Similarity-preserving hash for content-based audio retrieval using unsupervised deep neural networks

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ABSTRACT

Due to its efficiency in storage and search speed, binary hashing has become an attractive approach for a large audio database search. However, most existing hashing-based methods focus on data-independent scheme where random linear projections or some arithmetic expression are used to construct hash functions. Hence, the binary codes do not preserve the similarity and may degrade the search performance. In this paper, an unsupervised similarity-preserving hashing method for content-based audio retrieval is proposed. Different from data-independent hashing methods, we develop a deep network to learn compact binary codes from multiple hierarchical layers of nonlinear and linear transformations such that the similarity between samples is preserved. The independence and balance properties are included and optimized in the objective function to improve the codes. Experimental results on the Extended Ballroom dataset with 8 genres of 3,000 musical excerpts show that our proposed method significantly outperforms state-of-the-art data-independent method in both effectiveness and efficiency.

1. INTRODUCTION

With rapidly growing database of digital audio recordings, the novel retrieval strategies have received great attention. Early retrieval approach uses textual metadata describing the content of music audio (e.g., artist name, song title, album name, genre, or release year of music). In case such descriptions are not available, it is required content-based retrieval strategy that the perceptual aspects of the audio are utilized [1].

Content-based audio retrieval approach is generally solved with two steps: first, features are extracted from the audio file and then used to build indexes for searching. Two main issues of performing a search over a large database are search speed and efficient storage. The most interesting approach for handling these problems is binary hashing, where the high-dimensional features are encoded into compact binary codes.

There have been several hashing methods proposed in the literature. They can be devided into two categories, data-independent methods and data-dependent methods. Methods in data-independent category [2-7] use random linear projections or some arithmetic expression to construct hash functions. Without the training process, they are robust to data variation. However, such methods require long hash codes to achieve high precision. This increases the storage cost and degrades the search efficiency [8].

Methods in data-dependent category, also called learning to hash methods, aim to learn a set of hash functions from available training data that yield compact codes to achieve satisfactory search performance [9]. Existing data-dependent methods can be classified into unsupervised, supervised, and semi-supervised...
learning approach. Unsupervised hashing methods [10-12] use unlabeled data to build the hash functions where the neighbor distance (e.g., L2 norm) among the training data is preserved. Supervised or semi-supervised hashing methods [13-17] attempt to improve the quality of hashing by leveraging the semantic labels into the learning process. Compared with data-independent methods, it appears that data-dependent methods can achieve better accuracy with shorter codes [12, 14, 17]. However, data-dependent methods may be too dependent on the training data [18].

There are both advantages and shortcomings of using data-independent and data-dependent methods. However, the previous works of the two categories do not fully take into consideration the similarity preserving and this may degrade the retrieval performance. In this work, an unsupervised similarity-preserving hashing method for content-based audio retrieval is proposed. We develop a deep network with several hierarchical layers of nonlinear and linear transformations to learn compact binary codes where the similarity between samples is preserved. Furthermore, the independence and balance properties are included in the objective function to improve the codes. The proposed method is compared with the Shazam algorithm [3], the data-independent hashing method, in terms of accuracy, precision, recall, false positive rate, and the storage cost.

2. BACKGROUND
2.1. Learning to hash

Learning to hash attempts to learn a hash function \( y = h(x) \) that maps a high-dimensional input item \( x \in R^D \) to a compact code \( y \), aiming to improve the search performance [19]. There are 4 topics to consider for the learning to hash: (1) hash function, (2) similarity-preserving, (3) loss function, and (4) deep learning to hash.

2.1.1. Hash function

There are several ways to design hash functions. The most widely used hash functions are generalized by linear projection as shown in (1).

\[
y = h(X) = \text{sgn}(f(W^TX + b))
\]  

where \( y \in \{0,1\} \) or \( \{-1,1\} \), \( X = \{x_n\}_{n=1}^N \in R^{D\times N} \) is the training set which contains \( N \) samples, \( D \) is the dimension of input vector, \( W = \{w_k\}_{k=1}^K \in R^{D\times K} \) is the projection vector, \( K \) is number of hash bits, \( b \) is the bias variable, \( \text{sgn}(z) = -1 \) or 0 if \( z < 0 \) and \( \text{sgn}(z) = 1 \) otherwise, \( f(\cdot) \) is a predefined function which can possibly be neural networks or nonlinear function. However, using different \( f(\cdot) \) yields different hash function properties.

