Evolutionary Composition Using Music Theory and Charts

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***Abstract*—With the development of human science and technology, applications of computer are more and more comprehensive. Using artificial intelligence (AI) to drawing, thinking, and problem solving becomes a significant topic. Recently, research on automatic composition using AI technology and especially evolutionary algorithms is blooming and has received promising results. A common issue at the current evolutionary composition systems is their requirement for subjective feedback of human sensation as evaluation criterion, which is vulnerable to the fatigue and decreased sensitivity after long-time listening. This paper proposes using music theory with the information from music charts in the evaluation criterion to address this issue. Specifically, we generate the weighted rules based on music theory for the fitness function. The weights are determined according to the download numbers from music charts. These weights obtained can interpret the music style and render an objective measure of compositions. Experimental results show that the proposed method can effectively achieve satisfactory compositions.**

***Index Terms*—Evolutionary computation, automatic composition, music theory, fitness function, computational creativity, creative intelligence.**

I. Introduction

Computational creativity using computational intelligence and artificial intelligence technologies blooms in many fields, such as music, visual art, literature, architecture and industrial design. Particularly, automatic music composition receives much attention in that music plays an important role in nowadays human life and entertainment. In composing music, many elements need to be considered, e.g., rhythm, melody, texture, musical form, tone color and tonality. This variety gives the plenty of beautiful music; however, it also makes composition difficult.

Evolutionary algorithms have been utilized in automatic composition in view of its successes in dealing with large-scale complex problems. Genetic algorithm (GA) is especially commonly used in the music composition and accompaniment systems due to its recognized capability in search and optimization. The GA-based composition systems ordinarily evaluate the generated compositions based on the interaction with humans. Although this human feedback is of great use for evaluation, it suffers from the fatigue and decreased sensitivity after long-time listening, which makes this evaluation manner very exhaustive and impractical. Liu and Ting [1] proposed using music theory as the basis of music evaluation for GA to generate the dominant melody and accompaniments. Although the music theory provides an objective measure for music evaluation, the weight of each rule is determined by subjective personal experience. To solve this issue, the present study further employs the information from music charts to determine the weights for an objective evaluation. Through the music theory rules and weights, the proposed GA can generate music without depending upon subjective personal experience. In addition, we adopt the musical forms to improve the structure of compositions. The homophony is made up with accompaniment of the main theme. This study conducts simulations to examine the performance of the proposed evolutionary composition system.

The remainder of this paper is organized as follows. Section II reviews related work in evolutionary composition. Section III elucidates the proposed GA for composition. The experimental results are presented in Section IV. Finally, Section V gives the conclusions of this study.

II. Related Work

In the light of its effectiveness in global search and optimization, evolutionary computation is widely used in computational composition. McIntyre [2] first applied GA to generate four-part Baroque harmony. Laine and Kuuskankare [3] adopted GA to find the music functions and estimate their parameters for generation of music. The music functions serve as a logical and general music expression. Pazos et al. [4] used GA with the interaction of several musicians to build a model for creating rhythmic patterns. Further, Marques et al. [5] generated and weighted the composition rules as a basis for distinguishing good and bad music. By analyzing the features of good songs, Towsey et al. [6] divided them into five categories and utilized these features to evolve music by GA. In addition, Schoenberger [7] analyzed works of many famous composers like Bach based on Western tonal theory. Khalifa et al. [8] proposed adopting four motifs in composing music. These motifs are evaluated according to some grammar rules. Chen et al. [9], [10] presented the CFE framework considering feedback as a key element in music composition.

Some studies focus on automatic accompaniment. In addition to the dominant melody, accompaniment plays an important role in music because good accompaniment can effectively strengthen harmony, tighten the structure of tunes, and reinforce the expression of music. Luo et al. [11] developed a real-time accompaniment system for the sung voice. The system detects the pitches of the sung voice and accordingly creates the score from the mixture of sung voice and accompaniment. Experimental results show that this system is robust against noise and can provide good accompaniment for the sung voice. Chen et al. [12] designed a tempo-based accompaniment through analysis of the tempo and an interactive system. Additionally, Jo et al. [13] established a chord-based music composition system with an auto-accompaniment program to compose music for non-musicians. Simon et al. [14] trained a hidden Markov model with a music database and adopted this model to automatically choose chords for a vocal melody. The naive users can create a song by singing into a microphone. They can also experiment with different styles and chord patterns without music knowledge.

