

Retraction

Retracted: Using a Solution Construction Algorithm for Cyclic Shift Network Coding under Multicast Network to the Transformation of Musical Performance Styles

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] X. Wang, J. Geng, and Z. Li, "Using a Solution Construction Algorithm for Cyclic Shift Network Coding under Multicast Network to the Transformation of Musical Performance Styles," *Complexity*, vol. 2021, Article ID 9993396, 11 pages, 2021.

Research Article

Using a Solution Construction Algorithm for Cyclic Shift Network Coding under Multicast Network to the Transformation of Musical Performance Styles

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This paper presents a theoretical framework of the circular shift network coding system through the study of nonmultiple clustered interval music performance style conversion and the analysis of music conversion by using circular shift topology, and a series of basic research results of circular shift network coding is obtained under this framework. It reveals the essential connection between scalar network coding based on finite domain and cyclic shift network coding, designs a solution construction algorithm for cyclic shift network coding under multicast network, and portrays the multicast capacity of cyclic shift network coding. It overcomes the problem that the piano roll-curtain representation cannot distinguish between a single long note and multiple consecutive notes of the same pitch, describes musical information more comprehensively, extracts musical implicit style from the note matrix based on autoencoder, and better eliminates the potential influence of musical content on musical performance style. A two-way recurrent neural network based on the gated recurrent unit is used to extract a sequence of note feature vectors of different styles, and a one-dimensional convolutional neural network is used to predict the intensity of the extracted note feature vector sequence for a specific style, which better learns the intensity variation of different styles of MIDI music.

1. Introduction

Music is a way for human beings to express their emotions. Music can make people improve their ability to appreciate beauty, feel beauty, and experience beauty, stimulate human interest in learning, and contribute to the improvement of comprehensive artistic literacy. Music can also regulate human emotions, enabling people to relax, soothe their bodies and minds, reduce anxiety, improve sleep, and even be used for complementary medicine. Music is widely recognized as a universal language, and the innovation of musical artworks and the diversity of their performance styles also help to inherit and promote the profound traditional culture [1]. The vast amount of digital music has given rise to music information retrieval (MIR) technology, which combines computers and music and has numerous applications. The most typical application is automated

music generation, which is gaining popularity in the music industry because of its great potential for mass production of music under a user-specified style or genre. In recent years, with breakthroughs in artificial neural networks, deep generative models have become one of the leading techniques for automated music generation [2]. For example, the artificial intelligence music start up Juke deck has developed an artificial intelligence music composer, a system that writes original music entirely on its own, bringing artificial intelligence into music composition by training deep neural networks to understand music composition in more detail to build creative instruments. Deep generative models can not only generate new data but can also change the properties of existing data in principle and even pass properties between data samples.

Despite some promising advances, it is still difficult to produce natural and creative music through automation. In

general, algorithms with weak constraints tend to be too random and rarely produce music that resembles human hand-crafted music, although many of the compositions are interesting and creative from a contemporary perspective [3]. On the other hand, algorithms with strong constraints, either explicitly through rules or implicitly through training data, generate music that is mostly too monotonous and lacking in expressiveness. The development of image style transformation techniques has inspired the hope of solving these problems [4]. By separating and recombining musical contents and musical styles of different tracks, new music with creativity and expressiveness can be generated, and such work is called music style conversion. However, music differs from images in that it is more abstract in its presentation and possesses an inherent multilayered and multimodal character. In general, music has three different forms of representation: score, performance control, and sound. A score is a symbolic, highly abstract visual representation that effectively records and communicates musical ideas, while a sound is a set of continuous, concrete signal representations that encode all the details we can hear. Somewhere in between is performance control, because musical semantics and expression rely heavily on performance control, most typically MIDI, which does not record sound, but rather allows an electronic instrument to play a very complete piece of music by recording a series of performance instructions. Dependent on different forms of expression, music can be read, heard, and performed.

The musical style is a very vague term that can refer to any aspect of music, from high-level compositional features (such as key and chord sequence) to low-level acoustic features (such as sound texture and timbre). What musical content and style refer to sometimes varies from context to context. For example, in classical music, musical content can often be interpreted as the written form of a score (including harmony), while musical style is the performer's understanding and application of the score after adding his or her musical expression. Music changes over time, which makes learning music difficult for deep generative models [5]. Solving these problems would have exciting industrial applications. Most directly, it could be used as a tool for music creators to easily incorporate new styles and ideas into their work; indirectly, advances made in music style transformation could facilitate the development of music information retrieval techniques. So far, most studies have focused only on a particular level or form of musical expression, with different interpretations of musical style. According to the different interpretations, the nature of musical style transformation also has a lot of differences.