2.1.2. Similarity-preserving

The distance \( d_{ij} \) between two items \( x_i \) and \( x_j \) can be defined by the standardized Euclidean distance \( \|x_i - x_j\|^2_2 \) or others. The similarity \( s_{ij} \) between those items is often defined as a function of the distance \( d_{ij} \) (e.g., Gaussian function, cosine similarity, and so on). In addition, the semantic similarity approach is generally used in similarity search application. We can apply any distance to the hashing algorithm for semantic similarity, such as Euclidean distance, by defining semantic similarity \( s_{ij} = 1 \) for adjacent points and \( s_{ij} = 0 \) or \(-1\) for farther points.

In the hash coding space, the Hamming distance \( d_{ij}^H \) between the code \( y_i \) and \( y_j \) can be defined as \( \|y_i - y_j\|^1_1 = \sum_{k=1}^K |h_k(x_i) - h_k(x_j)| \). It is the number of binary digits where the values are different. Hamming similarity is defined as \( s_{ij}^H = K - d_{ij}^H \) for the codes valued by 1 and 0. For the codes valued by 1 and -1, the inner product \( s_{ij}^H = y_i^T y_j \) is defined as the similarity.

Let’s focus on the term of similarity preserving. In Figure 1(a), there is a set of three points \( (x_1, x_2, \text{ and } x_3) \) in an input space. By measuring the Euclidean distance between the points, we can find that \( x_1 \) is closer to \( x_2 \) than to \( x_3 \), i.e., \( x_1 \) is more similar to \( x_2 \) than \( x_3 \). The \( h(x_1), h(x_2), \text{ and } h(x_3) \) are the representations of \( x_1, x_2, \text{ and } x_3 \) in the hash coding space (or Hamming space), respectively. From the Figure 1(b), we can see \( h(x_1) \) is closer to \( h(x_3) \) while \( h(x_2) \) is far away. In this case, it shows that the similarities are not preserved. Figure 1(c), on the other hand, shows an example of the similarities that are well preserved.
2.1.3. Loss function

The loss function is intended to preserve the similarity order, i.e., minimize the difference between the nearest neighbor search result in the hash coding space and the search result in the input space. The loss function \( \text{Loss}(X, W) \) is defined as follows:

\[
\text{Loss}(X, W) = \arg \min \sum_{i,j \in X} \left\| d_{ij} - d_{ij}^H \right\|_2
\]

where \( X \) is the input data, and \( W \) is the projection vector.

Specifically, \( y_i = h(x_i) \) needs to be binary. This binary constraint leads to a difficult optimization problem. To solve the problem, we drop the binary constraint and let the codes be continuous. The codes are then binarized with thresholding. For binary constraint relaxation, various standard optimization techniques can be applied.

2.1.4. Deep learning to hash

The goal of learning to hash is to learn the specific hash functions that map high dimensional input vector to a compact binary vector that yields a good quality of retrieval and search speed [20]. For unlabeled data, an illustration of unsupervised deep learning to hash model that map the input vector \( x \in \mathbb{R}^D \) to compact binary codes is shown in Figure 2.
Assume that an unsupervised deep network consists of \(L+1\) layers. A binary vector \(y_i\) is generated by passing the input vector \(x_i\) through the network that contains multiple hierarchical layers of nonlinear functions. The binary code of \(x_i\) at \(l\)th layer can be calculated as follows:

\[
y_i = h(x_i) = \text{sgn}(F(x_i, W)) \tag{3}
\]

where \(F(x_i, W)\) is a composition of nonlinear transformations defined as follows:

\[
F(x_i, W) = f_1(\ldots f_L (f_1(x_i, w_{(1)}), w_{(2)}) \ldots w_{(L)}) \tag{4}
\]

where the vector \(x_i\) and the weight vector \(w_{(l)}\) are used as input, the projection \(x_{i+1}\) is produced by \(f_i(\cdot)\). The learning algorithm aims to learn a set of nonlinear weight vectors \(W = \{w_{(1)}, \ldots, w_{(L)}\}\) where the information from the input space is preserved.

