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Research on the Development of Music Information Retrieval and Fuzzy Search

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Abstract: With the popularization of modern broadband networks, many network resources are serving as media for the public to seek knowledge. In order to help users avoid spending hours searching for music-related information, establishing an efficient multimedia database is the main goal of the music retrieval system. Network music retrieval users are usually unfamiliar with the songs and can only remember a portion of the music track, so it is important to develop a fuzzy algorithm in music search. In this research, the function and frame of various current music retrieval systems are discussed, a comparative analysis is carried out, and a new fuzzy search feedback learning algorithm is proposed as a potential application and the futuristic trend of music retrieval systems, so as to improve the retrieval efficiency.

Keywords: Music information retrieval; Fuzzy search; Humming query; Acoustic fingerprint; Melody extraction

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1. Introduction

The music retrieval system (musical information retrieval) functions to retrieve partial information of music content and construct a database. By inputting key information that conforms to or matches the music database, the users search and identify the music information they need from a wide range of data. Different from simple text searching, network music retrieval is more difficult and complex because of the diversity of movement and tone. As the elements of music construction are more complex than words, many retrieval systems extract different index features as the key information for searching. The organizational structure of music is expressed through rationality and logic, and it also carries rich emotional connotations. Therefore, when extracting the key features of music attributes, each retrieval system is different, and the music interception content as well as the method of matching calculation also vary. The music retrieval system can make relevant comparisons and matches based on the retrieval of text, symbol, audio, video, music score, and spectrum analysis diagram. In addition, the retrieval system can automatically identify humming content and other means as the key to search. The main function of an online musical information retrieval system is to help users search music information through an index. Moreover, it helps develop potential customers of the music market and analyzes users' preferences based on historical behavioral data. Through the machine learning algorithm, these historical behavioral data can be learned via artificial intelligence (AI), and the retrieval efficiency can be further improved along with time.

2. Method and results

Fuzzy search refers to the required information, which can be determined based on the algorithm even if the input parameters are not exact. Through the designed algorithm, fuzzy search can retrieve a series of information related to parameters input. Certainly, not all of them are correct, but the most precise information will be shown at the top of the list through the computer's quick and intelligent processing, and users can then select the correct answer. Making fuzzy algorithms in music retrieval is particularly essential when music searchers desire to retrieve something unfamiliar, complex, or with minimal information of the content. Users can query the music track or playlist through fuzzy expression. Even if the searcher hums the ambiguous tunes or forgets a specific title, he or she will still be able to look for the corresponding one. Therefore, fuzzy search is common when using the music retrieval system.

There are many types of music with complex features. Based on specific music features, most of the existing retrieval systems extract them into numbers, symbols, or images, and these indexes are added to the retrieval system database. This study aims at discussing the infrastructure of various systems to help users understand the retrieval forms in searching for music resources. According to literature data and empirical research, a comparative analysis of existing music retrieval systems is carried out, the features of various functions and frames are explained, and the development of network music is analyzed using a fuzzy search system based on the utilization of a machine learning method. By adopting this method, users can gain access to music information more efficiently and accurately.