2. Related Studies

Wave Net experimented on a music generation task, and the results showed that both conditional and unconditional music models can produce harmonious music [6]. Leupin used Wave Net to build an autoencoder of the original audio waveform, which learns multiple embeddings that allow deformation between instruments, with meaningful insertions in the timbre to create realistic and expressive new

sounds [7]. Schiavio proposed a generic music transformation network, a method that enables musical genre transformation between different instruments, styles, and genres [5]. The method is based on a multidomain Wave Net autoencoder with a shared encoder and an implicit decoding space for end-to-end training of audio. Trowell first analyzed the audio signal and using harmonic tracking and then converted to the audio of another monophonic instrument using a known timbre model [8]. Using this method, even a whistling segment hummed casually can be transformed into a Beethoven style symphony or a Mozart style piano piece in a very short time with AI modification [9]. Koutrouvelis et al. proposed a flexible music style modification method that modifies the style of a given music segment to another style learned from a corpus of music segments [10]. This style modification is considered as an optimization problem, where the music will be optimized according to different objectives. The method is mainly oriented towards monophonic symbolic music but can be easily extended to polyphonic music. Alderisio et al. learn the structural properties of music by adding constraints in the process of generating music, and the results show that the method can control the high-level self-similar structure, pitch, and tonality of the music while maintaining the local coherence of the piece [11]. Daddario modelled pitch and rhythm for different styles of music separately and then created new melodies by combining the pitch model of one style with the rhythm model of another style [12].

Multiple waveforms are isolated from each other in the frequency domain with different spectral branches. Such a waveform design scheme fundamentally solves the interference between different waveforms for the pulsed Doppler regime using correlated receive matching filtering [13]. However, spectrum resources are very precious, and the spectrum bandwidth directly determines the resolution of imaging. This means that several times (this multiple is determined by the number of signals) the distance-to-resolution is sacrificed for the same spectral resources. This means that such an isolation method, although simple and thorough, cannot be universally applied to MIMO-SAR waveform design, because after all, bandwidth resources, as the most important resource directly related to imaging, are expected to be fully reused [14]. The separation between multiple waveforms is performed by different beams, which separates the different waveforms in the air domain. This scheme is also used in many azimuthal or distance-oriented multiantenna schemes. However, the conventional ScanSAR does not solve the problem that the azimuthal resolution and the mapping bandwidth cannot be increased at the same time, but the azimuthal resolution is sacrificed for the expansion of the distance mapping band [15]. The split-beam approach is useful for such applications, but firstly, the leakage of antenna directional map subflaps will lead to certain interference, and more critically, the split-antenna beam solution also greatly limits the application scenarios of MIMO, and for a large number of situations where different beams are required to face the same scene area, such as multivision or GMTI, this approach may not be able to meet the application.

The performance style conversion network consists of recurrent neural networks and convolutional neural networks. Ordinary recurrent neural networks can only learn very short dependencies due to the problem of gradient disappearance and explosion. However, the notes of music are not independent of each other, and they often have very long dependencies. The gated recurrent unit is a variant of the ordinary recurrent neural network, which has a simpler structure compared to another variant, the long and short-term memory. Music changes over time, and complete musical contextual information helps to analyze musical styles, while traditional one-way recurrent neural networks can only capture current and past information. One-dimensional convolutional neural networks can also handle sequential data with time translation invariance, which is faster compared to recurrent neural networks. Therefore, this paper uses a two-way recurrent neural network based on gated recurrent units and a one-dimensional convolutional neural network to build a performance style conversion network. This paper uses a bidirectional recurrent neural network based on gated recurrent unit to extract different styles of note feature vector sequences and uses a one-dimensional convolutional neural network to perform specific style velocity prediction on the extracted note feature vector sequences, and better learn different styles of MIDI. The dynamic changes of music have a very good guiding significance for the research of nonmultiple cluster interval cyclic shift topology on the transformation of music performance style.

3. Analysis of Nonmultiple Cluster Interval Cyclic Shift Topology Music Performance Style Transformation

3.1. Topological Analysis of Nonmultiple Clustered Tone Cyclic Shift. A musical genre or type is a traditional classification for the attribution of musical works. A musical genre or its subgenres can be identified by the musical techniques used, the musical style, the context, and the content and spirit of the subject matter. Common musical genres include classical, pop, folk, country, jazz, heavy metal, etc. Often, people will label a song with a genre after listening to it, which indicates that songs in the same genre seem to follow a similar style. In this article, the genre is used as a label for MIDI styles. Musical styles are not like specific attributes of music such as pitch and time value, and it is very difficult to try to parameterize musical styles [16]. If one listens closely to the performances of novice and experienced players, one can see that even when they play the same score, they each produce a different range of intensity variations. In the case of the piano, for example, the strength of the notes depends on the speed at which the piano player strikes the keys. The performer injects different intensity variations into the piece with his or her understanding of the musical style, resulting in different expressions. Therefore, it can be said that variation in intensity is a very important characteristic of musical performance style.

Audio is usually stored in two formats, a sound file, and a MIDI file. A sound file is original audio recorded through a recording device, which contains binary sample data of the real sound; a MIDI file records not the real waveform, but a series of event sequences that play notes through various sound output devices [17]. Musical Instrument Digital Interface (MIDI) is an electronic communication protocol used to define the codes needed for the performance and control of the music for performance devices such as electronic instruments, allowing synthesizers, computers, sound cards, and electronic instruments to control each other and exchange information instantly and is widely used in the field of composition. Today, computer sound cards are compatible with MIDI to realistically simulate the sound of an instrument.

