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(54) RECOGNIZER OF DIGITAL SIGNAL CONTENT

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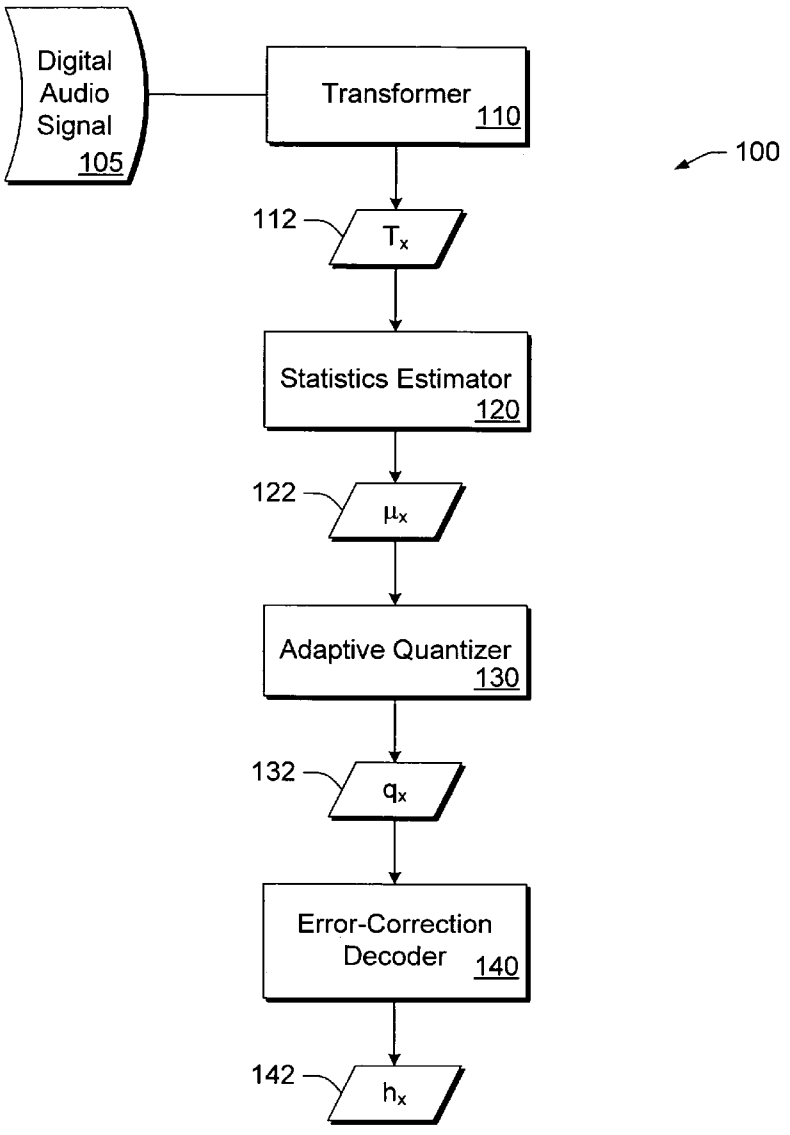
(52) **U.S. Cl.** **713/189**

(57) **ABSTRACT**

Described herein is a technology for recognizing the content of digital signals. The technology determines one or more hash values for the original content of a digital signal. The scope of the present invention is pointed out in the appending claims.



