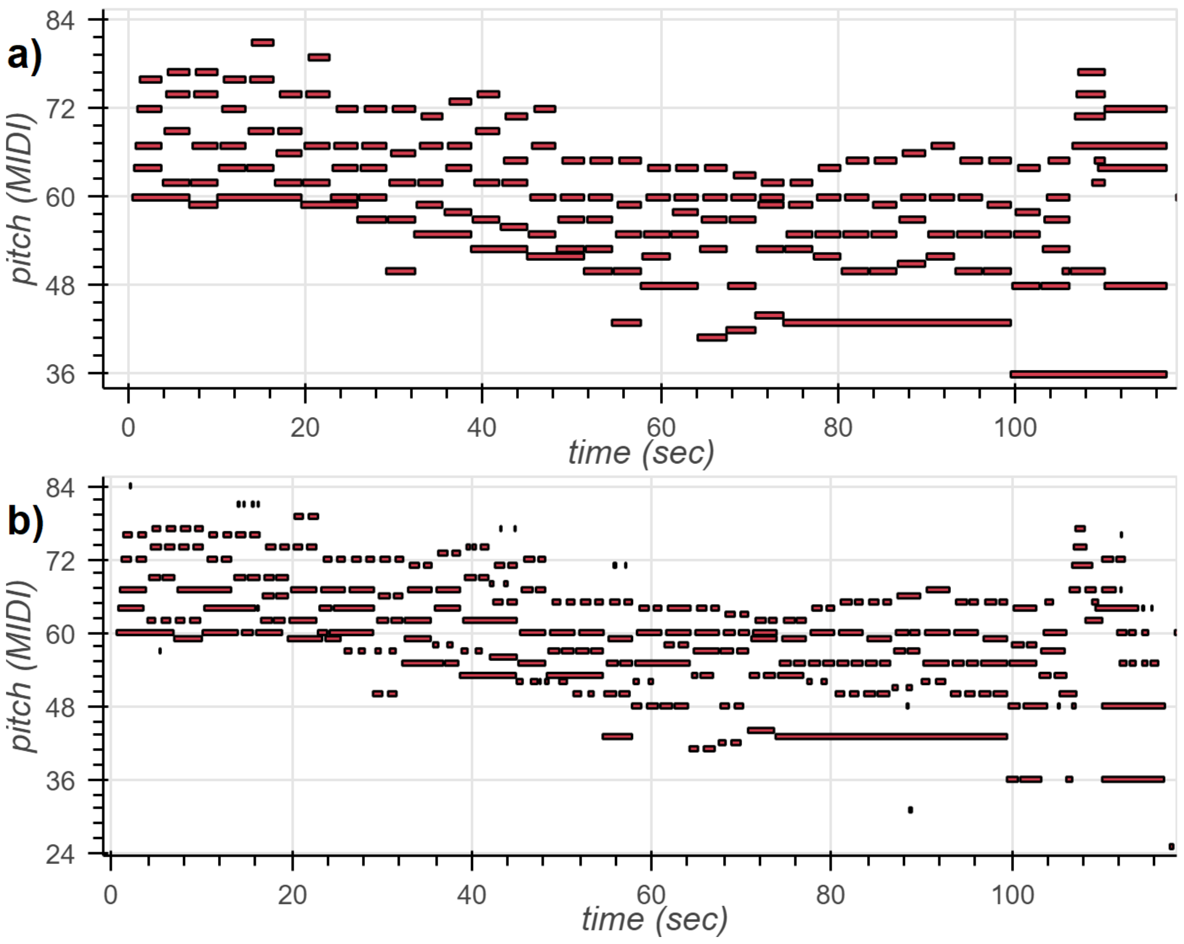


Figure 6.2 - Portion of the expected and resultant transcription of the BMW 846 Prelude in C Major musical piece. a) Expected transcription. b) Resultant transcription from our system (post-processing step 3).

Table 6.7 – Audible version from the resultant transcription of each step and the original version. The example used is the musical piece, BMW 846 Prelude in C Major musical piece from Bach, played in virtual piano. For those who are not viewing this work in the digital format, check Appendix, Section A, for the URL. The play button image was adapted with permission from (Schmidsi, 2019).

Stage/Step	**Tune**
Original	▶
Classifiers	▶
Post-processing step 1	▶
Post-processing step 2	▶
Post-processing step 3	▶

6.4.1. Comparison

As mentioned before, one of the main goals of this work was to compare the one-classifier-per-note approach with the traditional one. In the table below, a comparison is presented with other two current state-of-the-art works that apply the traditional approach and in addition also use the multi-layer perceptron technique and the same dataset.