2.1. Literature review

2.1.1. Origin and development of music retrieval system

Based on existing research, several scholars have shared the historical development of the music retrieval system by discussing on a single mode or specific retrieval technology. For example, in 2006, Nicola Orio first studied and analyzed the functions of music retrieval systems, in which he evaluated the classification of information and the methods of various retrieval systems [1]. Michael Casey reviewed the signal processing development in the system and elaborated its application based on the music content [2]. Schedl focused on songs, lyrics, musical instruments, orchestras, and other music recognition elements in his study, comparing the similarity of these elements [3]. The earliest computer music information retrieval system originated from the Boolean model of information retrieval [4], and based on the development of word vocabulary, many systems have been developed following that. In 1988, MPEG (Moving Picture Experts Group) was formally established. This group is dedicated to researching multimedia coding technology and has created a number of audit programs involving video and audio compression coding technology [5]. At the same time, the International Organization for Standardization (IOS) developed the multimedia content description interface and the multimedia content index [6]. In 1990, Mongeau and Sankoff presented the first automated frame for implementing music sequence alignment [7]. In 1995, Ghias initiatively proposed a system called Query by Humming (QBH) at the University of Southampton in the United Kingdom. Users can record a query segment of melody by humming [8]. From that, the computer program can obtain the pitch profile map of the input sound through autocorrelation and then convert the melody into symbol strings comprised of English letters – U, D, and R. The following step is to retrieve information from the database via information matching similarity, and then return the result list based on the matching similarity. However, the research conducted by Ghias is only the preliminary design of phonetics processing, which fails to achieve the real automatic identification and search function [9]. In addition, this kind of design is only limited to identifying the pitch of music tunes. The system began to add more attributes of audio to the matching database for retrieval. At the beginning of 2000, the popularity of MIDI contributed to the development of the retrieval system, which is based on mark images and MIDI recorded audio samples. This system can automatically locate and search the database established by MIDI files from the network as well as compare melody, rhythm, and musical notation [10]. With the rapid growth of online music resource platforms, such as iTunes, Spotify, and KKBox, scholars like Laurier, Grivolla, and Herrera have been advocating the establishment of a multi-mode retrieval database and the integration of index features with elements, such as text, number, video, audio, and sounds [11].

2.1.2. Development of a fuzzy search system

The existing multi-mode index system combines the index identification functions of audio, video, and text on the music segment with pictures related to the music content for search. These designs are helpful to the future application of multimedia digital libraries and music teaching. Although the design of a multi-mode retrieval system is still in the growing stage in terms of capacity, query function, and structure foundation, it can enhance the search efficiency and achieve practical results through the improvement of a search algorithm. The pursuit of the multi-mode index retrieval is for retrieval accuracy, but it is different from general text retrieval. Assuming that users of multimedia or music retrieval are not able to accurately hum complete tunes, or even accidentally hum incorrect melodies, the behavior of the searcher clicking on the results is therefore an additional way to judge the correctness of the retrieval besides relying on existing retrieval algorithms. That is to say, better accuracy can be achieved after the system receives feedbacks from the query results and learns them through the algorithm. Accordingly, a method is proposed based on users' click information feedback to allow the retrieval system to learn from it and improve the way a fuzzy search system operates.

2.2. Research method

Aiming at several music search websites that provide online services, including Naxos Music Library, Themefinder, and Midomi, the search efficiency and database content of the retrieval system are investigated through practical operation, and the average search analysis time of each system is recorded. The time truncation begins from the completion of manual input or humming to the search process, and the arrangement of the similarity comparison ends when browsing or clicking the work. Naxos Music Library, Themefinder, and Midomi represent different computational models. These three types of models are music retrieval systems based on text narration, music features as content by manual input, and music features as content by humming inquiry, respectively. Given that each user's assessment of inquiry skill is likely to differ, this experiment of evaluating three retrieval systems involves three users searching the assigned repertoire with the same computer. In the experimental process, 300 songs from various music genres were chosen by each participant, and the search time from each inquiry trial was recorded. In the end, the data were collected, the average search time was calculated, and the precision and efficiency of the retrieval systems were compared. Through this approach, a user-centric evaluation of music retrieval systems has been established. **Table 1** illustrates the experimental criteria and the average time using inquiry tools from Naxos Music Library, Themefinder, and Midomi.

Table 1. Inquiry experience using three types of music search websites

Website	Repertoire for search	Average time
Naxos Music Library	25 pieces from the Baroque era	17.09 seconds
	25 pieces from the Classical era	
	25 pieces from the Romantic era	
	25 pieces from the Contemporary era	
Themefinder	50 pieces composed by JS Bach (1685-1750)	
	25 pieces composed by Giacomo Puccini (1858-1924)	2 minutes and 16 seconds
	25 pieces composed by Dimitri Shostakovich (1906-1975)	
Midomi	50 pieces from rock music	4.9 seconds
	50 pieces from country music	

After examining various network music resources, suggestions have been put forward for improving the existing bottleneck of the system. Since each system provides either positive or negative similarity of the target items, one can assume that, to a certain degree, the users' feedback to the non-exact matches stands for another reference to evaluation. Therefore, a potential application of the network music retrieval systems is proposed as a new simulation algorithm inspired by the experiment.