2.2. Search with hashing

There are two strategies to perform a search with hashing, hash code ranking and hash table lookup [19]. For the hash code ranking, an exhaustive search is performed by comparing the distance (e.g., Hamming distance) between the query and the reference items. The items with the smallest distances, called nearest neighbors, are retrieved. However, the cost of computing the distance results in performance degradation. The alternative approach, hash table lookup aims to accelerate the search by reducing the distance computations. The inverse lookup database, called hash table, is composed of buckets which are indexed by the hash codes. Given the query, the matching items storing in the bucket are retrieved.

2.3. Audio fingerprinting

Audio fingerprinting is best known for its ability to identify an unknown audio recording by using its compact content-based signature so-called fingerprint [21]. It does this by converting the audio features into hash codes, aiming to uniquely identify an audio recording. The advantage of fingerprint is that, it reduces storage costs as fingerprint is relatively small. Moreover, the perceptual irrelevancies have been removed from fingerprint, resulting in efficient comparison and searching.

3. METHOD

The aim of this paper is to provide an efficient technique that yields a good quality of retrieval and computational efficiency. In this work, compact binary codes are learned for fingerprint indexing with unsupervised deep network in a way that the similarity between samples is preserved. Once, a short audio sample is taken to our content-based audio retrieval system, the system performs database lookup for matching track and then returns the song ID that the query is taken. As shown in Figure 3, the system is designed with three steps: (1) Fingerprint feature extraction, (2) Unsupervised similarity-preserving hashing, and (3) Sequence matching.

![Figure 3. The construction of proposed method for our content-based audio retrieval system](image-url)
3.1. Fingerprint feature extraction

Before fingerprint feature extraction is performed, the audio signal is converted into a common format for analysis. Next, the time-series audio signal is converted into time-frequency domain from which more meaningful information can be extracted. Below each aspect is detailed.

3.1.1. Preprocessing and transform

In this paper, the fingerprint extraction presented in [3] is applied. Firstly, we convert the input audio to mono signal and downsampled from the standard digital audio of 44.1KHz, to 8KHz, to make the data easier to handle, reducing database size, and increasing speed of the algorithm. The audio signal is then converted into the time-frequency representation. We perform a short-time fourier transform (STFT) with a window size of 64 ms, for good spectrum resolution [22] and a hop size of 32 ms. Figure 4 shows time-frequency graph so-called a spectrogram. On the horizontal axis is time, on the vertical is frequency, and on the third is intensity. Each point on the graph represents the intensity of a given frequency at specific time.

Figure 4. Spectrogram with peak intensities

3.1.2. Feature extraction

After converting the signal into the time-frequency domain, the features are then extracted from the spectrum. Due to their robustness to noise and distortions, the amplitude peaks in each frame are selected as candidate points. Each candidate point is paired with the adjacent peaks. The constellation map of paired points with coordinate list is shown in Figure 5. In this work, each candidate point is paired within 31 frequency bins and 63 time frames. Only the closest 3 peaks in time to each other are selected. Figure 6 shows the combinatorial association of a pair of two points which is called a ‘landmark’. For each pair, it consists of four components, the starting frequency $f_1$, the starting time $t_1$, the end frequency $f_2$, and the end time $t_2$.

Figure 5. A constellation map of paired points

Figure 6. The combinatorial association of a pair of two points
3.1.3. Audio fingerprint

For the landmark as mentioned above, the audio fingerprint can be defined as follows:

\[
\text{Fingerprint} = [f_1, \Delta f, \Delta t] \tag{5}
\]

where the frequency difference \( \Delta f = f_2 - f_1 \), and the time difference between the two points \( \Delta t = t_2 - t_1 \). The fingerprint is also associated with the offset time from the beginning of the audio file to the starting time \( t_1 \).