The above GA-based systems show their utility in generating dominant melody or accompaniment. However, evaluation of the composed music is still a key issue, especially for those using human feedback. The present study proposes utilizing music theory with the information from music charts in the evaluation criterion to address this issue. More details are given in following sections.

III. Genetic Algorithm for Composition

Genetic algorithm is widely used in search and optimization problems. The basic idea of GA is to simulate natural evolution through the selection, crossover, and mutation operators [15], [16]. Based on Darwinian Theory "Survival of the Fittest", GA is believed to be capable of evolving candidate solutions into better ones. The fitness function is used to evaluate the solution quality of chromosomes. The first step of GA is to represent candidate solutions as chromosomes subject to the problem to be solved. A set of chromosomes, called the population, is generated as the pool of evolution in GA. The evolution begins with initialization of the population. Then, the selection operator picks two chromosomes as parents out of the population. The two parents are performed with crossover to produce their offspring. The mutation follows to slightly change some genes in the offspring. This selection-crossover-mutation process repeats until the set of offspring is filled. Acting on the principle of survival of the fittest, the survivor operator draws the fittest chromosomes from the offspring population with (or without) the parent population. The survival chromosomes constitute the population for the next generation.

The proposed evolutionary composition system consists of two stages: evolution and post-processing. As Fig. 1 illustrates, the system first evolves compositions based on GA for a predetermined number of generations. Afterward, the best resultant composition from GA is processed with musical form and accompaniment to enhance its structure and euphony. A key issue at the use of GA for music composition is the design of fitness function, which guides the direction of evolution in

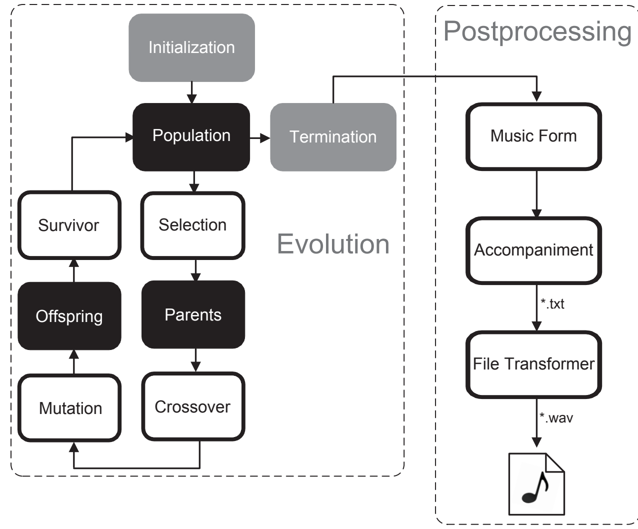

Figure 1. Flowchart for the evolutionary composition system

Table I
Encoding of notes

Note	Number	Note	Number
rest	-1	F	5
tenuto	-2	#F	6
		G	7
C	0	#G	8
#C	1	A	9
D	2	#A	10
#D	3	B	11
E	4	C (high)	12
		⋮	⋮

GA. In this study, we devise a fitness function based on music theory for evaluating compositions. Particularly, the weights of evaluation rules in the fitness function are derived from the download information of music charts. More details about the proposed evolutionary composition system are given below.

A. Representation

This study represents music sections according to Bach's 12 equal temperament. Specifically, each octave is divided into 12 equal notes denoted by C, #C, D, #D, E, F, #F, G, #G, A, #A, and B. Table I lists the note numbers used in the chromosome representation: Note C is encoded as number 0, #C as 1, D as 2, and so on. The music beat is set to four-fourths and the note length ranges from one sixteenth to a quarter, where tempo is variable. Figure 2 gives an example chromosome, where bar 1 consists of four quarter notes, i.e., E, E, F, and G; bar 2 contains dotted quarter note E, eighth note D, dotted quarter note D, and eighth rest.