2.3. Simulation algorithm

As the experiment involves both automatically extracted data and user annotated data, it is believed that human interaction with the retrieval system is an influential factor in the search process, by which the identity of matching items is eventually confirmed. The key to the concept of fuzzy search is fuzzy comparison, minimizing the editing distance and arranging the possible results by the best pair to form a list of information for user's reference. One method is the approximate matching of fuzzy strings. In this method, the simplest way is to use brutal force to calculate the editing distance between all substrings of string T and retrieval string P, and then select the one with the smallest distance. However, the running time of this algorithm is O (n^3 m). Compared with the string approximate matching method, image, and sound retrieval, a different algorithm is required – an acoustic fingerprint. An acoustic fingerprint is a digital digest extracted from the audio signal by a specific algorithm, which is applied to identify sound samples or to locate similar audio in the audio database. The purpose of the traditional music content information retrieval is to transform retrieval segments into feature sequences and compare them with the songs in the music database one by one to determine the target songs. Due to the increasing number of songs in the database, the search time increases linearly, making it difficult for content retrieval to be applied to large music databases. Therefore, it is very important to establish a more effective data information base in advance as it can greatly reduce the search time. This paper is different from previous papers since the latter focuses on how to search for correct songs using a single search request. Machine learning is proposed to regard each search result as feedback information so that the system can produce better results based on the click situation. The matching logic in searching is still consistent, but the user's click results become beneficial information in the system algorithm. The more the cumulative click results, the higher the search efficiency.

3. Results and discussion

Based on the retrieval function of network music, the characteristics of various existing music retrieval systems are summarized, and the frames and contents are briefly described in the following sections.

3.1. Music retrieval system based on text narration

Traditional music retrieval based on text narration has the same function as searching for song titles, lyrics, performers, publishers, and other tag information related to music texts on Google, YouTube, and other web pages. According to the tags provided by the query, the system searches information through classification via theme positioning. At the moment, this type of system has dominated the mainstream market and is simple to use. It is also divided into public websites and professional music databases. Public websites have the advantage of automatic positioning when the text information is incomplete, but the search accuracy may be lost. Using a professional music database means accurately inputting various text narratives related to the search items. The interface diagram of Naxos Music Library, as shown in **Figure 1,** is an example to illustrate that the full-text on-demand database needs to input detailed text narrative information, including song title, composer, genre, style, and number. Such a database is suitable for professional musicians to carry out specific music information collection. In addition, RILM, another major professional music search engine, is a complete collection of international music online literature. Since January 2021, it has joined in the encyclopedia of pop music in Mexico and Canada as well as the biography data database of country music, thus continuously expanding the scope of music search [12].

