A Novel Automatic Composition System Using Evolutionary Algorithm and Phrase Imitation

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***Abstract*—Music is a significant achievement of human activities and culture. Composing music is a complex and challenging task in that many factors, such as scale, key, chord, rhythm, and pitch, and their interactions need to be considered. With the advance of computer technology and artificial intelligence, automatic composition systems emerge and present some promising results. In particular, composing music through evolutionary algorithms has received increasing attention. Although evolutionary approaches are capable of generating compositions that follow music theory, these compositions are easily recognized as machine-made products due to their unpredictability in melodic progression, which is an important factor affecting a human's impression and feeling on a song. This paper aims for an automatic composition system that emulates human intelligence in music composition. Specifically, we propose the phrase imitation-based evolutionary composition (PIEC) to generate compositions by an evolutionary algorithm based on music theory and imitation of the characteristics and melodic progression of human-composed music. The PIEC conducts intraphrase and interphrase rearrangement to imitate the ascending/descending motion of phrases. Furthermore, we design four fitness functions for the PIEC to evolve compositions considering note distribution, interval variance, and music theory. The experimental results show that the proposed PIEC can effectively generate satisfactory compositions with the characteristics of the sample melody. The results also validate the effects of phrase imitation and the four fitness functions on evolutionary composition.**

***Index Terms*—Computational creativity, evolutionary algorithm, humanlike intelligence, music composition system, phrase imitation.**

I. Introduction

MUSIC is an important channel for humans to express feelings and emotions. Music theory is developed as a standard for music composition. The theory records and regulates the criteria for composing music. A complete music composition generally contains three components: music style, rhythm, and pitch sequence. Music style can be identified by the chord progression. Rhythm is characterized by the repeating beats in different phrases. Pitch sequence plays a key role and is usually viewed as the core of the composition. A piece of music can be separated into melody and accompaniment, where the melody conveys the major impression to the audience and the accompaniment is used to intensify harmony and music flavor.

Composing satisfactory music is very challenging and complex because all the aforementioned components and their interactions need to be considered. Some studies propose music systems using artificial intelligence technologies to analyze and create music. This manner has achieved considerable successes in automatic accompaniment. As for melody, despite some promising results, the enormous permutations of notes and beats still pose a big challenge to melody composition. Evolutionary algorithms have shown to be effective in various optimization problems [7], [8], [28], complex systems [23], [38], [41], and real-world applications [9], [16], [36]. Genetic algorithm (GA) is a well-known evolutionary algorithm and has succeeded in dealing with complex and large-scale problems [12], [15], [18], [29], [33], [35]. In view of this fruitfulness, GA is utilized in automatic composition and accompaniment system. In particular, the stochastic nature and search ability of GA are beneficial for automatic composition. The evolutionary composition approaches ordinarily utilize knowledge such as music theory, characteristics, and the experiences of performance or composition to imitate the human's composition. Horner and Goldberg [17] proposed a GA to compose melody between two predetermined music segments. Biles [2] developed the genetic jammer (GenJam), which uses GA to generate jazz solo segments. The fitness values of these segments are evaluated according to human feedback. Diaz-Jerez [11] proposed composing with Melomics, an automatic composition system using evolutionary approaches. The results have been successfully played or incorporated by professional musicians. Liu and Ting [21] presented a GA using fitness evaluation based on music theory to address the fatigue issue at human-assisted evaluation.

In evolutionary composition systems, the evolutionary algorithm can probably find a proper permutation of notes; however, the stochastic search may also lead to a weird melody if not guided by some music characteristics. This unexpectedness is like a double-edged sword: Beyond personal experience and preference in composition, the evolutionary algorithm can explore huge combinations and permutations of notes for a satisfactory melody. On the other hand, the melodies evolved without certain guidance and criteria usually lack regular repeated segments and composition character. Such kind of melodies has few memory points and thus is hard to remember. In general, the major challenge to evolutionary composition is how to compose music considering a huge variety of pitches, intervals, melodic directions, rhythms, and musical structures. The evolutionary algorithm can consider as many of these music characteristics to generate compositions as possible. Nonetheless, excessive considerations will probably mislead the search of the evolutionary algorithm, or some of the characteristics may be depressed in the resultant compositions. Therefore, an appropriate

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selection of characteristics and emulation of human composition is needed and beneficial for evolutionary composition.

This paper proposes the phrase imitation-based evolutionary composition (PIEC), which uses GA to generate a new melody with the characteristics of a sample melody composed by humans. More specifically, the PIEC creates melodies by imitating the arrangement of notes and rhythm in each phrase of the sample melody. The PIEC possesses three features. First, the PIEC performs intraphrase and interphrase rearrangement to make the phrase motion, i.e., ascending and descending, of new melodies consistent with that of the sample melody. Second, the PIEC reduces dissonant intervals by fixing inappropriate notes according to scale and chords. Third, we design four fitness functions for the PIEC based on the music characteristics of the sample melody. The four fitness functions involve the difference of note variance (NV), difference of interval variance (IV), rules of arrangement (RA), and hybrid evaluation. These fitness functions render guidance for the evolution of melodies as well as intensification on the imitation of the sample melody. The collaboration of these three features contributes to the balance of uniqueness of generated melodies and their similarity with the sample melody. By imitating phrases, the PIEC can attain compositions similar with the sample melody in phrase characteristics but dissimilar in notes within phrases.

The remainder of this paper is organized as follows. Section II reviews the related work. Section III sheds light on the proposed PIEC. The experimental results are presented and discussed in Section IV. Finally, Section V draws the conclusions of this paper.

II. Related Work

Evolutionary composition depends upon the great search power and stochastic nature of the evolutionary algorithm. It has become one of the main methods for automatic music composition. Evolutionary composition can be classified into three types: interactive, rule-based, and learning-based evolutionary composition. The following sections recapitulate the studies on these three types of evolutionary composition.

A. Interactive Evolutionary Composition

The evaluation of generated compositions has a vital effect on computer composition systems. Interactive evolutionary composition makes use of the listener's feedback for the fitness evaluation of the phrases or compositions generated by the evolutionary algorithm. Biles [2] used real-time human evaluation on the jazz solos created by the GenJam, a GA-based composition system using the chords, scales, and rhythms of the accompaniment. The fitness values of generated music segments are evaluated by the audience. However, after long-time listening, the audience lose their concentration and thus judge inaccurately due to fatigue. To solve this issue, Biles *et al.* [5] combined GenJam with a neural network, where the latter is used to learn human feedback. Biles further presented the details about the learning mechanism and the utilization of chords, measures, rhythms, and phrases for music composition in GenJam architecture [3], [4]. Johanson and Poli [20] and Tokui and Iba [37] both applied interactive genetic programming (GP) to compose music. The former used GP to evolve the pitches of notes, whereas the latter focused on the rhythm. Jacob [19] used an evolutionary algorithm to evolve the weights, phrase lengths, and transposition table for a new melody, given the motif and the chord progression. The evaluation requires the audience to evaluate only certain parts of music to reduce their loading.

Collaborating with musicians for professional feedback is another important direction in interactive evolutionary computation. Diaz-Jerez [11] adopted the compositions scored by professional composers in Melomics for automatic composition. Manaris *et al.* [24] designed an interactive music generator based on the Markov model, GA, and power laws. The system can interact with the human player's performance and respond with meaningful music.

Human feedback renders a direct evaluation of generated compositions. Nevertheless, the fatigue caused by repeatedly listening will gradually run out the human evaluator's patience and music sensitivity. It also limits the population size and the number of generations used for the evolutionary algorithm in composition.

