Computational Intelligence in Music Composition: A Survey

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***Abstract*—Composing music is an inspired yet challenging task, in that the process involves many considerations such as assigning pitches, determining rhythm, and arranging accompaniment. Algorithmic composition aims to develop algorithms for music composition. Recently, algorithmic composition using artificial intelligence technologies received considerable attention. In particular, computational intelligence is widely used and achieves promising results in the creation of music. This paper attempts to provide a survey on the computational intelligence techniques used in music composition. First, the existing approaches are reviewed in light of the major musical elements considered in composition, to wit, musical form, melody, and accompaniment. Second, the review highlights the components of evolutionary algorithms and neural networks designed for music composition.**

***Index Terms*—Computational intelligence, evolutionary computation, music composition, neural networks.**

I. Introduction

MUSIC plays an essential role in our daily life. It serves as a significant medium to entertain people, deliver messages, improve productivity, and express moods and emotions. Composing melodious music is a challenging task since many musical elements need to be considered, such as pitch, rhythm, chord, timbre, musical form, and accompaniment [99], [125]. In the past, music composition was usually accomplished by a few talented people. The algorithmic composition, which formulates the creation of music as a formal problem, facilitates the development of algorithms for music composition. The concept of algorithmic composition can be traced back to the *Musikalisches Würfelspiel* (musical dice game), which is often attributed to Mozart. In the game, a music piece is generated by assembling some music fragments that are randomly selected. Mozart's manuscript K.516f, written in 1787, is commonly viewed as an example piece of the musical dice game because it contains many two-bar fragments, even though the random selection by dice is not evidenced.

The algorithmic composition enables automatic composition by using computers and mathematics. In 1957, Hiller and Isaacson [60] first programmed the Illinois automatic computer (ILLIAC) to generate music algorithmically. The music piece was composed by the computer and then transformed into a score for a string quartet to perform. Xenakis [150] in 1963 created a program as an assistant to produce data for his stochastic composition. The research on algorithmic composition has significantly grown since then. Some overviews on automatic composition can be found in [9], [10], [45], [68], [107]. Moreover, there have been an abundant amount of software and applications for computer composition and computer-aided composition, such as Iamus [1], GarageBand [2], Chordbot [3], and TonePad [4]. Notably, the Iamus system [1] is capable of creating professional music pieces, some of which were even played by human musicians (e.g., the London Symphony Orchestra). GarageBand [2] is a well-known computer-aided composition software provided by Apple. It supports numerous music fragments and synthetic instrument samples for the user to easily compose music by combining them.

The methodology of algorithmic composition includes mathematics, grammar, and artificial intelligence. First, from a mathematical perspective, composing music can be viewed as a stochastic process and, therefore, the mathematical models such as Markov chains are useful for composition [34]. The music composition using mathematical models have the advantages of low complexity and fast response, which are adequate for real-time application. Sertan and Chordia [126] utilized the variable-length Markov model that considers the pitch, rhythm, instrument, and key, to predict the subsequent sequence of Turkish folk music. Prechtl *et al.* [116] generated music for games by using the Markov chains with musical features such as tempo, velocity, volume, and chords. Voss and Clark [146] observed and proposed the $1/f$ noise for composition. Hsü and Hsü [64], [65] adopted fractal geometry in the expression of music and presented the self-similarity for the musical form.

Second, music can also be regarded as a language with distinctive grammar [120]. Composing music turns out to be a process of constructing sentences using the musical grammar, which is usually comprised of the rules about rhythm and harmony. Howe [63] codified the musical elements in the multidimensional arrays and used the computer to compose music by determining the locations of pitches and rhythms through five operators. Steedman [128] and Salas *et al.* [122], [123] adopted linguistics and grammar to generate music. The proposed approaches describe music as a language, and then learn its patterns from music pieces, to build the model for composing a new melody.

Third, the advances of artificial intelligence (AI) promote its application to algorithmic composition. The composition

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systems based on AI technologies such as cellular automata [22], [100], knowledge-based systems [11], [42], machine learning [41], and evolutionary computation [101], [148], have received several encouraging results [47], [112]. In addition to composition, the AI technologies are applied to expressive performance of music [33], [78]. Recently, the use of computational intelligence (CI) in music composition has emerged. The CI techniques, including neural networks, fuzzy systems, and evolutionary computation, have achieved remarkable results and render powerful tools for modeling, learning, uncertainty handling, search, and optimization. These techniques have been applied to music composition. In particular, the evolutionary composition system progresses by making widespread use of genetic algorithm (GA) [59], [61], genetic programming (GP) [79], particle swarm optimization (PSO) [74], [75], ant colony optimization (ACO) [38], [39], and other evolutionary algorithms [121]. The population-based, quality-driven, and stochastic nature of evolutionary algorithms makes them especially suitable for music composition and computational creativity. Neural networks are often utilized in the learning and modeling processes for music composition. Bharucha and Todd [13] proposed a model using neural networks for the prediction of notes. This work is followed by plenty of studies on the use of neural networks to compose music. In addition, neural networks are applied to assist the evaluation of compositions [18], [58]. Fuzzy systems cater to the classification and analysis of music; nonetheless, they are seldom used for music composition.

This paper provides a survey on the CI techniques used in music composition to reflect the recent advances in this area. The survey is organized from two perspectives: musical elements and CI technology. First, in the light of musical elements, the task of music composition entails deliberating the musical form, creating the melody, and arranging the accompaniment. The musical form is associated with the fundamental structure, phrases, motives, and music genre. In composing a melody, the musical elements such as timbre, pitch, rhythm, harmony, and tune need to be properly assigned. The emotion is an advanced consideration in generating compositions. As for the accompaniment, the musicians arrange the main accompaniment, chords, and bass, to enhance the harmony and euphony of the composition. Second, the different aspects of the CI techniques need to be pondered upon for music composition. In the evolutionary composition systems, various designs for the representation, crossover, and mutation are proposed. The music systems using neural networks are developed to generate compositions and assist evolutionary composition. In addition, the evaluation of compositions is a paramount issue that needs to be addressed in the CI-based composition systems.

The paper is organized as follows. Section II reviews the studies on music composition using musical form, including motive, phrases, and genre. Section III reviews the approaches based on CI for composing the melody in terms of timbre, pitch, rhythm, and emotion. Section IV recapitulates the CI methods for the accompaniment arrangements. Section V surveys the designs of the CI techniques for music composition. Section VI provides some suggestions for future research topics. Finally, a summary of this paper is presented in Section VII.