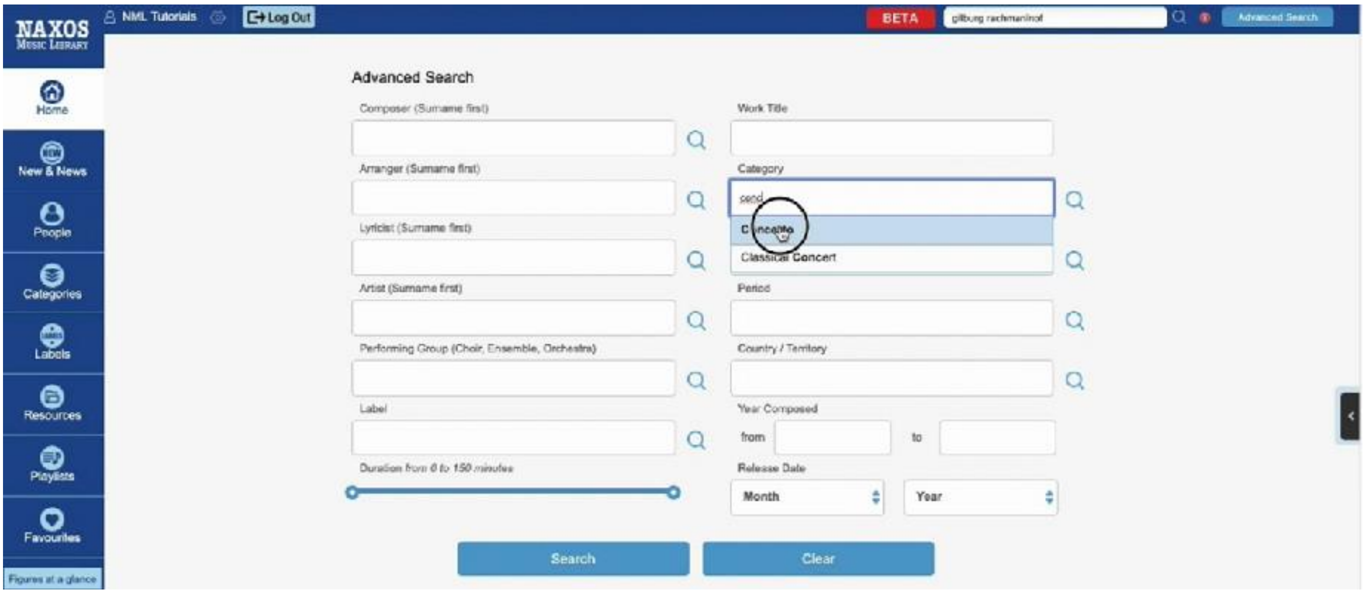

Figure 1. The interface of Naxos Music Library's retrieval system
(from Naxos Music Library, by Naxos Digital Services US Inc., 2021)

3.2. Music retrieval system based on music feature as content

Since users frequently fail to remember the entire text tag description when searching for data, such limitation contributes to the development of a content-based musical retrieval (CBMR) system based on music features [13]. CBMR overcomes the limitation in traditional musical retrieval that only uses text annotation for search by analyzing the music content and extracting its sound features to build a database. Nowadays, CBMR has evolved from manual input of melody coding to various ways for retrieval, such as inputting the humming melody via microphone and comparing audio files. As shown in **Figure 2**, the Themefinder interface indicates that in addition to outlining the form of melody, it is also equipped with multiple retrieval systems of other related music content descriptions, including the name of the composer, song name, keywords, scale, tonality, interval concept, rhythm, music style, and other options. Currently, the search capacity of this database allows one to search music from the 16th century and the classical period, as well as 8,382 local folk songs from 9 countries. However, the input music features still require the searcher to have professional knowledge; hence, this kind of retrieval system fails to meet the needs of most users who have not received professional music training. The humming retrieval system with melody pitch as an index has been introduced and gradually applied in the retrieval system [14].

Figure 2. The interface of Themefinder's music retrieval system
(from *Themefinder*, by Center for Computer Assisted Research in the Humanities, 1999-2000)

Rodger J McNab and Lloyd Smith from Waikato University in New Zealand used the MT (melody transcription) system to automatically translate humming query segments. The database system "MELDEX," which is based on folk songs, has the function of automatic calibration and can adjust the user's tone to the matching mode. The search option, including pitch comparison, absolute duration of rhythm length, melody direction, and rhythm similarity comparison, also adds a search function targeted to the MIDI text query [15]. This technology has been expanded to existing network humming retrieval systems, such as Midomi and NetEase Cloud Music. Such a service can achieve an accurate search of the song name by humming for about ten seconds, and the database mainly comprises of English songs.