B. Rule-Based Evolutionary Composition

The evolutionary algorithm in rule-based evolutionary composition uses explicit rules for the fitness function. The evaluation rules usually refer to music elements, such as rhythm, phrase, scale, or chord, from personal experience or music theory. Horner and Goldberg [17] proposed composing music by GA using static patterns. A complete composition is generated by iteratively creating a music segment that can bridge two music parts. McIntyre [27] used the four-part Baroque harmony to establish a stable progression. The notes are selected according to the given chords and distributed to the four music tracks. This design ensures the harmony and stability but limits the selection of nonharmonic notes. Tzimeas and Mangina [39] modified the input melodies to construct a new melody. Based on the patterns of jazz scale and rhythm, the input Baroque music is transformed to jazz music by GP. They further proposed the critically-damped-oscillator fitness function for flexibly adjusting the evolutionary direction according to the given genre and rhythm [40]. The various rhythms are formulated as multiple objectives, for which the weights are calculated by the similarity between candidate rhythms and the given rhythm. Ozcan and Ercal [31] provided a musical evolutionary assistant (AMUSE) to generate improvisations by using predetermined chords and rhythms. The AMUSE evaluates compositions using the information of intervals, pitch contour, and notes. Oliwa [30] designed a polyphony composition according to the features of jazz music, such as the tendency of scale, duration of notes, and coordination of musical instruments. Freitas and Guimaraes [13] used the nondominated sorting genetic algorithm-II to analyze melodies for the possible progression of harmony. Matić [26] utilized the input melodies as the basis for the evaluation of generated melodies. The fitness function is based on the mean and variance of intervals and the proportion of scale notes in a measure. Liu and Ting [21] proposed using the evaluation rules based on music theory in polyphony composition. The rules consider chord notes, leap, harmony, and rhythm.

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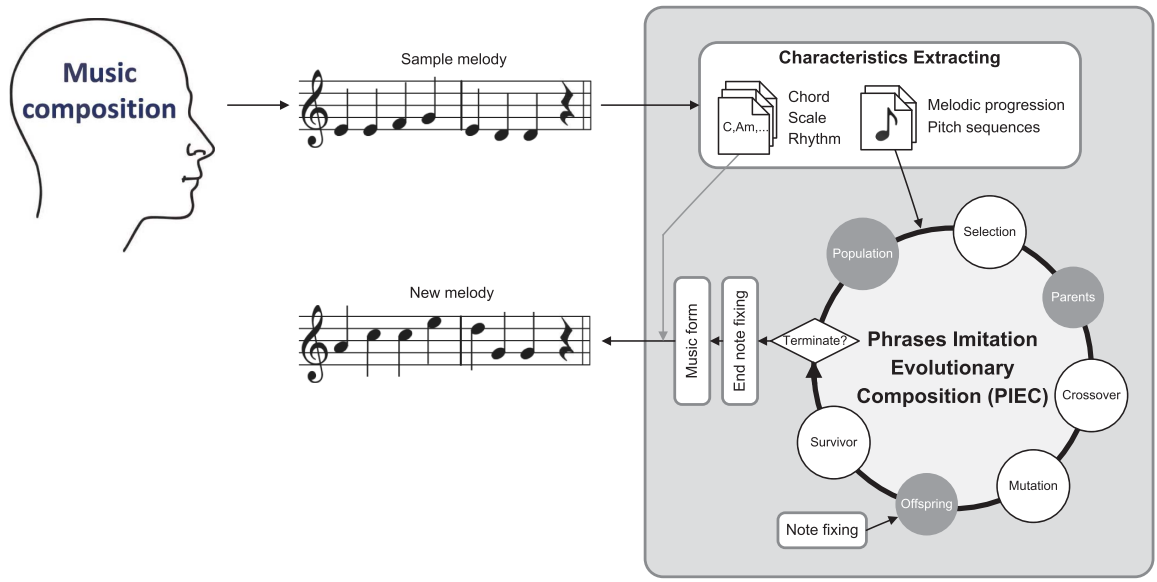

Fig. 1. Workflow of the proposed music composition system.

In general, rule-based evolutionary composition can efficiently generate compositions of a specific music genre. However, the resultant compositions are subject to the predetermined fixed rules in essence.

C. Learning-Based Evolutionary Composition

Learning-based evolutionary composition leverages music data to build the models for the evolutionary algorithm to compose music. Different from the interactive evolutionary composition, the learning-based evolutionary composition uses existing compositions or records instead of real-time human feedback. Gibson and Byrne [14] employed a neural network to establish the rhythm model and applied GA to find out all possible combinations of rhythms. Spector and Alpern [34] used Fahlman's quickprop algorithm and a neural network to find the characteristics of music. The results are then applied in the fitness evaluation of GP. Dannenberg *et al.* [10] proposed using Bayesian and linear classifiers to classify music data. The neural network is adopted to learn the music characteristics and applied to GA for generating music. Burton and Vladimirova [6] presented the adaptive resonance theory using a clustering algorithm to recognize the characteristics and classifications of compositions for the arrangement of percussion. Manaris *et al.* [25] used Zipf's law to examine the classifications of neural network among classical, popular, and unpopular music. The GP then uses the classification results to evolve new compositions. Ramirez *et al.* [32] utilized the information of records to build music models for pitches and rhythms. They used GA based on the models to create compositions. Acampora *et al.* [1] proposed the four-part harmony creation, which exploits the features of the four-part harmony as the basis of evaluating chord structure and harmony. They applied data mining to find several principles and used fuzzy control to determine the weights of these principles for evolutionary composition.

The learning-based evolutionary composition utilizes machine learning technologies to analyze, classify, or cluster music data. These results are commonly used for fitness evaluation in evolutionary composition. Although this method addresses the fatigue issue at the interactive evolutionary composition, the learning results may mislead the direction of the evolutionary search and bring about weird compositions.

The aforementioned studies reveal that melodic progression is less affected by some characteristics, e.g., arrangement of scale, repeats of rhythms, and progression of harmony. The information about melodic progression among phrases is useful for composition. The PIEC is designed to generate new compositions by imitating the melodic progression associated with note distribution and ascending/descending motions of the sample melody. More details of the proposed PIEC are given in the next section.

III. Proposed Composition System

The proposed music composition system aims to emulate human intelligence in music composition. As Fig. 1 shows, the system adopts human compositions as a basis to generate new melody. Given a sample melody, the proposed system analyzes and extracts its characteristics, including chord, scale, rhythm, melodic progression, and pitch sequences. These characteristics are used in the PIEC to generate new compositions. The proposed PIEC is a novel evolutionary composition approach that considers music theory and imitation of phrases at composition. Furthermore, this paper presents note fixing to adjust inappropriate notes during and after evolution. Music form is applied to improve the structure and euphony of compositions.

The PIEC follows the rhythm, chords, and scales of the sample melody and imitates its melodic progression among phrases for GA to compose new melodies. This paper develops the GA operators, melody imitation, note rearrangement, and evaluation of generated melodies for the PIEC. Algorithm 1 shows the evolutionary process of PIEC. The population initialization, parent selection, crossover, mutation, and survivor selection operators follow the paradigm of GA. After an offspring is generated, the PIEC additionally performs intraphrase and interphrase rearrangement on it to adjust notes for the imitation

Algorithm 1 PIEC

Initialize (P)
Evaluate (P)
repeat
  $C \leftarrow \emptyset$
  repeat
    $Parents \leftarrow$ Select(P)
    $c \leftarrow$ Crossover$(Parents)$
    $c \leftarrow$ Mutate(c)
    $c \leftarrow$ IntraPhraseRearrange(c)
    $c \leftarrow$ InterPhraseRearrange(c)
    $c \leftarrow$ DissonantToneFixing(c)
    Evaluate (c)
    $C \leftarrow C \cup \{c\}$
  until C is filled
  $P \leftarrow$ Survival(P, C)
until the terminal condition is satisfied
$P \leftarrow$ EndingNoteFixing(P)
$P \leftarrow$ MusicalForm(P)

TABLE I
REPRESENTATION OF PITCHES INTO INTEGERS

Helmholtz pitch notation	Integer
c	1
$c^\sharp, d^\flat$	2
d	3
$d^\sharp, e^\flat$	4
e	5
⋮	⋮
b	12
c^2 (one octave higher than c)	13
⋮	⋮
b^2 (one octave higher than b)	24
c^3 (two octaves higher than c)	25

of the sample melody. The note recognition and fixing mechanism fixes illegal notes. The resultant offspring is evaluated by one of the four proposed fitness functions. The evolutionary process continues until the termination criterion is satisfied. The following sections elucidate the designs for the composition system and PIEC.