In this thesis, a single-source multisource multihomed directed acyclic graph of a multicast network is used as the topology for discussion. It is assumed that both the transmitted and the data cell to be encoded are a Z -dimensional binary row vector. This assumption is consistent with the prevailing setting in real transmission scenarios. Unless otherwise stated, the linear solutions mentioned in this thesis are based on the binary domain and its extended domain C_L :

$$C_L = \begin{bmatrix} 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}. \quad (1)$$

The certainty and indeterminacy of music are also reflected in the issue of musical content, which is also a focal point of debate among schools of musical aesthetics. The definition of musical content is different, and different people have different views. The content of music mainly refers to the objective reality reflected by the embodied music, that is, through the reality of acoustic existence, hearing the natural phenomena depicted by music as well as the human thoughts and feelings and the reality of society, etc. Some people also believe that the content of music is the form of music itself and has nothing to do with the outside world:

$$C_\delta = \arg \min \left\{ \sup_{x \in \Omega_x} |b(x) - W^T S(x)| \right\}. \quad (2)$$

The specific performance is shown in formula (2), where $b(x)$ represents the form of music, and W and S represent the objective reality of music and the form of acoustic performance, respectively. On the issue of certainty and uncertainty in musical imagery, there is no such thing as who is important and who is not, but which aspect is emphasized will reflect different tendencies. Some point out that insistence on certainty is conservative and insistence on uncertainty is innovative. This sees only one side of the issue and ignores the other. In the history of musical development,

the debate between autodidacticism and heterodidacticism about the nature of music has never stopped, and from the results of the debate, although each has its reasoning, there is no unified conclusion, so that later on there is the emergence of syncretism to reconcile autodidacticism and heterodidacticism, but due to the uncertainty and polysemy of musical language, there is still no clear conclusion:

$$F_i^d(t) = \sum_{j \in K} \text{rand}_j F_{ij}^d(t). \quad (3)$$

The most important indicator of SAR waveform in azimuthal direction is the Doppler tolerance, and the most important tool to examine the Doppler tolerance is the radar fuzzy function. A fuzzy function is an effective tool widely used in radar waveform design and analysis. The expression of certainty and uncertainty of music image is shown in formula (3), and the $A(t, w)$ is the law of development:

$$x_i^* y_i = \text{int}\left(0.5 \text{int}\left(\frac{x_{i-1}}{S}\right)\right), \quad (5)$$

$$Q_N(w) = \frac{1}{2} \sum_{i,j} P_{ij} (1 - P_{ij})^2 + \|w^T X_b\|_2^2, \quad (6)$$

$$\phi_{m,n} = \frac{\|q_{m,n}\|^2}{\delta^2} \exp\left(-\frac{(q_{m,n} * z)}{2\delta^2}\right) * \left[e^{i(q_{m,n} * z)} - e^{-(\delta^2/2)}\right], \quad (7)$$

$$\frac{\partial L}{\partial \beta_j} = \sum_{i=1}^n \left[y_i - \frac{\exp(a + \sum_{j=1}^m x_{ij} \beta_j)}{1 + \exp(a + \sum_{j=1}^m x_{ij} \beta_j)} x_{ij} \right] = 0, \quad j = 1, 2, \dots, m. \quad (8)$$

There are a thousand Hamlets for a thousand audiences. Music should be both certain and uncertain, a dialectical unity of relative certainty and absolute uncertainty, to be exact. Without the relative certainty of content, there is no way to speak of the problem of understanding music, and it cannot be understood. It is also due to the existence of relativity that music is justified as an international language [18]. We also need to pay attention to the uncertainty of music; by ignoring uncertainty, there can be no rich forms and means of expression, and no innovation in understanding. For musical understanding, one should go to the point where musical certainty and uncertainty meet, and one should occupy the place between certainty and uncertainty. Any musical phenomenon is understandable and certain, but not open to any interpretation; musical phenomena are only reflections of real life. As long as we understand real life and the relationship between real life and musical phenomena, we will also naturally understand the certainty of music. However, to admit only absolute certainty is to emphasize one-sidedly the restraining role of real life on ideology and to admit only absolute uncertainty is to emphasize one-sidedly the role of ideology and ignore the restraining role of real-life on ideology, both of which are undesirable, as shown in Figure 1.

$$\text{STFT}[A(t, w)] = \int_{-\infty}^{+\infty} a(\tau) g(\tau - t) e^{-jw\tau} d\tau. \quad (4)$$

Externalizing the phenomena of life and psychoemotional phenomena into musical phenomena necessarily involves the orderly combination of different musical elements through human thinking activities, in which the externalized sound forms are not isomorphic with life and emotional activities and both qualitatively and quantitatively have undergone greater changes, and on the whole, the way the structure is instantly airborne contains some similarities in functional order. The $x_b y_i$ represent the actual performance of musical phenomena. P_{ij} is an evaluation method of musical phenomena. According to formulae (5) and (6), the shift performance of music performance style can be obtained:

Of course, taking aesthetics as the core of musical understanding is an inevitable development of the times, as we look at multiple musical cultures, and the conceptual system of music, including musical forms and musical techniques, takes on multiple forms. Thus, understanding music as culture is not a simple collage of musical and cultural content, but rather a way of thinking about and understanding music in a specific context. Drawing on the fruitful results of interdisciplinary, musical, and cultural studies and cross-cultural research, these new developments should be confronted and the philosophical study of musical understanding should be strengthened to integrate with the field of aesthetics. Aesthetic philosophy of music and practical philosophy are not opposed to each other, and the central place of aesthetics in aesthetic philosophy cannot be completely denied. Because aesthetic philosophy, as a trend of thought in a specific historical period, inevitably has its historical limitations. Its rationality should be seen; it is part of practical philosophy, but not equal to it. As a humanities discipline, music has a typical humanistic nature, and its study must be closely linked to humanities and social disciplines. The value of music is no single, and it is difficult to measure the value of music by numbers. The humanistic nature of music is inherited in history, and the