3.3. Retrieval system based on the physical characteristics of music

Due to the differences in grammar and expression between modern electronic synthetic music and traditional music, the users of the aforementioned music retrieval systems need to have basic knowledge of music theory, or they must be able to sing out a melody that meets the data standard pitch for searching. Scholars have begun to look at music structure from the perspective of physics and music moods [11]. The waveform frequency of sound shows the pitch and sound in music; its content can analyze the audio characteristic parameters by various signals and then extract the numerical value as the key feature, which can be used as the basis for retrieval and classification. In this way, the music index no longer focuses on the elements of music theory. The construction of a music comparison database based on audio-physical characteristics is still in the experimental stage. At present, the analysis and comparison technology of audio-physical characteristics is mostly applied in the security system. The technology can identify the voice of specific subjects by using voiceprint comparison. In environmental engineering, this technology is also used for noise detection or sound scene structure construction. Existing music network platforms, such as "bideyuanli" (https://bideyuanli.com/pp), can convert monophonic music from different musical instruments into the corresponding position diagram on the keyboard according to pitch spectrum analysis [13].

4. Future trend of network musical retrieval system

Having a comprehensive view of the aforementioned network retrieval systems based on various music features, most of the existing websites are designed for those with specific music preference and professional users, but recently, scholars have proposed various methods to simplify key music information by extracting the emotional characteristics of music [16]. Looking at the structure of music from a psychological perspective, the waveform frequency of sound displays the sensual property and intensity in music. Moreover, the lyrics, speed, and strength of music have emotional tension, and they express human emotions [17]. Based on the acoustic system, the characteristic elements of volume, tonality, pitch, rhythm, and timbre are all closely related to the psychological perception of human beings [18]. Although many technical theories of music retrieval systems based on physical and emotional characteristics have not been applied to the mass market network platform, acoustic fingerprint has been used in the field of financial information security, and emotion recognition models are being developed to contribute to related fields, such as music therapy as well as film and television production soundtracks [4]. The directions that will be discussed below represent the future development trend of online music services.

4.1. Application of artificial intelligence in fuzzy search

In view of the fact that most online music users do not have music information integrity when using music retrieval systems, programmers have developed a new technology – the automatic identification of music information. Existing smartphone software with music recognition functions, such as Beatfield Music Recognition, SoundHound, and other programs, enables users to enter the key information of segments to search.

However, the accuracy of fuzzy search is reflected in the correctness of the search result list. In view of the uncertainty of the input information, the optimization of the search results involves listing the best match with the highest probability at the start, and the others in order. In fact, every search result can be served as artificial intelligence (AI) learning. According to the machine learning principle of AI, if we can provide feedback to the algorithm with each click, there will be search results through AI learning. The application of AI in music emotion recognition will contribute to the application research of psychology and interdisciplinary learning. Therefore, based on this idea, a simple algorithm is proposed as discussed in the following section.

4.2. Fuzzy search algorithm of media resource management system

4.2.1. Basic concepts

It is known that the system will list the search results of the sequence based on the input information after the user performs fuzzy search. The user clicks on the correct result based on his or her cognition. If the user clicks only once, it will be regarded as the correct result, whereas the clicking of several results may mean that the last result is the best (most correct) one. Through this concept, a machine-learning algorithm is designed to allocate different weights to each clicked result and modify the retrieval results through the designed algorithm, so as to enhance the accuracy of the system.

4.2.2. Problem description

Suppose there is a music content-related database $D = \{M_1, M_2, ..., M_n\}$, where M*i* represents the *i*-th music data in the database. If M can be retrieved as comparable segment information, R, through function (string), R = {String (M*i*, P*i*, P*j*)}, then R represents the information segment retrieved from P*i* to P*j* in M*i*. The search algorithm used by the fuzzy search system, S, applied in the database, D, is A. If the user input (for example, the segment hummed freely) $I = \{m_1, m_2, ..., m_r\}$, A (*D*, I) = R can be correctly obtained through the query system, QS. This means that the correct data can be retrieved through the fuzzy search algorithm, A. In fuzzy search, the result is obtained from top to bottom (the top one has the highest degree of compliance, followed by the next one and so on); the result is $A(D, I) = \{L_1, L_2, ..., L_r\}$. The user generates the following click results: $CR = \{C_1, C_2, ..., C_f\}$, $f \leq r$; $C_1 = Li$, $1 \leq i \leq r$. C_1 represents the user's first click information, C_f represents the last one. $T = \{T_1, T_2, ..., T_f\}$, $f \leq r$, where T_f represents the user's residence time for each click of C_f. The weight is set as $W(C_f) = n\%$, $0 \leq n \leq 100$; this means that different weights are set on the click results to serve as the next retrieval learning material.