A. Representation and Genetic Operators

The PIEC uses integer strings to represent chromosomes in the GA. The genes of a chromosome are encoded by integers ranging from 1 to 25 to represent the pitches. According to the twelve-tone equal temperament, an octave contains 12 pitches. Table I lists the integer for each pitch, where a pitch is expressed as a lowercase letter using the Helmholtz pitch notation. For instance, integer 1 represents pitch c, and 13 denotes pitch c^2. Fig. 2 illustrates a chromosome and its corresponding notes in two measures in Ionian mode on C.

The PIEC randomly generates the initial population of chromosomes. Afterward, it performs selection, crossover, mutation, and survival operations to enhance chromosomes in the course of evolution. This paper adopts the two-tournament selection operator, which repeats choosing the better of two randomly picked chromosomes twice for a pair of parents. The two-point crossover then cuts each parent into three segments and exchanges the second segment of two parents to produce their offspring. Next, the random resetting mutation changes some genes to random values probabilistically. The select–crossover–mutate process continues until the offspring population is filled. The PIEC adopts the $(\mu + \lambda)$ strategy for the survivor selection; that is, the survivors are selected from the union of parent and offspring populations for the next generation.

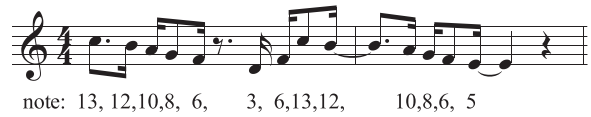

Fig. 2. Example of chromosome representation.

B. Melody Imitation

In this paper, we propose two approaches of rearranging notes to imitate the sample melody: intraphrase and interphrase rearrangement. In the rearrangement, the PIEC first analyzes the distribution of pitches and the occurrence order of phrases in the sample melody, given its scale and phrase information. The PIEC then uses the results to adjust the pitches of notes for imitating musical progression.

1) Intraphrase Rearrangement: The intraphrase rearrangement is designed to modify the note sequence within a phrase of compositions generated by GA. Restated, the order of pitches is rearranged to follow that of the sample melody. The intraphrase rearrangement consists of two steps: First, the notes in the phrase are sorted in ascending order of pitch values. For example, the sorted sequences of sample and new phrases in Fig. 3 are 1-2-3-4-5-5 and 1-5-5-8-10-15, respectively. Next, the notes of the new phrase are rearranged according to the order of pitches in the sample phrase; for example, pitch 8 of the new phrase is moved to the first position corresponding to the position of the fourth order in the sample phrase. Through intraphrase rearrangement, the resemblance in the progression of notes between sample and new phrases can be promoted.

2) Interphrase Rearrangement: The interphrase rearrangement focuses on the progression of phrases. Specifically, it shifts the pitches of all notes in the phrases of the new melody to mimic the progression of phrases in the sample melody. The mean of pitches in a phrase serves as a representative pitch for that phrase. Using integer representation, the mean can be calculated by

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

where x_i denotes the pitch value of the ith note and n denotes the number of pitches in the phrase.

The sequence of mean pitches is used to represent the progression of phrases. In the interphrase arrangement, the phrases are first sorted in ascending order of mean pitches. The pitch of each note in a phrase is then shifted according to the comparison

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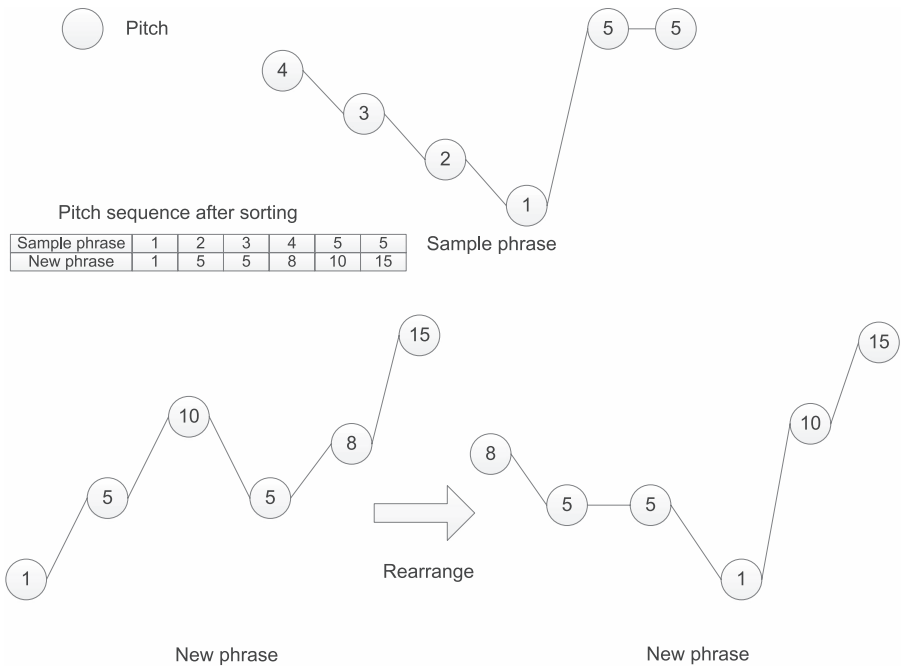
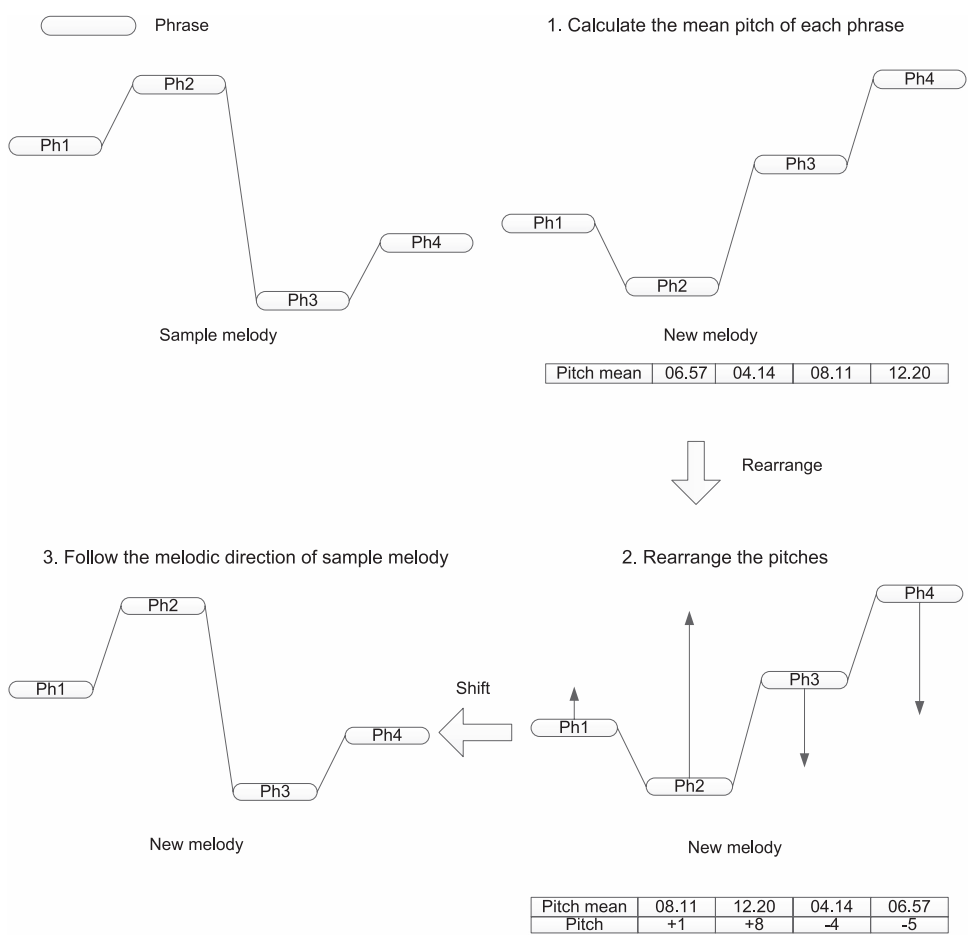