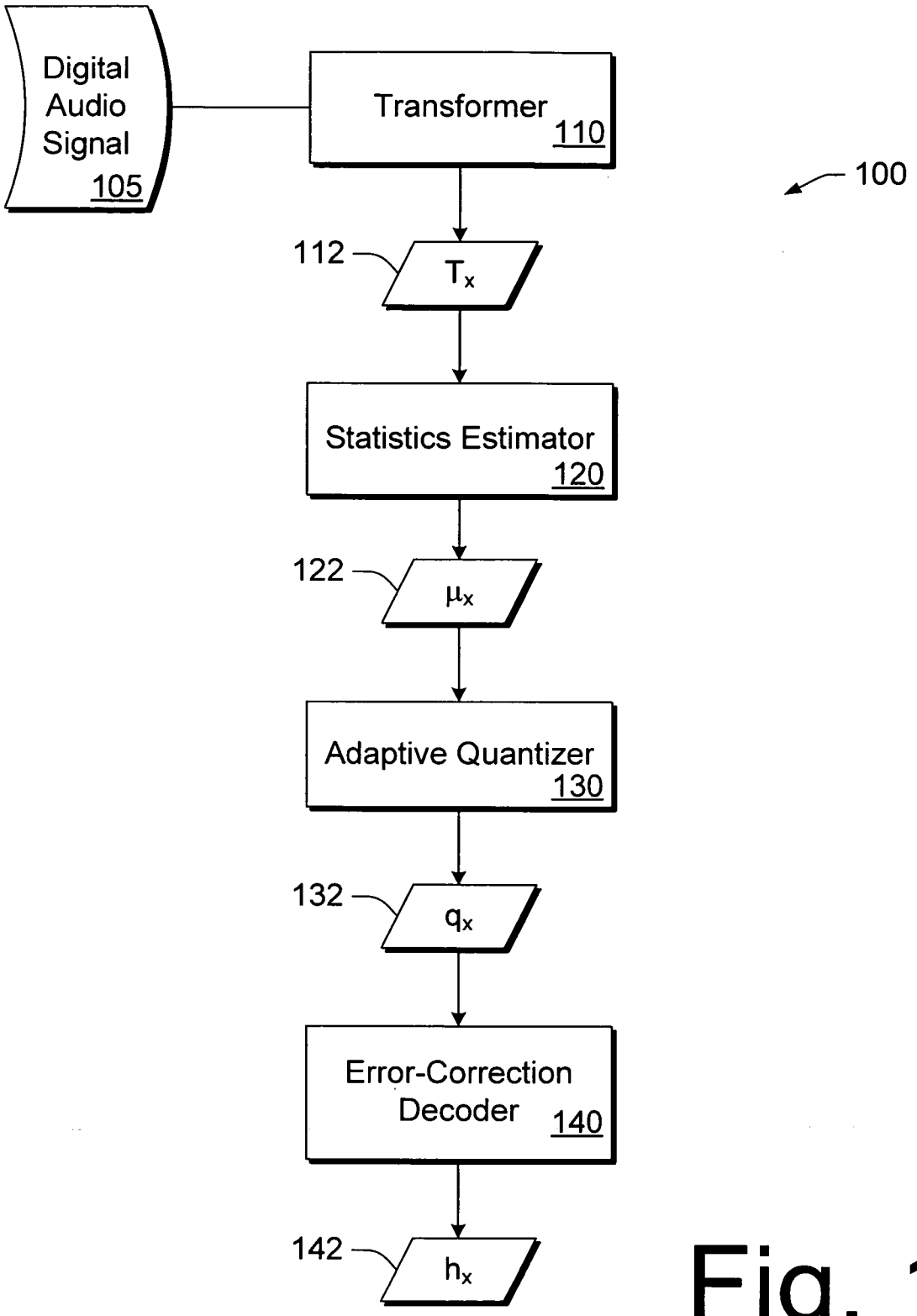

Digital Audio Signal 105
Transformer 110
100
112
T_x
Statistics Estimator 120
122
μ_x
Adaptive Quantizer 130
132
q_x
Error-Correction Decoder 140
142
h_x

