

text1
text2

Abstract

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graph TD; Init[Initialisation] --> Pop[Population]; Pop --> Term[Termination]; Pop -- Crossover --> Off[Offspring]; Off -- "Survivor Selection" --> Fit[Fittest Offspring]; Fit -- Mutate --> Pop;
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The flowchart illustrates the Genetic Algorithm process. It begins with 'Initialisation' (red box), which leads to 'Population' (blue box). From 'Population', the process can lead to 'Termination' (red box) or 'Offspring' (blue box) via 'Crossover'. 'Offspring' then undergoes 'Survivor Selection' to become 'Fittest Offspring' (blue box). Finally, 'Fittest Offspring' are 'Mutate' back into the 'Population', completing the cycle.

Figure 1: The genetic model, an overview of the important components.

1 Introduction

fitness functions where used in [4], one per type of user preference. These preferences are: transition, repetition, variety, range and mood.

In this paper, we emphasized on the structure of the individual songs. Instead of focusing on theories that define music to be better than others, we focussed on a master song that defines the theory similar to [7]. The similarities between the population and the master can be based on the result of an absolute comparison i.e. comparing the exact number of notes of the candidate, which is the to be rated song, to the master. However, these absolute ratings would result in a population that is exactly the same as the master song, this is not what we are looking for. We introduce a new way to rate the candidates: relative ratings.

2 Model

In the domain of music composition we lack a model that could judge the input, the fitness function, and our desired output may be ill-defined. In GenJam [3], the quality of the genetically produced solos are rated by human individuals. A human mentor gives "real-time feedback" which is used to derive a fitness score. Fitness can also be calculated by different aspects based on music theory as shown in [7], [2], [4]. By splitting the fitness function into subcategories, we are allowed to rate an individual song based on different aspects and set importance to certain preferred aspect. In [2], songs were compared to a well known group of songs. In [7], each bar of the song is rated by different criteria and summed up together to obtain the total fitness. The fitness is here calculated by the similarity between the to be rated individual and a reference individual or by reference values. Five

The initial population can consist of both random songs or non-random songs, these are called

GEN0. The next generation is calculated by applying a crossover function on *GEN0* to obtain *GEN1* which is the offspring. Each individual song in the offspring will be rated by the fitness function and obtains a score. Now we can select the best rated songs in *GEN1* and mutate them. This process is repeated until a certain condition is met or until user is satisfied with the results and manually terminates the loop.

3 Initialization

First, the initial population needs to be determined, we call it *GEN0* throughout this paper. *GEN0* usually consist of a mix of different songs from different genres making the initial population diverse. The size of the population, which is static during the execution, is decided here and is related to the number of parents.

4 Recombination

In the recombination step, a crossover function is used to pair parents in order to produce a child. This child will belong to the next generation. The model performs a uniform crossover, meaning each gene will be considered separately when pairing the parents [1]. For each song, the notes, chords and rests are considered as the genes of a song. Two parents produce only one child by uniformly selecting genes from one of the two parents. On figure 2, an example of two songs, that are considered as parents, are graphically displayed. During the crossover process, the model iterates over all the genes in both parents and selects only one or the other to pass to the resulting child. Both genes have an equal chance of being selected. On figure 3 a sample child of the corresponding parents is illustrated.

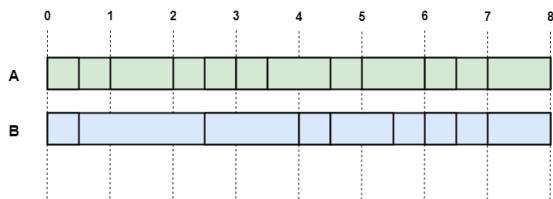


Figure 2: Graphical display of two parents A and B. Each rectangle represents a note, chord or rest with their corresponding length. The horizontal axis represents time.

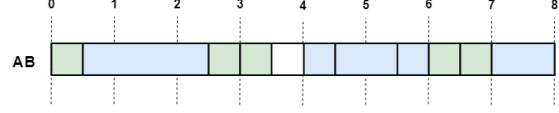


Figure 3: The child generated from the parents A and B.

Notice that there is a gap in the child song at time offset 3.5. This is the result of selecting parent B's gene at time offset 4 instead of the corresponding gene of parent A's at time offset 3.5.

At each recombination step, all the parents are paired with each other. If there are N parents, the number of children will be equal to $\frac{N*(N-1)}{2}$. After the recombination, the fitness of each child will be calculated.

5 The fitness function

A composition has multiple aspects that can be rated at each individual level, therefore, the fitness of an individual is determined by different **rating functions**. Each of these rating functions calculates a **score** for a particular **concept** of the song. The tendency to follow a musical scale within the composition is a concept for example. Every rating function calculates a score and to this score there is a predetermined weight attached that implies the importance of the rated concept. The total fitness of a song x is equal to the sum of the products of all rating functions S for each concept and their corresponding weights W .

$$TotalFitness(x) = \sum_{i=1}^C S_i * W_i$$

where C is the number of concepts.

A rating function calculates a score for a concept based on a reference. For the reference, an existing song is used. Throughout this paper, this reference song is called the **master song**. The goal is to generate songs that are similar to the master song. The master song defines the genre that the candidates have to follow. Each rating function R of a concept calculates a score based on the difference of the candidate song x to the master song m for that concept c .

$$R_{concept}(x) = difference(f_{concept}(x), f_{concept}(m))$$

With $f()$ a sub-function that gives a rating for the concept.

We introduce two ways to compare the master song with the candidate song: absolute and relative comparison. In the absolute comparison,

Materials & Methods

man

Results

results

Discussion

Discussion

Conclusions

concluded

5.1 Relative rating functions

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5.1.1 Zipf's law distance

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$$Occurrences(E) = \frac{1}{B} * L$$

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6 Survivor selection

After

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