Sample phrase	1	2	3	4	5	5
New phrase	1	5	5	8	10	15

Fig. 3. Intraphrase rearrangement.



Pitch mean	06.57	04.14	08.11	12.20

Pitch mean	08.11	12.20	04.14	06.57
Pitch	+1	+8	-4	-5

Fig. 4. Interphrase rearrangement.

of new and sample melodies in the order of mean pitches of phrases. As Fig. 4 shows, the sorted phrase sequence of the sample melody is Ph3-Ph4-Ph1-Ph2, while that of the new music is Ph2-Ph1-Ph3-Ph4 with mean pitches 4.14-6.57-8.11-12.20. For imitation to the sample melody, the pitch of phrase P1 should be shifted to be the second highest, that of phrase P2

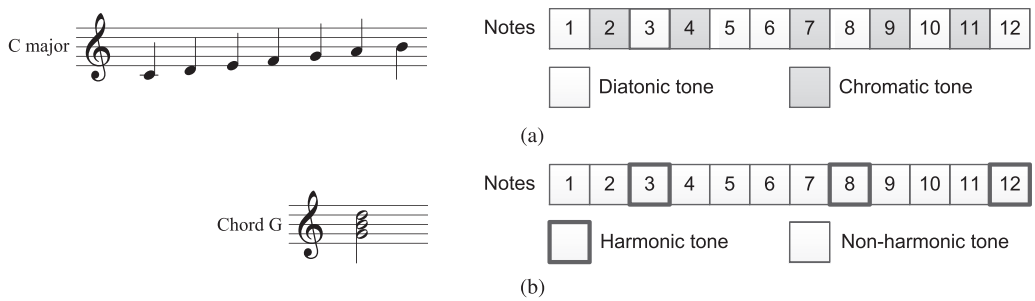


Fig. 5. Examples of diatonic and harmonic tones. (a) Diatonic tone. (b) Harmonic tone.

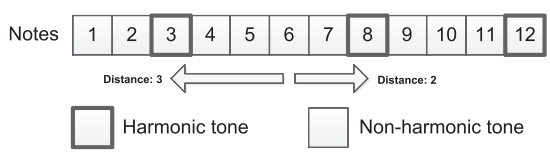


Fig. 6. Recognition of ending note.

should be shifted to be the highest, and so on. Therefore, the interphrase rearrangement increases the pitch of each note in Ph1 and Ph2 of the new melody by $\text{Round}(8.11 - 6.57) = 2$ and $\text{Round}(12.20 - 4.14) = 8$ semitones, respectively. Similarly, the pitch of each note in Ph3 and Ph4 is decreased by 4 and 6 semitones, respectively. The new melody can then have the same phrase sequence with the sample melody in terms of mean pitches.

C. Note Recognition and Fixing

The PIEC adopts two procedures to recognize and fix notes, including *dissonant* tones and inappropriate *ending* note. The dissonant tones are defined according to the chords and scales in the sample melody. For example, the notes in Fig. 5(a) are categorized into diatonic and chromatic tones according to the scale (C major): Diatonic tones are the members of the scale, whereas chromatic tones are not. In addition, the notes are classified into harmonic and nonharmonic tones given a chord: Harmonic tones are the chord notes, while nonharmonic tones are not. For the example of the G chord in Fig. 5(b), the chord notes d, g, and b are harmonic, and others are nonharmonic. A chromatic nonharmonic tone is defined as an illegal note. Illegal notes may be produced during initialization, crossover, and mutation operations. After mutation, the note recognition and fixing process checks the offspring and replaces its illegal notes with diatonic or harmonic tones at random to avoid the destruction of harmony.

Furthermore, the ending note must be a chord note. Fig. 6 illustrates the replacement of the ending note: If the note is not a chord note, it will be replaced by the nearest chord note. In case of equal distance to two nearest notes, it chooses the note according to the ascending/descending state of music progression. This process is performed on the chromosomes after GA evolution.

D. Fitness Function

The fitness function evaluates the performance of chromosomes and exerts a significant effect on the evolutionary search of GA. This paper devises four fitness functions based on different music characteristics. The first two fitness functions depend on the statistics of notes, the third is a rule-based evaluation, and the fourth hybridizes the first and third fitness functions for receiving their advantages. Note that chromosomes with low fitness values are preferred for these four fitness functions.

1) Difference of Note Variance (NV): This fitness function uses the statistics of pitches to describe the distribution of notes in a phrase. It evaluates chromosomes according to the difference between the generated melody and sample melody in the variance of pitches. Specifically, the variance of pitches in a phrase is computed by

$$\text{Var}_{\text{note}}(x) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2. \tag{2}$$

The fitness value is defined by

$$f_{\text{note}} = \sum_{i=1}^{N}\left|\text{Var}_{\text{note}}\left(Ph_i^{\text{new}}\right) - \text{Var}_{\text{note}}\left(Ph_i^{\text{sample}}\right)\right| \tag{3}$$

where N is the number of phrase and Ph_i^{new} and Ph_i^{sample} are the ith phrase of the new melody and sample melody, respectively. The fitness value reflects the difference of note distribution between new and sample melodies. This fitness function favors the melodies having similar variances with the sample melody.

2) Difference of Interval Variance (IV): This fitness function uses Matić's approach [26] to calculate the difference in variances of intervals between the generated and sample melodies. An interval y_i represents the distance of two adjacent notes, i.e., $y_i = x_{i+1} - x_i$. The mean and variance of intervals in a phrase Ph are given by

$$\bar{y} = \frac{1}{n-1}\sum_{i=1}^{n-1} y_i \tag{4}$$

$$\text{Var}_{\text{intvl}}(Ph) = \frac{1}{n-1}\sum_{i=1}^{n-1}(y_i - \bar{y})^2. \tag{5}$$

The fitness value based on the difference of interval variances is defined by

$$f_{\text{intvl}} = \sum_{i=1}^{N}\left|\text{Var}_{\text{intvl}}\left(Ph_i^{\text{new}}\right) - \text{Var}_{\text{intvl}}\left(Ph_i^{\text{sample}}\right)\right|. \tag{6}$$

Similar with the NV fitness, this fitness function prefers the generated melodies that have similar variances with the sample melody.