Fig. 1

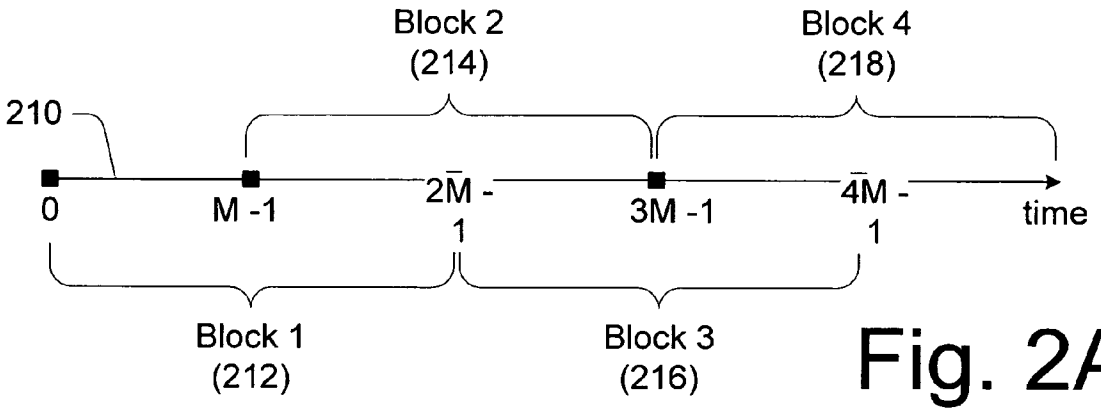


Fig. 2A

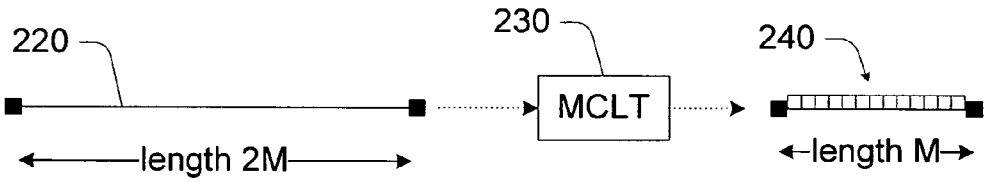


Fig. 2B

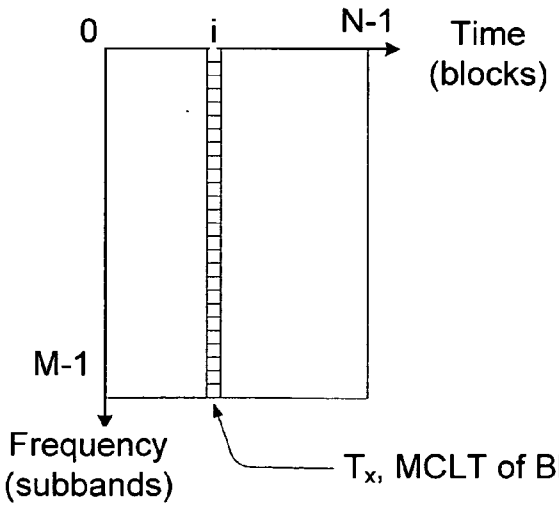


Fig. 2C

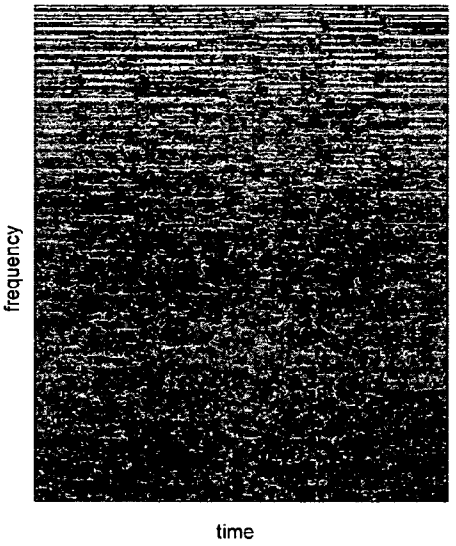


Fig. 3A-1

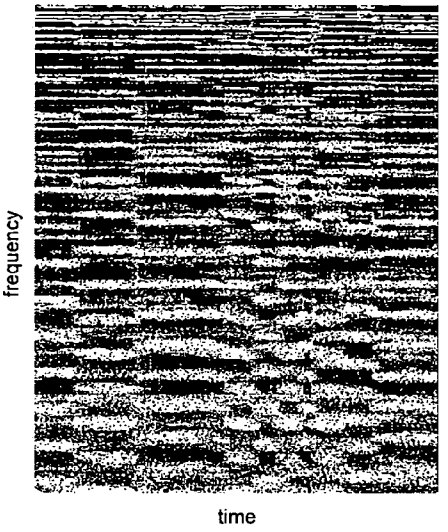


Fig. 3A-2

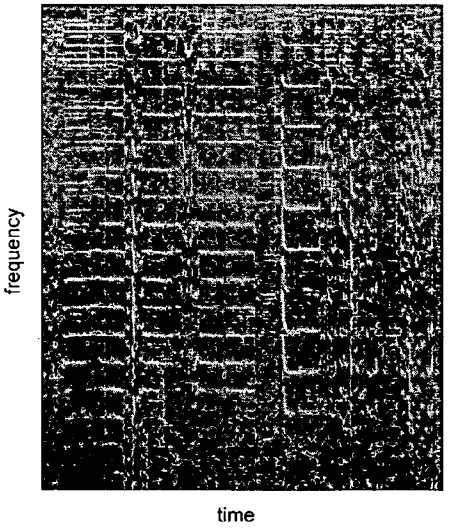


Fig. 3B-1

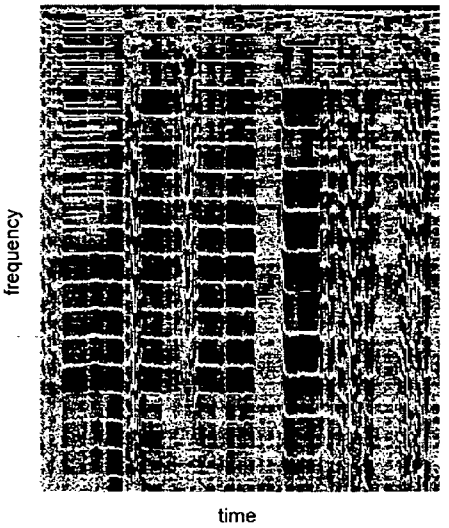