This fingerprint feature \([f_1, \Delta f, \Delta t]\) is used to generate hash code in [3]. The hash model can be defined as shown in (6).

\[
f_1 \times 2^{12} + \Delta f \times 2^6 + \Delta t \tag{6}
\]

where a fingerprint hash is composed of 8-bit frequency \( f_1 \), 6-bit frequency difference \( \Delta f \), and 6-bit time difference \( \Delta t \). Figure 7 shows an example of 20-bit hash address calculated from (6).

| [f_1, \Delta f, \Delta t] | Hash Function | Hash Address |
|--------------------------|--------------|--------------|
| [216, 18, 36]            | \( f_1 \times 2^{12} + \Delta f \times 2^6 + \Delta t \) | \( 885924 = 11011000010010100100 \) |

Figure 7. An example of 20-bit hash address

For a 16-bit fingerprint hash, it is composed of 6-bit frequency \( f_1 \), 5-bit frequency difference \( \Delta f \), and 5-bit time difference \( \Delta t \). The hash model can be defined as shown in (7).

\[
f_1 \times 2^{10} + \Delta f \times 2^5 + \Delta t \tag{7}
\]

After the hash code is calculated, the system then uses this code as an index for searching in the database. An exact matching algorithm is applied in [3]. Unlike the Shazam algorithm, we develop a deep neural network with multiple hierarchical layers of nonlinear and linear transformations to learn compact codes from these fingerprint features such that the similarity between samples is preserved. The details are described further in the next section.

3.2. Unsupervised similarity-preserving hashing (USH)

In this paper, the hash transformations are created by an unsupervised deep neural network. As shown in Figure 8, there are 5 layers in our deep network: the input layer consists of 20 nodes of input \( x_i \), the three hidden layers consist of 19, 18, and 16 nodes respectively, and there are 20 nodes of \( X_i \) in the output layer.

Figure 8. Our proposed unsupervised similarity-preserving hashing network (USH)
Our deep network is learned so that the output of the fourth layer can be used as the binary hash codes. For the network design, each node is composed of one input summation function and one output transformation function. The function \( f(\cdot) \) is used to combine information by the links from other nodes, as shown in (8).

\[
\text{node}_{in} = f(x_{(i),1}, x_{(i),2}, \ldots, x_{(i),n}; w_{(i),1}, w_{(i),2}, \ldots, w_{(i),n}) \tag{8}
\]

where \( x_{(i),1}, x_{(i),2}, \ldots, x_{(i),n} \) are the inputs to the node, \( w_{(i),1}, w_{(i),2}, \ldots, w_{(i),n} \) are the associated weights, \( l \) indicates the layer number, and \( n \) is the number of input nodes. The output activation function \( a(f(\cdot)) \) is shown in (9).

\[
\text{node}_{out} = a_{(i)}(\text{node}_{in}) = a_{(i)}f(\cdot) \tag{9}
\]

Let \( H_l \) be the sum of product of input \( x_i \) and weight \( w_i \). \( H_l = \sum w_i x_i \), the functions of the nodes from layer 1 to layer 5 of our proposed network are defined as follows:

Layer 1: In this layer, the nodes only convey inputs to the nodes of the next consecutive layer. The functions of the \( i \)-th node are shown as;

\[
f_{(1),i} = x_{(1),i} \quad \text{and} \quad a_{(1),i} = f_{(1),i} \tag{10}
\]

Layer 2: For this layer, the sigmoid function is used as activation function. Let \( x_{(2),i} = a_{(1),i} \) and \( H_{(2),i} = \sum w_{(2),i} x_{(2),i} \). Thus, the functions of the \( i \)-th node are defined as;

\[
f_{(2),i} = \frac{1}{1 + e^{-H_{(2),i}}} \quad \text{and} \quad a_{(2),i} = f_{(2),i} \tag{11}
\]

Layer 3: In this layer, the sigmoid function is applied for activation function. Let \( x_{(3),i} = a_{(2),i} \) and \( H_{(3),i} = \sum w_{(3),i} x_{(3),i} \). The functions of the \( i \)-th node are defined as;

\[
f_{(3),i} = \frac{1}{1 + e^{-H_{(3),i}}} \quad \text{and} \quad a_{(3),i} = f_{(3),i} \tag{12}
\]

Layer 4: The output of each node in this layer will be used as the binary codes. During training, these codes are used to reconstruct the input data at the output layer. The hyperbolic tangent function is particularly used as activation function in this layer. Let \( x_{(4),i} = a_{(3),i} \) and \( H_{(4),i} = \sum w_{(4),i} x_{(4),i} \). The functions of the \( i \)-th node are defined as;

\[
f_{(4),i} = \frac{e^{H_{(4),i}} - e^{-H_{(4),i}}}{e^{H_{(4),i}} + e^{-H_{(4),i}}} \quad \text{and} \quad a_{(4),i} = f_{(4),i} \tag{13}
\]