TABLE II
EVALUATION RULES OF ARRANGEMENT

No.	Rule
1	$(y_{i,j}^{\text{new}} = 0) \oplus (y_{i,j}^{\text{sample}} = 0)$
2	$(x_{i,j}^{\text{new}} \in H) \wedge (y_{i,j}^{\text{new}} > 9)$
3	$(x_{i,j}^{\text{new}} \in D_4) \wedge ((x_{i,j+1}^{\text{new}} \notin \{D_3, D_5\}) \vee (y_{i,j}^{\text{new}} > 2))$
4	$(x_{i,j}^{\text{new}} \in D_7) \wedge ((x_{i,j+1}^{\text{new}} \notin D_1) \vee (y_{i,j}^{\text{new}} > 1))$
5	$(x_{i,j}^{\text{new}} \in \{D_1, D_2, D_3, D_5, D_6\}) \wedge (y_{i,j}^{\text{new}} > 5)$

3) Rules of Arrangement (RA): This fitness function evaluates chromosomes according to music theory. Let $x_{i,j}$ denote the jth pitch in the ith phrase, $y_{i,j} = x_{i,j+1} - x_{i,j}$ denote the interval, and superscripts new and sample indicate the new melody and sample melody, respectively. Table II lists the five evaluation rules, where H denotes the set of harmonic tones and D_k denotes the set of kth diatonic tones. The first rule examines whether sample and new melodies both use repeated notes (i.e., $y_{i,j} = 0$) at the same time. If either $y_{i,j}^{\text{new}}$ or $y_{i,j}^{\text{sample}}$ is zero, it implies that the progression directions are different, and the evaluation value is thus added by one. The second to fifth rules examine the identity of notes and the distance of intervals. The second rule penalizes the excessively large interval $(|y_{i,j}^{\text{new}}| > 9)$ from a harmonic note $x_{i,j}^{\text{new}} \in H$, where the tolerance value 9 is determined by the largest interval of the six combinations of major triad and minor triad plus their inverted chords. The third rule is defined as follows: If note $x_{i,j}^{\text{new}}$ belongs to the set of fourth diatonic tone D_4, its subsequent note should be in D_3 or D_5 within interval $y_{i,j}^{\text{new}} \leq 2$ (major second) to ensure that the disharmony can be solved. Similarly, the fourth rule is associated with note $x_{i,j}^{\text{new}} \in D_7$ with interval $y_{i,j}^{\text{new}} \leq 1$ (minor second). The last rule regularizes that, if $x_{i,j}^{\text{new}}$ belongs to D_1, D_2, D_3, D_5, or D_6, it can be followed by any note within the perfect fourth, i.e., $y_{i,j}^{\text{new}} \leq 5$.

This fitness function examines all notes of the chromosome. Whenever a rule is matched, the evaluation value is increased by one. The final score acts as the fitness value of the chromosome. A higher fitness implies a more serious violation of music theory. Thus, chromosomes with low fitness are preferred.

4) Hybrid Evaluation: The hybrid approach is designed for gaining the advantages of NV and RA evaluation. The NV evaluation considers the note distribution in phrases, while the RA evaluation guides the search for good compositions through the evaluation rules based on music theory. The hybrid evaluation sums up the fitness values obtained from NV and RA fitness functions. Considering the fact that the ranges of NV and RA fitness values are different, we standardize the fitness values by

$$f'_{\text{note}} = \frac{f_{\text{note}} - \mu_{f_{\text{note}}}}{\sigma_{f_{\text{note}}}} \tag{7}$$

$$f'_{\text{rule}} = \frac{f_{\text{rule}} - \mu_{f_{\text{rule}}}}{\sigma_{f_{\text{rule}}}} \tag{8}$$

where μ_f and σ_f are the mean and standard deviation of fitness values of the population, respectively.

The hybrid fitness value is defined by

$$f_{\text{hybrid}} = f'_{\text{note}} + f'_{\text{rule}}. \tag{9}$$

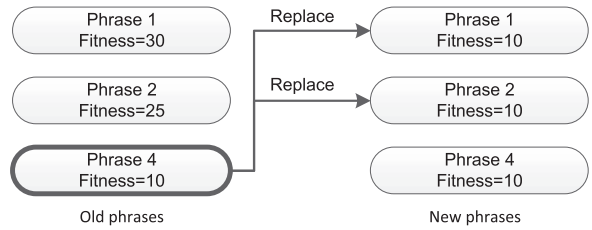


Fig. 7. Example of adjustment using musical form.

TABLE III
PARAMETER SETTING FOR THE PIEC

Parameter	Value
Representation	$c_i \in \{1, 2, ..., 25\}$
Initialization	Random
Parent selection	2-tournament
Crossover	2-point crossover
Crossover rate	$p_c = 0.9$
Mutation	Random resetting
Mutation rate	$p_m = 1/\text{chromosome\_length}$
Survival selection	$\mu + \lambda$
Population size	500
Generations	600

This evaluation is expected to acquire the advantages of fitness evaluation based on phrase characteristics and music theory.

E. Musical Form

The PIEC further utilizes the musical form of the sample melody to enhance the structure and euphony of generated compositions. In the light of musical form, some phrases will occur repeatedly in different positions of a composition. For following the musical form of the sample melody, the PIEC first identifies the phrases of the generated composition that are corresponding to the repeated phrases in the sample melody. These identified phrases are then adjusted by the manner of Liu and Ting [22] to establish the musical form: The best phrase replaces the other phrases. For example, in Fig. 7, phrase 4 holds the best fitness and is thus used to replace phrases 1 and 2 in the generated melody. In this way, the generated compositions can have the same musical form as the sample melody.

IV. EXPERIMENT RESULTS

This paper conducts a series of experiments to generate music and examine the performance of the proposed composition system. Table III lists the parameter setting for the PIEC in the experiments. The PIEC follows the rhythm, chords, and scales of the sample melody and uses GA to compose new music. In addition, the PIEC imitates the melodic progression of phrases in the sample melody through intra-/interphrase rearrangement and fitness function. In the experiments, we investigate the effects of the four proposed fitness functions, which involve the NV, IV, RA, and hybrid evaluation. The following presents and discusses the results from the PIEC adopting Christian Petzold's "Menuet in G major, BWV Anh 114" as the sample