Fig. 3B-2

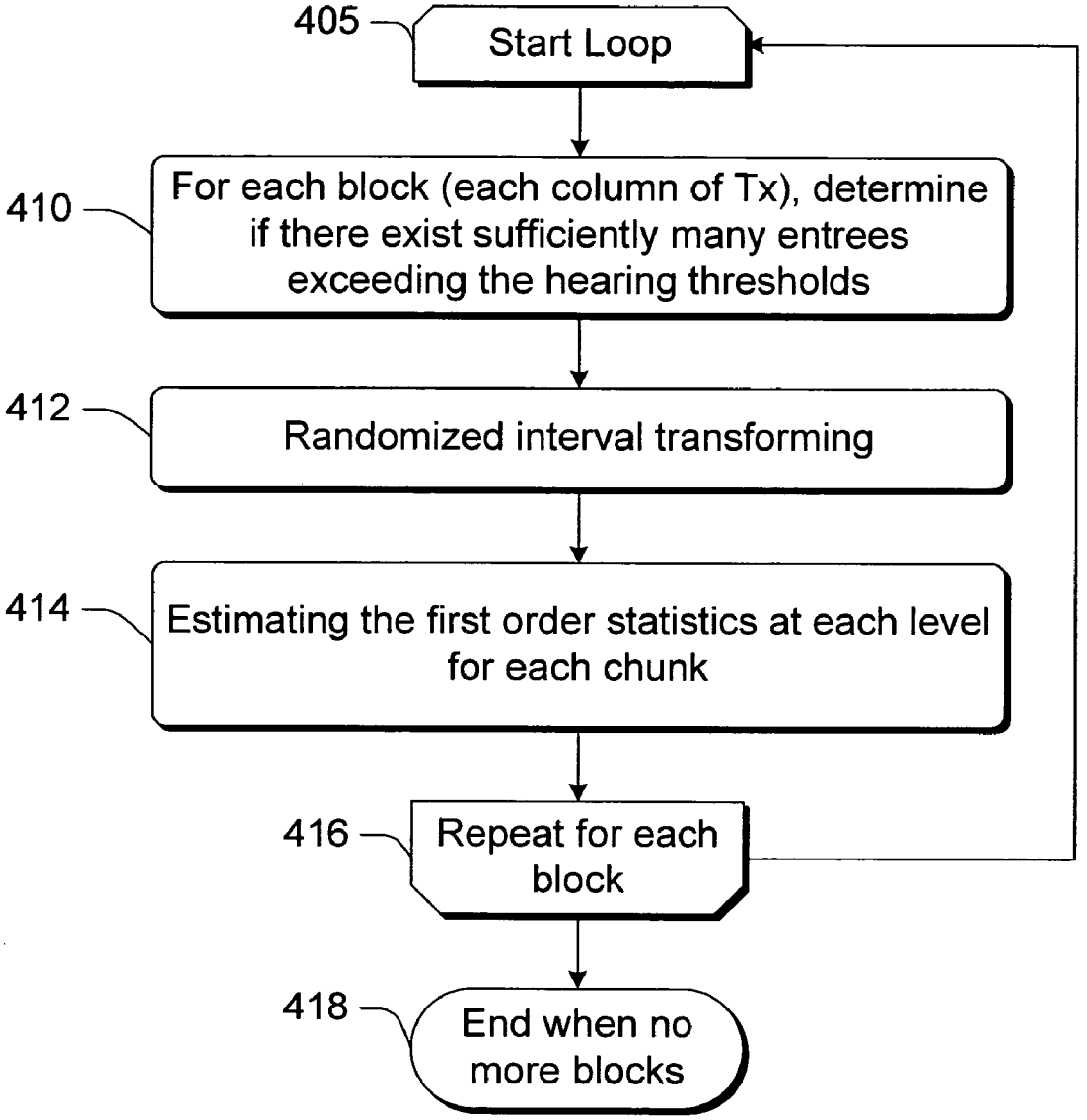

405
Start Loop
410
For each block (each column of Tx), determine if there exist sufficiently many entrees exceeding the hearing thresholds
412
Randomized interval transforming
414
Estimating the first order statistics at each level for each chunk
416
Repeat for each block
418
End when no more blocks