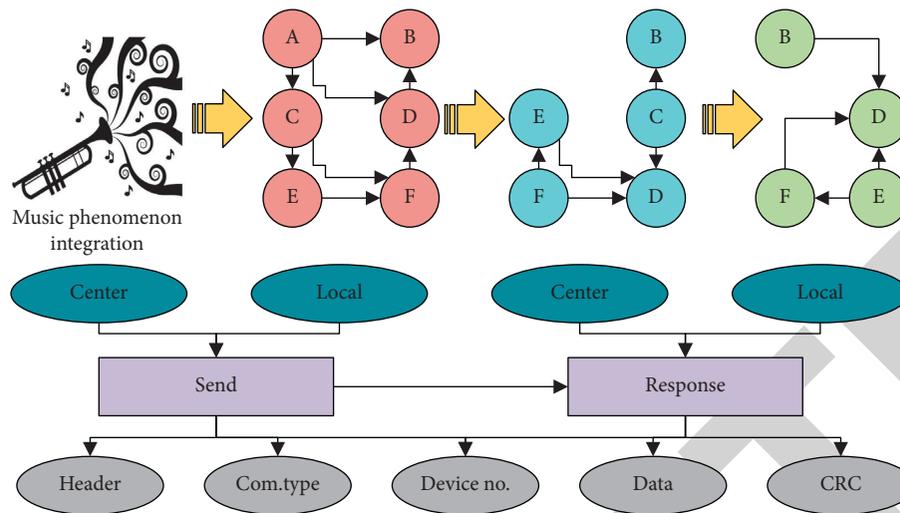


FIGURE 1: Cyclic shift topology framework.

continuous development of the times needs to combine it with specific philosophical trends and literary theories for interpretation.

3.2. Analysis of Musical Performance Style Change. MIDI can be thought of as a time sequence composed of many different MIDI events, and to be able to feed MIDI files into a neural network, the MIDI information must first be converted into a matrix representation. The Piano Roll matrix is one of the most common representations, inspired by the piano rolls used to operate automatic pianos, usually made through the recorded performances of famous musicians [19]. Typically, the pianist will sit at a specially designed recording piano, and the pitch and duration of any notes played will be marked or punched on the blank roll, including sustains and soft-pedal durations.

The piano curtain matrix represents a musical composition in a similar way to a musical score, where the vertical and horizontal axes represent the pitch and time step, respectively. The values of the elements in the piano roll-curtain matrix indicate the intensity of the notes played at the current time step for a particular pitch. The time axis of the piano roll-off matrix can be either absolute or symbolic timing. For absolute timing, the actual time at which the note appears is used; for symbolic timing, the velocity information needs to be removed so that each beat has the same length. There are 128 possibilities for the pitch of MIDI notes. Since MIDI notes can be of any length, it is necessary to resample the MIDI file to discretize the time. For example, when using symbolic timing and setting the time resolution to 24 ticks per beat, a bar of 4/4 beats with only one track can be represented as a 96 128 dimensional matrix.

A MIDI piece can be thought of as a sequence of notes of different pitches and timbres, often with some inherent similarity to the same style, and the human perception of musical style comes mainly from listening to musicians live or recorded back. Often, the intensity of each note is not

described in detail in the score, and the representation of musical style relies on the performer's understanding of the piece. Thanks to the development of music storage formats, it is possible to reproduce the original performance by recording the musician's live performance and playing it back with the help of a music format such as MIDI. The intensity of each note played is exhaustively recorded in MIDI, yet it is difficult for humans to discover the intrinsic connections even by parsing MIDI files. In this paper, we use the note matrix and the intensity matrix to represent the music content and performance style, extract the music implicit style by autoencoder, and turn the performance style conversion into using the music implicit style to fit the intensity matrix and use deep learning to build a performance style conversion network to learn the relationship between the two. The network is trained by MIDI of different styles in the dataset, to realize the automatic conversion of performance styles.

The note matrix and the intensity matrix are obtained from the MIDI music, and the music implicit style is extracted from the note matrix using the encoder in the pretrained autoencoder. Music is a time-varying sequence of notes, and based on the analysis of network models commonly used to deal with the sequence problem in the previous sections of this chapter, this paper will use a combination of recurrent neural networks and convolutional neural networks to build a performance style conversion network. Since the output of the network contains many different styles, this is a multioutput model, and using shared layers can reduce the learning parameters of the network [20]. Recurrent neural networks are widely used to deal with sequential problems, and they use memory states and present inputs to predict future information, because they only consider past information, which is not enough to comprehensively understand the musical context, and because GRU is a simpler structure than LSTM, the shared layer of the performance style transformation network designed in this paper uses a bi-directional GRU layer. This paper uses a one-dimensional

convolutional neural network to predict the intensity matrix by regression from the sequence of note feature vectors output from the shared layer that already contains contextual information, as shown in Figure 2.