4.2.3. Effectiveness of the algorithm

The effectiveness of the algorithm is mainly based on the feedback rules set in this paper. Notably, music retrieval is different from searching for knowledge. The former is unique because it usually stops when a potential track is found. Therefore, this feature lays a foundation to set the following rules, so as to make the system more efficient through feedback. The rules are stated in **Figure 3**.

From the above information, it can be seen that this algorithm does not change the original retrieval system, and users can provide materials through feedback, thus the algorithm can be learned more effectively, which affects the accuracy of subsequent search results. Therefore, any method that can modify these rules and set the weight to make the algorithm more refined is worthy of further research. Rooted in the results, the ambiguous information from the search process forms a basis for machine learning, which involves human interactions with MIR systems and can be used for future music retrieval applications.

Algorithm

If there is a network database, D, of music features, and any retrieval system, QS, is adopted, when the user enters any length of music segment, I, the retrieval system will produce the following retrieval results, $A(D, I) = \{L_1, L_2, ..., L_r\}$ according to its searching algorithm, A. The algorithm is as follows:

Input: I = $\{m_1, m_2, ..., m_r\}$

Through the fuzzy search system, S, the information can be obtained.

Output: $A(D, I) = \{L_1, L_2, ..., L_r\}$.

According to the retrieval results, after the user clicks the query information, the learning materials are generated.

Click Result: $CR = \{C_1, C_2, ..., C_f\}$, $f \leq r$. $C_1 = Li$, $1 \leq i \leq r$.

Feedback and Processing: At this stage, different weights of clicked results are set according to several rules.

(1) If the user only clicks once, the clicked item is the positive solution, and the weight is set to 100%.
(2) If the click result is more than (including) two times, the weight of the last result is given as $W(L_f) = 50\%$.
(3) The weight of the other items will be set as following: $W(L_f) = (T_f / (T_1 + T_f) + 50 / (50 + f)\%$, $0 \leq n \leq 100$.
(4) For those that have not been clicked, the weight is set to zero.
(5) When the same data is retrieved for a second time, the ranking will be arranged according to the new weight. If the weight is set to zero, the ranking will be arranged according to the original search algorithm, A.

Figure 3. Fuzzy search algorithm based on feedback learning (originally credited by Chih Ming Hu)

5. Conclusion

In the era of rapid internet development and the vigorous production of audio-visual resources, the semantics and shape of music pose a challenge for digitization from a single aspect. The development trend of music retrieval systems is in the direction of using fuzzy search and multi-mode retrieval systems. Such development aims to equip users in searching for the music they need. The main goal of establishing a multi-mode index system is to help users flexibly use various index features that may enhance the degree of identification to find information with multiple options.

In addition, the social networking platform will have a significant impact on future users and multimedia retrieval systems. The co-evolution of cognitive and social systems, as evidenced by user recommendations, tagging, and other functional data related to social networking sites, is worthy of further discussion by scholars [19]. Music retrieval systems have the potential to become platforms that not only provide information but also connect music lovers and creators. This paper is written in hope to inspire more researchers to be involved in the improvement and development of network multimedia retrieval systems, and that more in-depth research will be conducted in the future to make up for the shortcomings of this paper.