Fig. 4

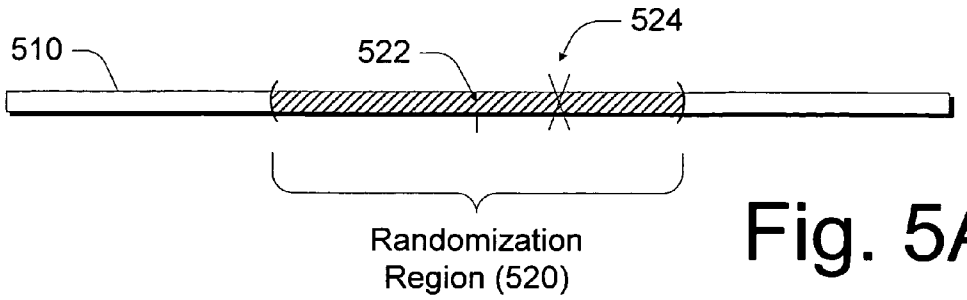


Fig. 5A

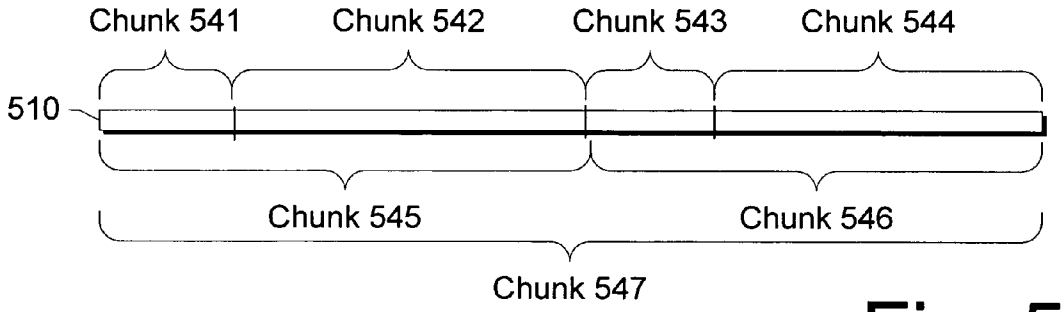


Fig. 5B

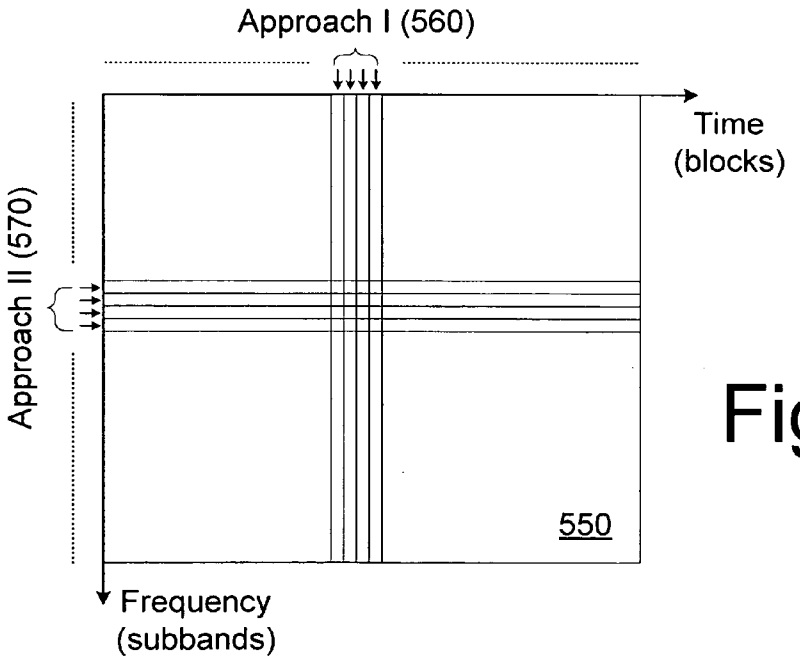


Fig. 5C

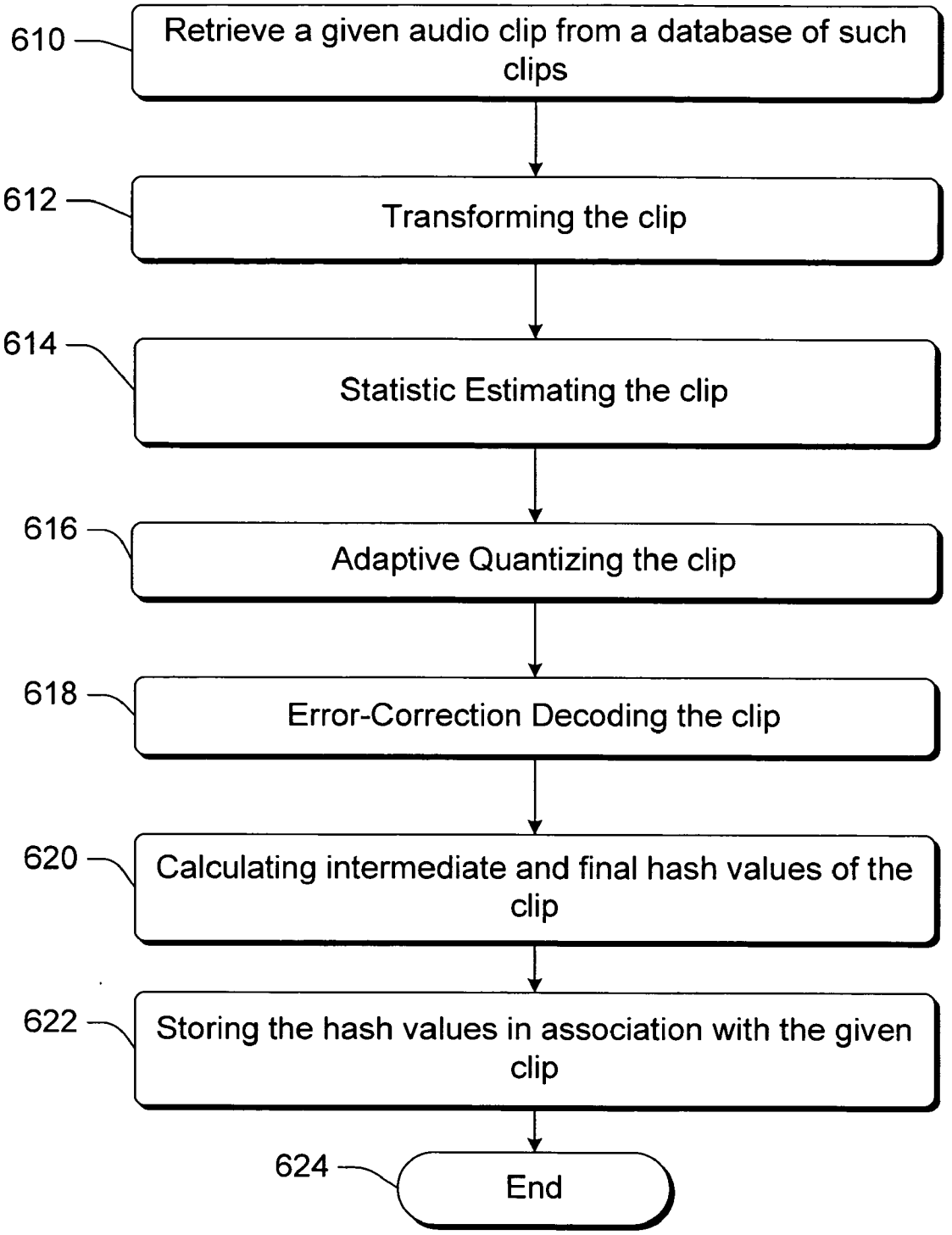

610
Retrieve a given audio clip from a database of such clips
612
Transforming the clip
614
Statistic Estimating the clip
616
Adaptive Quantizing the clip
618
Error-Correction Decoding the clip
620
Calculating intermediate and final hash values of the clip
622
Storing the hash values in association with the given clip
624
End