Table 6.8 - Comparison with other similar state-of-the-art works. [1] Sigtia et al., 2016a. [2] Kelz et al., 2016.

Approach	**Frame-based**			**Onset only**		
	P	***R***	***F***	***P***	***R***	***F***
ANN [1]	65.66	70.34	67.92	**62.62**	**63.75**	**63.179**
ANN [2]	76.63	70.12	73.11	---	---	---
Ours	**84.94**	**76.46**	**80.47**	61.81	61.54	61.64

The table shows that our model was able to surpass significantly other models in terms of frame-based metrics and, at the same time, reaches similar results in terms of onset only metrics. An important point, regarding the first work ([1]) is that it uses a *language model* to improve the results. A language model consists on a system that detects patterns from (other) previously played notes in order to predict the following ones. This commonly leads to an improvement of the transcription, especially in musical pieces that follows a certain pattern. In our model we did not use a language model because it was out of the scope of the work. Nevertheless, for future improvements, a language model could be built in order to improve the transcription results.

To finish, a comparison is presented with other three systems that implement other types of more recent artificial neural networks, like a Recurrent Neural Network (RNN) or a Convolutional Neural Network (CNN).

Table 6.9 - Comparison with other artificial neural network techniques.

Approach	**Frame-based**			**Onset only**		
	P	***R***	***F***	***P***	***R***	***F***
RNN [1]	67.89	70.66	69.25	64.64	65.85	65.24
CNN [1]	72.45	76.56	74.45	**67.75**	**66.36**	**67.05**
CNN [2]	80.19	**78.66**	79.33	---	---	---
Ours	**84.94**	76.46	**80.47**	61.81	61.54	61.64

Note that even when our results are compared with the ones obtained with these networks, it still has higher frame-based metrics and, at the same time, comparable results in note-based metrics. This demonstrates the viability of our approach.

6.5. Impact of the onset algorithm

As previously stated, during some of the steps of the post-processing stage our transcription system resorts to an onset algorithm (Martins, 2008) in order to improve the transcription results. This algorithm is not perfect and according to our study it has an f-measure of around 78% on the overall musical pieces contained in the MAPS dataset. Thus, those missing and/or falsely detected onsets have a negative impact in our system.

To have an insight of that impact, we have repeated the experimental setup for both the *fix notes duration according to onsets* (step 2) and *fix onsets* (step 3) of the post-processing stage, but, this time, using a perfect onset algorithm. In the end, the obtained results should demonstrate the full efficiency of our system and not the dependency that it has on the original onset algorithm.

The table that follows present a comparison with the other works with the results yielded using the perfect onset algorithm.

Table 6.10 - Comparison with the results obtained with the perfect onsets algorithm.

Approach	**Frame-based**			**Onset only**		
	P	***R***	***F***	***P***	***R***	***F***
ANN [1]	65.66	70.34	67.92	62.62	63.75	63.179
ANN [2]	76.63	70.12	73.11	---	---	---
RNN [1]	67.89	70.66	69.25	64.64	65.85	65.24
CNN [1]	72.45	76.56	74.45	67.75	66.36	67.05
CNN [2]	80.19	**78.66**	79.33	---	---	---
Ours	84.94	76.46	80.47	61.81	61.54	61.64
Ours with perfect onsets	**86**	77.23	**81.36**	**72.56**	**73.12**	**72.80**

From the table above, we can notice that the final results of our system are fully dependent on the performance of the onset algorithm used. By using an improved version of an onset algorithm, our model was able to surpass in both evaluation metrics the current state-of-the-art works, even the ones that apply a newer ANN technique. This is clear indication that the one-classifier-per-note approach is a viable way of addressing the multi-pitch estimation problem.

6.6. Summary

This chapter described the achieved results from our proposed model. Recall that our transcription system was able to surpass current state-of-the-art works in frame-based metrics and at the same time reaches comparable results in note-based metrics. In addition, we have also observed that the performance of the applied onset algorithm, directly influences the final performance of our system. Therefore, if a better onset detection algorithm could be used, our system could reach or even surpass the current state-of-the-art works regarding to note-based metrics, while additionally improving on the remaining metrics.

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7. Conclusion and future work

One of the main aims of this work was to check the viability of the one-classifier-per-note approach using artificial neural networks. To accomplish that, we elaborated an initial study to find out the current state-of-the-art works, related to the AMT field, which combined artificial neural networks with the traditional approach. From this, we established that a classical deep learning technique was preferable in order to have a baseline comparison.