B. Fitness Function

Evaluation criterion is crucial to automatic composition systems. To address the fatigue issue of human feedback, this study adopts 42 evaluation rules selected from music theory as the basis of fitness function. The weights of evaluation rules

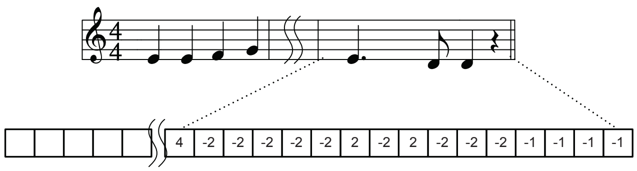

Figure 2. Chromosome representation

are determined according to the download information from music charts. The proposed evaluation method holds two major advantages: First, the evaluation criterion is consistent. Since the compositions are scored by the music theory rules, the evaluation is objective and not affected by personal experience or preference as in the traditional human-machine-interaction manner. Second, the evaluation is stable. The human-assisted evaluation suffers from human fatigue and the decrease of musical sensitivity after long-time listening. The evaluation using the proposed rules based on music theory can serve as an effectual guideline for the GA to generate satisfactory compositions.

1) Evaluation Rules: Given the harmony and musical structure, 42 rules are selected (cf. Table III) for music evaluation according to music theory [17][18]. The first 16 rules consider the harmony of tones by dealing with the different conditions of chord notes, which can efficiently exclude the disharmonious noise. The 17th and 18th rules dominate the structure of each phrase, making them complete and controlling the length. The 19th to 24th rules handle the resolution and the process of active and inactive tones. The last 18 rules consider the scales and leaps in order to generate smooth and rational melodies.

The fitness function sums up the scores of a composition from each rule. Formally, the fitness function for a chromosome (composition) $\boldsymbol{x}$ is defined by

$$f(\boldsymbol{x}) = \sum_{i=1}^{42} w_i C_i(\boldsymbol{x}), \tag{1}$$

where w_i represents the weight of rule i and C_i denotes the count of rule i in composition $\boldsymbol{x}$.

2) Weight Vector: This study proposes using the information from music charts rather than personal experience to determine the rule weights for an objective evaluation of compositions. Specifically, we choose 33 songs of the rock band "Guns N' Roses" from the GProTab.net website [19], which provides the download number of each song to reflect its popularity in the chart. Table II shows the 33 song names and their download numbers. Next, we count the matches of the rules and songs as the matrix

$$\mathbf{C} = \begin{bmatrix} c_{11} & \cdots & c_{1r} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mr} \end{bmatrix},$$

where c_{ij} represents the count number of the rule j in song i. This count indicates the usage frequency and importance of rules.

Table II
SONG NAME & DOWNLOAD NUMBER

Song name	#Downloads
Sweet Child O'Mine	24044
Don't Cry	16664
November Rain	8084
Paradise City	7610
Patience	3630
Civil War	3264
Nightrain	2679
The Godfather Theme	2498
Estranged	2193
Live And Let Die	1782
You Could Be Mine	1648
Ain't It Fun	1588
Used To Love Her	1236
14 Years	1211
Breakdown	1189
My Michelle	1184
It's So Easy	857
Wild Horses	834
Anything Goes	733
Double Talkin' Jive	723
Don't Damn Me	701
Back Off Bitch	667
Yesterdays	616
Get In The Ring	611
Out Ta Get Me	542
Think About You	460
Hair Of The Dog	448
Pretty Tied Up	401
Dust N' Bones	340
Raw Power	278
Nice Boys	274
The Garden	272
You Ain't The First	231

By regarding the download numbers $\mathbf{f} = [f_1 \ldots f_m]^{\intercal}$ of m songs as their fitness values, the weights of rules for fitness function can then be derived by

$$\begin{bmatrix} w_1 \\ \vdots \\ w_r \end{bmatrix} = \mathbf{C}^{-1}\mathbf{f} = \begin{bmatrix} c_{11} & \cdots & c_{1r} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mr} \end{bmatrix}^{-1} \begin{bmatrix} f_1 \\ \vdots \\ f_m \end{bmatrix}. \tag{2}$$

Table III lists the counts and rule weights obtained from the download information of Guns N' Roses' 33 songs. The resultant weights provide the foundation of evaluating compositions and the direction for the process of evolution. For example, the first rule "The rhythm of chord notes" and its weight value -87 indicate that a penalty is imposed to long chord notes. Given that the second to fifth rules add positive scores to the chord notes for different conditions, the penalty of the first rule can avoid monotonous composition consisting of only chord notes. The 25th to 42nd rules for the scale and leap, moreover, make the compositions more flexible and interesting since the common leap can obtain a high positive score.

