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Turning Music Into Game

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Chapter 1

Abstract

Music games present a highly pervasive new platform to create, perform and appreciate music. In this project we will attempt creating a music rhythm game which, given a music track, extracts its features to generate a level without human intervention.

This report details the design of such a program and evaluates its effectiveness. The development of the program has lead to the discovery of new and powerful algorithms in music analysis, as well as successfully demonstrating the power of computers in developing creative works.

Chapter 2

Acknowledgments

I would like to thank my supervisor, Iain Phillips, for his sharp insight into the problems encountered, and his uncanny ability to immediately suggest a good solution for each one.

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Chapter 3

Introduction

> Music and games share a fundamental property: both are playable, offering their listeners and operators an expressive experience with the framework of melody and rhythm [1].

As the quote suggests, both games and music have one thing in common — the act of playing. Just as player's character might die in an attempt to complete a level, causing him to lose the game, the pianist can fail at the attempt of performing a musical piece.

Perhaps this analogy inspired programmers to develop a new genre of games - music games. Music games are games in which players interact with music. Possibly the most commonly known franchises in this genre are Guitar Hero, Rock Band and Dance Dance Revolution. In this type of games user has to follow the indicators on the screen telling him which buttons to hit.

The concept of a music game stormed the industry in 2005, after Guitar Hero was released. The project soon turned into the fastest new video game franchise to reach $1 billion in retail sales in the history of the business, with Guitar Hero III being the first game to reach $1 billion [2].

However, a limited amount of songs transcribed and adjusted to the game play soon caused the popularity of such music video games to decline. Some brave fans of the franchises took it upon themselves to transcribe songs to create new levels. The producers, seeing the tendency, started releasing the in-app purchases to enable the players to extend their library and thus, keep the users.

Due to the time consuming and difficult nature of the process of manually adding new songs, most players usually limit themselves to pre-processed songs provided by the game producers, not really taking advantage of the full capabilities of the games.

This project aims to change the way users look at the music rhythm games. We are creating a game which will allow them to upload any song they would like and automatically generate a Guitar Hero-like level corresponding to it.

This will be achieved by implementation of a melody extraction from polyphonic music signals algorithm using pitch contour characterisation. The algorithm consists of four parts - sinusoid extraction, salience function, pitch contour creation and melody selection. In this approach, pitch contours - time continuous sequences of pitch candidates, are grouped using auditory streaming cues. To filter them, we define a set of contour characteristics, which help distinguish between melodic and non-melodic contours. This leads to the development of new voicing detection, octave error minimisation and melody selection techniques [3].

We will then design and develop an algorithm for mapping the extracted to a series of buttons on the screen to create an interesting and challenging game for a user, as no literature describing such problem was found so far.

In addition to this, we will attempt to develop a mood extraction algorithm to dynamically generate surroundings in the game. Specifically, we treat music emotion recognition as a regression problem to predict the arousal and valence values (AV values) of each music sample directly, which then can be used to generate unique surroundings for every level generated. This continuous view of music emotion makes the proposed music emotion recognition system free of the inherent ambiguity issue. In addition to this, because there is more freedom in describing a song compared to defining and assigning mood classes, the subjectivity issue is alleviated to some extent. [4].

The music emotion recognition will be achieved by designing and training a neural network to predict listeners' mean valence and arousal ratings associated with musical pieces.

With this project we would also like to show that sophisticated academic music analysis techniques can be combined together and applied to real world problems in an efficient and reliable manner.

Finally the project aims to be more than just a research study of feasibility. The result of successful completion will be an application of sufficient reliability and quality that it can be released to, and used by, untrained computer users. To our knowledge, it is the only computer game allowing people to generate Guitar Hero-like levels that also generates the surroundings tailored to every music track.

Chapter 4

Background

In this section, we investigate different types of music games [5], along with a deeper look into Guitar Hero, on which we base our main concept for the gameplay. This is followed by a discussion of the most applicable publications in music analysis, on finding the main melody in a musical track in particular.

4.1 Music Video Games

A music video game can be defined as a type of game that uses music or rhythm as an integral part of gameplay. This may involve pressing buttons in time with a song, whether on a conventional controller, and instrument controller or some kind of dance mat, singing into a microphone or creating original music. Players can often perform different parts of the same song together in local multiplayer games or over the Internet, providing enjoyable social experiences [7].

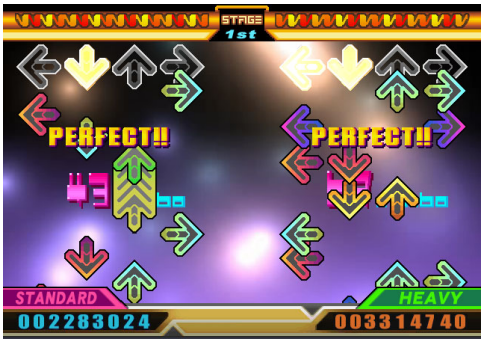


FIGURE 4.1: Screenshot from Dance Dance Revolution, an example of a rhythm music game [6].

Some games exhibit a sandbox style that encourages a free-form gameplay approach whereas other a hybrid style, which combines musical elements with more traditional genres, for example puzzle games or shooters.

Below we will briefly go over different types of music video games that can be found on the market.

(A) is - Internal Section - an example of a generative hybrid music game [8].

(B) SimTunes - an example of a free form music game [9].

FIGURE 4.2: Examples of music video games.

4.1.1 Music Memory Games

The goal of the music memory game is to score a player on their musical memory. Music track is presented to the user who then has to provide an appropriate response to each prompt from the game. Games may be based on different primary musical aspect (whether it is the rhythm, pitch or volume). However, a vast majority of the releases available on the market are rhythm-based.

Rhythm games typically focus on dance or the simulated performance of musical instruments, and require players to press buttons in a sequence dictated on the screen. Doing so causes the game's protagonist or avatar to dance or to play their instrument correctly, which increases the player's score [10]. An example of such games could be Guitar Hero or Dance Dance Revolution.

4.1.2 Hybrid Music Games

Hybrid music games are characterised by substantial and meaningful interactions between a player and the music game in a game that apparently belongs to a non-musical genre. This type of games can be further split into two sub-types.

Generative music video games make use of user's actions. By monitoring interaction with the surroundings in the game, the mechanism generates sounds that are then integrated into the soundtrack, permitting the player's direct interaction with the score. This encourages the creation of a synesthetic experience — when upon stimulation of one sense others activate, causing an involuntary experience. An example of such game could be Rez, which is a simple rail shooter. However, thanks to integrating sounds generated by player completing the normal task of rail-shooting, the musical score is dynamic.

(A) Screenshot from Guitar Hero - player is attempting to play a song [11].

(B) A guitar shaped controller used in the game [12].

FIGURE 4.3: Guitar Hero components

Reactive music games, in contrast to generative one, employ music to determine the gameplay. In such games, the player takes cues from soundtrack to devise his gameplay. For example, iS - internal section, uses the music to determine the dynamics of the non-musical components of the game.

4.1.3 Free Form Music Games

In free form music games, the main task of the user is to create content. This form of music game is often compared to non-game music synthesisers. Free form music games are somewhere between generative hybrid music games and non-game utilities, depending on the degree to which their gameplay relies on a driving underlying plot-line. An example of such game could be SimTunes, where the user is painting a picture using large pixels and each colour represents a musical note.

4.2 Case Study - Guitar Hero

Guitar Hero is one of the most popular franchises in the history of music games. The first of the series was published in 2005 by RedOctane and Harmonix. In the games, players instrument-shaped game controllers to simulate playing the instruments across numerous rock music songs. It is widely considered a highly entertaining game fully embracing the rhythm-based music game.

4.2.1 The Controller

Rather than a typical gamepad, Guitar Hero uses an instrument-shaped controller (guitar in the earlier releases, bass, microphone and drums in more recent ones). Playing the game with the guitar controller simulates playing an actual guitar, except it uses five

coloured “fret buttons” and a “strum bar” instead of frets and strings, and an analogous mapping for the other instruments. They incorporate most of the real life techniques and motions that an instrumentalist would perform on a real instrument.