The input layer's input is the music implicit style extracted from the encoder part of the pretrained autoencoder, the autoencoder model is first pretrained, the weights of the encoder part of it are obtained, the encoder architecture is constructed, the trained weights are loaded, each layer of the encoder is frozen, and the output of the encoder is used as the input of the performance style conversion network. The hidden layer is used to learn the relationship between the implicit style of music and the real intensity matrix, and a shared bidirectional GRU layer is used to reduce the training parameters of the network, obtain the note feature vector sequence, use the same sublayer for each style, and in each sublayer, use 3 stacked 1D convolutional layers to learn the intensity distribution based on the note feature vector sequence, and in the back of each 1D convolutional layer, also batch normalization is used after each 1D convolutional layer to make the prediction effect closer to the real intensity distribution and to ensure the nonlinear expressiveness of the model.

Strength indicates the strength of a note when it is played. On the piano, for example, the loudness of a note depends on how hard or fast the piano player strikes the keys. The score is usually marked with intensity markings, which can be divided into more than a dozen levels, as shown in Table 1.

In music, variations in intensity are an important means of expressing music and can convey a wealth of emotions. Generally speaking, the higher the value of intensity, the more majestic the music, and the lower the value of intensity, the more subdued the music. For beginners, the most common mistake is that they are not able to control the intensity of their playing, and they tend to ignore the intensity markings on the score, thinking that the only important components of music are the notes, which often results in joyless playing [21–24]. As we usually say, “lack of musicality” refers to the lack of richness and variation in the intensity of a player's playing. Tone allows one to distinguish between the sounds of different instruments or people. Different tones can be distinguished from each other, even when they are of the same pitch and intensity.

In music, a beat is a pattern and accent position exhibited by a cyclic occurrence of bars or beats. In this case, the beat is the unit of time. The time value of a beat can be expressed using notes of different time values, for example, the time value of a beat can be a quarter note, which is often referred to as a beat in quarter notes. For example, when the tempo of a piece is 60 beats per minute, each beat is one second and half a beat is one-half a second; when the tempo of a piece is 120 beats per minute, each beat is half a second, half a beat is one-quarter a second, and so on [25–28]. For example, when a quarter note is used as a beat, a whole note is equivalent to four beats; when an eighth note is used as a beat, a whole note is eight beats. In each cycle of the beat, when there is only one strong note, the unit beat with the strong note is the

strong beat, and the unit beat without the strong note is the weak beat; when there is more than one strong note, the first unit beat with the strong note is the strong beat, the other unit beats with the strong note are the second strong beat, and the unit beat without the strong note is the weak beat. The beats can be combined into measures, with the downbeat being the first beat of each measure and the upbeat being the last beat of the previous measure immediately before the downbeat.

4. Analysis of Results

4.1. Analysis of Nonmultiple Cluster Tone Cyclic Shift Topology Results. The probability of randomly constructing permutation-based codes satisfying the solution is the same; however, this probabilistic discussion is based on the code length Z being sufficiently long. This does not indicate how fast or slow the performance of the two asymptotically reachable for shorter code lengths. The probability of both randomly constructed linear codes satisfying a linear solution is shown in Figure 3.

It can be found that although the success rate of constructing a solution for a linear code based on permutation converges to 1 faster than that of a cyclic shift code, in fact, at a not so large code length $L = 128$, the difference between the two is already small and both are very close to 1. The number of nonzero local coding cores that can be used for a cyclic shift code with a count of 1 is much smaller than the number of permutation operations, but sometimes the increase in the number of optional local coding cores is not so. This can also be verified by the solvability conclusions of some special networks. We have shown that when the parameter $n \geq 4$, for the $(n, 2)$ -combinatorial network plotted in Figure 4, neither of these two classes of networks exists for any block length L and number 8. By mathematical induction, it is similarly simple to show that for any block length L , neither of the above networks has a linear solution for permutation-based linear codes with a selectable number of local coding kernels.

Finally, it should be added that the current study of the asymptotic solvability of the cyclic shift codes is limited to the multicast networks with a single source and multiple hosts and does not involve the derivation and analysis of the optimal outer bound in general networks, so the asymptotic optimal nature of the cyclic shift codes in general networks cannot be derived. It is noted that the fuzzy functions of the four signals have a similar shape to a fish fin, which implies that the signals have a relatively good Doppler tolerance for imaging.

In this case, you can merge a multitrack MIDI into a single-track MIDI and save the merged single-track MIDI as a new MIDI. As shown in Figure 5, a piano roll-up is drawn using Midi Editor before and after the merging of tracks, using different colors to distinguish the different tracks, the leftmost is the MIDI pitch corresponding to the piano keyboard, and different lengths of rectangular bars along the horizontal axis time steps are used to represent the different notes. The length of the rectangular bar indicates the time value of the note. Merging tracks only changes the number of tracks in the MIDI file,