Layer 5: This layer is the output or reconstruction layer. To preserve the similarity between samples, thus, the target outputs are given the same as the inputs of layer 1. Let \( x_{(5),i} = a_{(4),i} \) and \( H_{(5),i} = \sum w_{(5),i} x_{(5),i} \). The functions of the \( i \)-th output node are defined as;

\[
f_{(5),i} = H_{(5),i} \quad \text{and} \quad a_{(5),i} = f_{(5),i} \tag{14}
\]

To achieve the efficient binary codes, we include constraints in the objective function so that the codes have 4 properties: (1) belonging to \( \{1, -1\} \), (2) similarity-preserving, (3) independent, and (4) balancing. In this paper, the method presented in the UH-BDNN [23] is applied to optimize the objective function which is defined as follows:

\[
\begin{align*}
\min_{W, b, \lambda} \text{Loss} &= \frac{1}{2N} \| X - (W_{(L-1)}Y + b_{(L-1)} \times [1]_{1 \times N}) \|^2 \\
&+ \frac{\lambda_2}{2} \sum_{l=1}^{L-1} \| W_l \|^2 + \frac{\lambda_3}{2N} \| H_{(L-1)} - Y \|^2 \\
&+ \frac{\lambda_4}{2} \| H_{(L-1)}^T H_{(L-1)} - I \|^2 + \frac{\lambda_4}{2N} \| H_{(L-1)} [1]_{N \times 1} \|^2 \\
st. Y \in \{1,-1\}^{K \times N}
\end{align*}
\tag{15}
\]

Similarity-preserving hash for content-based audio retrieval using ... (Petcharat Panyapanuwat)
where $X \in \mathbb{R}^{D \times N}$ is a set of $N$ training data with $D$ dimension, $Y \in \{1, -1\}^{K \times N}$ is output binary code of $X$, $K$ is number of bits, $L$ is number of layers, $W_{(l)}$ is weight matrix between layer $l + 1$ and layer $l$, $b$ is bias vector for nodes in layer $l + 1$, $H_{(l)} = f_{(l)}(w_{(l-1)}H_{(l-1)} + b_{(l-1)}[1]_{x \times n})$ is the output values of layer $l$, $H_{(1)} = X$, $f_{(l)}$ is activation function of layer $l$, and $\lambda_1 - \lambda_d$ are the parameters for optimizing the objective function.

The first term of (15) makes sure that the binary code allows a good reconstruction of $X$. The second term is a weight regularization that encourages the network to keep the weights small in order to reduce overfitting. The third term measures the equality constraint violation. The fourth term is the independence,

$$
\phi = \frac{1}{r} \sum_{j \in R} \sum_{i \in S} x_{ij} y_{ij} - \frac{1}{r} \sum_{j \in S} \sum_{i \in R} x_{ij} y_{ij}
$$

$$
\Delta f = \frac{1}{N} \sum_{(x, y) \in D} \left( y - \hat{y}(x) \right)^2
$$

As shown in (16) is to ensure that each bit of the binary codes belongs to $\{1, -1\}$. After the efficient codes are produced from deep-learning network, these codes are used as search index in our content-based audio retrieval system. The song ID, $t_1, f_1, \Delta f$ and $\Delta t$ are stored at their hash address in the database. Table 1 shows the representation of information data.

### Table 1. Representation of information data

| Method      | Index                | Information Data             |
|-------------|----------------------|------------------------------|
| USH         | 16 bits Hash Address | Song ID, $t_1, f_1, \Delta f, \Delta t$ |
| Shazam [3]  | 16-bit / 20-bit Hash Address | Song ID, $t_1$ |