C. Genetic Operators

Genetic algorithm selects chromosomes as parents from the population and then performs crossover and mutation operations to generate their offspring. This study adopts the binary tournament selection in view of its good performance. The binary tournament selection chooses the fitter of two

Table III
RULES OF FITNESS FUNCTION & WEIGHT

	Rules based on music theory	number of counts	weight value
1	The rhythm of chord notes	4410	-87
2	The note is a chord note	13300	44
3	The note is a chord note (chord root note)	284	504
4	The note is a chord note (chord 2nd note)	223	234
5	The note is a chord note (chord 3rd note)	304	95
6	The note of phrase cadence is the chord note	331	846
7	The note of phrase cadence is not the chord note	1397	-168
8	The note is the first note in a phrase and is a chord note (chord root note)	156	745
9	The note is the first note in a phrase and is a chord note (chord 2nd note)	132	839
10	The note is the first note in a phrase and is a chord note (chord 3rd note)	192	885
11	The note is the last note in a phrase and is a chord note (chord root note)	135	3584
12	The note is the last note in a phrase and is a chord note (chord 2nd note)	149	380
13	The note is the last note in a phrase and is a chord note (chord 3rd note)	149	1372
14	The note is the last note in a phrase and is a chord note (chord 4th note)	101	1687
15	Chord note on stress	557	441
16	Invalid note on stress	175	-2216
17	Integral phrase	146	359
18	Phrase exceed 3 bars	296	-30
19	From active tone to inactive tone	178	-691
20	Resolution from active tone to inactive tone	147	-542
21	From active tone to active tone	1115	-182
22	Resolution for chord	106	34
23	From inactive tone to inactive tone	2018	276
24	From inactive tone to active tone	475	-941
25	Process of scale (ascending)	1523	40
26	Process of scale (descending)	1980	223
27	Process of third leap (ascending)	1971	-33
28	Subsequent process of third leap (ascending)	198	-307
29	Process of third leap (descending)	239	176
30	Subsequent process of third leap (descending)	358	-55
31	Process of fourth leap (ascending)	259	-249
32	Subsequent process of fourth leap (ascending)	134	1085
33	Process of fourth leap (descending)	112	36
34	Subsequent process of fourth leap (descending)	231	81
35	Process of fifth leap (ascending)	201	634
36	Subsequent process of fifth leap (ascending)	119	99
37	Process of fifth leap (descending)	255	54
38	Subsequent process of fifth leap (descending)	104	77
39	Process of sixth leap (ascending)	78	10
40	Subsequent process of sixth leap (ascending)	247	34
41	Process of sixth leap (descending)	388	19
42	Subsequent process of sixth leap (descending)	531	7

randomly picked chromosomes from the population as a parent. Performing this selection twice yields a pair of parents for the following crossover and mutation operations.

The crossover operator generates offspring by recombining the parental information. For the music composition, the crossover needs to be specially designed since arbitrary recombination of two parents can hardly result in acceptable compositions. This study introduces the notion of crossover unit into the 2-point crossover to address this issue. In the modified 2-point crossover, the cutting points can only lie between bars. Accordingly, the crossover randomly cuts two selected parents and then exchanges the bars in the way of order crossover to generate offspring (cf. Fig. 3).

Next, the mutation operator slightly changes the offspring for exploring the problem space. Subject to the integer chromosome representation, this study uses the random resetting mutation. This mutation operator probabilistically replaces one randomly-picked note with a random value.

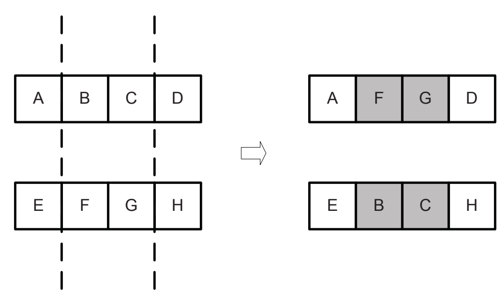

Figure 3. Crossover for compositions

For the survivor selection, we adopt the $(\mu + \lambda)$ strategy that merges the parent and offspring populations to compete for survival into the next generation.