II. Composition Using Musical Form

Music composition involves many musical elements, such as timbre, pitch, rhythm, motive, phrase, and chord. Figure 1 summarizes the musical elements in composition, which can be divided into three major categories: musical form, melody, and accompaniment. Musicians usually deliberate over the musical form as the basic structure and then fill in pitches to construct the melody. Afterward, the accompaniment is assigned to strengthen the harmony or complement the composition.

This section reviews the research on the utilization of musical form in CI-based composition systems. Moreover, we discuss the music genre as an advanced consideration for composing music.

A. *Musical Form*

Musical form serves as the fundamental structure of a composition. While composing music in a specific genre, composers consider the musical form to establish its framework and then develop motives and phrases. For example, the form AABA is ordinarily applied in sonatas, and ABAB and ABCA are commonly used in modern popular music. The musical form constitutes the main frame of a composition, where the notes will be filled in to construct the melody afterward.

In the composition system, Xu *et al.* [151] adopted four conventional forms of popular music, i.e., ABAB, ABAA, AAAA, and ABBB (or ABCA). The first two motives are repeated in these forms for intensification. Liu and Ting [86] considered the musical forms used by a famous Asian pop-music singer. Although musical form is a fundamental component in music composition, there exist few studies addressing this issue in the CI-based composition approaches. Design and development of musical form is hence a direction for future studies.

B. *Motive*

Motive represents the minimum component repeating in some phrases. The form of repeats can be classified into two types: sequence imitation and repetition imitation. The former indicates that the repeated motives are similar but different, whereas the latter requires they are identical. Both types of imitation are beneficial to cultivate the hook for the music and make phrases or compositions memorable.

1) Sequence Imitation: Ricanek *et al.* [119] considered the thematic bridging issue at music composition. They designed a fitness function favoring the similarity between phrases for sequence imitation. In the composition system of Papadopoulos and Wiggins [111], the users can specify their preferred motives. The fitness function for the GA will count the interval patterns matched. Towsey *et al.* [136] also took the features of patterns into account. The sequence imitation and repetition imitation are achieved by copying three or four notes from repeated rhythm patterns and repeated pitch patterns, respectively. Calv and Seitzer [24] used GA to generate the melodic motives and adopted the genetic algorithm traversal tree (GATT) to construct the musical structure. The fitness function especially rewards the intervals matching the Fibonacci sequence.

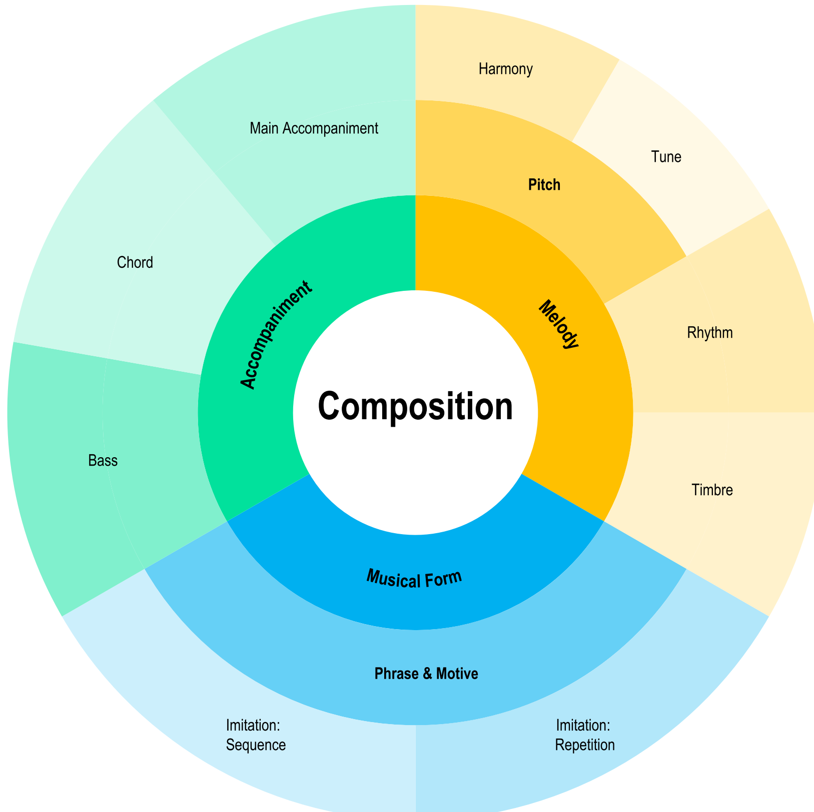

Fig. 1. Musical elements in composition.

Long *et al.* [89] claimed that the melody and rhythm in different phrases should be similar for the coherent effect. When generating a new phrase, the system checks if the previous melody can be partially adopted. Loughran *et al.* [90] used grammatical evolution (GE) to generate the sequences for a long melody. The composition was created by merging the top four individuals obtained from the final generation. The best individual will share its motifs with others, which will be slightly varied in regards to rhythm and pitch.

2) Repetition Imitation: The system proposed by Chiu and Shan [28] repeats the motives resting upon the analysis on the structure of input music. It divides the phrases into several segments to form the motives. Liu and Ting [84], [85] and Wu *et al.* [149] observed and applied three types of repetitions commonly used in the creation of music. According to the type of repetition, the measures involving the repetition are compared and the best one will replace others to form the repetition. Liu and Ting [86] adopted both the repetition imitation and sequence imitation to mimic the composition of a famous Asia pop-music singer. The better motif in the generated music will replace other motifs originating from the musical form in the original song.

C. Genre

Music genre is an important consideration for composition. A genre is formed by a composition style in a specific region, culture, instrument, or group. Composing music for a certain genre involves three elements: rhythm, scale, and structure. Most genres have unique rhythm patterns or scales. For example, Chinese music uses the pentatonic scale composed of only five pitches. In addition, music genres usually have special structures.

Jazz is a music genre popularly studied in the CI and non-CI based composition systems because of its salient features in scale and rhythm. For composing jazz music, Papadopoulos and Wiggins [111] proposed a GA with a representation and a fitness function based on the jazz scales. Biles [16], [17] developed the GenJam system supporting the trade four in jazz impromptu. The GenJam is capable of improvisation through interaction with the jazz player. Tzimeas and Mangina [138] presented a GA-based system to transform the compositions of Bach into jazz music. The user, who must be familiar with jazz music, listens to an input song of Bach and identifies the notes with a jazz flavor during the evolutionary process of GA.