4.2.2 The Gameplay

The actual game itself works exactly as many other music titles do. At the bottom of the screen, a number of (varying depending of level of difficulty) buttons is shown. In each attempt, a series of notes moves across the screen and when a note aligns with a button, player is supposed to press a corresponding button, gaining points depending on the accuracy. If the player failed to achieve a certain amount of notes — his performance meter stays low for a longer time, he loses the game.

However, there are a couple minor improvements that Harmonix has made to the general music game formula. By pressing buttons with really good accuracy in a song, a player is able to build up Star Power, which when unleashed, doubles up current point multiplier. Star Power also adds a bit of a strategic element - player not only earns more points when it is activated, but he can also raise your performance meter faster, enabling him to last longer when encountering a trickier part of a song.

4.2.3 The Critique

Without a doubt, Guitar Hero features a great selection of music. However, there will always be tracks missing, regardless of how many versions of Guitar Hero are released. People have different tastes and limiting a game to a set of tracks that everybody is supposed to enjoy is a really hard task.

Some more advanced users familiar with Computer Science attempted to transcribe songs and to create new levels. However, this process was really difficult, consisting of many laborious stages and requiring an additional midi files with separated guitar track. This discouraged an average user from fully making use of game’s capabilities. The producers, seeing the tendency, started releasing the in-app purchases to enable the players to extend their library and thus, keep the users.

As there is a clear need for custom music extension to the game, implementing a feature of uploading some music preferred by the player would definitely improve user satisfaction. However, this has not been achieved yet as the task itself is quite complex. Moreover, enabling the users to load in some music would deprive the company of their income sources.

4.3 Introduction to Music Analysis

Automatic music analysis is the automated extraction of relevant perceptual information (notes, instruments, etc.) from music files (like mp3s). First attempted in the 1970s at Stanford University [Moorer], it remains an unsolved problem. The problem is highly multifaceted and interdisciplinary, requiring the extraction of musical notes, instruments, percussion, emotion, etc., and drawing from fields as varied as computer science, mathematics, biology, physics, psychology, and electrical engineering. The problem's difficulty lies in a necessity to reverse-engineer the human brain.

For a long time people were researching ways of estimating the fundamental frequency, be it with monophonic music recording or multi-pitch estimation. Melody extraction differs from both of those problems — unlike monophonic pitch estimation it handles polyphonic tracks and in contrast to multi-pitch estimation, it must also include a mechanism for source identification, to spot the voice carrying the melody within the polyphony. To be able to evaluate the performance of the new algorithms, annual Music Information Retrieval Evaluation eXchange (MIREX) has been running since 2005. In this campaign, different models are evaluated against the same sets of music collections in order to obtain a quantitative comparison between methods and assess the accuracy of the current state-of-the-art in melody extraction [13].

4.3.1 Pitch, Tones, Fundamental Frequency

Pitch is the most natural way of ordering sounds on a frequency-related scale. If sounds whose frequency is clear and stable enough to be distinguished from noise, they can be compared among one another as "lower" or "higher". Pitch is not an objective physical property — it depends on anatomy and physiology of the auditory system, which is a subject of an extensive study called psychoacoustics.

A semitone is the smallest musical interval commonly used in Western tonal music. Two semitones constitute a tone.

The fundamental frequency f_0 is defined as the lowest frequency of a periodic waveform. A harmonic (or a harmonic partial) is any of a set of partials that are whole number multiples of a common fundamental frequency. This set includes f_0, which is a whole number multiple of itself (1 times itself).

Fundamental frequency can be thought of as the physical property most closely related to perception of pitch. This is why in this context pitch and fundamental frequency can be used interchangeably.

4.3.2 Polyphonic Music

Polyphony is a word derived from Greek poluphōnosis meaning more than one sound — a texture consisting of two or more simultaneous lines of independent melody. This can be contrasted with homophony, where musical parts move generally in the same rhythm and one dominant melodic voice is accompanied by chords or monophony, where only one voice is found.

However, in our case, the term polyphonic will simply refer to any type of music in which two or more notes can be played simultaneously. This can be achieved either by playing in different instruments (for example, voice, guitar and bass) or a single instrument capable of playing more than one more at a time (like a piano).

4.3.3 Melody

The concept of "melody" ultimately relies on the judgment of people listening. This is why it will vary depending on the application context - whether we want to determine symbolic melodic similarity or transcribe a music track.

In order to have a clear framework to work within, the Music Information Retrieval (MIR) community has adopted in recent years the definition proposed by [14], "...the melody is the single (monophonic) pitch sequence that a listener might reproduce if asked to whistle or hum a piece of polyphonic music, and that a listener would recognise as being the 'essence' of that music when heard in comparison".

In practice, research has focused on "single source predominant fundamental frequency estimation" — which means a search for a main melody coming from a single sound source throughout the song analysed. As we can see, the subjective element is still present in this description of a melody as there might not be a definite way of deciding what predominant is. However, it fits well with our project's objective — generating a game level based on changes in the pitch.

4.3.4 Filter

Any medium through which the music signal passes, whatever its form, can be regarded as a filter. However, we do not usually think of something as a filter unless it can modify the sound in some way.

A digital filter is a filter that operates on digital signals, such as sound represented inside a computer. It is a computation which takes one sequence of numbers (the input signal) and produces a new sequence of numbers (the filtered output signal) [15].

4.3.5 Short Time Fourier Transform

Short-time Fourier transform (STFT), is a signal processing method which is used in analysis of non-stationary signals with statistic characteristics varying with time. In particular, STFT extracts several frames of the signal to be analysed with a window that moves with time. If we set the window size to be narrow enough, each frame extracted can be viewed as stationary so that Fourier transform can be used. With the window moving along the time axis, the relation between the variance of frequency and time can be identified [16].

The short time Fourier transform of a time-domain signal y is denoted by the matrix $F \times N$, F being the Fourier transform size and N the number of analysis frames.

4.4 Main Melody Extraction from Polyphonic Music

In this section we will go over two different approaches to the problem of main melody extraction from polyphonic music, using source separation and a salience function. Then we will compare both methods to determine which one is more suitable for our project.

4.4.1 Source Separation Based Approach

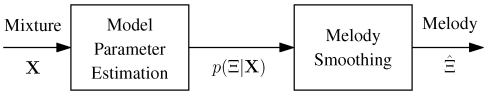


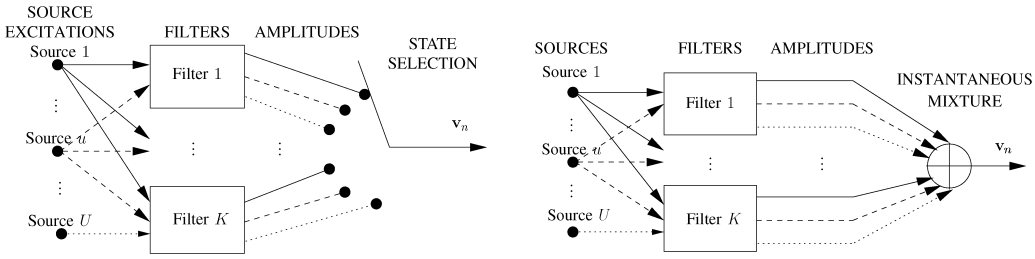
FIGURE 4.4: Outline of system proposed by Durrieu: X is the STFT of the mixture signal, $p(\Xi|X)$ the posterior probability of a given melody sequence, and $\hat{\Xi}$ the desired smooth melody sequence [17].

In polyphonic tracks the main melody can be represented by a specific source/filter model. In case of the leading vocal part, the vocal cords are treated as a source and the voice tract as a linear acoustic filter.