After establishing both the type of ANN technique and the dataset to be used, we pursued with several preliminary experiments. These, were a fundamental step for our model because it shaped the way that the transcription is performed. We noticed that both a pre-processing and post-processing stage should be taken into account, in order to improve the whole performance of the system. The pre-processing stage would transform the sound signal into a more appropriate representation, while the post-processing stage would aim at fixing errors in the original transcription.

In the end, our model was able to surpass current state-of-the-art-works regarding the frame-based metrics and, at the same time, reaching comparable results in note-based metrics. Even when we compare with other works that apply newer ANN techniques, our model is still better in frame-based metrics. This indicates the viability of the one-classifier-per-note approach.

7.1. Future work

For future work, we would like to propose an improvement of the onset algorithm used. As demonstrated, if a better onset algorithm is applied our transcription system would perform better. Thus, a possible solution could be to create an additional ANN to reduce the number of false positives from the original onset algorithm or, instead, create a from-scratch onset algorithm using deep learning techniques, like some authors propose (Lacoste and Eck, 2005), (Eyben et al., 2010) and (Schlüter and Böck, 2014). Apart from that, also those onsets could be filtered by musical note, where not only the onset algorithm will detect if a given onset occurs but also which musical note corresponds to.

Planning ahead, now that we have baseline results using classical ANNs, a next step would be to use more sophisticated ones, such as RNNs or CNNs. Also, a different type of data representation could be tested, such as the constant-Q transform, because the separation of the frequency bins using this technique is more closely related to the real separation of the musical notes than the FFT.

Apart from that, a *language model* system could also be created, like some authors suggest (Sigtia et al., 2014) and (Sigtia et al., 2016a). It was out of the scope of this work to create a language model, but, for future improvements, the incorporation of this additional system could lead to an improvement on the transcription results.

To conclude, an *attention* mechanism could also be applied during the classification stage. This mechanism consists on making the ANN focusing only or mostly on a given part of the input data. In our case, by using the one-classifier-per-note approach, the ANN responsible for detecting some specific note should only/mostly focus on the frequency bins related to the fundamental frequency or its harmonics, which could lead to an improvement in the results obtained.

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Appendix

A. Metadata

The existent metadata fields generated are as follows:

Table A.0.1 - Metadata fields.

Field name	**Description**
filename	Tune filename.
piano_type	Piano used during the recording of the tune.
music_type	Type of tune. In our case it is always a musical piece.
nr_of_sounds	Number of tunes.
nr_of_notes_by_frames	Mean of the number of musical notes per frame.
nr_frames	Total amount of frames.
nr_of_notes	Total amount of frames that contain musical notes. If a frame contains two musical notes it is counted twice.
nr_frames_with_note	Number of frames that contains at least one musical note.
nr_frames_without_note	Number of frames that does not contain any musical note.
nr_notes_per_frame	Number of musical notes per each frame.
nr_of_notes_by_noteid	Number of frames per each musical note that contain the given note.
nr_of_notes_per_music	Number of musical notes per musical piece.
nr_of_notes_played	Number of musical notes played.
nr_of_notes_played_by_noteid	Number of times that a musical note has been played.
nr_of_non_zeros_per_frame	Number of samples per frame that have the value of zero.

Apart from the metadata above, additional metadata regarding to each musical note and also the overall dataset is created. This consists on data such as the number of frames per *chord size*. That is, the number of frames that contain 1, 2, 3, 4 or many more (simultaneous) musical notes. Also, metadata related to the percentage of appearance per each musical note is generated. An example of a set of metadata files can be found in (Gil et al., 2018a).

B. Default classifiers

In this work, three classifiers were created for the preliminary experiments, each one responsible for detecting one of the following musical notes: 40, 55 and 60 (MIDI notes). Note that the classifier responsible for detecting the musical note 55 was used during all the preliminary experiments, whereas the other two, only participated in specific cases. None of them applied any type of optimization techniques, while the used hyperparameters were as follows:

Table B.0.2 - Hyperparameters used on the default classifiers.

Hyperparameter(s)	**Values**
Model architecture	Original cone shape model (see Table C.0.3)
Weights initialization (hidden layers)	Initialization according to (He et al., 2015)
Weights initialization (output layer)	Xavier initialization (Glorot and Bengio, 2010)
Optimizer	Adam
Momentum	Off
Learning rate	1×10^{-4}
Activation function (hidden layers)	Leaky relu
Activation function (output layer)	Softmax
Loss function	Cross entropy

C. ANN models

In this section, technical details regarding some of the models tested during the preliminary experiments are described.