Figure 4. Form 1-1

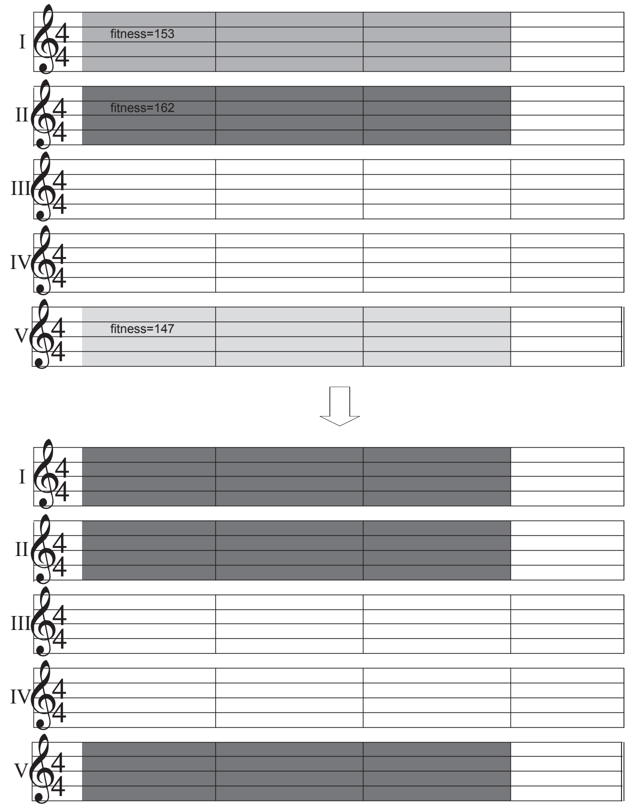

Figure 5. Form 1-2

D. Post-processing

After the evolution stage, the post-processing is further performed to improve the composition generated by GA. The post-processing consists of two steps, viz., musical form and accompaniment, to euphonize the resultant composition from GA.

1) Musical Form: Musical form is generally considered in composition. The first step of post-processing modifies the composition according to two musical forms. For a 20-bar composition, we divide it into five four-bar sections and apply the following two musical forms.

Form 1: The first musical form deals with sections I, II, and V. The post-processing randomly chooses one of the following three forms to apply.

1) The first two bars of sections I, II, and V must be identical. As Fig. 4 illustrates, according to this musical form, we replace the first two bars of sections I, II, and V with the best (highest score) of them, i.e., the first two bars of section V in the example.
2) The first three bars of sections I, II, and V must be identical. Figure 5 shows that the first three bars of sections I, and V are replaced with that of section II because it has the highest score among the three sections.
3) The first three beats of the first two bars in sections I, II, and V must be identical. In the example of Fig. 6, the first three beats of bar 2 are substituted for those of bar 1 in section I, given the score of bar 2 is higher than that of bar 1.

Form 2: The second musical form concerns sections III and IV. This musical form regulates that the first two bars of sections III and IV should be identical. In implementation, we replace the first two bars of sections III and IV with the better of them (see Fig. 7).

2) Accompaniment: This study adopts the two accompaniments proposed in [1] for the generated dominant melody. First, the main accompaniment is also based on music theory and focuses on tone harmony and rhythm complementary. The intervals between the melody and main accompaniment provide important information for evaluation of tone harmony. The notes of main accompaniment appear when the melody is scant or empty. This manner can make the whole music more integrated. Second, the chord accompaniment harmonizes and makes up the rhythm for the melody as well as the main accompaniment. Through varying the chords, four types of

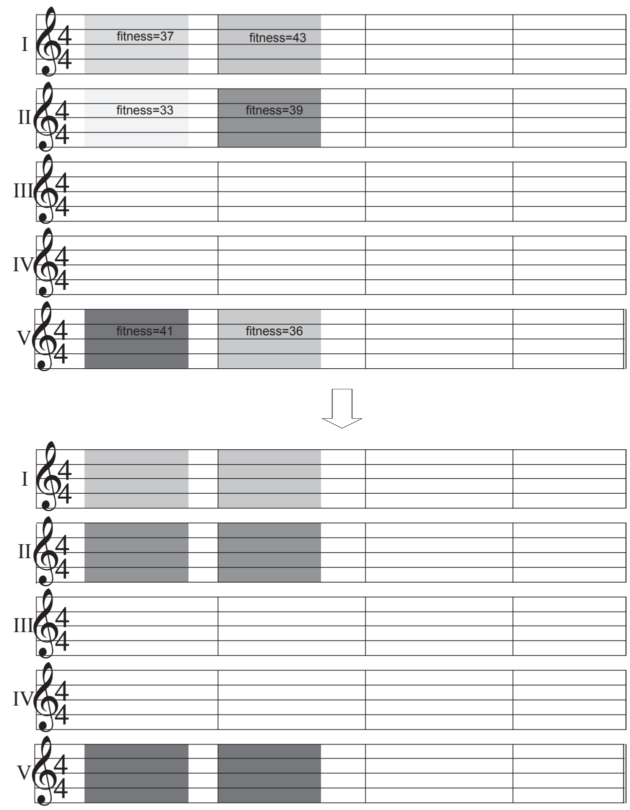

Figure 6. Form 1-3

Figure 7. Form 2

chord accompaniments are used to match the note density of the melody and main accompaniment.