Fig. 6

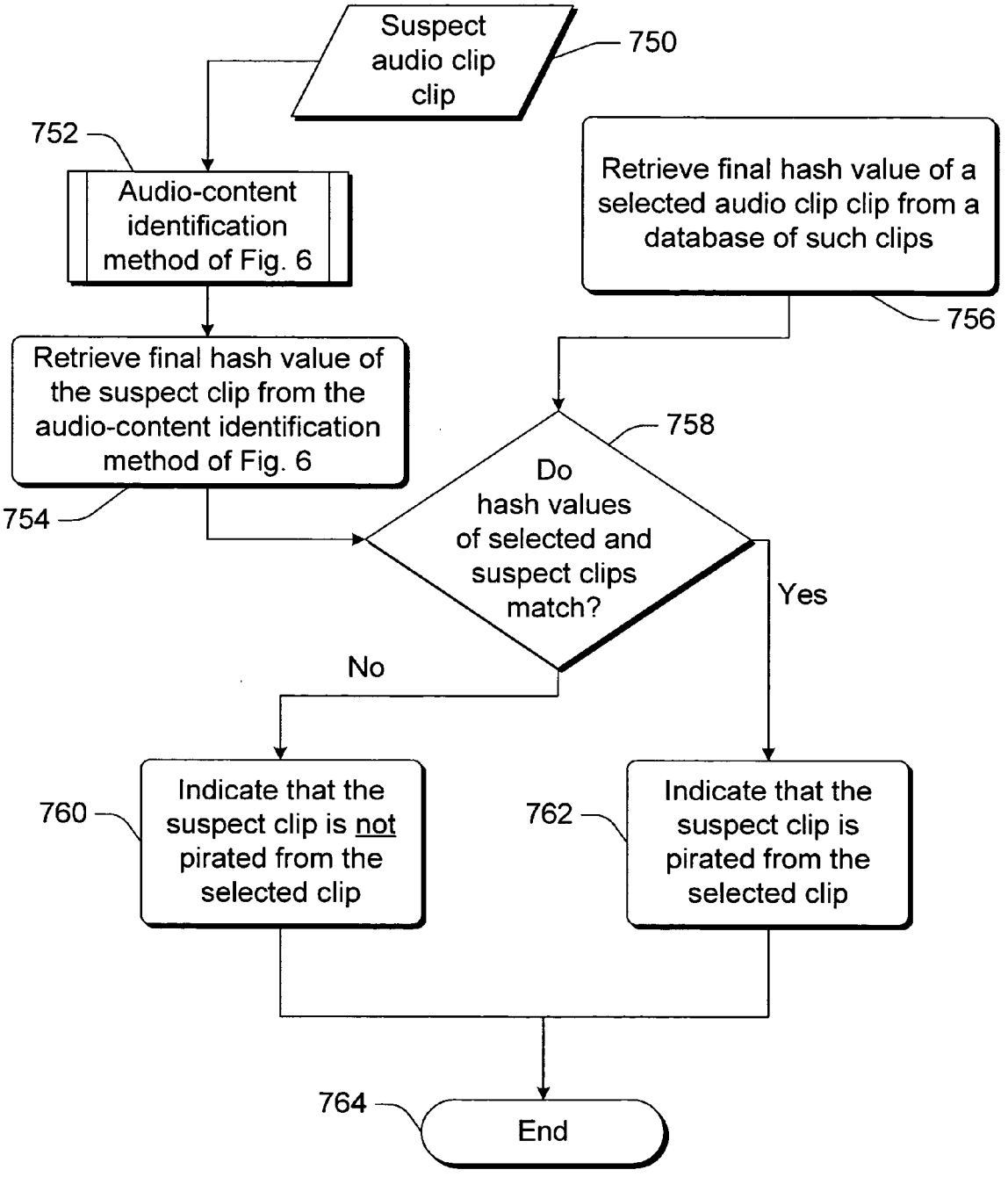

Suspect audio clip clip
750
752
Audio-content identification method of Fig. 6
Retrieve final hash value of a selected audio clip clip from a database of such clips
756
Retrieve final hash value of the suspect clip from the audio-content identification method of Fig. 6
754
758
Do hash values of selected and suspect clips match?
Yes
No
760
Indicate that the suspect clip is not pirated from the selected clip
762
Indicate that the suspect clip is pirated from the selected clip
764
End

Fig. 7

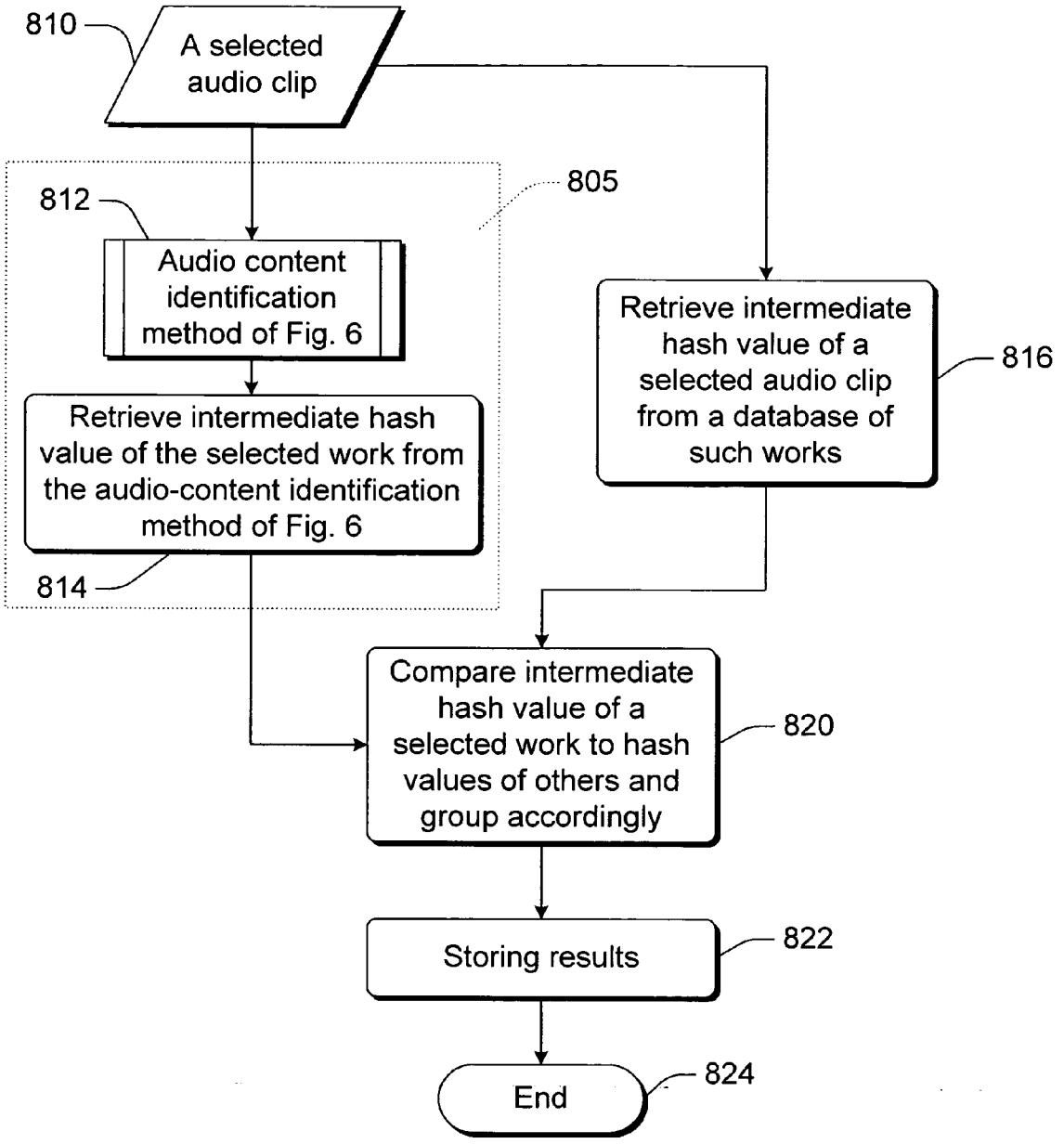

810
A selected audio clip
805
812
Audio content identification method of Fig. 6
Retrieve intermediate hash value of the selected work from the audio-content identification method of Fig. 6
814
Retrieve intermediate hash value of a selected audio clip from a database of such works
816
Compare intermediate hash value of a selected work to hash values of others and group accordingly
820
Storing results
822
End
824