In their paper from 2011 [17], authors presented an algorithm in which they assume that at any given time the signal observed is a mixture of two elementary signals - one corresponding to the main source and one to the background music. Therefore, the signal can be represented in an equation $x(t) = v(t) + m(t)$, where $v(t)$ stands for the source of the main melody and $m(t)$ is the background music. Interestingly, this equation also holds for the short time Fourier transform (STFT) X, V and M respectively: $X = V + M$. The models proposed by Durrieu essentially aim at constraining the shapes of these STFT using temporal and spectral constraints.

The likelihood of the vocal part V is calculated using two different frameworks.

The first submission uses the source/filter Gaussian scaled mixture model (GSMM). In this model the source element refers to the excitation of the vocal folds and is therefore linked to the fundamental frequency of the sound f_0, while the filter part is characteristic



(A) Schematic principle of the generative GSMM. Each source u is filtered by each filter k. For frame n, the signal is then multiplied by a given amplitude and a "state selector" then chooses the active state.

(B) Schematic principle of the generative IMM. At each frame, all the U sources, each filtered by K filters, are multiplied by amplitudes and added together to produce the leading voice signal.

FIGURE 4.5: Diagram of both models presented in the paper [17].

of the vocal tract shape. This space of possibilities is then discretised so that we consider one possible filter frequency response, which is then used to calculate the likelihood of the vocal part knowing the filter and f_0.

Figure 4.5a A) shows the diagram of the GSMM model for the main voice part. Each source excitation u is filtered by each filter k. The amplitudes for a frame n and for all the couples (k, u) are then applied to each of the output signals. At last a "state selector" sets the active state for the given frame.

The second model was derived from the first one to find a solution that would be more efficient to compute. The authors came up with a formulation that keep the source/filter model within an instantaneous mixture framework (IMM). In this model, for each source a set of filters is defined and at each frame, once every source is filtered and multiplied by a given amplitude, they are all added together.

The background music signal $m(t)$ can be thought of as a mixture of R independent Gaussian sources $m_r(t)$. Each of the sources is centred and characterised by its power spectral density (PSD), which describes how the power of a signal or time series is distributed over the different frequencies. PSD can be estimated using a Covariance Method. Due to the linearity of the Fourier transform, $M(f, t)$, the STFT of m, is also the instantaneous mixture of the R spectra $M_r(f, t)$ of the sources: $M_r(f, t)$. This together with STFT and an amplitude coefficient associated with each source is used to calculate the likelihood for each of the frequency bins. Let $M_t(f)$ be the STFT of the background signal at frame t and frequency bin f, then we write its likelihood.

Once the parameters are estimated using the maximum likelihood criterion for each of the model, the Viterbi smoothing of the melody line is applied, obtaining a trade-off between the smoothness of the melody and its global energy in the signal. The Viterbi algorithm is a dynamic programming algorithm for finding the most likely sequence of hidden states – called the Viterbi path – that results in a sequence of observed events [18].

The authors then parametrise the transitions between the possible main melody without disabling jumps from one note to the other. Using Wiener filtering - digital signal processing reducing the noise, using an statistical estimate of the signal using a desired data without such noise, a framework is implemented to separate the source. This way separated signals are obtained. Computing the energy for each frame of the separated main melody and thereafter thresholding allowed to discriminate between spurious notes and true positives.

4.4.2 Salience Based Approaches

This approach has been the most popular so far, with majority of algorithms evaluated at MIREX implementing it. It and can be split into several smaller stages, as seen in Figure 4.6. In particular, a method implemented in paper [3] seems to be quite promising.

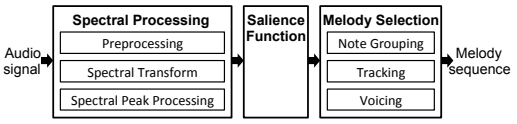


FIGURE 4.6: Block diagram of four main blocks of the system by Salamon and Gómez: sinusoid extraction, salience function computation, pitch contour creation and melody selection [13].

Usually as a first step, some sort of preprocessing is applied to the audio signal, usually to enhance the frequency content where we expect to find the melody. In particular, Salamon and Gómez apply an equal loudness filter, which enhances the frequencies to which the human ear is more perceptually sensitive, by taking a representative average of the equal loudness curves and filtering the signal by its inverse.

This stage is followed by spectral transform — the signal is chopped into time frames and a transform function is applied to obtain a spectral representation of each frame. This is achieved by applying the Short-Time Fourier Transform given by:

$$X_l(k) = \sum_{n=0}^{M-1} w(n) \times x(n + lH) e^{-j\frac{2\pi}{N}kn} \tag{4.1}$$

with a window length of 46.4ms. Here, $x(n)$ is the time signal, $w(n)$ the windowing function, l the frame number, M the window length, N the FFT length and H the hop size. Thanks to choosing a relatively small hop size, Salamon and Gómez achieve sufficient frequency resolution to identify different notes while maintaining adequate time resolution to track pitch changes in the melody over a short time.

Having done this, we move to frequency/amplitude correction, where the spectral peaks are detected and used to construct a salience function. To avoid a relatively large error in the estimation of the peak frequency caused by binning them in the process of FFT, peak's instantaneous frequency and amplitude are calculated.

As we can see in Figure 4.6, those three steps constitute the spectral processing. But at the core of the salience based algorithms lies the multi-pitch representation, i.e. the salience function — a representation of pitch salience over time. The peaks of this

function form the f_0 candidates for the main melody. In the algorithm described by Salamon and Gómez, this computation is based on harmonic summation, where the salience of a given frequency is computed as a sum of the weighted energies found at harmonics (integer multiples) of that frequency. Using only the peaks for the summation allows the authors to discard less reliable values and apply further frequency corrections.

The salience function presented in the paper covers a pitch range of nearly five octaves from 55Hz to 1.76kHz.

Peaks of the salience function at each frame are now potential f_0 of the main melody. At this point some methods for melody extraction attempt to track the melody. However, Salamon and Gómez filter out the non-salient peaks, first by comparing them to the highest peak in the frame and then to a value computed using salience mean and standard deviation of all remaining peaks (in all frames). Now the peaks are grouped into pitch contours - time and pitch continuous sequences of salience peaks as shown in Figure 4.7.

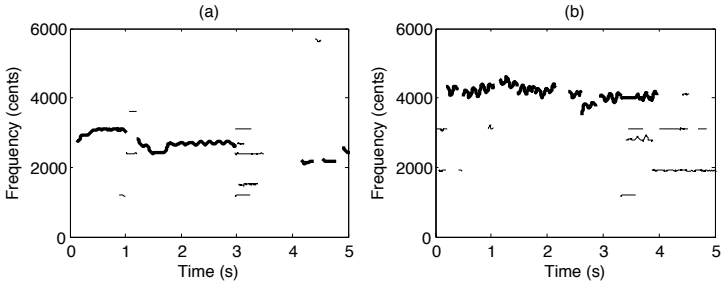


FIGURE 4.7: Pitch contours generated from excerpts of (a) vocal jazz and (b) opera. Melody contours are highlighted in bold [3].

Having created the pitch contours, Salamon and Gómez are faced with the task of determining which one belongs to the main melody. The authors define features based on contour pitch, length and salience.

Given the peaks of the salience function, we now have to determine which pitch values belong to the melody. This process is initiated by grouping peaks into continuous pitch contours, out of which a melody is selected later.

The next main block in this algorithm shown in Figure 4.6 is the melody selection which is comprised of three steps: voicing detection, octave error minimisation/pitch outlier removal, and final melody selection. As the name suggests, the aim of the voicing detection is to determine when the melody is present.

To filter out these contours Salamon and Gómez take advantage of the contour mean salience distribution. By setting the threshold to a value slightly below the average contour mean salience of all contours in the excerpt C_s, we can filter out a considerable amount of non-melody contours. The authors define the following voicing threshold τ_v based on the distribution mean C_s and its standard deviation $\sigma_{\overline{s}}$:

$$\tau_v = C_s - v \times \sigma_{\overline{s}} \tag{4.2}$$

The parameter v determines the lenience of the filtering - a high v value might keep the false melody contours and a low value might filter out the melody contours.