The following table details the original and reduced Cone shape model. This model, reduced Cone shape, was used during the experimental setup.

Table C.0.3 - Details of the Cone shape model. The table on the left contains the details regarding the original shape and the table on the right the reduced one.

Original Cone shape model	
Layer	*Number of neurons*
Input layer	2048
1st hidden layer	1025
2nd hidden layer	513
3rd hidden layer	257
4th hidden layer	129
5th hidden layer	65
6th hidden layer	33
Output layer	1

Reduced Cone shape model	
Layer	*Number of neurons*
Input layer	2048
1st hidden layer	256
2nd hidden layer	128
3rd hidden layer	64
4th hidden layer	32
5th hidden layer	8
Output layer	1

The table that follows gives a description of the tested Diamond shape model.

Table C.0.4 - Details of the Diamond shape model.

Diamond shape model	
Layer	*Number of neurons*
Input layer	2048
1st hidden layer	2560
2nd hidden layer	3072
3rd hidden layer	3584
4th hidden layer	3072
5th hidden layer	2560
6th hidden layer	2048
7th hidden layer	512
8th hidden layer	128
9th hidden layer	32
10th hidden layer	8
Output layer	1

The following two tables describe the two Linear shape models that were experimented, based on the models of two state-of-the-art works (Sigtia et al., 2016a, p.) and (Kelz et al., 2016).

Table C.0.5 - Details of the Linear shape model. The table on the left contains the details related to the original Linear shape model while the one in the right the reduced Linear shape model.

Original Linear shape model (based from Kelz et al., 2016**)**	
Layer	*Number of neurons*
Input layer	2048
1st hidden layer	512
2nd hidden layer	512
3rd hidden layer	512
Output layer	1

Reduced Linear shape model (based from Sigtia et al., 2016a, p.**)**	
Layer	*Number of neurons*
Input layer	2048
1st hidden layer	125
2nd hidden layer	125
3rd hidden layer	125
Output layer	1

Also, the table that follows details the model applied during the post-processing stage.

Table C.0.6 - Tiny Linear shape model, used in all post-processing units.

Tiny Linear shape model	
Layer	*Number of neurons*
Input layer	9 (step 1), 18 (step 3) or 27 (step 2).
1st hidden layer	5
2nd hidden layer	5
3rd hidden layer	5
Output layer	1 (step 1 and 2) or 3 (step 3)

D. Transcription examples

To have a better insight of the efficiency of our system, several transcription examples can be found in:

https://bitbucket.org/matapatos/mei-cm_ml_pitchdetection/src/master/transcription_examples/

The URL above has a folder composed by three sub-folders, each one holding piano pieces from the different testing sets used. These sub-folders are, afterwards, composed by five folders: *originals*, *labels*, *classifiers*, *step_1*, *step_2* and *step_3*. The last four folders, *classifiers*, *step_1*, *step_2* and *step_3*, contain the examples of the transcribed pieces according the given step and/or stage. The *originals* folder has the original musical pieces that were used to test our system, and the *labels* folder contains the expected audible version according to the labels. The difference between the *originals* and the *labels* is that the second one does not take into account the volume of the note (velocity in MIDI terminology), which is preferable in our case for comparing the resultant transcription with the expected one.

Automatic music transcription using a one-classifier-per-note approach

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Abstract

This paper describes a new approach to the automatic music transcription problem. The architecture of this approach consists on an artificial neural network per each possible note, plus an additional one (per note) for post-processing. We refer to the main artificial neural networks as *classifiers* and the additional ones, used for post-processing, as *post-processing units*. From our knowledge, it is the first time that a comparison of several classifiers with the traditional one-single classifier approach is done. In addition, to the best of our knowledge, it is the first time that an artificial neural network is applied as a post-processing method in the problem of automatic music transcription.

Keywords: Automatic Music Transcription, Multi-Pitch Estimation, Artificial Neural Networks

1 Introduction

Automatic music transcription (AMT) is the process of detecting the notes that are present in a musical piece, via a machine. This work focuses on a variant of this problem, called multi-pitch estimation, which consists in identifying the pitched notes present in a polyphonic musical piece. A common method applied to this problem is *artificial neural networks* (ANNs). ANNs have been applied successfully to several complex problems. In this paper we present a novel approach of automatically transcribing piano music by using several ANNs.