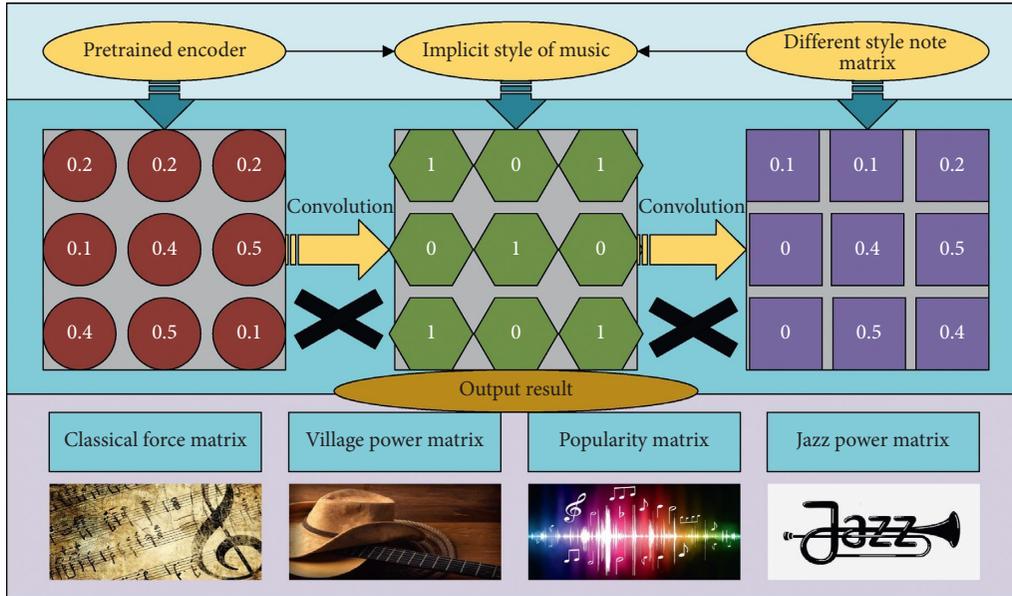


FIGURE 2: Performing style switching network.

TABLE 1: Note strength representation.

Strength mark	Strength description	ID
Ppp	Extremely weak	12
Pp	Very weak	13
P	Weak	14
mp	Medium to weak	15
mf	Medium to strong	16
F	Strong	17
Ff	Very strong	18
Pff	Extremely strong	19

but the pitch, time value, intensity, and position of all the notes in the MIDI file should not change before or after merging the tracks.

After merging all the multitrack MIDI files, each MIDI of different styles is first analyzed and shifted in terms of intensity type, and the MIDI files with sparse intensity types are eliminated. The temporal resolution of MIDI is thirty-two notes; that is, the smallest note is thirty-two notes, and a sample is randomly selected. Figure 5 is the first dimensional 128 time steps in the note matrix representing the sample using mat plot lib, that is, four bars of the piano roll-up diagram, where the horizontal axis represents the time steps, and the vertical axis represents the pitch.

4.2. Results of Music Performance Style Conversion. Using the pretrained encoder model, we train the performance style transformation network, which is a multitask learning process to learn the intensity matrix representation of several different performance styles, and by adding a shared layer, we can make the network learn a better-generalized representation for a specific style. For each style learning task, three stacked one-dimensional convolutional layers with 88 filters and 16 convolutional kernels are used 64, 32, and 16, respectively, with expansion ratios of 1, 2, and 4,

respectively, each 1D convolutional layer followed by a batch normalization layer, and a fully connected layer containing 88 nodes for the output layer, using wrappers acting at each time step. This article adopts the alternate training method. If the two networks are trained separately, they will change the parameters of the shared convolutional layer. Therefore, a technique is needed to share the convolutional layer for the two networks instead of training separately. In the paper, a 4-step training method is used to optimize the parameters by selecting the network.

The loss function of each style is optimized using the Adam optimizer with an initial learning rate of 0.001, and the real intensity matrices of different styles are normalized and used as the prediction target of the performance style conversion network. The network is trained with 150 iterations.

As shown in Figure 6, the loss variation curve during the training process, the horizontal axis indicates the iteration rounds, epochs, and the vertical axis indicates the loss, the final loss of the training set is 0.0037, and the loss of the validation set is 0.0045. In the actual work process of the network, an inputted symphony fragment will be converted and translated into a special musical instrument, but the most amazing ability of this model does not stop there. When inputting a musical instrument that the model has never seen before, it can still work perfectly through the automatic encoding and decoding process! This proves that the encoder in the model can indeed extract the generalized features in music and express them in the hidden space. I have not seen this instrument in time. This is the core concept of many generative algorithms, and GANs and vibrational autoencoding have used this idea to create a lot of fascinating work.

Figure 7 shows a classical style MIDI segment, which is expressed as a note matrix and an intensity matrix. After the note matrix is fed into the performance style conversion

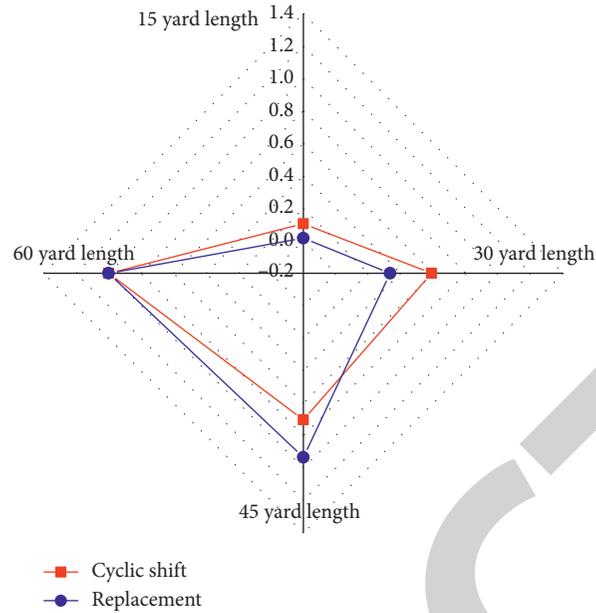


FIGURE 3: Probability of linear codes satisfying linear solutions.