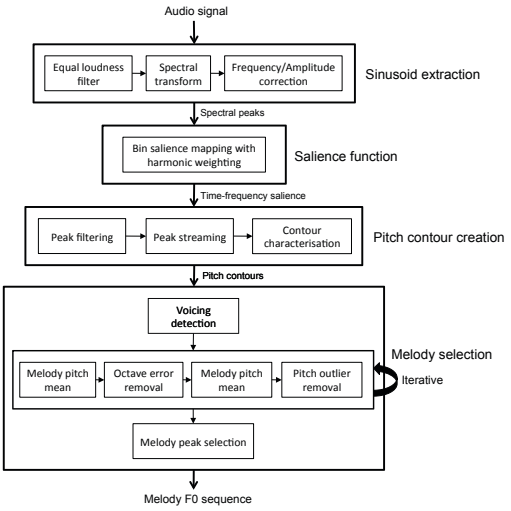


FIGURE 4.8: Block diagram of four main blocks of the system by Salamon and Gómez: sinusoid extraction, salience function computation, pitch contour creation and melody selection [3].

It is also important to note that detecting certain characteristics in the contour increases a probability of it being the melody contour, for example in case of detecting a vibrato - a regular, pulsating change of pitch, used to add expression to vocal and instrumental music. [19]

Next step in the melody selection described by Salamon and Gómez in their paper is octave errors and pitch outliers removal.

In particular, the octave errors are the main sources of errors in melody extraction systems, when a multiple or submultiple of f_0 is reported as the main melody.

To detect such errors, contour trajectories are compared by computing distance between their values on a per-frame for the region they overlap in and computing the mean over this region. If the mean distance is within 1200 ± 50 cents, the contours are considered octave duplicates.

Secondly, Salamon and Gómez use the relationship between neighbouring contours (in time) to decide which of the duplicates is the correct one. Their approach is based on two assumptions: firstly, that most (though not all) of the time the correct contour will have greater salience than its duplicate (the salience function parameters were optimised to this end). Secondly, that melodies tend to have a continuous pitch trajectory avoiding large jumps, in accordance with voice leading principles.

The method iteratively computes the $\overline{P(t)}$ - pitch trajectory that represents the time evolution of the melody's pitch. It then detects and removes an octave duplicate as well as the "pitch outliers" – contours more than one octave above or below the pitch mean and then it is recalculated. Authors empirically discovered that 2 iterations of this process are enough to get a good approximation of the true trajectory of the melody, which is then passed to the final stage of the model - the final melody selection.

At this stage, there is often only one peak to be chosen as the main melody. When there is still more than one contour present in a frame, the melody is selected as the peak belonging to the contour with the highest total salience $C_{\sum s}$. If no contour is present the frame is regarded as unvoiced.

4.4.3 Comparison of both approaches

In their paper [13], authors attempted to compare multiple melody extraction algorithms created since 2005. One of the methods, used also by MIREX, is based on the per-frame comparison, considering different measures:

Voicing Recall Rate - the proportion of frames labeled as melody frames in the ground truth that are estimated as melody frames by the algorithm.

Voicing False Alarm Rate - the proportion of the frames labeled as non-melody in the ground truth that are mistakenly estimated as melody frames by the algorithm.

Raw Pitch Accuracy - the proportion of melody frames in the ground truth for which f_τ is considered correct (i.e. within half a semitone of the ground truth).

Raw Chroma Accuracy - as raw pitch accuracy, except that both the estimated and ground truth f_0 sequences are mapped onto a single octave. This gives a measure of pitch accuracy which ignores octave errors.

Overall Accuracy - this measure combines the performance of the pitch estimation and voicing detection tasks to give an overall performance score for the system. It is defined as the proportion of all frames correctly estimated by the algorithm, where for non-melody frames this means the algorithm labeled them as non-melody, as for melody frames the algorithm both labeled them as melody frames and provided a correct f_0 estimate for the melody (again, within half a semitone of the ground truth).

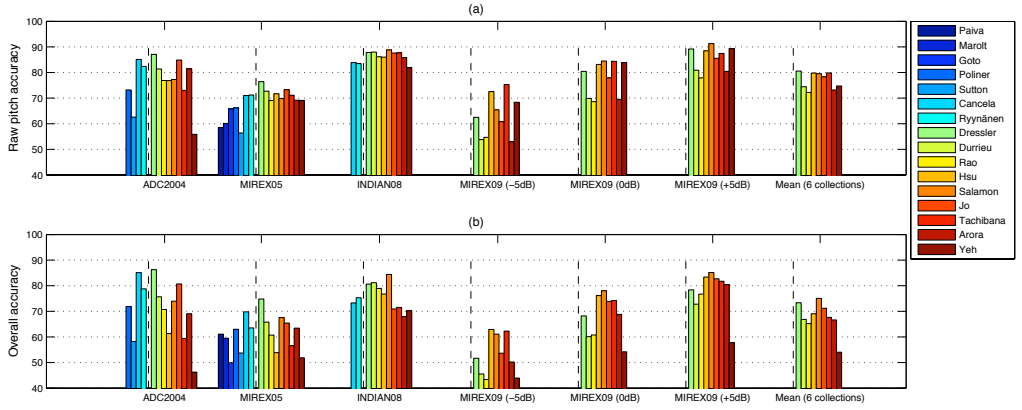


FIGURE 4.9: a) Raw pitch accuracy and b) overall accuracy obtained in MIREX by 16 melody extraction algorithms evaluated in [13]. The vertical dashed line separates the algorithms that were only evaluated on some collections (left of the line) from those evaluated on all six collections (right of the line) [13].

In Figure 4.9. the authors presented results obtained by the algorithms evaluated at MIREX. To get a general idea of the performance of the algorithms, it is sufficient to focus on two evaluation measures. The raw pitch accuracy, presented in Figure 4.9 a) represents how well the algorithm tracks the pitch of the melody. The overall accuracy

on the other hand, as shown in Figure 4.9 b), combines this measure with the efficiency of the algorithm's voicing detection, meaning the voicing-related measures are also reflected in this measure.

As we can see, some collections are generally hard to analyse (for example MIREX09 -5db), in general the collections yield different results for different algorithms. This allows us to spot pros and cons of each approach investigated.

We can also notice that the raw pitch accuracy gradually improved from 2005 to 2009, after which it stayed relatively unchanged. Overall we can see that the average pitch accuracy over a collection lies between 70-80%.

On the other hand, when it comes to overall accuracy, the performance goes down compared to the raw pitch accuracy for all algorithms due to voicing detection being factored into the results. The importance of this step depends on the intended use of the algorithm. Generally, the overall accuracy results lie between 65-70%.

Finally, an important factor in assessment of an algorithm is its complexity. While deriving O-notation is too complex for some of the algorithms, generally it is observed that algorithms involving source separation are significantly more computationally complex than salience based approaches Unfortunately, there is no specific data provided by Salamon and Gómez [9] or by Durrieu [5] on their algorithms.

In conclusion, we believe the solution proposed by Salamon and Gómez is better fitted to the purpose of this project. The paper presents it in a much clearer way and, what is most important, it outperforms the one created by Durrieu significantly, as seen in Figure 4.9. In addition to this, according to tendency it is less computationally expensive, which is quite important when it comes to game designing as we do not want to keep the user waiting for a long time for his level to generate and load.

4.5 Introduction to Neural Networks

An Artificial Neural Network (ANN) is an information processing paradigm that can be thought of humans' attempt to simulate the brain electronically. Its first conceptual model was developed by Warren S. McCulloch, a neuroscientist, and Walter Pitts, a logician, in 1943. In their paper, "A logical calculus of the ideas imminent in nervous activity", they describe the concept of a neuron, a single cell living in a network of cells that receives inputs, processes those inputs, and generates an output. Their work served as foundation for designing a computational model based on the brain to solve certain kinds of problems.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. Their most common

application in computing today is to perform one of these "easy-for-a-human, difficult-for-a-machine" tasks, often referred to as pattern recognition. Thanks to being implemented on computers, they have higher computational capabilities than any human being - calculating a cube of 9124 in memory is not straightforward for us, but a computer can come up with an answer almost immediately. On the other hand, thanks to their structure, they can tackle problems not easy to solve by a simple computer, like facial recognition or regression analysis. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.