3.3. Sequence matching

For the query step, a sequence of query features is generated to a set of compact hash codes and used for searching in the inverse lookup database. Let $Q$ represent a set of sequences of query features, $Q = \{q_1, q_2, \ldots, q_M\}$, where $q_m$ is a query at order $m$, $m = 1, 2, \ldots, M$, and $M$ is the total number of sequences. The learning hash function $H: q_m \rightarrow h(q_m)$, is used to map the query features to binary hash codes. We can define $Q = \{q_m\}_{m=1}^M$ to the corresponding binary codes as follows:

$$
Y = H(Q) = \{h(q_1), h(q_2), \ldots, h(q_M)\}
$$

where $Y$ is the hash codes of $Q$, $Y \in \{1, -1\}^{K \times Q}$, and $K$ is the number of bits. After learning deep network, we obtain a set of items that indexed by the hash address. Let $s_m = \{x_{m1}, x_{m2}, \ldots, x_{mn_m}\}$ be a set of items of $q_m$, $x_{mi} \in \mathbb{R}^{S \times 1}$ be the information vector that are stored in the database, and $n_m$ is the number of items of $q_m$. Given $S = \{s_m\}_{m=1}^M$ is a set of $s_m$ where $m = 1, 2, \ldots, M$, the sequence matching process is shown in Figure 9.

![Figure 9. Our proposed sequence matching](image-url)
As can be seen in Figure 9, assume that \( Q = \{ q_1, q_2, q_3 \} \), and get the binary codes \( H(Q) \), we obtain a set of \( S_m \), \( s_1 = \{ x_{11}, x_{12}, x_{13}, x_{14} \}, s_2 = \{ x_{21}, x_{22} \}, s_3 = \{ x_{31}, x_{32}, x_{33} \}, \) and \( S = \{ x_{11}, x_{12}, x_{13}, x_{14}, x_{21}, x_{22}, x_{31}, x_{32}, x_{33} \} \). One nearest neighbor search \( \text{NN}(q_m) \) for a query item at order \( m \) from \( S_m \) is defined as follows:

\[
\text{NN}(q_m) = \arg \min_{x_m \in S_m} \| x_m - q_m \|_2
\]

(18)

where \( \| x_m - q_m \|_2 \) is the \( L_2 \)-norm between \( x_m \) and sequences \( q_m \). Given \( R_Q = \{ \text{NN}(q_m) \}_{m=1}^{M} \) is a candidate items set of \( Q \). We also apply a time offset constraint for improving the accuracy of the sequence matching. The time offset constraint \( |T_{x_m} - T_{q_m}| \) is the absolute difference between \( T_{x_m} \) and \( T_{q_m} \). It can be defined as follows:

\[
|T_{x_1} - T_{q_1}| = \cdots = |T_{x_M} - T_{q_M}|
\]

(19)

where \( T_{x_m} \) and \( T_{q_m} \) are the offset time of reference file \( x_m \) and query \( q_m \), respectively. The constraint of offset time can be analyzed that a sequence of candidate items should occur with the same absolute difference among the time sequences. Our proposed has the following procedures.

In summary, the proposed audio retrieval algorithm is based on two parts, the similarity (minimum distance) between the audio query and the song in the reference database, and the absolute difference among the time sequences.

Algorithm: Similarity-preserving hash for content-based audio retrieval using unsupervised deep neural networks

**Input:**
- \( M = \{ m_i \}_{i=1}^{N} \): reference set;
- \( Q \): query set;

**Output:**
- \( \text{SID} \): Song ID is returned by proposed algorithm.

**Step 1:**
Extracting fingerprint features \( X = \{ x_i \}_{i=1}^{N} \in R^{D \times N} \) from the reference dataset.

**Step 2:**
Learning hash where \( x_i \in R^D \) is an input vector. The objective function defined as equations 15-16. In this step, we apply the learning function \( h(q) \) for audio fingerprint \( q \) in step 3.

**Step 3:**
Sequence matching
1. The query sample is divided into \( M \) fingerprints \( Q = \{ q_m \}_{m=1}^{M} \).
2. \( s_i = \{ \}, A = \{ \}, S = \{ \}, R_Q = \{ \} \) for \( i = 1, 2, \ldots, M \) do
   \[ \text{index}_i = h(q_i) \]
   \[ s_i = \text{all items in } A(\text{index}_i) \text{ are collected into } s_i \]
   \[ S = S \cup s_i \]
   end
   for \( i = 1, 2, \ldots, M \) do
     \[ \text{Aux} = \max \text{Value} \]
     for \( j = 1, 2, \ldots, \text{sizeOf}(s_i) \) do
       if \( \| x_j - q_i \|_2 < \text{Aux} \)
       \[ \text{Aux} = \| x_j - q_i \|_2 \]
       \[ \text{absTime} = |T_{s_j} - T_{q_i}| \]
       \[ \text{SID} = SID_{s_j} \]
     end
     end
     \[ R_Q = R_Q \cup \{ \text{SID}, \text{absTime} \} \]
   end
3. Finding max frequency of each Song ID of \( R_Q \) where they have same absolute difference among the time sequences.

