# Evolutionary Composition Based on Music Theory

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***Abstract*—With the development of human science and technology, the applications of computer are more and more widely. Using artificial intelligence (AI) to drawing, thinking, problem-solving becomes a popular topic. Recently, research on automatic composition using AI technology is blooming and has received some promising results. However, there still exist several issues at computer composition, one of which is the way to evaluate music. This study develops a genetic algorithm to compose music and proposes using music theory as an objective evaluation for the composed music. Moreover, we utilize music form to enhance the structure of compositions and integrate them with accompaniment for homophony. Experimental results show that the proposed method can effectively achieve satisfactory compositions.**

## I. Introduction

Music is a part of our life. Although listening music is easy, creating it is by no means simple: Various musical elements need to be considered when composing music, such as rhythm, melody, texture, musical form, tone color and tonality. This variety gives the plenty of beautiful music; on the other hand, it makes composition difficult. With the advance of computer technology, some thought of automatically composing music by computer. Artificial intelligence has attracted attention in computer-aided or computer-enabled composition.

In particular, evolutionary computation is widely used in view of its recognized capability in global search and optimization. McIntyre [1] first used genetic algorithm (GA) to generate four-part Baroque harmony. Laine and Kuuskankare [2] introduced functions in music generation and adopted GA to find the music functions and estimate their parameters. The music functions help to express music in a logical way and make it easy to generalize. Pazos et al. [3] established a model for creating rhythmic patterns based on GA with the interaction of several musicians. To export some rules of composition, Marques et al. [4] weighted the rules as a basis for distinguishing good and bad music. Further, Towsey et al. [5] analyzed the features of good songs, divided them into five categories, and utilized these features to evolve music by GA. Schoenberger [6] utilized Western tonal theory to analyze works of many famous composers such as Bach. In addition, Khalifa et al. [7] proposed composing a song with four motifs and evaluated them according to some grammar rules. Chen et al. [8], [9] presented the CFE framework given that feedback is a key element in music composition.

A key issue at computer composition using AI or GA techniques is how to evaluate the compositions. Although human feedback is of great use for evaluation, the required interaction between human and composition system (machine) is very exhaustive and impractical. This study proposes using music theory to evaluate the candidate compositions *objectively*, instead of depending upon subjective personal experience. Specifically, we develop a GA to compose music given the chords and tonality. The fitness function is based on the rules of music theory. Further, musical forms are used to improve the structure of compositions. The homophony is made up with accompaniment of the main theme.

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

## II. Evolutionary Composition

The proposed evolutionary composition system consists of two stages: evolution and postprocessing. 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

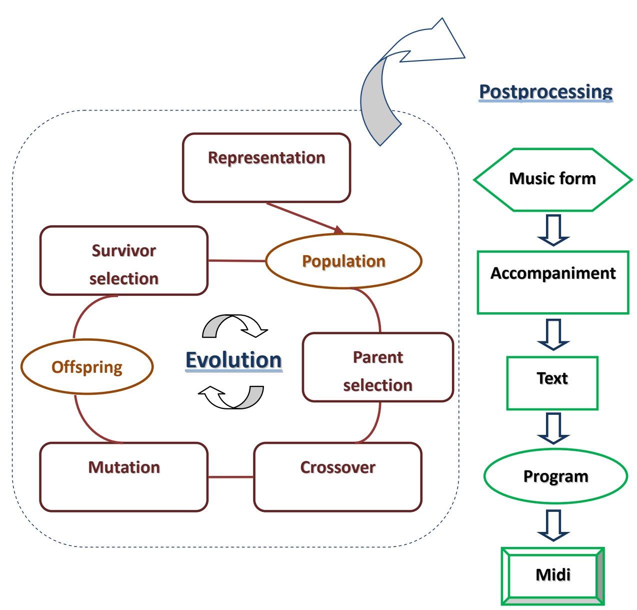



Figure 1: Flowchart for the evolutionary composition system

and accompaniment to enhance its structure and euphony. The final composition is then output as a MIDI file.

### A. Genetic Algorithm for Composition

There have been some studies on automatic composition using GA. A key issue at the use of GA for composition is the design of fitness function, which guides the direction of evolution in GA. In this study, we devise a fitness function for evaluating compositions based on music theory. More details for the proposed GA for composition are given below.

*1) Representation:* In this study, music sections are represented by a series of numbers for a chromosome. According to Bach's 12 equal temperament, each octave is divided into 12 equal notes denoted by C, #C, D, #D, E, F, #F, G, #G, A, #A, and B. In C major scale, note C is represented by number 0, #C by 1, D by 2, and so on (see Table I). In addition, we fix music beat at four-fourths and limit the range of note length from one sixteenth to a quarter, where tempo is variable. In the example of Fig. 2, bar 1 consists of four quarter notes, i.e., E, E, F, and G; bar 4 consists of dotted quarter note E, eighth note D, dotted quarter note D, and eighth rest.