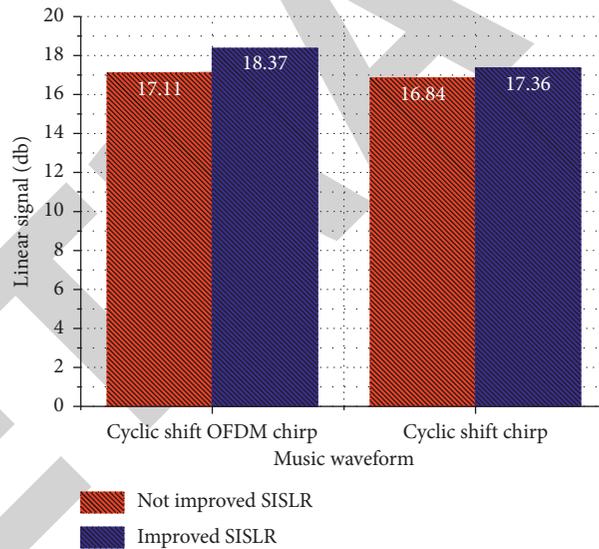


FIGURE 4: Comparison of SISLR for cyclic shift OFDM chirp and cyclic shift chirp signals.

network, the predicted output of the four intensity matrix effects and the actual intensity matrix effects are different. The horizontal axis represents the time step, and the vertical axis represents the pitch. The darker the color, the smaller the intensity value, and the brighter the color, the larger the intensity value, which shows that the intensity of different styles of intensity matrices have different ranges of intensity changes. The range of intensity change of real intensity matrix and predicted classical intensity matrix is the same, and the range of intensity change of country, pop, and jazz is about the same.

To evaluate the effect of music performance style conversion, most studies rely on the subjective perception of people. To balance the data set, the country style

with the lowest number of samples is used as the benchmark, and 9924 samples are taken from different styles of MIDI, making a total of 39,696 samples to form the strength classification data set, of which 80% is used as the training set and 20% is used as the test set. The strength classifier is trained with the loss function of classification cross-entropy. The final accuracy of the strength classifier was 94.52% on the training set and 86.91% on the test set, and the classification accuracy for each style on the test set is shown in Figure 8.

From Figure 9, it can be seen that for the same style, the performance style conversion network can keep the original style unchanged after conversion, and for different styles, the performance style conversion network is

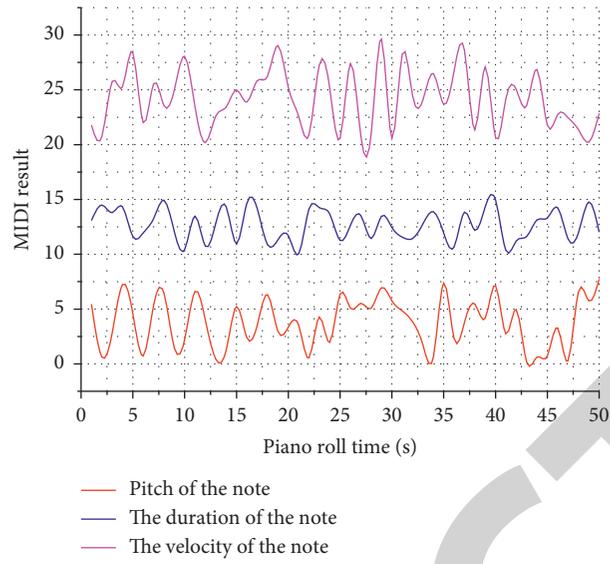


FIGURE 5: Piano roll-up diagram before and after track merging.

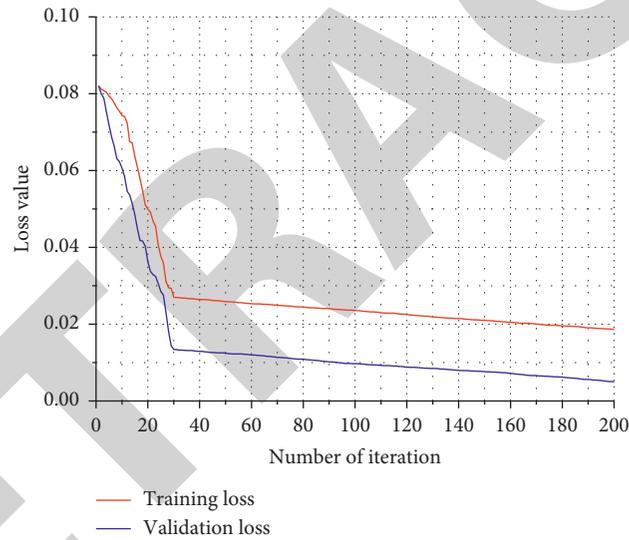


FIGURE 6: Performance style switching network loss change curve.