4.5.1 Models

The computational systems we write are procedural; a program starts at the first line of code, executes it, and goes on to the next, following instructions in a linear fashion. On the other hand, neural network are "connectionist" computational systems. A true neural network does not follow a linear path. Rather, information is processed collectively, in parallel throughout a network of neurons.

Neural networks are made up of many artificial neurons. There are many different ways of connecting neurons to create a neural network. The number of them depends on a task the network is designed for.

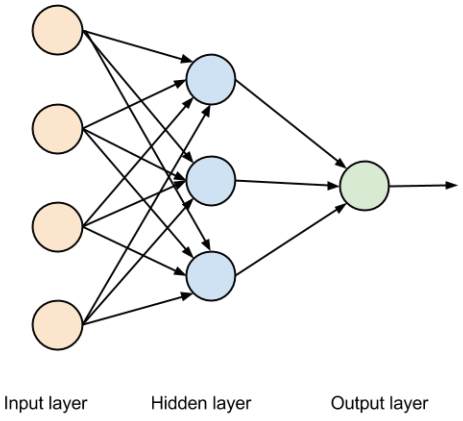


FIGURE 4.10: Diagram of a simple neural network with 4 input nodes, 3 nodes in a hidden layer and one output node.

An example system depicted in Figure 4.10 has three layers. The first layer has input neurons (marked red) which send data via synapses to the second layer of neurons (colour blue). Each input into the neuron has its own weight associated with it. A weight is simply a floating point number and they allow us to adjust our network to improve the training outcome. The weights in most neural nets can be both negative and positive, therefore providing excitatory (carrying information) or inhibitory (regulating the activation of excitatory neurons) influences to each input.

As each input enters the nucleus, it is multiplied by its weight. The nucleus then sums all these new input values which gives us the activation. If the activation is greater than a threshold value, the neuron outputs a signal. If the activation is less than the threshold, the neuron outputs zero. This is typically called a step function.

One type of neural network is called a feedforward network named after the way the neurons in each layer feed their output forward to the next layer until we get the final output from the neural network.

Each input is sent to every neuron in the hidden layer (marked blue) and then each hidden layer's neuron's output is connected to every neuron in the next layer. There can be any number of hidden layers within a feedforward network but one is usually enough to suffice for most problem. There can be any number of neurons in each layer, depending on the problem that is being solved.

4.5.2 Training

Once a network has been structured for a particular application, it is ready to be trained. In the beginning, the initial weights are chosen randomly. There are two approaches to training - supervised and unsupervised. Supervised training involves a mechanism of providing the network with the desired output either by manually "grading" the network's performance or by providing the desired outputs with the inputs. Unsupervised training is where the network has to make sense of the inputs without outside help.

Majority of networks utilize supervised training. Unsupervised training is used to perform some initial characterization on inputs [20].

Supervised Training

In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually tweaked. The set of data which enables the training is called the "training set". During the training of a network the same set of data is processed many times as the connection weights are ever refined.

Unfortunately, some networks never learn. This could be caused by the input data not containing the specific information from which the desired output is derived. Networks can also fail to converge if there is not enough data to enable complete learning.

Ideally, there should be enough data so that part of the data can be held back as a test. Many layered networks with multiple nodes are capable of memorizing data. To make sure the network is learning significant patterns rather than plainly memorizing the data, supervised training needs to hold back a set of data to be used to test the system after it has undergone its training.

If a network simply cannot solve the problem, the designer then has to review the input and outputs, the number of layers, the number of elements per layer, the connections between the layers, the summation, transfer, and training functions, and even the initial

weights themselves. Those changes required to create a successful network constitute a process wherein the "art" of neural networking occurs.

Another part of the designer's creativity governs the rules of training. There are many laws (algorithms) used to implement the adaptive feedback required to adjust the weights during training. The most common technique is backward-error propagation, more commonly known as back-propagation, which we will describe later.

Yet, training is not just a technique. It involves a "feel", and conscious analysis, to insure that the network is not over-trained. Initially, an artificial neural network configures itself with the general statistical trends of the data. Later, it continues to "learn" about other aspects of the data which may be spurious from a general viewpoint.

When finally the system has been correctly trained, and no further learning is needed, the weights can, if desired, be saved. This way it can be used for predicting the output values for new, unseen data.

Unsupervised Training

The other type of training is called unsupervised training. In unsupervised training, the network is provided with inputs but not with desired outputs. The system itself must then decide what features it will use to group the input data. This is often referred to as self-organization or adaption.

At the present time, unsupervised learning is not well understood. This adaption to the environment is the promise which would enable science fiction types of robots to continually learn on their own as they encounter new situations and new environments. Life is filled with situations where exact training sets do not exist. Some of these situations involve military action where new combat techniques and new weapons might be encountered. Because of this unexpected aspect to life and the human desire to be prepared, there continues to be research into, and hope for, this field.

4.5.3 Backpropagation algorithm

A Backpropagation network is a network that learns by example. Given the desired input and output data telling the network what we want it to do, it changes its weights so that, when training is finished, it produces the required output for a particular input. Backpropagation networks are ideal for Pattern Recognition and Mapping Tasks.

The algorithm starts by first setting up all the network's weights to be small random number. Next, the input pattern is applied and the output calculated (called the forward pass). The calculation is likely to give an output which is completely different to what we passed in as the expected value, since all the weights are random. The error of each neuron is calculated (expected output - actual output). This error is then used mathematically to change the weights in such a way that the error will get smaller. In

other words, the actual input of each neuron will get closer to its expected output. This part is called the reverse pass. The process is repeated again and again until the error is minimal.

Backpropagation algorithm has some problems associated with it. Perhaps the best known is associated with local minima. This occurs because the algorithm always changes the weights in such a way as to cause the error to fall. But the error might briefly have to rise as part of a more general fall. If this is the case, the algorithm will "gets stuck" (because it cannot go uphill) and the error will not decrease further.

There are are several solutions to this problem. One is very simple and that is to reset the weights to different random numbers and try training again (this can also solve several other problems). Another solution is to add "momentum" to the weight change. This means that the weight change this iteration depends not just on the current error, but also on previous changes. For example:

$$W+ = W + Currentchange + (Changeonpreviousiteration * constant) \tag{4.3}$$

4.6 Mood Detection

It is well known that music can convey emotion and modulate mood. That is why the relation between musical sounds and their influence on the listener's emotion has been well studied.

4.6.1 Emotion Classification

Currently, there is no standard method to measure and analyze emotion in music. However, a psychological model of emotion has found increasing use in computational studies.

In 1989, in his publication [21], J. A. Russell noticed that set of emotional dimensions such as displeasure, distress, depression, excitement etc. are interrelated in a highly systematic fashion. He claimed these relationships can be represented in a spacial model in which concepts fall in circle in the following order: pleasure, excitement, arousal, distress, displeasure, depression, sleepiness and relaxation. Depiction of the model is presented in Figure 4.11a.

A somewhat similar model was described in 1989 by R. E. Thayer. Thayer's two-dimensional emotion model offers a simple but quite effective model for placing emotion in a two-dimensional space [22]. In the model, the amount of arousal and valence is measured along the vertical and horizontal axis, respectively.

Diagram 4.11b depicts the relation between valence and arousal values and the moods perceived by people. As we can see, the high arousal is connected to how energetic the

(A) Model proposed by J. A. Russell. (B) Model proposed by R. E. Thayer [4].

FIGURE 4.11: Diagram of both models for representing emotions.

music is, whereas valence refers to how positive (or negative) the emotions in the track are.

4.6.2 Related Literature

Some studies have explored the relationship between physiological activity experienced by a listener and perceived emotion, be it facial expression or speech recognition of even heartbeat and respiratory changes [23]. Others have explored the relationship between perceived emotion and the musical/acoustic features themselves.