Aside from jazz, other music genres are also considered in the composition systems using CI. The GA composer of McIntyre [98] focuses on the four-part Baroque harmony, consisting of soprano, alto, tenor, and bass. In light of the Baroque genre, the fitness function includes the rules specially designed for chord spelling, doubling, voice leading, smoothness, and resolution. Dimitrios and Eleni [36] proposed the SENEgaL to create Western Africa rhythm music. In the system, they introduced different styles of Western Africa rhythm: Gahu, Linjen, Nokobe, Kaki Lambe, and Fanga. Each type has different rhythmic patterns that are played on two or more instruments. The user can specify the proportion of Western Africa patterns considered while composing music. Wang *et al.* [147] extracted the features, including the repeat rhythm patterns and special intervallic motives, from Chinese Jiangnan ditties. They found that the Jiangnan ditties have many three-note and four-note intervallic motives; precisely, more than 80% are three-note intervallic motives. Hence the fitness function rewards the intervallic motives to form the specialty of Chinese Jiangnan ditties.

Some studies have focused on the composition style of a specific musician or a music group. Liu and Ting [85] determined the weights for the rule-based fitness function by using the music and charts information of the famous rock band Guns N' Roses. They [86] further utilized the sequential pattern mining technique for the patterns of Jay Chou's composition style. The patterns obtained are used as the genes for the GA to create new compositions.

III. Composition of Melody

This section introduces the musical elements and the studies of using CI-based techniques in the composition of melody.

A. Timbre

Timbre represents the tone color of sound. When composing music, timbre should be considered and properly arranged because each instrument or vocal type (soprano, contralto, tenor, baritone, and bass) has its sound characteristics. The instruments and vocals, for example, have their characters and need to be organized for the ensemble. Timbre can be classified into two types: instrument and vocal. For instrumental music, many instruments have their own unique tones, which should be considered when composing music for them. In addition, playing techniques, e.g., the bowing techniques for violin, influence the timbre of instruments and hence may be taken into account in composition. As for vocal music, the compositions are subject to the timbre of each part, i.e., soprano, alto, tenor, and bass, of the singers.

Timbre can be applied to the evaluation criterion for the assignment of instruments. Wang *et al.* [147] extracted the features from Chinese Jiangnan ditties for the fitness function, in which the timbre serves as an evaluation criterion using the spectral centroid to fit the instruments. Dimitrios and Eleni [36] proposed the SENEgaL system generating the Western Africa rhythm music. In the interactive interface, the user can choose different timbres of drum to play the music. Considering the elements and playing techniques of drums, Dostál [40] designed a chromosome representation for GA to generate drum rhythms in the human-like rhythmic accompaniment system.

B. Pitch

Assigning the pitch for each note is a paramount task in music composition. The assignment pertains to range, tune, and harmony of pitches. Tune is associated with the sequence of pitches, whereas harmony concerns the concurrence of multiple pitches.

1) Range: In the assignment of pitches, the composers must include the range of instruments or vocals for consideration. The violin, for instance, has a limit of four and a half octaves in playable notes, although the range is determined by the player's skills. A composition system therefore needs to consider whether the generated tunes or chords are playable or not; otherwise, the composition will turn out to be a meaningless adornment with musical notations.

Regarding the range of playable pitches, Tuohy and Potter [137] presented a music system using GA, where the pitch range is specifically determined for guitars in the composition. Some studies concern the polyphonic music composition. In [84], [85], the tracks for different instruments are represented and composed separately according to their individual pitch ranges and playing techniques. The rhythmic composition focuses on the features of rhythm, e.g., the stroke, flam, drag, and ruff of drumming. Oliwa [108] designed a GA-based system treating the tracks of lead guitar, rhythm guitar, rock organ/piano, and drums. The representation of each track is specialized according to the purpose, pitch range, and the playing techniques of the instruments.

The limitation of pitch is crucial to vocal music. A common genre is the four-part choral music, comprising the soprano, alto, tenor, and bass. McIntyre [98] proposed using GA to generate the four-part Baroque chorus. The fitness function takes account of the vocal range; moreover, the system suggests leaving proper spacing between the voice and the melody in all four parts. Phon-Amnuaisuk *et al.* [114] also used the fitness function to keep the pitches within the proper range. Donnelly and Sheppard [37] and Maddox [91] considered the vocal range in the fitness evaluation of the four-part chorus music, where each part should exclude the out-of-range pitches. Geis and Middendorf [57] presented an ant colony optimizer to generate the four-part accompaniment, for which the vocal range is also considered in the fitness evaluation. Long *et al.* [89] developed a composition system for human singing. The system restricts the use of pitches to the range of two octaves that humans can sing. Muñoz *et al.* [104] formulated the construction of the figured bass as an optimization problem. With the input of a bass line, the local composer agents cooperate with the population-based agents to generate the complete four-part music pieces.

2) Tune: Tune is a pivotal musical component that affects the listenability of a composition. It is associated with the intervals between pitches and is usually used as the basis for the assessment of a melody. Assigning the sequences of pitches for a good tune is difficult due to the enormous combinations and constraints on the notes. A considerable number of studies have proposed different CI-based methods to deal with this problem. The methods can be divided into four types: generating the whole-tune, combining music segments, constructing note by note, and imitation.

First, the most common way is to generate the whole tune at one time. This way is usually used in the evolutionary composition systems, where the series of notes can be generated randomly or using some specially designed operators.

1) Several studies have created the tunes at random and then used the fitness evaluation to sort out the good tunes [8], [92], [96], [97], [108], [110], [136], [155]. Papadopoulos and Wiggins [111] constructed the tunes given the chord progression. The pitches are assigned randomly from the notes of the corresponding chords. In the GA proposed by Towsey *et al.* [136], the tunes are evaluated according

to 21 musical features regarding pitch, tonality, and contour. The pitch features are used to fix the pitch range and measure the pitch diversity; the tonality features keep the proportion of non-scales and dissonant intervals; the contour features deal with the tendency of melody, decrease large leaps, and handle the return of large leaps. Marques *et al.* [96] manipulated the tunes according to the intervals between consecutive notes. Blackwell and Bentley [19]–[21] designed a PSO approach to generate the tune, of which the pitch, volume, and the duration of notes are represented as a particle. Geis and Middendorf [57] manipulated the ants to crawl around the notes for composing the tune.