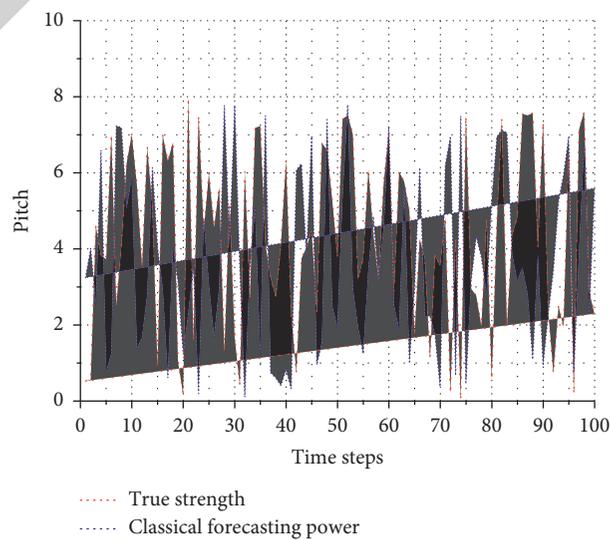


FIGURE 7: Matrix of predicted strengths of different styles.

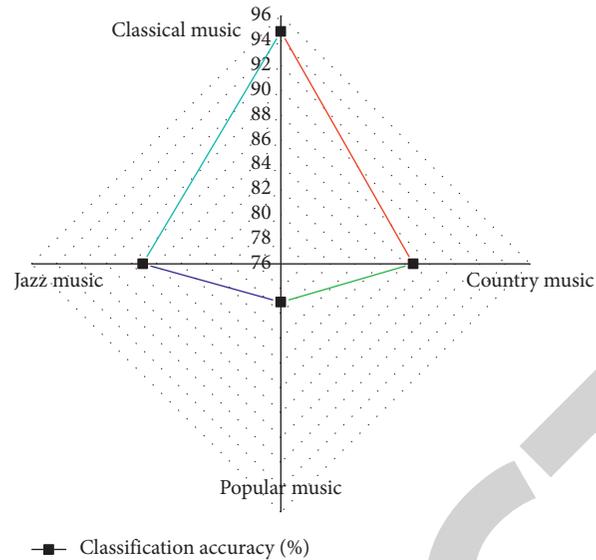


FIGURE 8: Accuracy distribution of force classifiers on the test set.

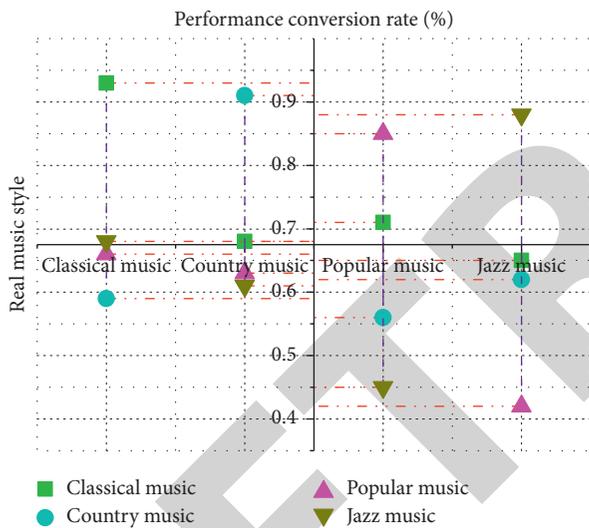


FIGURE 9: Average style conversion strength of the test set.

influenced by the original style of the song, among which, the conversion intensity between jazz and pop styles is the lowest, which may be due to the similarity of the intensity distribution of the two styles, because some jazz is easily classified as pop, and this paper considers the performance style from the angle of intensity alone. Considering the performance styles, in general, the performance style conversion effect is better.

The purpose of objective evaluation using a strength classifier is to verify that the style has been transformed while evaluating whether the transformed piece can produce effects close to those of human performance depends on the subjective perception of the human being. Therefore, in this paper, we developed an online audition platform, where the original MIDI is paired with the predicted intensity values and saved as a new MIDI piece, invited music lovers to judge the converted MIDI piece,

and statistically analyzed whether the auditions could distinguish between the different performances of human and machine, to judge whether the model described in this paper could produce a performance effect close to that of a human.

5. Conclusion

Style conversion research is an important issue in many fields of artificial intelligence, including image style conversion, text style conversion, and music style conversion. Compared with image style conversion, another style conversion research is relatively lagging, and the main problems faced include lack of parallel datasets to provide annotation for style conversion; lack of reliable evaluation criteria; and effective representation of styles. As an effective way for human beings to express their emotions, music composes and supports human spiritual life and has an indispensable role in entertainment, education, and medical treatment. Music has two important aspects: composition and performance. In terms of expression, it can be divided into sound, score, and performance control, and according to the different forms of musical expression, musical style conversion can be divided into timbre style conversion, performance style conversion, and composition style conversion. In the MIDI music information representation, a quantitative representation method of MIDI music content and music performance style based on note matrix and intensity matrix is proposed to overcome the problem that the piano roll-curtain representation cannot distinguish between a single long note and multiple consecutive notes of the same pitch and to describe music information more comprehensively, and an automatic encoder-based music implicit style extraction from the note matrix is proposed. The implicit style of music is extracted from the note matrix. The extracted note feature vector sequences are

extracted using a GRU-based bidirectional recurrent neural network, and the intensity of the extracted note feature vector sequences is predicted using a one-dimensional convolutional neural network to better learn the intensity variations of different styles of MIDI music.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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