One of the first publications on emotion detection in music is credited to Feng, Zhuang, and Pan [24]. They employ Computational Media Aesthetics, that is, analysing two music dimensions to detect mood for music information retrieval tasks. The two dimensions – tempo and articulation, are extracted from the audio signal and are mapped to one of four emotional categories; happiness, sadness, anger, and fear. After that, feature called relative tempo is calculated, and after the mean and standard deviation of the feature called average silence ratio in the presented computational articulation model are calculated, a simple Back Propagation neural network classifier is trained to detect mood.

Different approach was applied by Kim and André [23]. To collect physiological data set, a musical induction which leads subjects to real emotional states was used over many weeks. They used four-channel biosensors to measure electromyogram, electrocardiogram, skin conductivity, and respiration changes. From that, they retrieve a wide range of physiological features and are analysed to find the best emotion-relevant ones and correlate them with emotional states. Finally, the classification of four musical emotions (positive/high arousal, negative/high arousal, negative/low arousal, and positive/low arousal) is performed by using an extended linear discriminant analysis (pLDA)

In publication by Yang, Lin, Su and Chen [4], the authors presented a tool which recognises a mood in a musical track, allowing a user to then choose the song they want to play by deciding on emotions it is supposed to represent. Specifically, the authors formulate music emotion recognition as a regression problem to predict the arousal and valence values (AV values) of each music sample directly. For this purpose, they adopt Support Vector Regression (SVR) as classifier using a number of chosen features.

Potentially, the second approach described seems more appropriate for our project as it allows for better granularity in the melody emotion detection and, hence, wider variety of changes in the game's environment. However, this area of the project is left to be further researched.

4.7 Level Generation

It is not really surprising that there is no current literature on the problem of automatically generating Guitar Hero buttons given an arbitrary piece of music. However, we believe an algorithm can be developed where the buttons can be mapped to the f_0 in the main melody extracted by main melody extraction algorithm.

Chapter 5

Design and Implementation

In this chapter we will go over the implementation process of the project. We will describe various choices we made, justifying them in the context of our objectives.

First we will describe our solution to the mood detection problem. We first try to determine which musical features are the most correlated to the AV values of the music's emotion. Then, by training a neural network with data containing chosen features we will create a way of determining the arousal and valence value of any musical track, which will be later used in the implementation of our game. In addition to this, by investigating the impact of different parameters we will make sure out network has as good performance and accuracy as possible.

Next, we will move on to main melody detection by looking at two algorithms - one using source separation based approach and the other using the salience based approach. We will evaluate performance of both of them on data from recent pop culture to determine their performance and fitness in this project.

The next section will describe our attempt to automated music segmentation.

Last, but not least, we will talk about the game itself, its architecture, flow of use and design choices made.

5.1 Mood Detection

A common reason for engaging in music listening is that music is an effective means of conveying and evoking emotions. Although they may be subjective, based in part on the listener's cultural and musical background or preferences, there are commonalities in perceived emotion across different listeners based on the characteristics of the music. Several studies have attempted to predict emotion conveyed during music listening. In our approach, we decided to represent the emotion connected to the music using a two-dimensional space with valence on the x-axis and arousal on the y-axis, first proposed by R. E. Thayer [22].

As we described in Section 4.6.1, there is a relation between valence and arousal values for a musical track and the moods perceived by people. In essence, the high arousal is connected to how energetic the music is, whereas valence refers to how positive (or negative) the emotions in the track are.

In our exploration we decided to base our research on data collected in "1000 Songs for Emotional Analysis of Music" music library [25], to avoid personal bias in assessing the mood of the song. The songs in the dataset were annotated by more than 300 crowdworkers on Amazon Mechanical Turk. Each song was annotated for arousal and for valence separately.

5.1.1 Choice of Features

Using Essentia library [26], we implemented an extractor to retrieve certain features from a song, which we would expect to have certain impact on the perceived mood of a musical piece:

average loudness - dynamic range descriptor. It rescales average loudness into the [0,1] interval on a per window basis. The value of 0 corresponds to signals with large dynamic range, 1 corresponds to signal with little dynamic range. This could indicate the level of the arousal, with higher loudness implying higher arousal value. We believe this relation could be quite intuitive - sad or peaceful songs tend to be quiet whereas excited or angry emotions are usually linked to louder tracks.

means and derivatives of variance of rates of silent frames in a signal for thresholds of 20, 30 and 60db. We believe that the values could influence the arousal levels, as the more and the bigger the silent gaps, the sadder / more peaceful the track seems to be, implying the low arousal value. When examining multiple musical tracks we have noticed that the happier or angrier songs can also have such silent gaps, but they tend to be much shorter.

dynamic complexity - computed on 2 second windows with 1 second overlap. The dynamic complexity is the average absolute deviation from the global loudness level estimate on the dB scale. It is related to the dynamic range and to the amount of fluctuation in loudness present in a recording. We believe this feature would have an impact on both examined values. However, similarly to the loudness level, arousal should be influenced more - as more dynamic songs (excited or angry) are more likely to suffer from loudness changes, whereas more phlegmatic ones (sad or peaceful) tend to keep the same dynamic complexity level.

BPM - beats per minute value according to detected beats. This feature should be correlated with the arousal level - intuitively, the faster the song, the more energetic it seems.

spectral centroid - centroid statistics describing the spectral shape. It indicates where the "center of mass" of the spectrum is. Perceptually, it has a robust connection

with the impression of "brightness" of a sound - an indication of the amount of high-frequency content in a sound. Timbre researchers consider brightness to be one of the perceptually strongest distinctions between sounds [27], and formalize it acoustically as an indication of the amount of high-frequency content in a sound. That is why we believe the spectral centroid might be related to both valence and arousal.

spectral RMS (root mean square) - in physics it is a value characteristic of a continuously varying quantity, such as a cyclically alternating electric current or a sound. It is obtained by taking the mean of the squares of the instantaneous values during its duration or a cycle. This is linked to the loudness of the sound. This is why we believe that it might have an impact on arousal, but we do not exclude its impact on valence.

spectral energy - the energy Es of a continuous-time signal x(t) defined as:
$Es = \langle x(t), x(t) \rangle = \int_{-\infty}^{\infty} |x(t)|^2 dt$.
Signal energy is always equal to the summation across all frequency components of the signal's spectral energy density. There have been some research focusing on relation between spectral energy and singing voice. In particular, in their paper [28], S. Ferguson, D. T. Kenny and D. Cabrera were investigating the relation between the value and the experience of male singers. This makes for an interesting case worth considering in our research.

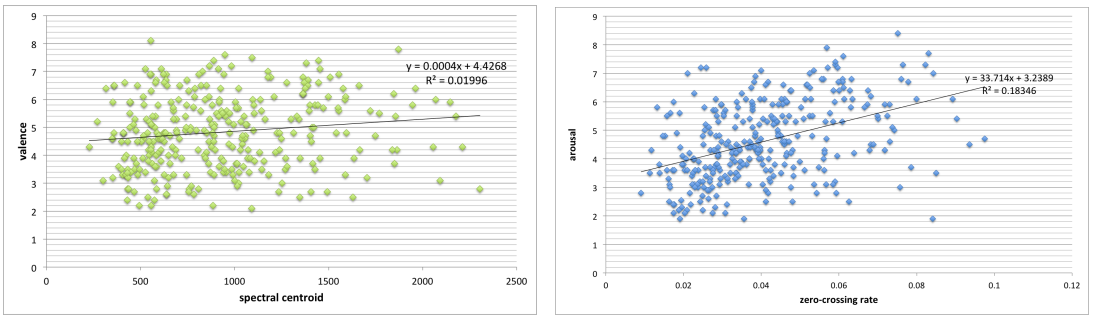
mean and derivative of variance of beat loudness - spectral energy computed on beats segments of audio across the whole spectrum, and ratios of energy in 6 frequency bands. We suspect that the low value of the beat loudness could imply a low arousal.

key and its scale estimated key and its scale (major or minor) using Temperley's profile. Scale commonly known to have a big influence on our perception on music [29]. It seems to be mostly the result of cultural conditioning. When we listen to tunes we rely heavily on our memory for the body of music we've heard all our life. Constantly touching base with our musical memory back catalogue helps to generate expectations of what might come next in a tune, which is an important source of enjoyment in musical listening.

scale and key of the chords key taken as the most frequent chord, and scale of the progression, whether major or minor. This and the key features could have an impact on the valence value.

means of zero-crossing rate - the rate of sign-changes along a signal, i.e., the rate at which the signal changes from positive to negative or back. This feature has been used heavily in music information retrieval, being a key feature to classify percussive sounds. We believe it could be related to the arousal value. ZCR is defined formally as:
$ZCR = \frac{1}{T-1} \sum_{t=1}^{T-1} \mathbb{I}\{s_t s_{t-1} < 0\}$

pitch salience of a spectrum - given by the ratio of the highest auto correlation value of the spectrum to the non-shifted auto correlation value. Pitch salience was



(A) A graph representing a correlation between spectral centroid and valence values.