Table I: Representation for 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 |
| | | ⋮ | ⋮ |

| Bar | Chromosome | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4 | -2 | -2 | -2 | 4 | -2 | -2 | -2 | 5 | -2 | -2 | -2 | 7 | -2 | -2 | -2 |
| 2 | 7 | -2 | -2 | -2 | 5 | -2 | -2 | -2 | 4 | -2 | -2 | -2 | 2 | -2 | -2 | -2 |
| 3 | 0 | -2 | -2 | -2 | 0 | -2 | -2 | -2 | 2 | -2 | -2 | -2 | 4 | -2 | -2 | -2 |
| 4 | 4 | -2 | -2 | -2 | -2 | -2 | 2 | -2 | 2 | -2 | -2 | -2 | -2 | -2 | -1 | -1 |

Figure 2: Example chromosome

*2) Fitness Function:* As aforementioned, evaluation criterion is key to automatic composition. In this study, we propose using music theory to provide an objective measure for the fitness of compositions. Although many rules exist in the music theory, we selected only the most important ones and weighted them empirically for fitness evaluation:

- Chord notes (for example, C, E and G are chord notes for chord C):
  1) Positive score $(+3)$ for chord notes.
  2) Positive score for a phrase beginning with chord notes ($+10$ for root and $+6$ for others); otherwise negative score $(-8)$.
  3) Positive score $(+10)$ for a phrase ending with chord notes; otherwise negative score $(-10)$.
- Note resolution, i.e., the move from a dissonant note to a consonant note:
  1) Positive score $(+4)$ for chord notes followed by others.
  2) Positive score $(+2)$ for chord notes followed by chord notes.
  3) Positive score $(+2)$ for notes followed by the nearest chord notes (for example, given chord C, note D followed by note C or E gains positive score; so does note B followed by note C).
  4) Negative score $(-1)$ for no resolution.
- Stepwise motion:
  1) Positive score $(+3)$ for the interval between two notes being a major second or minor second.
- Leap:
  1) Positive score $(+2)$ for a leap starting with a chord note.
  2) Negative score $(-10)$ for a leap augmented fourths (diminished fifths).
  3) Negative score $(-2)$ for a leap of seventh major or seventh minor.
  4) Negative score $(-2)$ for a leap to dissonant notes and next to a chord.

The fitness function evaluates a composition by summing up the scores from the above rules. Such evaluation holds two major advantages. First, the evaluation criterion is consistent. Since the compositions are scored according to the music theory rules, the evaluation is not affected by the personal experience or preference in the traditional human-machine-interaction manner. Second, the evaluation is stable. The human-assisted evaluation suffers from fatigue and the decrease of musical sensitivity after a long time of listening. The evaluation based on the proposed rules, although not including all theories for different genres, can serve as an effective guideline for the GA to evolve into and result in satisfactory compositions.

*3) Genetic Operators:* The genetic operators in GA include parent selection, crossover, mutation, and survivor selection. For the parent selection, the proposed GA adopts the 2-tournament selection, which selects as a parent the fitter of two randomly picked chromosomes from the population. The selected parents are further performed with crossover and mutation to produce their offspring.

The crossover for composition needs to be specially designed in that arbitrarily exchanging two parts of parents can hardly result in acceptable compositions. To address this issue, we introduce the notion of *crossover unit* to the order crossover [10]. More specifically, the cutting points of order crossover can only be between bars. As Fig. 3 shows, the crossover randomly cuts two selected parents, and then exchange the bars in the way of order crossover.

Mutation slightly changes the genetic information of a chro-

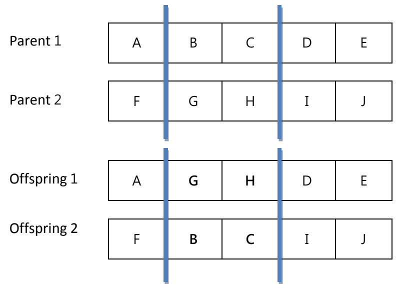



Figure 3: Crossover for compositions

mosome and helps to explore the problem space. This study uses the random resetting mutation. This mutation operator probabilistically changes one randomly-picked note with a random value. In this study, we set the probability (mutation rate) as $1/\text{chromesome\_length}$.

For the survivor selection, the proposed GA simply replaces the parental population with the offspring population for the next generation.

### B. Postprocessing

*1) Musical Form:* After the evolution stage, the postprocess is further performed to improve the proto-composition generated by GA. First, we modify the compositions according to the structures of basic musical forms, which have been widely used in composition. This study considers three musical forms listed below.