The traditional approach to AMT, especially when ANNs are applied, consists in having a single classifier that detects and transcribes all the musical notes of a piano (Figure 1a) [1], [2] and [3]. However, in this work, several classifiers are created, each one responsible for detecting and transcribing a specific musical note (Figure 1b). The rationale behind this idea is the well-known "divide and conquer" approach, where a larger hard problem is divided into smaller sub-problems. Hypothetically, these sub-problems should be easier to solve than the original one, possibly boosting the performance of the whole AMT system.

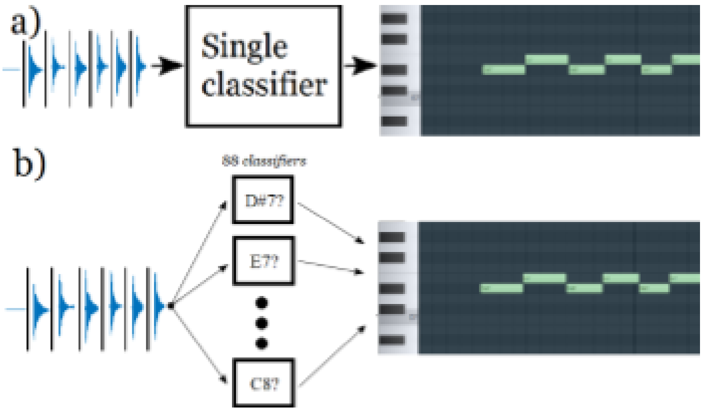

Figure 1 - Illustration of a) the traditional single all-notes classifier approach and b) the many one-note classifiers approach.

In general, the AMT process starts by splitting the musical piece wave (time domain), into smaller chunks, called frames. For each frame, 4096 samples are taken so that a frequency domain signal is produced. Given that the second half of this signal mirrors the first half, only the first 2048 values are taken as input for the notes classifier. The classifier (in our case, a set of classifiers) gives as output, the musical notes that are believed to be present in the frame.

After the classification process, errors are common. This means that some notes that are not present in the frame are identified as being there and/or some notes that are in the frame are not identified. Post-processing techniques can be used to correct these mistakes. We also propose an additional ANN based post-processing step.

The rest of the paper is organized as follows: Section 2 presents the proposed model, while Section 3 presents and discusses the main results. To finish, conclusions and future work are given in Section 4.

2 Proposed model

In this section a deeper analysis of the proposed model is presented. This analysis is composed by four major parts: dataset creation, pre-processing, classifiers and post-processing.

2.1 Dataset

To be able to compare our approach to already existent ones, we use the same musical pieces from *Configuration 1*[1], based on the MAPS [4] dataset. *Configuration 1* consists in four folds, each one with 216 musical pieces for training and 54 pieces for testing. As a result, since AMT usually works with 88 musical notes (corresponding to the notes of a grand piano), we have 88 classifiers and 88 post-processing units per fold. This results in a total of 352 classifiers and 352 post-processing units. Accordingly, each classifier will also have its own specific dataset.

2.2 Pre-processing

Regarding ANNs, a fundamental key point to consider is that good quality data is needed to achieve good results. For this purpose, three sequential transformations in the data have been done: (1) transform the input data into the time-frequency domain; (2) removal of meaningless data, like frames with silence; (3) choosing the best ratio between frames with and without a specific musical note.

2.3 Classifiers

The classifiers consist on the traditional feed-forward neural networks. Other more recent techniques could have been chosen as, for example, Convolutional Neural Networks. However, we wanted to have a baseline to be used in the future when experimenting with more powerful techniques.

After preliminary experiments, where a vast variety of hyperparameters and optimization techniques combinations were tested, the chosen classifiers configuration was the following: The ANN has 2048 inputs (samples from the signal FFT), 5 hidden layers, where each layer has the size of *previous_layer_size/2*, with the first one having 256 units and an output layer with one unit (yes or no output). Hidden layers units apply the *leaky relu* activation function and the output layer uses the *sigmoid* function. The optimizer chosen is *Adam* [5] and the *learning rate* is $1e^{-6}$. Also, the loss function used is the *cross entropy*. Finally, the optimization techniques used are the *dropout* [6] with a probability of 15%, noisy gradients [7] with probability of 70% and a standard deviation of 0.05. Data is also shuffled [8] each iteration (music pieces sequence and frames shuffling).

In the end, these hyperparameters and optimization techniques improved significantly the performance of the classifiers not only in terms of evaluation metrics but also in reducing the needed time for training.