Fig. 8

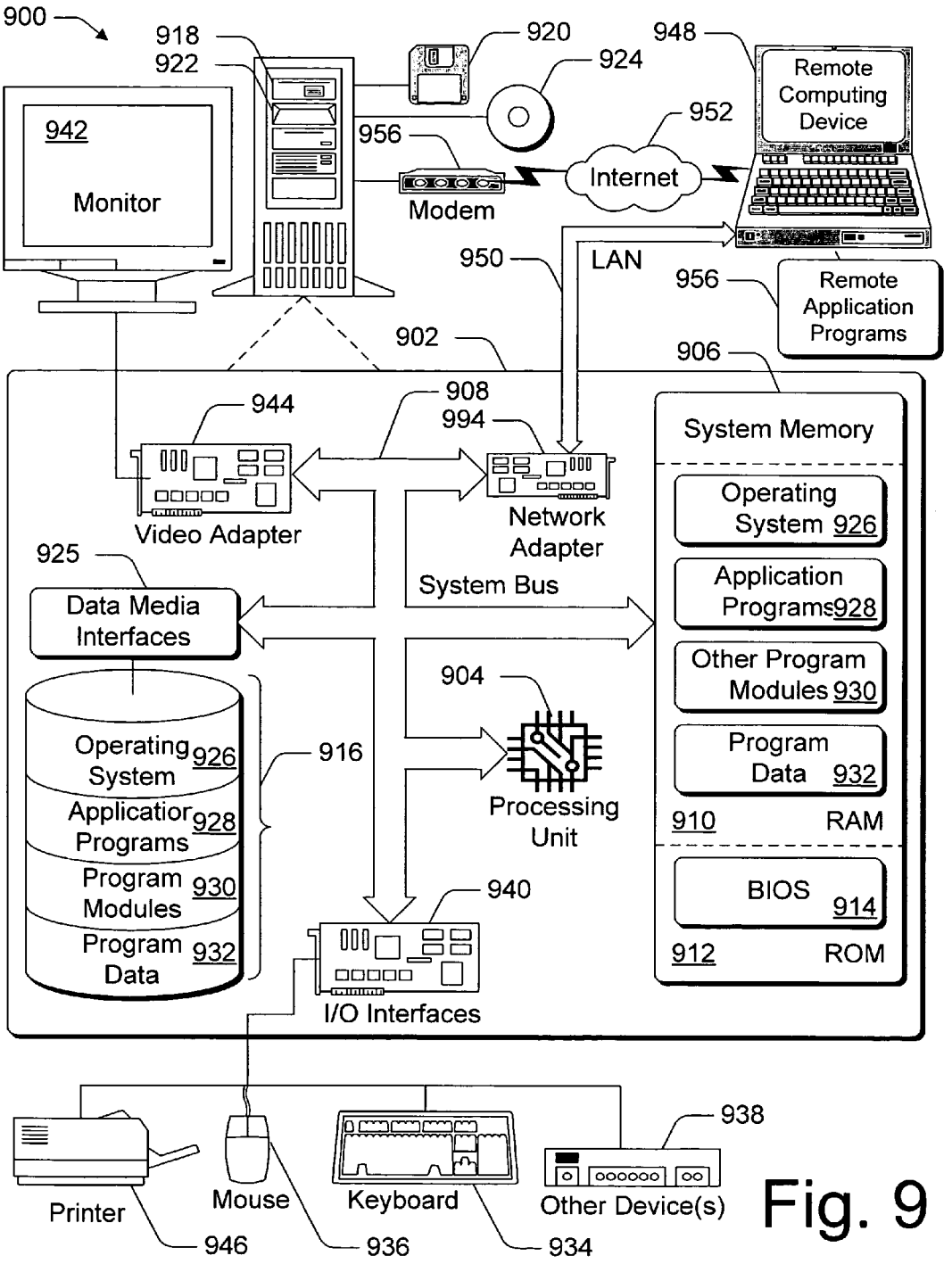

900
918
922
920
924
948
Remote Computing Device
942
Monitor
956
Modem
952
Internet
950
LAN
956
Remote Application Programs
902
906
908
994
944
Video Adapter
Network Adapter
System Memory
Operating System 926
Application Programs 928
Other Program Modules 930
Program Data 932
910 RAM
BIOS 914
912 ROM
925
Data Media Interfaces
System Bus
904
Processing Unit
916
Operating System 926
Application Programs 928
Program Modules 930
Program Data 932
940
I/O Interfaces
938
Printer
Mouse
Keyboard
Other Device(s)
946
936
934

Fig. 9

RECOGNIZER OF DIGITAL SIGNAL CONTENT

RELATED APPLICATIONS

[0001] This application is a continuation of and claims priority to U.S. patent application Ser. No. 09/843,254, filed Apr. 24, 2001, the disclosure of which is incorporated by reference herein.

BACKGROUND

[0002] Digital audio signals offer many advantages over conventional media in terms of audio quality and ease of transmission. With the ever-increasing popularity of the Internet, digital audio clips have become a mainstay ingredient of the Web experience, buoyed by such advances as the increasing speed at which data is carried over the Internet and improvements in Internet multimedia technology for playing such audio clips. Everyday, numerous digital audio clips are added to Web sites around the world.