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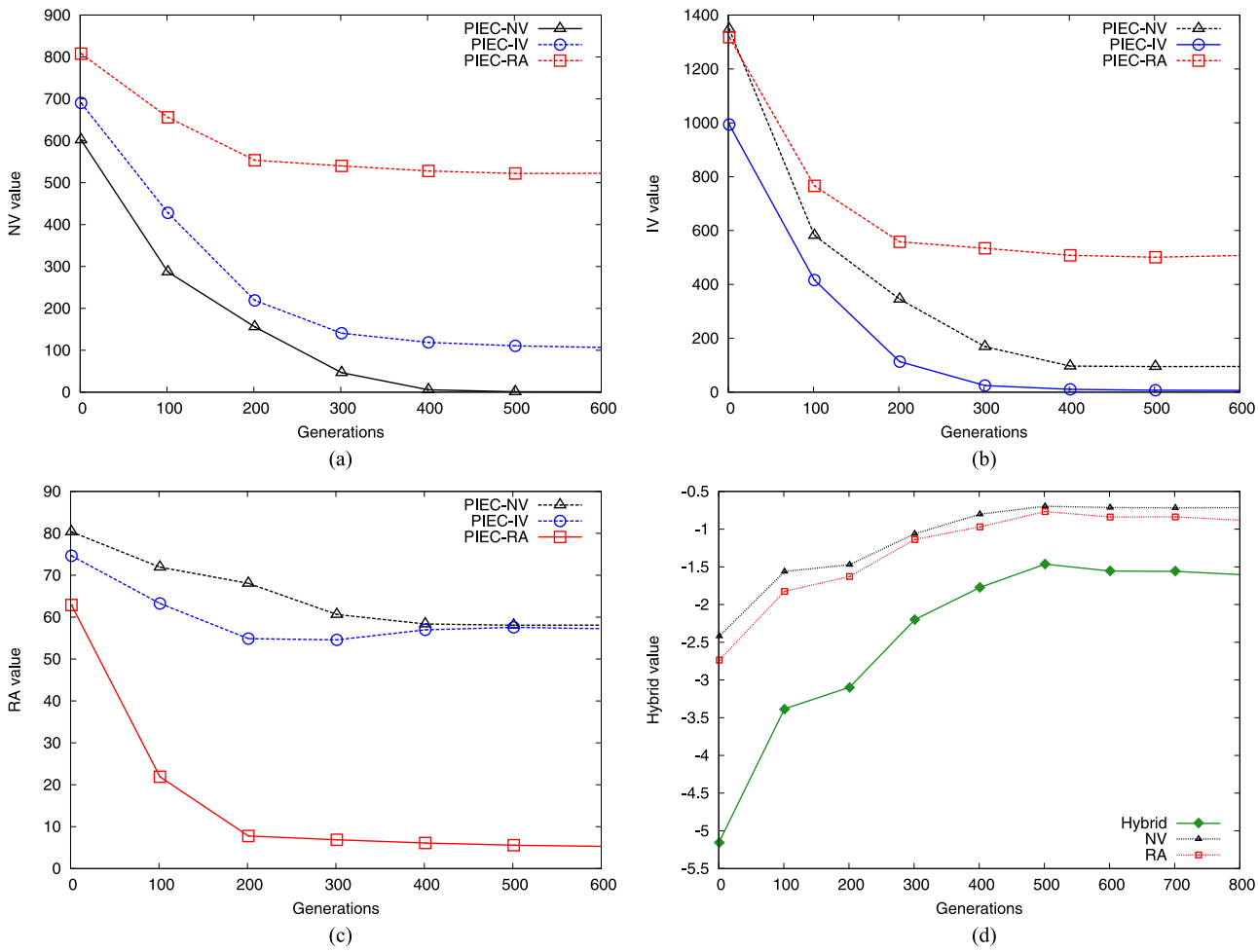

Fig. 8. Variation of NV, IV, RA, and hybrid evaluation values against generations for PIEC using different fitness functions. (a) NV value; (b) IV value; (c) RA value; (d) hybrid value.

melody. More experimental data and results can be downloaded via http://cilab.cs.ccu.edu.tw/PIEC_Compositions.zip.

Fig. 8 shows the progress of NV, IV, and RA evaluation values against generations over 30 runs of PIEC using NV, IV, and RA fitness functions. The experimental results show that NV, IV, and RA evaluation values decrease with evolution, particularly for the PIEC using the corresponding fitness function. This outcome reflects that the fitness functions can resolve the difference from the sample melody. Figs. 9 and 10 show the compositions obtained from PIEC-NV and PIEC-IV, respectively. The results indicate two features of PIEC-NV and PIEC-IV: First, NV involves the note distribution in a phrase, whereas IV depends on intervals used to describe the relationship between notes. Therefore, PIEC-NV focuses on reducing the difference in note distribution, while PIEC-IV aims to decrease the difference in intervals from the sample melody. In particular, PIEC-IV is suitable for evolving the phrases with continuous ascending or descending in that IV evaluation helps to maintain the intervals between notes. Second, the results in Fig. 8(a) and (b) indicate that PIEC-NV and PIEC-IV converge after 400 generations, where the decreases of NV and IV values both retard due to the fixation of notes and intervals in phrases. Regarding PIEC-RA, the results in Figs. 8 and 11 reflect that PIEC-RA prefers harmonic tones for the notes, which causes the widespread use of harmonic tones in phrases and thus increases the occurrence of repeated notes. Owing to the RA evaluation based on music theory, PIEC-RA seldom generates disharmonic melodies. The melodies generated by PIEC-RA, nonetheless, may sound strange and machine-made since the evaluation does not refer to the music characteristics of the sample melody, which is reflected in the large difference of variances in the NV and IV evaluation.

The aforementioned experimental results indicate the effects of evaluation methods on evolutionary composition: PIEC-NV and PIEC-IV consider imitating the distribution and relationship of notes in the phrases of the sample melody, respectively, but may result in disharmonic compositions. On the other hand, PIEC-RA takes music theory into account to generate harmonic melodies but omits the music characteristics of the sample melody. The PIEC-Hybrid is proposed to gain the advantages from NV and RA evaluation. According to the results in Fig. 8(d), PIEC-Hybrid can achieve compositions with low values of both NV and RA evaluation. In addition, the composition obtained from PIEC-Hybrid (cf. Fig. 12) excludes disharmonic notes and has a similar note distribution with the sample melody.

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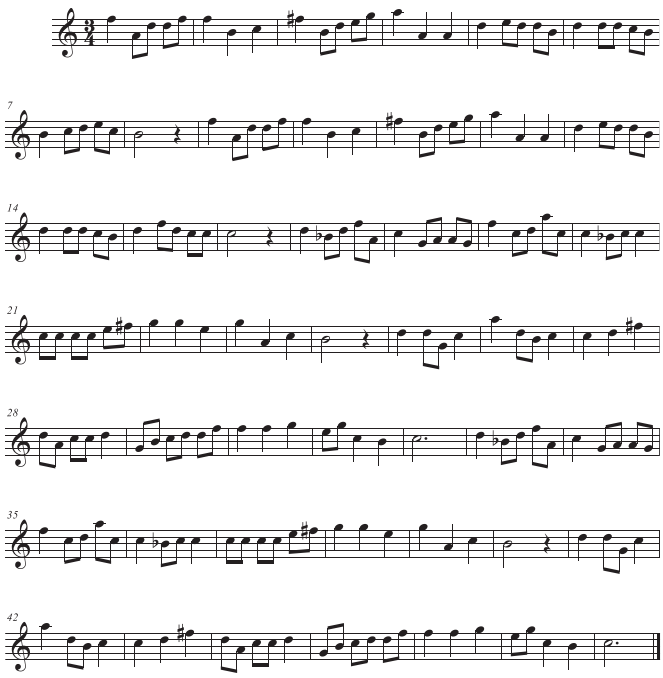

Fig. 9. Resultant composition of PIEC-NV.

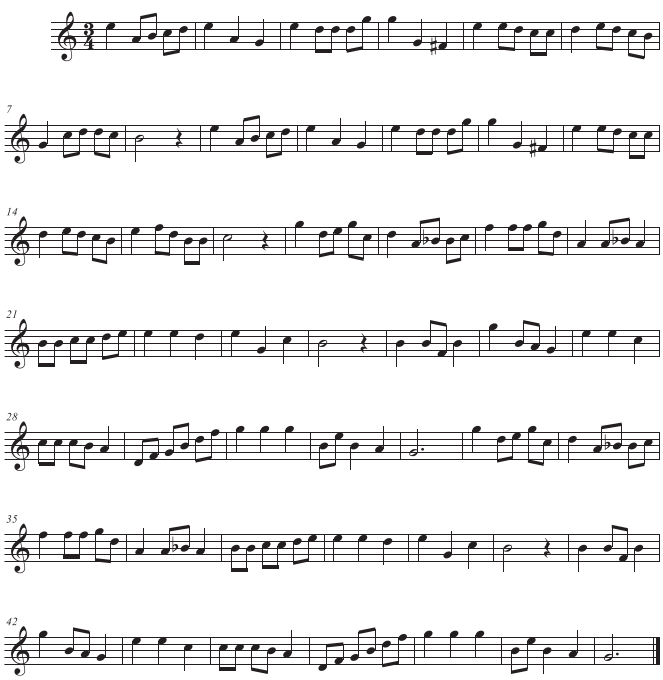

Fig. 10. Resultant composition of PIEC-IV.