- Musical form 1: For a 16-bar composition, we divide it into four four-bar sections. The first musical form regulates that the first two bars of sections I, II, and IV are identical. In practice, as Fig. 4 illustrates, we reset the first two bars of sections I, II, and IV with the best (highest fitness) of them, i.e., that of section IV in the example.
- Musical form 2: Similarly, the second musical form regulates that the first three bars of sections I, II, and IV should be identical. Figure 5 shows that the first three bars of sections I, and IV are replaced with that of section II because it has the highest fitness among the three sections.
- Musical form 3: The third musical form regulates that the first three beats of the first two bars should be identical for sections I, II, and IV. In the example of Fig. 6, the first three beats of bar 1 are replaced with those of bar 2 for section I in that the corresponding fitness value of bar 2 is higher than that of bar 1.

*2) Accompaniment:* Next, we add the accompaniment with the chords based on the main theme to enrich the music. This study adopts three forms of accompaniment. Figure 3 presents the three accompaniment forms for chords C (0-4-7) and G (7-11-14). The postprocessing randomly chooses a musical form and an accompaniment for a composition.

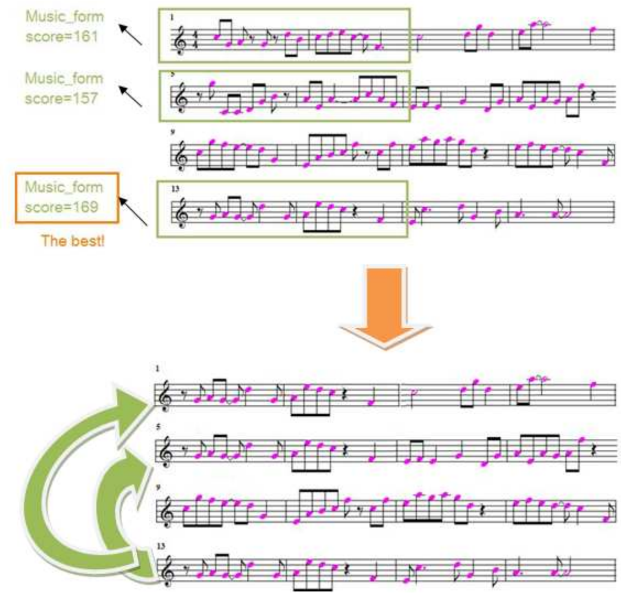



Figure 4: Procedure for musical form 1

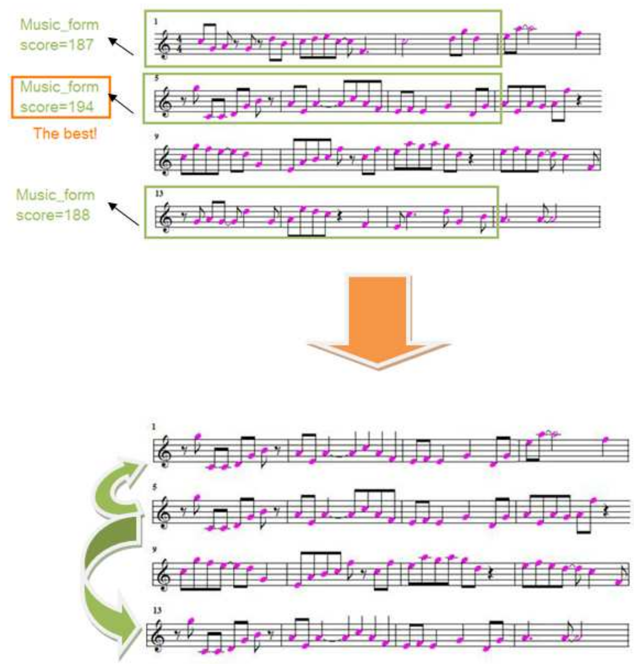



Figure 5: Procedure for musical form 2

## III. Experimental Results

This study conducts several experiments to generate music and evaluate the performance of the proposed evolutionary composition system. Table II lists the parameter setting of GA used in the experiments. The termination criterion is set to be 500 generations.