2) Instead of random creation, the music theory about consonance, chord information, and music patterns are also employed to generate the tunes. Biles [16]–[18] used the chord information and jazz theory to assign the notes appropriate for impromptu. In the composition systems of Unehara and Onisawa [109], [140]–[142], a tune is generated from the database of music theory. Maeda and Kajihara [92] utilized the twelve-tone technique to create simple music pieces. The process begins with a tone row created by twelve tones and then evolves depending upon the harmonious degree. Liu and Ting [85] proposed creating tunes for consonance hinged on the chords in each measure. The T-Music composition system [89] handles the tunes considering the chord progression and cadence. The system follows the cadence principle to assign the ending note of phrase.

3) Some studies have utilized the mathematical equations or human assistance in the construction of tunes. Yoon [154] used fractals with musical seed data to generate meaningful music segments. Phon-Amnuaisuk *et al.* [114] presented the four-voice harmony system, in which the user inputs the soprano information as the tune, and the GA then harmonizes it by generating the alto, tenor, and bass parts. Reddin *et al.* [118] proposed a composition system based on GE, which adopts six measurements, i.e., pitch variety, dissonance, pitch contour, melodic direction stability, note destiny, and pitch range, for the fitness function to handle the tune. Loughran *et al.* [90] used GE to create tonal music. The tunes are generated with reference to the grammar, such that most notes are in the middle range of piano.

4) The pitch range and scale are concerned in the generation of tunes. For example, Loughran *et al.* [90] restricted the pitch range to four octaves by grammar, while Donnelly and Sheppard [37] limited the range to an interval of 13th and the interval of consecutive notes to 9th. Kaliakatsos-Papakostas *et al.* [73] developed a hybrid system using PSO to create the musical features of tune and rhythm, which will be used in the evaluation criterion for GA. Osana *et al.* [53], [76], [131] generated the tunes using the features on pitch, rhythm, and chord progression obtained from the sample melody. Wang *et al.* [147] proposed a composing system for the Chinese Jiangnan ditty. They first extracted the features, including pitch range, melodic interval, mode, note duration, timbre, rhythm pattern, and intervallic motive, from the existing Jiangnan ditties, and subsequently used the features for the fitness evaluation. The tunes are handled through the Chinese pentatonic mode.

Second, the tune can be constructed by combining musical patterns or pieces. Chiu and Shan [28] used pattern mining to extract the features, including motif, chord, and structure, from the input music. The extracted motifs are selected to compose the tune for a melody, where the selection depends on the chord sequences to ensure the harmony of the melodic progression. Liu and Ting [86] proposed using frequent pattern mining to extract the musical patterns repeatedly used by a composer. The tune is created by assembling these patterns.

The third way is to generate the series of notes sequentially. The rationale behind this approach is that the current and the previous notes provide the information for determining an appropriate pitch or rhythm for the subsequent notes. The neural networks and grammatical models are often used in this approach. Bharucha and Todd [13], [133] designed a neural network to predict the next note, given the current note as input. The learning process of the neural network is performed with culture-specific modes and chords. Mozer [102], [103] used the recurrent neural network (RNN) to predict notes for creating the composition. The RNN was trained with a number of Bach's music pieces and traditional European folk songs. Chen and Miikkulainen [26] also adopted neural networks to address the tune issue. They used a whole measure as the input data to generate its subsequent measure. The generated tunes are then examined for transposition. Chen *et al.* [27], [52] used a table defining the fitness of notes based on the music theory to create the initial sequences of notes. Tomari *et al.* [135] employed the N-gram model to predict the next note in the evaluation of compositions. The N-gram model was trained with 30 Japanese children's songs.

Fourth, the tune can be formed by imitating the existing music. Wu *et al.* [149] and Ting *et al.* [132] presented a novel composing system, which initializes the population with existing songs. In particular, the system addresses the issue of tunes by imitation; that is, it attempts to change the notes in phrases without altering the melodic progression of the original song. Tuohy and Potter [137] developed a system to convert music pieces into the compositions appropriate for guitar playing. The conversion includes four considerations for the tune: 1) The arranged note should be playable for a guitar instead of a causal assignment; 2) the fitness function rewards consecutive notes in a moving line; 3) the notes occurring in both of the original and new compositions are preferred; and 4) the chord notes are important but should not be abused. Alfonseca *et al.* [8] proposed creating the tunes by the minimal normalized compression distance. Vargas *et al.* [145] tried to mimic the composition process of musicians to create music pieces. They used a music database to initialize four measures as a lick and constructed the tunes in accordance with the given chords and scales.

3) Harmony: Harmony is associated with two formations of pitches: 1) The vertical one concerns multiple pitches, from the same or different tracks, sounding at the same time (beat); and

2) the horizontal one is related to multiple pitches sounding in tandem to form the chord progression. Harmony is crucial to music composition. A proper arrangement of pitches can achieve the consonance, thereby making music delightful and peaceful. In the composition systems using evolutionary algorithms, harmony is ordinarily considered in the fitness function. For the four-part chorus, the four parts can be viewed and handled as four different instruments sounding human voices. Phon-Amnuaisuk *et al.* [114] dealt with the harmony in the four-part chorus through several criteria to avoid parallel unison, parallel perfect fifths, parallel octaves, crossing voices, and hidden fifths. Maddox [91] developed a GA for the four-part chorus. For harmony, the fitness function penalizes the parallel fifths, parallel unison and octaves, leap greater than one octave, improper resolution of a large leap, and overlapping voices. Donnelly and Sheppard [37] examined the harmony for generating the four-part chorus by GA. The harmonic rules are defined in the fitness function to avoid the parallel octaves, parallel fifths, and dissonant intervals such as seconds, fourths, and sevenths.

Chords serve as an important basis for forming harmony. The chord progression constitutes the orientation of pitches in a melody. Some studies have utilized this notion to tackle the harmony in music composition. McIntyre [98] used GA to generate a four-part Baroque chorus. The GA handles harmony in the fitness function that considers several conditions in the chords, including chord correspondence, start and stop notes in chords, and resolutions for chords. Marques *et al.* [96] presented a fitness function favoring the concurrent notes that can conform to a chord, especially the major or minor chord, for forming the harmony. Chang and Jiau [25] addressed the harmony issue by adopting the suitable chords for a melody.

The harmony of notes across multiple tracks is another issue in music composition. Oliwa [108] presented a GA-based composition system, in which the fitness function regulates that the lead guitar should use the chords corresponding to those used by the rhythm guitar and the piano for harmony. Xu *et al.* [151] adopted the music theory, harmonics, as the basis for fitness evaluation. The fitness function treats harmony via mapping the mode to the chord progression. In addition, each period (A to C) of generated music has its own rules to maintain harmony. Liu and Ting [84] proposed using the music theory rules derived from consonance to tackle the harmony issue across the tracks of different instruments. The fitness function rewards the consonance of the main, bass, and chord accompaniments that are evolved through GA.