This paper further investigates the influences of the four fitness functions on evolutionary composition. According to the design of NV and IV fitness functions, the sample melody has the best fitness; however, this best fitness can also be achieved by other compositions because the two fitness functions are devised to tolerate certain variation in note or interval. As for the RA and hybrid fitness functions, they both consider the fitness according to music theory. The sample melody may not gain the best fitness value due to some potential violation with music theory. By and large, the four fitness functions

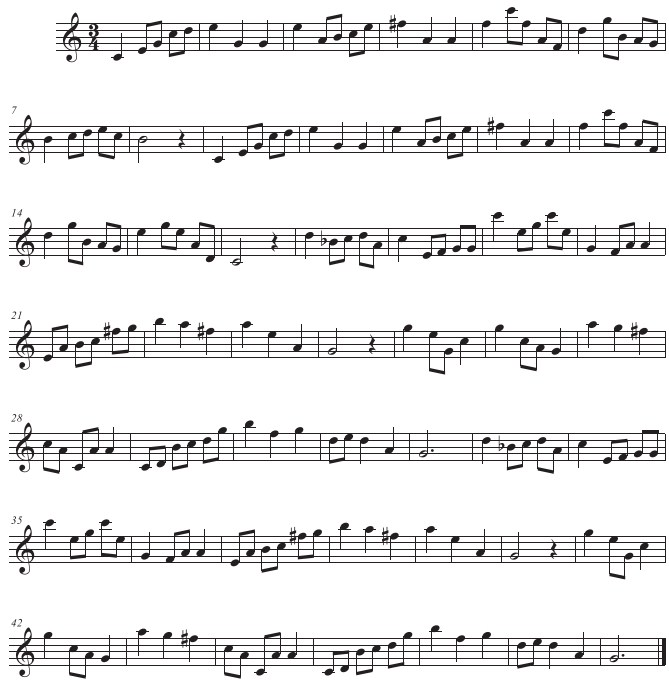

Fig. 11. Resultant composition of PIEC-RA.

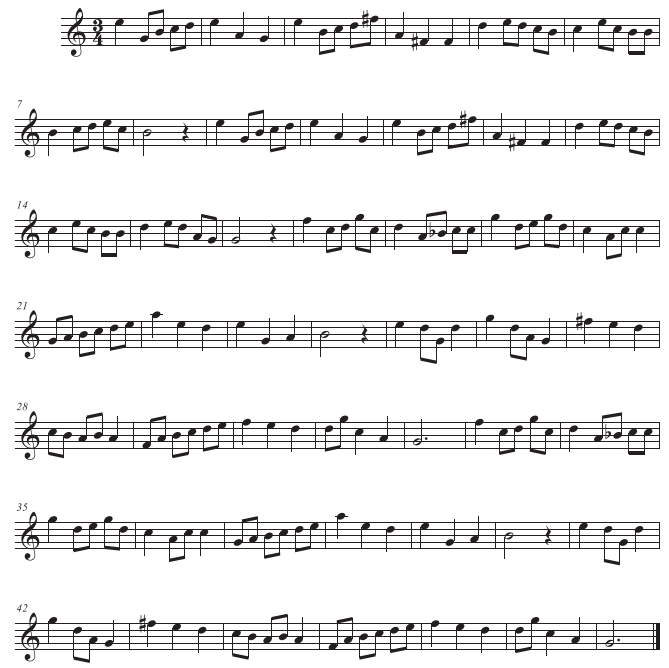

Fig. 12. Resultant composition of PIEC-hybrid.

TABLE IV
COMPARISON OF THE COMPOSITIONS GENERATED BY PIEC USING DIFFERENT FITNESS FUNCTIONS

	PIEC-NV	PIEC-IV	PIEC-RA	PIEC-Hyb
Motion similarity	75%	76%	**99%**	**99%**
Variance of notes	**0.32**	94.45	498.25	12.25
Variance of intervals	96.39	**3.49**	452.97	69.73

facilitate imitating the sample melody by generating compositions similar yet different in various facets. Table IV compares the motion (ascending/descending) similarity of adjacent notes, variance of notes, and variance of intervals between the sample

TABLE V
COUNTS OF TICKING "SIMILAR" AGAINST DISSIMILAR FOR EACH COMPARISON PAIR OF MELODIES

Music	Smp:NV	Smp:IV	Smp:RA	Smp:Hyb	NV:IV	NV:RA	NV:Hyb	IV:RA	IV:Hyb	RA:Hyb
1	33	30	31	31	33	25	31	27	30	25
2	33	29	27	31	30	27	33	27	31	27
3	32	31	29	33	29	28	29	27	31	27
4	33	30	30	32	32	27	33	29	32	26
5	32	30	27	33	30	27	31	27	30	27
6	32	32	28	30	33	26	32	26	30	26
7	33	30	27	32	30	25	33	27	31	29
8	32	31	29	32	31	26	32	26	30	26
9	32	33	27	33	32	28	30	27	29	29

TABLE VI
p-VALUES OF ONE-TAILED SIGN TEST ON SIMILARITY BETWEEN TWO MELODIES

Music	Smp:NV	Smp:IV	Smp:RA	Smp:Hyb	NV:IV	NV:RA	NV:Hyb	IV:RA	IV:Hyb	RA:Hyb
1	1.05E-09	1.73E-06	2.09E-07	2.09E-07	1.05E-09	2.99E-03	2.09E-07	2.54E-04	1.73E-06	2.99E-03
2	1.05E-09	1.12E-05	2.54E-04	2.09E-07	1.73E-06	2.54E-04	1.05E-09	2.54E-04	2.09E-07	2.54E-04
3	1.84E-08	2.09E-07	1.12E-05	1.05E-09	1.12E-05	5.84E-05	1.12E-05	2.54E-04	2.09E-07	2.54E-04
4	1.05E-09	1.73E-06	1.73E-06	1.84E-08	1.84E-08	2.54E-04	1.05E-09	1.12E-05	1.84E-08	9.39E-04
5	1.84E-08	1.73E-06	2.54E-04	1.05E-09	1.73E-06	2.54E-04	2.09E-07	2.54E-04	1.73E-06	2.54E-04
6	1.84E-08	1.84E-08	5.84E-05	1.73E-06	1.05E-09	9.39E-04	1.84E-08	9.39E-04	1.73E-06	9.39E-04
7	1.05E-09	1.73E-06	2.54E-04	1.84E-08	1.73E-06	2.99E-03	1.05E-09	2.54E-04	2.09E-07	1.12E-05
8	1.84E-08	2.09E-07	1.12E-05	1.84E-08	2.09E-07	9.39E-04	1.84E-08	9.39E-04	1.73E-06	9.39E-04
9	1.84E-08	1.05E-09	2.54E-04	1.05E-09	1.84E-08	5.84E-05	1.73E-06	2.54E-04	1.12E-05	1.12E-05