(B) A graph representing a correlation between zero-crossing rate and arousal values.

FIGURE 5.1: Chosen results of bivariate correlation with multiple regression.

designed as quick measure of tone sensation. Unpitched sounds (non-musical sound effects) and pure tones have an average pitch salience value close to 0 whereas sounds containing several harmonics in the spectrum tend to have a higher value. Application: characterizing percussive sounds. We think the value could have an effect on both the valence and arousal.

mean and derivative of variance of sensory dissonance (to distinguish from musical or theoretical dissonance) of an audio signal given its spectral peaks. Sensory dissonance measures perceptual roughness of the sound and is based on the roughness of its spectral peaks. Given the spectral peaks, the algorithm estimates total dissonance by summing up the normalized dissonance values for each pair of peaks. These values are computed using dissonance curves, which define dissonace between two spectral peaks according to their frequency and amplitude relations. Dissonance could be related to low valence.

5.1.2 Correlation Between Features and Mood Perception

As a first step towards understanding the pattern by which audio features might account for emotion ratings, we conducted correlational analyses between features and mean valence/arousal ratings from the data set. We performed a bivariate correlation analysis with the valence/arousal ratings as the dependent variable, and each of the 22 features as the explanatory variable. Example of the results we achieved can be seen in Figure 5.1. We found significant correlation between *valence* and *dvar and mean silence60, dvar of silence30, dynamic complexity, spectral centroid, spectral RMS, spectral energy, zero-crossing rate, pitch salience, and both mean and dvar of dissonance*. For *arousal*, we noticed correlation with *spectral centroid, pitch salience, zero-crossing rate*, both *mean* and *dvar* of *silence60, spectral energy, mean dissonance* and *dynamic complexity*.

Values of all the features were then normalized between 0 and 1 to prepare them for the neural network training.

5.1.3 Neural Network for Mood Prediction

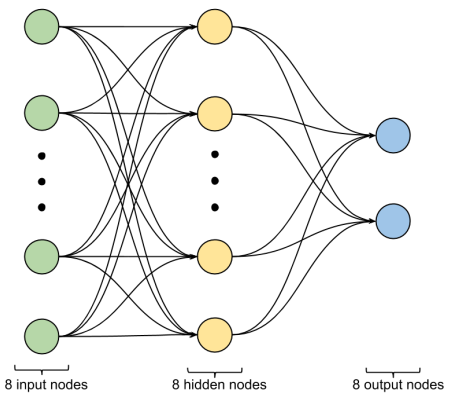


FIGURE 5.2: A diagram depicting the structure of our artificial neural network for mood detection.

Our goal was to train the network to predict mean participant valence and arousal values for musical excerpts. Our first network implementation was a supervised, feedforward network with backpropagation. The input consisted of normalized values of 8 features: *spectral centroid, pitch salience, zero-crossing rate, silence60 mean and dvar, mean dissonance, dynamic complexity* and *spectral energy*. The network had two outputs - arousal and valence.

As all the training data was normalised, the input and output values were within a range of 0 to 1. The training set consisted of 50 input and output arrays. Each input array had 8 values, one per audio feature, and its corresponding output array had the two desired arousal and valence values.

The network's task was to provide the valence and arousal values based on the 13 audio features. The output values fell within a range of 0 to 1. Since desired outputs were average valence/arousal ratings provided by participants on a scale from 1 to 9, the network outputs were rescaled back. The training set consisted of eight input and output arrays. Each input array had 13 values, one for each audio feature, and its corresponding output array had the two desired arousal and valence values. The connection weights from input to the hidden nodes and from hidden nodes to the output ones were initialised to random numbers.

The network was built, trained, and tested using the pyBrain python library for neural network implementation.

We trained our network for 10000 epochs with many different sizes of the hidden layer and default values for all the other parameters. The performance based on that can be seen in Table 6.1.

As we can see, the optimal solution is the one with 8 nodes in the hidden layer. To avoid overfitting the network, we kept the number of hidden units equal to the number of input units.

Having found the optimal number of nodes in the hidden layer, we moved on to find the learning rate parameter. We started our search by setting it to 0.3 and reducing it over time. The results we found can be found in Table 5.2.

In the end, we came up with the network which can be seen on Figure 5.2.

No. of Nodes	RMSE
1	0.0885458989882
2	0.0881453943244
3	0.0873850620651
4	0.086553779403
5	0.0862146793784
6	0.0860987534316
7	0.0861442944822
8	0.0850460538049
9	0.085143906777
10	0.0852984563213
15	0.085547018396
20	0.0854215840659
50	0.0856472028298

TABLE 5.1: Table showing the root mean square error for training the network for given number of nodes in the hidden layer.

Learning Rate	RMSE
0.3	0.0846361666437
0.25	0.0827496336912
0.2	0.080513130655
0.15	0.0807476303566
0.1	0.0792817515366
0.05	0.0805650982375
0.01	0.085863454125

TABLE 5.2: Table showing the root mean square error for training the network for given learning rate parameter value.

5.2 Main Melody Extraction

5.3 The Game

In this section, we will go over the architecture and the design choices made when planning and implementing our game.

The game is written mostly in Swift, a multi-paradigm, compiled programming language created by Apple Inc. for iOS and OS X development. It was first introduced at Apple's 2014 Worldwide Developers Conference (WWDC). Swift is designed to work with Apple's Cocoa and Cocoa Touch frameworks, building on the best of C and Objective-C, without the constraints of C compatibility. It adopts safe programming patterns and adds modern features to make programming easier, more flexible, and more fun [30].

We chose this language as we wanted to create a game for the OS X platform. In addition to this, the author also had a personal interest in learning the language.

5.3.1 Data Storage

The game relies on preserving user's scores and the levels generated by them. We need a way of storing them and all the information retrieved when analysing the songs to avoid regenerating the levels for the same song, for example if the user has a music piece they particularly like.

Core Data is the standard way to persist and manage data in both iPhone and Mac applications. It is an object graph and persistence framework provided by Apple in the Mac OS X and iOS operating systems.

Core Data describes data with a high level data model expressed in terms of entities and their relationships plus fetch requests that retrieve entities meeting specific criteria. Code can retrieve and manipulate this data on a purely object level without having to worry about the details of storage and retrieval.

Core Data allows data organised by the relational entity–attribute model to be serialised into XML, binary, or SQLite stores.

Core Data is also a persistent technology, in that it can persist the state of the model objects to disk. But the important takeaway is that Core Data is much more than just a framework to load and save data - it is also about working with the data while it is in memory. We decided to use Core Data rather than a separate database as our game only needs to store data used by the current user, that will be utilised almost immediately after loading into memory.

The model might cause some intensive memory usage if we decide to create a big amount of users, however, as it is an offline game that can be played on a personal machine, in contrast to web application, the number of users should remain relatively small.