C. Rhythm

Rhythm endows the connection between notes as well as an essential factor in another dimension, by contrast to the dimension of pitch, to be considered in composition. It assigns the duration for each note (including the rest note) to make the music vivid or form a specific genre. Establishing rhythms is not easy because of the huge variety in allocating notes to the beats.

Like handling the pitch, several evolutionary composition approaches utilize the fitness evaluation to find the appropriate rhythms. Maeda and Kajihara [93] included rhythm in the evaluation criteria of their GA for automatic composition [92]. The fitness values are determined by the duration, ratio, and time interval. Moreover, they proposed another evaluation criterion regarding the rhythm and the statistics on the timing variation of sound. Wang *et al.* [147] presented a fitness function that evaluates the rhythms using statistical results. The frequent durations and rhythm patterns in the extracted compositions are rewarded with a high fitness value.

Moreover, Towsey *et al.* [136] devised a GA that evaluates the rhythms according to the rhythmic features, including the note density, rest density, rhythmic variety, rhythmic range, and syncopation. Tomari *et al.* [135] used the N-gram model for the evaluation criterion. The N-gram model was learned from 30 Japanese children's songs. To deal with rhythm, the model considers the transition of rhythm every two bars. Long *et al.* [89] developed the T-music system, which takes into account the rhythm components, such as the length of the last note in a phrase, and the similarity of rhythm between two phrases. Loughran *et al.* [90] used GE to establish the rhythms. The system prefers short notes in the grammar because the authors argued that the existence of many long notes will make the music dull. In Oliwa's rock music composition system [108], the fitness function also rewards short notes for a fast tapping and playing of the lead guitar.

Rhythm is a major issue at percussion accompaniment. Dostál [40] developed a human-like rhythmic system that generates the drum's rhythm for accompaniment. The fitness function favors the coincidence of beats in the melody and drum accompaniment. Yamamoto *et al.* [152] proposed an interactive GA to generate the drum fill-in patterns, which are represented by no-sound, snare drum, high-tam, low-tam, floor-tam, open-high-hat, and closed-high-hat.

Some studies use neural networks to model rhythms and assist the fitness evaluation. Gibson and Byrne [58] adopted a neural network as the fitness function for GA in composition. The system first learns the rhythm and then responds with the goodness of the input rhythm. Chen and Miikkulainen [26] proposed a neural network to generate melodies. The system adjusts the duration of notes to form the rhythm. Yuksel *et al.* [155] combined RNN and evolutionary algorithm to manage the tune and rhythm simultaneously. The neural network is trained with a set of pitches and duration of notes. Tokui and Iba [134] applied the interactive GA and GP to create the rhythmic patterns. The back-propagation neural network is applied to model user's evaluation, in order to reduce the number of interactive evaluations and lessen the fatigue caused.

Few studies propose directly using the rhythm of the original composition and focus the efforts on the assignment of tunes. For instance, Liu and Ting [86] mined the frequent musical patterns consisting of both tune and rhythm. Music composition turns out to be a task of recombining the patterns, thereby arranging the rhythm as well. Chiu and Shan [28] also used music pattern mining for composition. The rhythm assignment was omitted since the structure of measures in their system was predetermined.

D. Emotion

The emotion conveyed through music is also a key consideration in music composition. The emotion of a composition is associated with timbre, rhythm, chord progression, scale, etc. For example, the bright timbre and fast tempo are usually used to express spirited, happy, and excited emotions.

Zhu *et al.* [157] designed an interactive GA to generate compositions with a specified emotion. They adopted the KTH rule system [51], which models the performance principles used by musicians, for the evaluation rules. The weights of the rules are determined by the response (happy or sad) of users. Onisaw *et al.* [109] also used an interactive evolutionary system to compose a joyful or sorrowful melody to reflect the user's feeling. They concluded that a joyful melody is harder than a sorrowful melody to evaluate because the former needs to consider more elements, such as rhythm and tempo. Xu *et al.* [151] introduced the harmony emotion rules to their composing system, which employs a major mode with fast tempo for happiness and a minor mode with slow tempo for sadness.

IV. Composition with Accompaniment

Accompaniment is vital to reinforce the melody. Good accompaniment can promote harmony, enhance the music structure, and intensify the expressiveness of the compositions. The accompaniment can be divided into three parts: main accompaniment, chord accompaniment, and bass.

A. Main Accompaniment

The main accompaniment usually collocates with the melody note by note to make up or intensify it. Acevedo [7] used the counterpoint method for a GA to build the main accompaniment of the input melody. The fitness function considers different aspects of the accompaniment: The proportion of notes in the same key and the length of measures in the generated accompaniment should be similar with those in the input melody. The beginning and ending notes need to be consonant with the melody. The intervals and repetitions of notes are also limited. Liu and Ting [84] developed a GA for making the polyphonic accompaniment, where the three accompaniments (main, bass, and chord) have their own fitness functions. The main accompaniment was designed to enhance the harmony and complement the insufficient rhythm in the melody.

B. Chord Accompaniment

Chord accompaniment is one of the key factors in music composition. The music would become boring and monotonous without the chords supporting harmony. The CI techniques for handling the chord accompaniment can be classified into two types: Some assume the chords are given and compose the music accordingly; some produce the chord progression while creating the composition.

For the first type, supposing the chord progression is predetermined, the composition system will focus on the search for the appropriate pitches, scales, rhythms, and so on. The GA developed by Liu and Ting [84] evaluates the fitness of compositions according to the chords given by the user. The chords follow a predefined progression but will be evolved into different forms by the GA. Furthermore, they [86] proposed generating compositions by following the original chord progression. The chords are employed to evaluate the consonance with the generated melody. Xu *et al.* [151] presented a varying chord progression for harmony. The selection of chords depends on the mode, intervals, ending parts, and three different periods. Chiu and Shan [28] used the pattern mining technique to extract chord progressions from the input music. These progressions are adopted as the basis for evaluating the sequence of randomly selected chords, where a high similarity in chord progression leads to a high fitness value.

For the second type, chords and melody are handled concurrently. Chang and Jiau [25] developed a system to automatically generate chords for the melody in two phases: The local recognition phase determines the chord candidates according to the common chord templates and rhythm. The global decision phase further selects the most suitable chords from the candidates based on the chord progression rules. Nakamura and Onisawa [106] designed an interactive GA system to construct the chord sequence. The chords are evolved with the compositions by the GA with the listener's feedback.