IV. Experimental Results

Several experiments are carried out to evaluate the performance of the proposed evolutionary composition system. Table IV presents the parameter setting for the GA in the experiments. The length of compositions is set to be 20 bars. The obtained compositions are further processed with the orchestral instrument and guitarZ virtual studio technology (VST). Some sample results (WAV files) can be downloaded via http://cilab.cs.ccu.edu.tw/CIC2013.zip.

Table IV
Parameter setting of GA

Parameter	Value
GA type	Generational
Representation	Integer
Chromosome length	320 (20bars)
Population size	32
Selection	Binary tournament
Crossover	Modified 2-point
Crossover rate	0.9
Mutation	Random resetting
Mutation rate	1/320
Survivor	$\mu + \lambda$
Termination	1000 generations

Figure 11 plots the progress of mean best fitness over 30 runs of the proposed GA. The figure shows that GA can effectively increase the fitness values of the melody. The sample music files also demonstrate the improvement in euphony achieved by GA. Figures 8–10 compare the compositions obtained from different stages of the evolutionary composition system. The initial composition has many discordant notes and has a loose structure for whole music. The leap between notes is disorganized and somehow random, reflected on the low fitness values of initial compositions. The proposed GA substantially improves the composition: First, the disharmony is greatly reduced for tuneful scale. Second, the proposed fitness function encourages GA to compose in consideration of music theory. Third, the process between notes is mature and rational. Finally, the post-processing enhances the composition generated by GA in structure, harmony, and euphony.

In the light of fitness value, random compositions at initialization score only near 18400, whereas the average score (fitness value) of proto-compositions obtained from GA ranges from 19000 to 19200. The post-processing further increases the score by 500 to 600 points on average. In addition, the evolutionary composition based on music theory is very effective in excluding disharmony and noisy melodies. According to the audience with music background, the resultant compositions sound harmonious and follow the sense of melody progress.

Figure 8. Resultant composition from initialization

Figure 9. Resultant composition from GA

Figure 10. Resultant composition from GA with post-processing

V. Conclusions

This study proposes an evolutionary composition system based on music theory and charts. Specifically, we develop a GA for composition and design its fitness function using weighted rules based on music theory. In particular, this study proposes using the information from music charts to determine the weights of rules. The resultant proto-compositions are further modified considering musical form and integrated with accompaniment.

The proposed evolutionary composition has three major advantages. First, the stochastic property of GA produces diversity in the generated melodies. Second, the evaluation is utterly objective and overcomes the drawbacks of human-assisted evaluation suffering from fatigue and preference. With the proposed fitness function, one can further examine a song's score in terms of music theory. The weights obtained can represent the style of the songs and serve as the basis for an objective evaluation of compositions. Third, the use of musical form makes the resultant compositions more structured.

Experimental results show that the proposed method can effectively achieve satisfactory compositions. Based on music theory, the evolutionary composition avoids generating disharmony and noisy melodies. According to the audience with music background, the resultant compositions sound harmonious and follow the sense of melody progress.

Some tasks remain for future work. First, more music theory rules should be considered. Second, the derivation of weights can use the information from other music charts for composition of different music genres.

Acknowledgment

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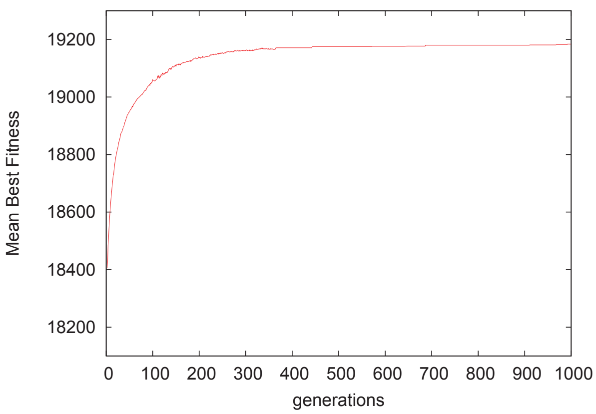

Figure 11. Progress of the mean best fitness against generations

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