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References

[1] Orio N, 2006, Music Retrieval: A "Tutorial and Review". Foundations and Trends in Information Retrieval, 1(1): 1-90. DOI: 10.1561/1500000002

[2] Casey M, Veltkamp R, Goto M, et al., 2008, Content-Based Music Information Retrieval: Current Directions and Future Challenges. IEEE, 96(4): 668-696. DOI: 10.1109/JPROC.2008.916370

[3] Schedl M, Gomez E, Urbano J, 2014, Music Information Retrieval: Recent Developments and Applications. Foundations and Trends in Information Retrieval, 8(2-3): 127-261. http://dx.doi.org/10.1561/1500000042

[4] Veltri S, Giovanni M, Schaffhauser-Linzatti M, 2014, Measuring Intellectual Capital in the University Sector Using a Fuzzy Logic Expert System. Knowledge Management Research & Practice, 12(2): 1-18. http://dx.doi.org/10.1057/kmrp.2012.53

[5] Boyce JM, Dore R, Dziembowski A, et al., 2021, MPEG Immersive Video Coding Standard. Proceedings of the IEEE, 109(9): 1-16. https://doi.org/10.1109/JPROC.2021.3062590

[6] Benetos E, Dixon S, Giannoulis D, et al., 2013, Automatic Music Transcription: Challenges and Future Directions, Intelligent Information Systems, 41(3): 407-434. https://doi.org/10.1007/s10844-013-0258-3

[7] Mongeau M, Sankoff D, 1990, Comparison of Musical Sequences. Computer and the Humanities, 24: 161-175. https://doi.org/10.1007/BF00117340

[8] Ghias A, Logan J, Chamberlain D, et al., 1995, MULTIMEDIA '95: Proceedings of the Third ACM International Conference on Multimedia, November 5-9, 1995: Query by Humming-Musical Information Retrieval in an Audio Database. Association for Computing Machinery, New York, US, 231-236. https://doi.org/10.1145/217279.215273

[9] Futrelle J, Downie JS, 2003, Interdisciplinary Research Issue in Music Information Retrieval: ISMIR 2000-2002. Journal of New Music Research, 32(2): 121-131. DOI: 10.1076/jnmr.32.2.121.16740

[10] Downie JS, 2003, Music Information Retrieval. Annual Review of Information Science and Technology, 37: 295-340. https://doi.org/10.1002/aris.1440370108

[11] Laurier C, Grivolla J, Herrera P, 2008, Proceedings of the 7th International Conference on Machine Learning and Applications (ICMLA), December 11-13, 2008: Multimodal Music Mood Classification Using Audio and Lyrics. IEEE, San Diego, CA, 688-693. https://doi.org/10.1109/ICMLA.2008.96

[12] Naxos Digital Services US Inc., 2021, Naxos Music Library. https://www.naxosmusiclibrary.com/login

[13] Hu X, Kando N, 2012, Proceedings of the 13th International Society for Music Information Retrieval Conference (ISMIR 2012), October 8-12, 2012: User-Centered Measures Versus System Effectiveness in Finding Similar Songs. ISMIR, Porto, Portugal, 331-336. http://dx.doi.org/10.5281/zenodo.1416868

[14] Center for Computer Assisted Research in the Humanities, 1999-2000, Themefinder. http://www.themefinder.org/help/about/

[15] McNab RJ, Smith LA, 1996, Melody Transcription for Interactive Applications, University of Waikato, New Zealand.

[16] Weisling A, Xambo A, 2018, Proceedings of the Twelfth International Conference on Tangible, Embedded, and Embodied Interaction, March 18-21, 2018: Beacon: Exploring Physicality in Digital Performance, Association for Computing Machinery, New York, United States, 586-591. https://doi.org/10.1145/3173225.3173312

[17] Singhi A, Brown DG, 2014, Proceedings of the 15th International Society for Music Information Retrieval Conference, October 27-31, 2014: On Cultural, Textural, and Experimental Aspects of Music Mood. ISMIR, Taipei, Taiwan, 3-7.

[18] Hizlisoy S, Yildirim S, Tufekci Z, 2021, Music Emotion Recognition Using Convolutional Long Short Term Neural Networks, Engineering Science and Technology. An International Journal, 24(3): 760-767. https://doi.org/10.1016/j.jestch.2020.10.009

[19] Kimmerle J, Cress U, Held C, 2010, The Interplay Between Individual and Collective Knowledge: Technologies for Organizational Learning and Knowledge Building. Knowledge Management Research & Practice, 8(1): 33-34. https://doi.org/10.1057/kmrp.2009.36

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