C. Bass Part

The bass part is an important element helping to stabilize the progression of music. For composition, Liu and Ting [84] proposed evolving the bass line using GA. In the composition system, the candidate bass lines are generated with reference to the chords used. The fitness function evaluates the bass lines according to their harmony with the melody and other accompaniments.

In addition, for the four-part music, the bass part is ordinarily composed of chord notes, especially the root of chord. The relevant studies have been described in Section III-B.

V. Designs of Computational Intelligence

This section introduces the various designs of computational intelligence techniques for music composition. First, we recapitulate the studies on the operators used in the evolutionary composition systems. Next, we review the neural networks proposed for music composition. The research on the application of fuzzy systems to music is also briefed. Finally, the subsection reviews the methods for the evaluation of compositions.

A. Evolutionary Computation

Evolutionary algorithms have been widely used for automatic composition and achieved several favorable results. The design of an evolutionary algorithm pertains to representation, selection, crossover, mutation, and fitness function.

1) Representation: The integer string is commonly used as the representation for the elements of music composition, such as timbre, pitch, and rhythm. Unemi and Nakada [143], [144] presented a two dimensional array as the representation for the guitar, bass and drum. The representation indicates the information of both the rhythm and the notes for the three tracks. The proportion of rest and tenuto are determined with respect to the representation form. Papadopoulos and Wiggins [111] proposed a representation resting on the degrees of scale relative to the current chord for composing a jazz melody. The representation is capable of handling the information about the scales and responding chords rather than only the absolute pitches. Vargas *et al.* [145] designed an improved chromosome representation using a numerical sequence based on the chords assigned to the measure. For example, the chord Cmaj7 corresponds to a major scale (avoid 4th) according to the musical theory. Therefore, the available notes will be C, D, E, G, A, B, octave C, octave D, octave E, and so on, which are indicated by the numbers 1 to 15 for representation.

Instead of a fixed length, Donnelly and Sheppard [37] proposed the variable length chromosome for representation of the four-part music composition. Each chromosome contains four parts for the musical line, namely, soprano, alto, tenor, and bass. The variable length representation allows the composition to grow and shrink caused by the insertion and deletion of the mutation operator, respectively. Oliwa [108] presented different representations for the tracks of instruments, including the lead guitar, rhythm guitar, keyboard, and drums, considering the differences in their components and playing techniques. For instance, the representation for the lead guitar preserves the space for the tapping technique, while that for the drum is based on the rhythm patterns. Biles [16] took account of the pitches and rhythms in the representation. In addition, the notes of hold and rest are considered as events. The chromosome uses the information about the chords and scales to ensure the represented notes are playable by human players, which is critical for the impromptu interactive process.

2) Crossover: The well-known crossover operators, such as k-point crossover and uniform crossover, are usually applicable to the evolutionary algorithms for music composition. In addition, some studies have developed special crossover operators that consider the musical characters or enhanced performance.

Marques *et al.* [96] devised the note crossover and octave crossover. The former regulates that the crossover should take place in the note with sound; namely, the rest and tenuto notes are excluded. The latter keeps the tone of the chosen note but exchanges in one octave. Vargas *et al.* [145] suggested that the crossover should avoid disrupting compositions. The proposed crossover operator produces valid compositions according to the distance of intervals. Likewise, Liu and Ting [84], [85] proposed placing the cutting points between measures to prevent destroying the structure of music sections. Wu *et al.* [149] designed three crossover operators considering different restrictions: 1) The chord-based switch locates the cutting points between measures with absolutely identical chords; 2) the root-based switch picks the cutting points between the measures having up to one different note and the same root of chords; and 3) the analogous switch is similar to the root-based switch but permits cutting points locating between the measures with different roots of chords.

3) Mutation: Some studies have devised the mutation operator to improve the efficiency in composing music. Beyond simply flipping genes, Biles [16] presented two mutation operators with musical meaning. The first mutation operator alters chromosomes in light of transposition, retrograde, rotation, inversion, sorting, and retrograde-inversion. The second operator acts as a high level mutation processing musical phrases. Marques *et al.* [96] proposed two mutation operators on the notes and octave. The note mutation is performed on the notes excluding the rest and tenuto notes. The octave mutation shifts the pitch of the selected note by one octave. Matić [97] designed three mutation operators to increase the fitness of compositions. The first mutation operator shifts a tone into its lower octave to reduce the number of large intervals. The second operator changes the pitch if the current note is dissonant with its subsequent note. The third mutation simply swaps two consecutive notes. Donnelly and Sheppard [37] presented a series of mutation rules: repeat, split, arpeggiate, leap, upper neighbor, lower neighbor, anticipation, delay, passing tone, deleting note, and merging note. When performed, the mutation probabilistically selects one of the rules to change the composition. Vargas *et al.* [145] developed three mutation operators to ensure the consistency of phrases. These mutation operators retain the pleasant sound without damaging the results of crossover by transposing two down, octave, and hemiola operators. The transpose two down operator shifts an entire phrase down by two tones to introduce diversity to the phrase without destroying the consonance. The octave operator decreases a note with a large interval by one octave to reduce the horizontal interval. The hemiola operator repeats a group of notes throughout a phrase.

B. Neural Networks

Neural networks are often used to evaluate compositions or predict notes in music composition. In these applications, neural networks are trained to model the evaluation or arrangement of musical elements. Regarding the evaluation, neural networks are commonly adopted to assist the fitness function in the evolutionary composition systems. Biles *et al.* [18] adopted the neural networks as the fitness function for the impromptu system GenJam. Tokui and Iba [134] employed neural networks to model the user's preference and thereby mitigate the fatigue issue at interactive composition. Burton and Vladimirova [23] applied the adaptive resonance theory (ART) network for the fitness evaluation in GA. The ART network is trained to model the clusters of drum patterns in various genres of music, including rock, funk, disco, Latin and fusion.

As for the prediction of notes, Bharucha and Todd [13], [133] utilized neural networks to predict the next note. After the learning process, the neural network is seeded with an initial value and then generates a new composition note by note. Similarly, Chen and Miikkulainen [26] adopted a neural network to generate the next measure, given the current ones. The neural network takes both the tune and rhythm into account. Mozer [102], [103] trained an RNN with the music pieces of Bach and traditional European folk songs to generate compositions. In addition, he proposed learning the AABA phrase patterns in order to maintain the musical structure. Eck and Schmidhuber [43], [44] suggested using the long short-term memory (LSTM) to improve the composition process of RNN. Considering the issue that the compositions made by RNN usually lack the global structure, the LSTM is adopted to learn the musical chord structure. The authors believed the well-trained chord structure can form a cycle for a global musical structure. Liu *et al.* [87] also proposed using RNN to generate music. Specifically, they adopted the resilient propagation (RProp) in place of the common backpropagation. The LSTM was adopted to solve the issue at the long phrases. Franklin [48] compared several types of RNN for music composition and presented a composition system using the LSTM and music representation. Coca *et al.* [29], [30] applied the chaotic algorithm [31] to generate chaotic melodies for inspiration. The proposed RNN system has two input units: melodic and chaotic units. The former is devised for learning, whereas the latter is used for inspiring the composition process.