5.3.2 Menu

Although not usually adopted in OS X games, we decided to follow the Model-View-Controller design pattern in implementing our application. We believe it was a right choice as the complexity of the main menu would have to be then supported throughout the played level. This would not only be a performance strain, but would also cause the code to be messy.

When first facing the menu, the user has an option of creating an account, logging in as a user or playing a quick game, not requiring any user data. The quick game is essentially an ability of playing one of the predefined levels, without a choice of creating a new one.

Once the user has created an account or chosen an existing one, they can either follow the level creation or level loading option. If they choose to create a new level, they have to select a file from their hard drive they would like to use as the base for their level. Otherwise, they go to the window, where they can select a level and either play it or remove it from their catalogue.

5.3.3 Level Description

Once we move on to playing a game, the `GameViewController` unpacks the `GameScene` - an object representing a scene of content in Sprite Kit.

Sprite Kit provides a graphics rendering and animation infrastructure that can be used to animate arbitrary textured images, or sprites. Sprite Kit uses a traditional rendering loop where the contents of each frame are processed before the frame is rendered. Sprite Kit does the work to render frames of animation efficiently using the graphics hardware. Sprite Kit is optimized so that the positions of sprites can be changed arbitrarily in each frame of animation.

Sprite Kit also provides other functionality that is useful for games, including basic sound playback support and physics simulation. In addition, Xcode provides built-in support for Sprite Kit so that you can create complex special effects and texture atlases directly in Xcode. This combination of framework and tools makes Sprite Kit a good choice for games and other apps that require similar kinds of animation [31].

In the game scene, there is a set of buttons at the bottom of the screen. Players use the strum bar along with the fret buttons to play notes that scroll down the screen. The Easy difficulty only uses the first three fret buttons, that is, the green, red, and yellow. The Medium difficulty uses the blue button in addition to those three, and Hard and Expert use all five buttons.

The score is calculated based on how many scrolling notes we manage to hit. Every time we hit, the performance bar on the right side of the screen goes up, otherwise it goes down. If it hits the minimum, it the player loses. However, if the player manages to keep the performance level at the maximum for an appropriate amount of time, the number of the points scored for the new notes gets doubled until he misses a note or wins the level.

The player can at any time pause, stop or replay the game.

5.3.4 Melody Detection as a Game Changer

5.3.5 Impact of the Mood on the Level

5.4 Main Section 2

Chapter 6

Evaluation

Game developers use personal preferences and creative programming techniques and tools to develop games with the hopes of successful market penetration. Often, in the course of development, the needs of the end user are lost.

Evaluation can occur during various times during the design and development life cycle of a game – early, in the middle, late, and at the end. However, not all types of evaluation methods can be applied during all phases of design and development.

6.1 Formative

Formative evaluation is any evaluation that takes place before or during a project's implementation with the aim of improving its design and performance. It is essential for trying to understand why a program works or does not, and what other factors (internal and external) are at work during a project's life. Formative evaluation does require time but it significantly improves the likelihood of achieving a successful outcome through better program design

6.1.1 Single-Condition Study

Throughout the course of the design and development of the game we will be conducting studies by asking small groups of people to play our game. The main aims of this type of study is to learn about the opinion the game causes and to observe reactions of the players while they are testing it. This helps avoiding people being biased. We would like to observe the pace at which they learn the rules without being instructed in person, telling us whether the user interface is intuitive, if they find the game challenging, which would be visible in their scores and their engagement (do they try different songs over and over again or do they get bored after 10 minutes of playing?).

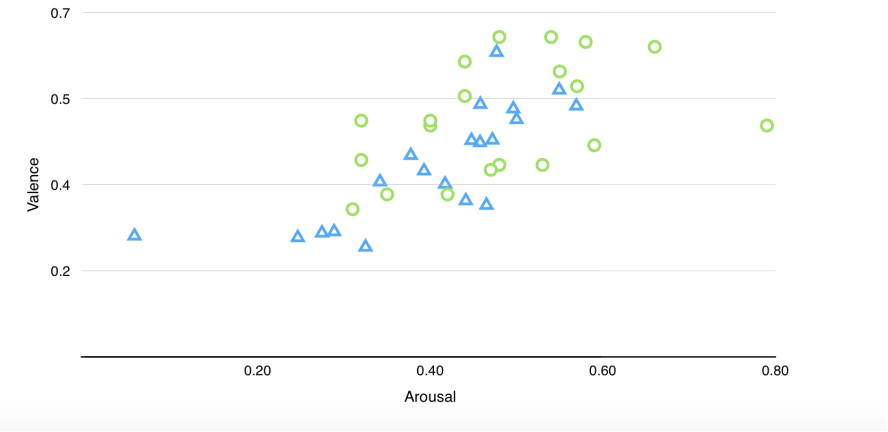


FIGURE 6.1: A plot of the expected and predicted .

6.2 Summative

Summative evaluation looks at the impact of an intervention on the target group. It is outcome-focused more than process focused. Typically, the findings are used to help decide whether a program should be adopted, continued, or modified for improvement

6.2.1 Evaluation of Mood Detection system

We wanted to use neural networks to calculate valence and arousal ratings of songs using audio features we extract.

We computed the mean error between participant ratings and network-predicted outputs across all segments of all test melodies. The network's performance total RMSE was 0.148004365696 on scale from 0 to 1 or 36.4%. The network predicted at an average accuracy of 63.6% for all 20 segments. The plot of the expected and predicted values can be seen in Figure 6.1.

Results from the static network indicate that a network can be trained to identify statistical consistencies across audio features abstracted from music and satisfactorily predict valence/arousal values that closely match mean participant ratings.

6.2.2 Comparison to Original Songs

In order to evaluate the quality of the gameplay generated by our program, we will test our game with songs already existing in the original Guitar Hero game and compare the output we get with its already defined levels. However, to make that possible, the music track we feed to our program must be an instrumental version of the same song as Guitar Hero's songs are mapped onto the key presses by looking at the guitar line of the song, not the main melody. We can then create statistics of correctly identified, false alarm and missed buttons.

expected arousal	expected valence	predicted arousal	predicted valence
0.31	0.3	0.444431	0.317472
0.35	0.33	0.328461	0.223183
0.57	0.55	0.460908	0.435624
0.44	0.53	0.380779	0.409680
0.58	0.64	0.480053	0.619061
0.32	0.48	0.061191	0.245715
0.4	0.47	0.278070	0.251782
0.55	0.58	0.461282	0.513407
0.32	0.4	0.250095	0.242515
0.44	0.6	0.451006	0.439964
0.48	0.39	0.503161	0.482461
0.59	0.43	0.572258	0.510141
0.54	0.65	0.345153	0.355842
0.66	0.63	0.499413	0.504208
0.4	0.48	0.475201	0.440776
0.53	0.39	0.552490	0.542544
0.79	0.47	0.468336	0.308246
0.47	0.38	0.420469	0.351254
0.42	0.33	0.396124	0.378217
0.48	0.65	0.292138	0.254419

TABLE 6.1: Table showing the root mean square error for training the network for given number of nodes in the hidden layer.

6.2.3 Melody Extraction Testing

To evaluate our implementation of the melody extraction algorithms we can use the technique used at Music Information Evaluation eXchange, described in section 2.4.3 of the report. In particular, we can compare the performance of our implementation when tested on the samples used during MIREX to the official statistics presented in papers [3, 13].

Another way of evaluating the game is creating a set of songs and generating levels for them. After that a trained Guitar Hero player can play those levels. If the buttons were consistently on time with the notes then the melody extraction and game synchronisation techniques are considered to work.

6.2.4 Questionnaires

Questionnaires are one of the most common and popular tools to gather data from a large number of people. They generally consist of a limited number of questions that ask participants to rate the effectiveness of various aspects of the activity. The questions should focus on the key points we are trying to evaluate.

Questionnaires tend to be short in order to reduce the amount of time respondents need to complete them, and therefore increase the response rate.

We plan on writing questions that are quantitative and generally consist of close-ended questions (tick the box, or scales), as the open ended questions tent to make data analysis and reporting more difficult.

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