[1] More details at: http://www.eecs.qmul.ac.uk/~sss31/TASLP/info.html.

2.4 Post-processing

As mentioned earlier, a post-processing method can correct errors from the classifier or set of classifiers, which in turn impacts significantly the results of an AMT system. In this work we applied an ANN for this task. The motivation is due to two main factors: firstly, ANNs are good problem solvers and secondly, to our best knowledge, they have never been applied as a post-processing method in the AMT problem.

These post-processing units were trained with the outputs of a classifier. Since the output layer of each classifier applies the sigmoid function as activation function, the output consists in a probability value. As a result, for each frame, a probability value is given. From these outputs, a sequence of 9 elements is then used in order to determine the value in the middle of that sequence (9 inputs and 1 output). The result is an ANN that, not only considers the current frame, but also the previous and following four frames, in order to verify whether the same musical note is in the middle frame or not.

We created three types of post-processing units: (1) *one for all*, where a single unit would be responsible to post process all the notes, (2) *one per each*, where a post-processing unit would be responsible to post process a specific note, (3) *improved one per each*, which is similar to (2) but where the input data is previously transformed with several pre-processing techniques. These pre-processing techniques consist in shuffling the sequence of frames, as well as, an adequate balance between middle frames that contain a positive correct label, frames with a negative correct label and wrongly classified frames.

Post-processing units are trained once the classifiers have been trained. The motivation for this is that we wanted a stable output result from the classifiers, so that post-processing can adapt quickly to each classifier. Each post-processing unit was trained using the same hyperparameters and optimization techniques as the classifiers, except for the learning rate, that had a value of $1e^{-5}$, and the model architecture of the ANN. Three hidden layers were used, each one with five neurons.

From our preliminary experiments, we were able to conclude that the post-processing unit *one for all* was not able to successfully improve the results of the whole system. On the other side, both post-processing units, *one per each* and *improved one per each* significantly improve the global performance of the system. Nevertheless, the best one was the *improved one per each*, especially with musical notes that are not so frequent in the dataset. Therefore, this filter is being used as our post-processing method in our final experiments.

3 Results

In this section, results and a comparison with similar techniques used in other state of the art works are presented. Initially, the metrics used for comparison are introduced. Then, the results from our model per each fold are shown, and finally, a comparison with other research works is presented.

3.1 Metrics

To compare our model, we have taken into consideration frame-based metrics [9], more specifically, *precision* (P), *recall* (R) and *f-measure* (F). These evaluation metrics consist in comparing the transcribed binary output with the MIDI ground truth, frame by frame. Mathematically this can be expressed as:

$$P = \sum_{t=1}^{T} \frac{TP[t]}{TP[t] + FP[t]} \tag{3.1}$$

$$R = \sum_{t=1}^{T} \frac{TP[t]}{TP[t] + FN[t]} \tag{3.2}$$

$$F = \frac{2 * P * R}{P + R} \tag{3.3}$$

where *TP[t]* represents the number of true positives for the event (frame) at *t*, *FP* is the number of false positives and *FN* is the number of false negatives.

3.2 Comparison with other approaches

We compare our results with the ones achieved in [1] and [2], two state of the art works. Both works used *Configuration 1* as their dataset. The results are presented in Table 1. We only present results obtained with the classifiers, because final results with post-processing are not available yet. However, preliminary experiments show that post-processing improves the results.

The results show that our approach has slightly better results regarding recall. Results are not as good for precision and F-measure when compared to the other two works, although they are close to the ones obtained in [1], where post-processing is used. We consider these results as promising, given that they are a first approach, and we expect that they improve after adding post-processing.

Table 1 - Results of the average of the four folds from *Configuration 1*.

Model	*P*	*R*	*F*
Hybrid DNN [1]	65.66	70.34	67.92
Framewise DNN [2]	**76.63**	70.12	**73.11**
One-classifier-per-note ANN	62.08	**72.06**	66.65

4 Conclusions and future work

In this paper, we present a novel *divide and conquer* approach to tackle the AMT problem. Our first results show that this is a promising path, since the results are close to other state of the art works. Indeed, preliminary experiments show that the ANN based post-processing process described in the paper is able to improve the results.

To conclude, there is plenty of space for future work. For instance, in the case of the classifiers, other techniques can be used, like *recurrent neural networks* or *convolutional neural networks*. In addition, the post-processing units could also use other type of technique or, instead, incorporate the transcription results from other classifiers to better extract patterns from the data.

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