Figure 8 depicts the progress of mean best fitness over 15 runs of the proposed GA. The figure shows that the GA can increase the score of compositions in the course of evolution. Figure 9 further compares the compositions obtained from

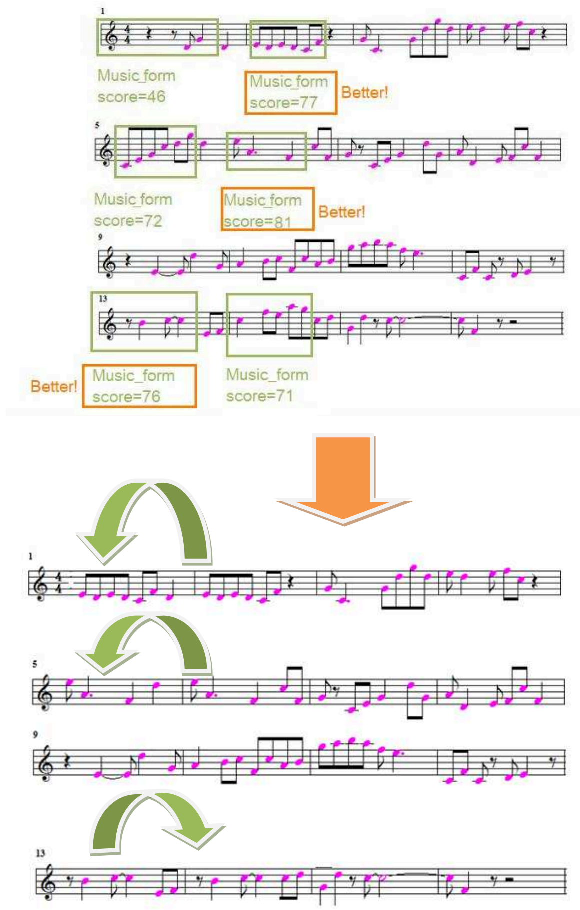
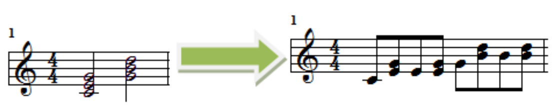
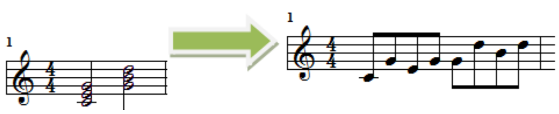


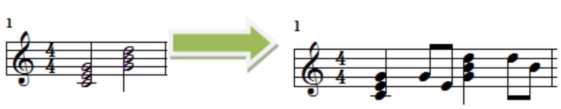

Figure 6: Procedure for musical form 3



(a) Form 1



(b) Form 2



(c) Form 3

Figure 7: Accompaniment forms

different stages. In the light of fitness values, random compositions at initialization score only near 600, whereas the average score (fitness value) of proto-compositions obtained from GA ranges from 1100 to 1250, and the postprocess can increase the score by 50 to 60 points on average. The evolutionary composition based on music theory, furthermore, is very effective in

Table II: Parameter setting

| Parameter | Value |
|---|---|
| GA type | Generational |
| Representation | Integer |
| Chromosome length | 256 (16 bars) |
| Population size | 32 |
| Selection | 2-Tournament |
| Crossover | Order |
| Crossover rate | 0.9 |
| Mutation | Random resetting |
| Mutation rate | 1/256 |
| Survivor | Replacement |
| Termination | 500 generations |

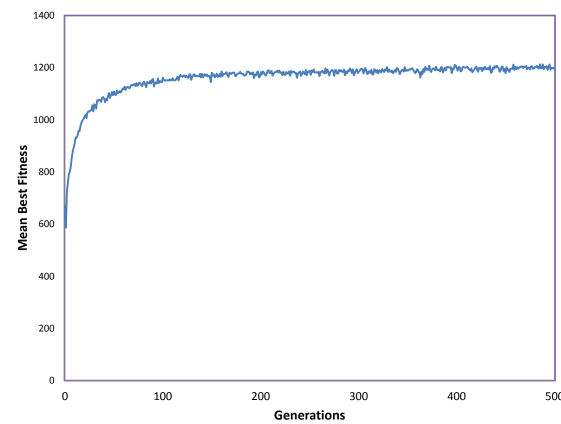



Figure 8: Progress of mean best fitness

excluding disharmony and noisy melodies. According to the audience with music background, the resultant compositions sound harmonious and follow the sense of melody progress. Some examples of the results (MIDI files) can be downloaded via http://cilab.cs.ccu.edu.tw/EvoMusic_CEC2011.zip.

## IV. Conclusions

This study presents an evolutionary composition method based on music theory. Specifically, we develop a GA for composition and design the fitness function using music theory 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 based on music theory is objective and overcomes the drawbacks of human-assisted evaluation in fatigue and preference. With the proposed fitness function, one can further examine a song's score in terms of music theory. 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. Future work can also take more factors into account, such as genre. Second, the weights of rules affect the resultant compositions. Finding an appropriate setting for them will significantly improve the work.

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(a) Initial composition

(b) Composition generated by GA

(c) Postprocessed composition

Figure 9: Resultant compositions at three stages: a) the initial composition, b) the composition obtained from GA, and c) the composition after postprocessing.