4. EXPERIMENTAL AND PERFORMANCE ANALYSIS

4.1. Database

The performance of our proposed USH method is evaluated on the Extended Ballroom dataset freely available in [24, 25]. The dataset consists of 4,180 musical excerpts of 13 genres with a length of 30 seconds each. The audio quality of this data is 44.1kHz, 192-kbps, stereo, mp3 format. In this work, the audio signal is downsampled to 8kHz, to make the data easier to handle as previously mentioned. The training set (also used as reference database for retrieval) is composed of 3,000 tracks from 8 genres, the same rhythm class as our previous works [26, 27]. A set of 1,000 audio queries with a length of 10 seconds each are
randomly selected from those 3,000 tracks. Another set of 200 audio queries comes from audio files that
do not appear in the database, in order to analyze the false positive rate. Each audio sample is represented by
a 20-dimensional feature vector extracted by fingerprint algorithm. Table 2 shows the number of samples in
the database and the query set.

| Set       | Number of tracks | Length of segment (s) | Number of samples |
|-----------|------------------|-----------------------|-------------------|
| Database  | 3,000            | 30                    | 441,184           |
| Query     | 1,200            | 10                    | 67,785            |

4.2. Performance evaluation

4.2.1. Effectiveness of retrieval

On a total of 1,200 audio queries, the retrieval results obtained from our proposed USH method and
state-of-the-art data-independent method, the Shazam algorithm, are shown in Table 3. The false negative
(FN) refers to the incorrect identification that the query audio does not exist in the database when it does,
true positive (TP) refers to the correct identification of the audio recording from the query, false positive (FP)
refers to the incorrect identification of the wrong recording when the correct recording does not exist in
the database, and true negative (TN) refers to the correct identification that no audio recording matches the query.
According to the experimental results, we obtain higher percentage of accuracy (88.92%) for the proposed USH
than state-of-the-art data-independent method, the Shazam algorithm (71.67% for 16-bit hash code, 87.42%
for 20-bit hash code). Figure 10 shows the retrieval accuracy comparison between the two different methods.

| Method      | FN  | TP  | FP  | TN  |
|-------------|-----|-----|-----|-----|
| USH 16-bit  | 114 | 866 | 19  | 181 |
| Shazam 16-bit| 290 | 710 | 50  | 150 |
| Shazam 20-bit| 132 | 868 | 19  | 181 |

Figure 10. The retrieval accuracy of the proposed USH and the Shazam algorithm

The effectiveness of the USH is evaluated through the experiments and compared with state-of
the-art data-independent method in terms of precision, recall, F1 score, and false positive rate [28], as follows:

\[
Precision = \frac{TP}{TP+FP} \times 100 
\]  \hspace{1cm} (20)

\[
Recall = \frac{TP}{TP+FN} \times 100 
\]  \hspace{1cm} (21)

\[
F1 \text{ score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} 
\]  \hspace{1cm} (22)

\[
False \text{ Positive Rate} = \frac{FP}{FP+TN} \times 100 
\]  \hspace{1cm} (23)

As can be seen in Table 4, we obtain higher precision and recall values for the proposed USH than
state-of-the-art data-independent method both in 16-bit and 20-bit hash code. The F1 score (in the fourth
column) shows the overall effectiveness of two different methods. Furthermore, the USH has a significantly
lower percentage of false positives (9.50%) than state-of-the-art data-independent method (25.00%) for the same 16-bit hash code. Its shows the superior performance of the USH on short codes.

Table 4. Effectiveness comparison between USH and state-of-the-art data-independent method

| Method      | Precision | Recall | F1 score | % False positive |
|-------------|-----------|--------|----------|------------------|
| USH 16-bit  | 97.90     | 88.60  | 93.02    | 9.50             |
| Shazam 16-bit| 93.42     | 71.00  | 80.68    | 25.00            |
| Shazam 20-bit| 97.86     | 86.80  | 92.00    | 9.50             |

4.2.2. Storage cost

As a result of our proposed USH method, the 20-bit fingerprint features can be mapped into the 16-bit binary code. Hence, it significantly reduces the database size by 16-fold, resulting in higher search performance.