C. Fuzzy Systems

The notions of fuzzy sets and fuzzy logic are widely used in the classification of music genre [12], [46], [115], recognition of music emotions [50], [72], [153], recommendation systems [81], [113], music retrieval [88], [129], [156], copyright protection [77] and authentication [82]. Although these approaches focus on processing audio signals and metadata rather than create music compositions, they can be used to deal with the emotion and music genre in the compositions. In addition, fuzzy sets and logic can further assist the evaluation of compositions owing to the intrinsic fuzzy nature of the music genre, emotion, and evaluation.

D. Evaluation of Compositions

The CI techniques ordinarily require feedback to adapt the model or guide the evolution. Evaluation of the existing or generated compositions caters for the major feedback and has a vital influence on the learning and evolutionary process. As the above sections described, various designs for the fitness function are presented to deal with the pitch, harmony, rhythm, and accompaniment in music composition.

The evaluation methods used in CI for music composition can be classified into three categories: interaction-based, rule-based, and learning-based. The following recapitulates the studies on these three types of music evaluation.

1) Interaction-based Evaluation: The interaction-based evaluation relies on the listener's feedback on the generated music. The methods collect the listener's responses, e.g., evaluation scores, preferences, or physiological signals such as heartbeat, pulse, and skin conductance, to a sample phrase or composition; and then use the collected information to evaluate the sample. The interaction-based evaluation methods provide a direct and useful way to evaluate the generated compositions; therefore, they are commonly used in CI/AI-based composition systems.

Based on the interactive evaluation, several studies proposed the interactive evolutionary algorithms (IEAs) for music composition [130]. In the IEAs, the fitness of a composition is determined as per the listener's evaluation result. Johanson and Poli [71] presented an interactive GP to arrange the pitches of notes, while Tokui and Iba [134] devised another interactive GP to evolve the rhythm of compositions. Yoon [154] proposed a composition system based on fractals and GA, which relies on the evaluation results from the listeners to evolve the generated compositions. Nakamura and Onisawa [105] developed a lyrics/music composition system that considers the user's impression and music genre. Given the user's choice about genre, the system creates the lyrics using the Markov chain and a lyrics database, while the music is composed of the melody and one of the three accompaniments for the genre. The combination of the music and lyrics is then evaluated by the user.

Instead of an entire composition, some evaluation approaches require the listeners to take note of and evaluate only certain parts of the composition to lighten their loading. The GenJam system [14] uses the real-time human evaluation on the segments of generated jazz solos. Jacob [67] developed an IEA to evolve the weights, phrase lengths, and transposition table for a new melody, given the motif and the chord progression. Like GenJam, the IEA requires the audience to evaluate a partial composition to reduce the loading in evaluation. Onisaw *et al.* [109] designed an interactive composition system to generate the emotional melody. The listeners evaluate only four bars as to whether or not the melody transfers the correct emotion. Unehara and Onisawa [140] adopted the interaction with humans for choosing their favorite 16-bar music. Fukumoto and Ogawa [54] proposed an interactive differential evolution (IDE) for creating the eight-note sign sounds. The evaluation of the sounds generated by the DE is based on comparison: Each time the listeners choose their preferred one from two sounds, and from four sounds at different evolutionary phases in the first and second experiments, respectively. The authors further compared the performances of the IDE and IGA in music composition [55], [56]. Chen *et al.* [27], [52] utilized the user's feedback, in the form of preference scores, to evaluate the music phrases generated by the proposed evolutionary algorithm. The fitness of a music block is defined by the average score of all the music phrases containing this block.

Another form of interaction-based evaluation is through the collaboration with musicians for professional feedback. The GenJam [16], [17] can do trade fours at a jazz impromptu. It listens to the human player performing four bars and then converts the music into the chromosome structure to evolve. The resultant chromosome soon responds to accomplish the trade fours. Diaz-Jerez [35] developed the composition system Melomics, which makes use of the professional composers' scored results. Manaris [94] designed an interactive music generator using GA, Markov model, and power laws. The music generator creates music in response to the human player's performance.

The results of interaction-based evaluation provide a genuine feedback on the compositions. However, a crucial issue lies in the fatigue caused by the repeated listening, which gradually runs out of human evaluator's patience and decreases their music sensitivity. Hence, the number of evaluations based on interaction is usually very limited in order to maintain the quality and consistence of the evaluation results.

2) Rule-based Evaluation: The rule-based evaluation adopts explicit rules for evaluation of generated compositions. The evaluation rules are developed according to personal experience or music theory in composition, considering the musical elements such as rhythm, phrase, scale, and chord. The rule-based evaluation renders the objective measures, by contrast to the personal and subjective measures of interaction-based evaluation. Moreover, the rule-based evaluation saves the high cost at interaction and benefits the efficiency of the fitness evaluation in evolutionary music composition.

Horner and Goldberg [62] presented a GA that creates compositions by iteratively producing the segments bridging music parts, where the fitness evaluation depends upon the predetermined static patterns. Phon-Amnuaisuk *et al.* [114] adopted some evaluation rules from music theory considering leaps and intervals. Özcan and Erçal [110] used the evaluation rules based on notes, intervals, and pitch contour, in their GA for generating improvisations. Oliwa [108] proposed a GA using a set of fitness functions tied to different instruments in rock music. For example, the fitness function for the notes of a lead guitar is associated with the ascending/descending tone scale, tapping, and flatten. Matić [97] presented a fitness function that compares the mean and variance of intervals, and the proportion of scale notes in a measure between the generated melodies and the input melodies. Acampora *et al.* [6] adopted a set of evaluation rules concerning the progression of notes in creating the four-part harmony. More specifically, the rules are involved with the modulation and tonality of the subsequent chords. The composition system of Geis and Middendorf [57] evaluates the melody and the four part accompaniments separately. The evaluation rules for the melody consider the smoothness, contour, resolution, and end-of-tonic, whereas that for the accompaniments considers the chord, voice distance and leading, progression, smoothness, and resolution. Towsey *et al.* [136] defined the 21 pitch, tonality, and contour features hinged on the music theory and used them in the evaluation rules. Freitas and Guimaraes [49] used a bi-objective evaluation method to address the dissonance and simplicity of harmony. The fitness functions are based on six rules considering the triads, dissonant chords, invalid pitches and chords, unison, and tomic position. Liu and Ting [84] proposed evaluating the compositions according to the music theory. They adopted a set of rules associated with chord notes, leap, harmony, and rhythm in the fitness evaluation. This method was further applied to an automatic composition system based on phrase imitation [132].