TABLE VII
PREFERENCE COUNTS IN THE PAIRWISE COMPARISONS AMONG THE SAMPLE MELODY AND FOUR PIEC COMPOSITIONS

Music	Smp:NV	Smp:IV	Smp:RA	Smp:Hyb	NV:IV	NV:RA	NV:Hyb	IV:RA	IV:Hyb	RA:Hyb
1	16:19	18:17	20:15	15:20	19:16	19:16	17:18	22:13	16:19	15:20
2	18:17	17:18	22:13	19:16	23:12	24:11	19:16	16:19	15:20	16:19
3	15:20	20:15	22:13	16:19	21:14	20:15	15:20	17:18	17:18	18:17
4	17:18	20:15	20:15	17:18	20:15	21:14	18:17	19:16	16:19	15:20
5	18:17	17:18	21:14	18:17	18:17	20:15	15:20	17:18	15:20	13:22
6	17:18	17:18	20:15	16:19	18:17	17:18	16:19	20:15	17:18	17:18
7	19:16	17:18	18:17	17:18	19:16	24:11	15:20	16:19	18:17	16:19
8	17:18	18:17	19:16	16:19	19:16	20:15	17:18	16:19	16:19	16:19
9	19:16	17:18	19:16	15:20	18:17	19:16	15:20	17:18	17:18	15:20

melody and the compositions generated by PIEC using the four fitness functions. According to the results, PIEC-NV and PIEC-IV have the most similar distributions of notes and intervals with the sample melody, respectively. The PIEC-RA gains higher motion similarity than PIEC-NV and PIEC-IV in that the intra-/interphrase rearrangement tangles with the NV and IV evaluation. However, PIEC-RA performs poorly in the imitation of note and interval distributions. By contrast, PIEC-Hybrid achieves as high motion similarity as PIEC-NV does and attains comparably low variances of notes and intervals as PIEC-NV and PIEC-IV. This outcome validates that PIEC-Hybrid gains the advantages of PIEC-NV and PIEC-RA.

To evaluate the composition results, we conducted a survey on the similarity and preference among the sample melody and the generated melodies. The survey includes nine sets, each consisting of one sample melody (Smp) and four melodies generated by PIEC using NV, IV, RA, and hybrid fitness functions. For each set, the participants listen to two melodies randomly selected from the five melodies and answer two questions: 1) whether they are similar and 2) which one is preferred. Each pair of comparison includes 35 questionnaire results. First, Table V shows that most listeners believe the two melodies are similar (≥ 25 out of 35 counts). We further carried out a one-tailed sign test on the counts. With confidence level $\alpha = 0.05$, the p-values on Table VI validate that the PIEC can generate compositions similar with the sample melodies. Second, we investigate the preference among the five melodies. Tables VII and VIII present the counts of preference in the pairwise comparisons and their corresponding z-scores, respectively. To explore the rank of the five approaches (i.e., sample, NV, IV, RA, and hybrid), we consider the sums of z-scores for one approach against the other approaches. According to Fig. 13, the melodies generated by PIEC-Hybrid are more preferred than the sample melodies for eight out of nine music, whereas the melodies generated by PIEC-IV and PIEC-RA are mostly inferior to the sample melodies. In general, the survey results show that the PIEC can imitate the sample melody and generate similar compositions; in addition, PIEC using the hybrid fitness function can achieve melodies preferable to the sample melody.

TABLE VIII
z-SCORES ON THE RESULTS OF PAIRWISE COMPARISONS AMONG THE SAMPLE MELODY AND FOUR PIEC COMPOSITIONS

Music	Smp:NV	Smp:IV	Smp:RA	Smp:Hyb	NV:IV	NV:RA	NV:Hyb	IV:RA	IV:Hyb	RA:Hyb
1	-0.107634	0.035817	0.180012	-0.180012	0.107634	0.107634	-0.035817	0.328072	-0.107634	-0.180012
2	0.035817	-0.035817	0.328072	0.107634	0.404678	0.483739	0.107634	-0.107634	-0.180012	-0.107634
3	-0.180012	0.180012	0.328072	-0.107634	0.253347	0.180012	-0.180012	-0.035817	-0.035817	0.035817
4	-0.035817	0.180012	0.180012	-0.035817	0.180012	0.253347	0.035817	0.107634	-0.107634	-0.180012
5	0.035817	-0.035817	0.253347	0.035817	0.035817	0.180012	-0.180012	-0.035817	-0.180012	-0.328072
6	-0.035817	-0.035817	0.180012	-0.107634	0.035817	-0.035817	-0.107634	0.180012	-0.035817	-0.035817
7	0.107634	-0.035817	0.035817	-0.035817	0.107634	0.483739	-0.180012	-0.107634	0.035817	-0.107634
8	-0.035817	0.035817	0.107634	-0.107634	0.107634	0.180012	-0.035817	-0.107634	-0.107634	-0.107634
9	0.107634	-0.035817	0.107634	-0.180012	0.035817	0.107634	-0.180012	-0.035817	-0.035817	-0.180012

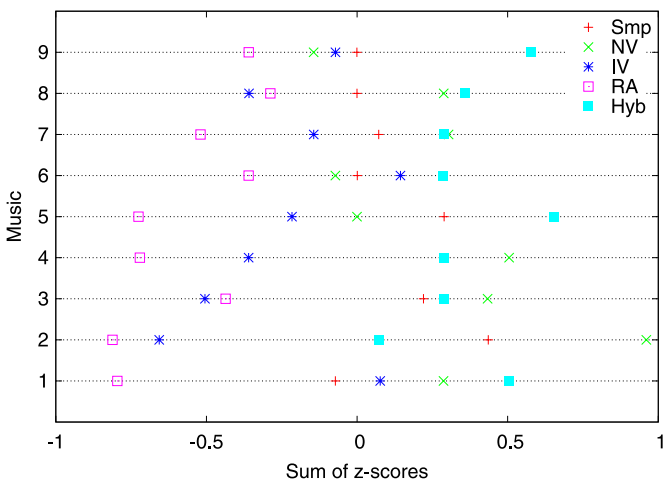

Fig. 13. Comparison of sums of z-scores with respect to the sample melody (Smp) and PIEC using NV, IV, RA, and hybrid fitness functions.

V. CONCLUSION

This paper has proposed a novel automatic composition system to compose music using evolutionary algorithm and phrase imitation considering human intelligence in music composition. The proposed PIEC follows the rhythm, chords, and scales of a sample melody and generates melodies by GA and imitation of the melodic progression of phrases in the sample melody. Specifically, the imitation focuses on three music characteristics: motion of phrases, note distribution, and interval distribution. The intraphrase and interphrase rearrangement methods are devised to mimic the ascending/descending motion within and between phrases, respectively. Furthermore, we design four fitness functions for the PIEC to evolve compositions considering different music characteristics. The NV fitness function evaluates compositions according to the similarity with the sample melody in note distribution. Likewise, the IV fitness function considers the variance of intervals in phrases. The RA fitness function evaluates compositions according to five evaluation rules based on music theory. Finally, the hybrid method combines NV and RA fitness functions to gain their advantages.

Several experiments are carried out to examine the performance of PIEC and its generated compositions. The experimental results show that the PIEC can compose satisfactory compositions through evolution and imitation of the melodic progression of phrases. This paper further investigates the effects of the four fitness functions. PIEC-NV and PIEC-IV can generate compositions with similar distributions of notes and intervals to the sample melody, respectively. PIEC-RA can effectively exclude disharmonic notes and achieve proper compositions in terms of music theory. PIEC-Hybrid possesses the advantage of PIEC-NV in imitating note distribution in phrases and that of PIEC-RA in generating harmonic melody. The survey results show that PIEC can imitate and compose melodies similar with the sample melody; in addition, PIEC-Hybrid ordinarily achieves melodies preferable to the sample melody. These outcomes validate the effectiveness of the proposed PIEC in music composition.

Future work includes some directions. First, PIEC follows the rhythm of the sample composition. In addition to melody, the evolution of rhythms is a challenging yet promising direction for evolutionary composition. Second, the technology of extracting chords and scales from the sample melody can increase the automatic level of PIEC's imitation. Third, PIEC aims to imitate the sample melody for generating compositions that are close to human-made character. The imitation, nevertheless, may result in compositions too similar to the sample music. The way to maintain the music characteristics without strong resemblance is an important topic for future work. Moreover, music style can be considered in the melody imitation operators and evaluation methods such as RA to enhance composition.

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