4.3. Discussion

The performance of the proposed USH for large audio database retrieval is evaluated through the experiments and compared with state-of-the-art data-independent hashing method, the Shazam algorithm, on a test set of 3,000 audio recordings. The experimental results support the effectiveness of the USH with high precision and recall values at 97.90% and 88.60% respectively. For the satisfactory results, the hash codes produced from our proposed method have similarity preserving property, i.e., the similarity items are mapped to the same hash code, the dissimilarity items are mapped to another one. The data-independent methods do not take into account for this property.

The Shazam algorithm has higher percentage of false positives (25.00%) than the USH (9.50%) for the same 16-bit hash code. It shows that the Shazam algorithm is more likely to give incorrect identifications for the short-length codes and that is of inferior performance in audio retrieval. Furthermore, if the database size is increased tremendously in the future, it is most likely that the Shazam algorithm would result a significant number of false positive matches.

Let’s consider the collection S of the USH and the Shazam algorithm which effect to the accuracy of audio retrieval. For the Shazam algorithm, the collection S consists of the data items where the search algorithm tries to find only the matching items for those search queries regardless of similarity preserving, and this may result in losing a number of relevant data. For the collection S of our proposed USH method consists of candidate data items where the search algorithm focuses on the similarity between the search queries and the items in the database. As shown in Table 5, with the collection S of the USH, the Song ID 48 is correctly identified by the two data items with the smallest distance (distance=1) at the same time offset. For the Shazam algorithm, the relevant song cannot be retrieved.

Table 5. Example of the collection S of the proposed USH and the Shazam algorithm

| Method      | Song ID  | Time offset | Distance | Number of item(s) |
|-------------|----------|-------------|----------|-------------------|
| USH 16-bit  | 150      | 128         | 16       | 2                 |
|             | 1043     | 239         | 28       | 2                 |
|             | 936      | -232        | 32       | 2                 |
|             | 48*      | 152         | 1        | 2                 |
|             | 306      | 228         | 48       | 2                 |
|             | 2455     | 516         | 24       | 2                 |
|             | 690      | 3720        | 32       | 1                 |
|             | 690      | 2726        | 32       | 1                 |
| Shazam 16-bit| 2732     | 164         | -        | 2                 |
|             | 847      | 19          | -        | 2                 |
|             | 684      | 2871        | -        | 1                 |
|             | 674      | 4475        | -        | 1                 |
|             | 675      | 2584        | -        | 1                 |
|             | 676      | 1564        | -        | 1                 |
|             | 676      | 4739        | -        | 1                 |
|             | 677      | 1820        | -        | 1                 |
| Shazam 20-bit| 1174     | 52          | -        | 1                 |
|             | 1176     | 557         | -        | 1                 |
|             | 1230     | 218         | -        | 1                 |
|             | 706      | 363         | -        | 1                 |
|             | 340      | 395         | -        | 1                 |
|             | 48       | 153         | -        | 1                 |
|             | 93       | 448         | -        | 1                 |
|             | 139      | 453         | -        | 1                 |

* Refers to the system correctly identifies the audio recording
The major factors for our superiority are that 1) the similarity-preserving hash codes produced from our proposed USH method, and 2) the audio retrieval algorithm proposed composes of 2 metrics, one is the $L_2$-norm, and the other is absolute offset time difference. These factors increase the ability to identify the candidate items according to the similarity level of audio sample and the songs in the reference database. And this significantly improves the retrieval performance.

5. CONCLUSION

In this paper, an unsupervised similarity-preserving hashing (USH) method for content-based audio retrieval is proposed. We develop a deep network with multiple hierarchical layers of nonlinear and linear transformations to learn compact hash codes where the similarity between samples is preserved. The independence and balance properties are included and optimized in the objective function to improve the codes. The experimental results on the Extended Ballroom dataset show the superiority of our proposed method over state-of-the-art data-independent method. It is suggested future work should be focused on extending USH to supervised hashing by leveraging the semantic labels to enhance the retrieval performance.

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