The rule-based evaluation methods are useful for creating the compositions of a specific music genre. Some studies leverage the music theory or the well-formed music structure for a genre, e.g., Baroque and jazz, to construct the evaluation rules. McIntyre [98] took account of the four-part Baroque harmony in the fitness evaluation. Given the chords and the four-part Baroque style, the GA arranges the notes to the four music tracks whilst considering the harmony and stability in the progression. Tzimeas and Mangina [138] constructed a GA to transform the Baroque music to jazz music. The fitness is determined by a critically-damped-oscillator function for varying the evolutionary direction in accordance with the genre and rhythm [139]. In addition, they used multiple objectives to deal with the rhythm, where the weights of the objectives are defined by the similarity to the target rhythm. Wang *et al.* [147] focused on the Chinese Jiangnan ditty. The fitness function in the proposed composition system uses the features extracted from several Jiangnan ditties, including range, melodic interval, mode, note duration, timbre, rhythm pattern, and intervallic motive. Oliwa [108] designed polyphony composition depending on the features of rock music, such as the tendency of scale, duration of notes, and coordination of musical instruments.

3) Learning-based Evaluation: The learning-based evaluation constructs the models from music data for the evaluation of compositions. Machine learning techniques, such as neural networks, are widely used for the evaluation model. Furthermore, they are applied to analyze, cluster, or classify the music data, and the results are employed as the basis for evaluation. Gibson and Byrne [58] utilized neural networks to construct the model for the fitness evaluation on the combinations of rhythms. Spector and Alpern [127] used neural networks with Fahlman's quickprop algorithm to characterize and evaluate music in the GP-based composition system. Dannenberg *et al.* [32] applied the linear and Bayesian classifiers on music data and also utilized neural networks to extract the characteristics of music for creating compositions. Burton and Vladimirova [23] designed a GA for the arrangement of percussion, in which the fitness function evaluates compositions according to the results of a clustering algorithm on the music data. Similarly, Manaris *et al.* [95] developed a GP method using a fitness function based on the classification results (classical, popular, and unpopular music) of neural networks. Osana *et al.* [53], [76], [131], [135] trained N-gram models with 30 Japanese children's songs for evaluating the compositions. They further improved the N-gram model by additional evaluation rules. Yuksel *et al.* [155] established an RNN as the model for evaluating compositions. The RNN was trained using a series of human compositions. During training, the neural network takes the input notes sequentially and the output is the pitch and duration of the next note.

The learning-based evaluation methods can be incorporated with the interaction-based or rule-based evaluation methods. Ramirez *et al.* [117] used a classification approach and a GA to learn the rule-based expressive performance model. Compared to interaction-based evaluation, the learning-based evaluation methods leverage the extant compositions and their evaluations, instead of using real-time feedback from humans. Hence, the learning-based evaluation methods can be used to reduce the loading and fatigue issue at interaction-based evaluation. Biles *et al.* [15], [16], [18] used neural networks in GenJam to learn the feedback to the generated impromptu Jazz music. The neural networks help to moderate the distraction and unstable evaluation caused by the fatigue from long-time listening.

VI. Future Directions and Topics

In this section, we present a number of directions and topics for future research.

A. Representation

Most of the existing studies have adopted simple representations for the pitches and duration. These representations, nonetheless, cannot support the diverse use of musical symbols, such as triplet, vibrato, and ornament. The design of new representation for supporting comprehensive usage of musical symbols will benefit the composing of music. In addition, a representation that can exclude inappropriate settings for the elements (e.g., pitches, chords, and beats) is desirable.

B. Evaluation

As aforementioned, evaluation of the generated compositions is imperative for the CI-based composition approaches. However, there exist some weaknesses in the extant designs of evaluation methods. The interaction-based evaluation can reflect the user's genuine preference among the generated compositions, but its practicability seriously detracts from the fatigue and decreased sensitivity caused by the long-time listening. The rule-based evaluation provides a fast way to evaluate the compositions; however, the determination of the rules and their weights raises another problem to be addressed. The learning-based evaluation can build the evaluation model from the music data but encounters the issues existing in the machine learning methods, such as training time, model construction, and fidelity.

To design an evaluation approach that can address the above issues is a crucial research direction for the CI-based composition systems. A promising way is to hybrid the three evaluation methods to remedy their own weakness. For example, learning-based approaches can be used to build the surrogate for the interaction-based evaluation to reduce the time and human loading at interaction [69], [70], [83]. The evaluation rules in the rule-based approaches can serve as the basis of an evaluation model, while the learning-based methods are capable of learning the weights from personal experiences or music data.

C. Deep Learning

Deep learning has thrived and gained many exciting achievements over recent years [80], [124]. For example, the famous music streaming service company, Spotify, adopts the deep learning technique to analyze the user's preferences for better service and experience. In music composition, Huang and Wu [66] presented a work on the generation of music through deep learning. They used a multi-layer LSTM and character-level language model to learn the musical structure. In addition, Google has recently released their Magenta project [5], which uses the RNN on the TensorFlow platform to generate piano melody. Although the current results are preliminary, to explore the great potential of deep learning in music composition is a significant topic for future research.

VII. Conclusions

Computational intelligence plays a pivotal role in algorithmic composition. This paper presents a survey on the research of CI in music composition. In this survey, we review and discuss the CI techniques for creating music in the light of musical elements and algorithmic design. The first part reviews the existing approaches for dealing with the three principal elements in music composition, i.e., musical form, melody, and accompaniment. The second part recapitulates the various designs of evolutionary algorithms and neural networks for creating compositions. In addition, we categorize the evaluation methods into interaction-based, rule-based, and learning-based evaluation, and discuss the existing approaches for these three types of evaluation manners.

The above reviews and discussions show that the CI techniques are highly capable and promising for algorithmic composition. This survey also reflects the importance of evaluation, representation, and learning of compositions in musical creativity. Enhancement and advanced designs on these aspects are suggested as the significant directions for future research on CI in music composition.

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