[0003] An audio "clip" indicates an audio signal (or bit stream), in whole or part. A clip may be stored and retrieved, transmitted and received, or the like.

[0004] As audio clip databases grow, the needs for indexing them and protecting copyrights in the audio clips are becoming increasingly important. The next generation of database management software will need to accommodate solutions for fast and efficient indexing of digital audio clips and protection of copyrights in those digital audio clips.

[0005] A hashing technique is one probable solution to the audio clip indexing and copyright protection problem. Hashing techniques are used in many areas such as database management, querying, cryptography, and many other fields involving large amounts of raw data. A hashing technique maps a large block of data (which may appear to be raw and unstructured) into relatively small and structured set of identifiers (the identifiers are also referred to as "hash values" or simply "hash"). By introducing structure and order into raw data, the hashing technique drastically reduces the size of the raw data into short identifiers. It simplifies many data management issues and reduces the computational resources needed for accessing large databases.

[0006] Thus, one property of a good hashing technique is the ability to produce small-size hash values. Searching and sorting can be done much more efficiently on smaller identifiers as compared to the large raw data. For example, smaller identifiers can be more easily sorted and searched using standard methods. Thus, hashing generally yields greater benefits when smaller hash values are used.

[0007] Unfortunately, there is a point at which hash values become too small and begin to lose the desirable quality of uniquely representing a large mass of data items. That is, as the size of hash values decreases, it is increasingly likely that more than one distinct raw data can be mapped into the same hash value, an occurrence referred to as "collision". Mathematically, for an alphabet of cardinality A of each hash digit and a hash value length l, an upper bound of all possible hash values is A^l. If the number of distinct raw data is larger than this upper bound, collision will occur.

[0008] Accordingly, another property of a good hashing technique is to minimize the probability of collision. However, if considerable gain in the length of the hash values can be achieved, it is sometimes justified to tolerate collision. The length of the hash value is thus a trade off with probability of collision. A good hashing technique should minimize both the probability of collision and the length of the hash values. This is a concern for design of both hashing techniques in compilers and message authentication codes (MACs) in cryptographic applications.

[0009] Good hashing techniques have long existed for many kinds of digital data. These functions have good characteristics and are well understood. The idea of a hashing technique for audio clip database management is very useful and potentially can be used in identifying audio clips for data retrieval and copyrights protection.

[0010] Unfortunately, while there are many good existing functions, digital audio clips present a unique set of challenges not experienced in other digital data, primarily due to the unique fact that audio clips are subject to evaluation by human listeners. A slight pitch or phase shifting of an audio clip does not make much difference to the human ear, but such changes appear very differently in the digital domain. Thus, when using conventional hashing functions, a shifted version of an audio clip generates a very different hash value as compared to that of the original audio clip, even though the audio clips sound essentially identical (i.e., perceptually same).

[0011] Another example is the deletion of a short block of time from an audio clip. If the deleted block is short and in an otherwise quiet portion of the clip, most people will not recognize this deletion in the audio clip itself, yet the digital data is altered significantly if viewed in the data domain.

[0012] Human ears are rather tolerant of certain changes in audio clips. For instance, human ears are less sensitive to changes in some ranges of frequency components of an audio clip than other ranges of frequency components. Human ears are also unable to catch small stretching and shrinking of short segments in audio clips.

[0013] Many of these characteristics of the human auditory system can be used advantageously in the delivery and presentation of digital audio clips. For instance, such characteristics enable compression schemes, like MP3, to compress audio clips with good results, even though some of the audio clip data may be lost or go unused. There are many audio clip restoration/enhancement algorithms available today that are specially tuned to the human auditory system. Commercial sound editing systems often include such algorithms.

[0014] At the same time, these characteristics of the human auditory system can be exploited for illegal or unscrupulous purposes. For example, a pirate may use advanced audio processing techniques to remove copyright notices or embedded watermarks from an audio clip without perceptually altering the audio clip. Such malicious changes to the audio clip are referred to as "attacks", and result in changes at the data domain.

[0015] Unfortunately, a human is unable to perceive these changes, allowing the pirate to successfully distribute unauthorized copies in an unlawful manner. Traditional hashing techniques are of little help because the original audio clip and pirated copy hash to very different hash values, even though the audio clips sound the same.

[0016] Common Attacks. The standard set of plausible attacks is itemized in the Request for Proposals (RFP) of IFPI (International Federation of the Phonographic Industry) and RIAA (Recording Industry Association of America). The RFP encapsulates the following security requirements:

[0017] two successive D/A and A/D conversions,

[0018] data reduction coding techniques such as MP3,

[0019] adaptive transform coding (ATRAC),

[0020] adaptive subband coding,

[0021] Digital Audio Broadcasting (DAB),

[0022] Dolby AC2 and AC3 systems,

[0023] applying additive or multiplicative noise,

[0024] applying a second Embedded Signal, using the same system, to a single program fragment,

[0025] frequency response distortion corresponding to normal analogue frequency response controls such as bass, mid and treble controls, with maximum variation of 15 dB with respect to the original signal, and

[0026] applying frequency notches with possible frequency hopping.

[0027] Accordingly, there is a need for a hashing technique for digital audio clips that allows slight changes to the audio clip which are tolerable or undetectable (i.e., imperceptible) to the human ear, yet do not result in a different hash value. For an audio clip hashing technique to be useful, it should accommodate the characteristics of the human auditory system and withstand various audio signal manipulation processes common to today's digital audio clip processing.

[0028] A good audio hashing technique should generate the same unique identifier even though some forms of attacks have been done to the original audio clip, given that the altered audio clip is reasonably similar (i.e., perceptually) to a human listener when comparing with the original audio clip. However, if the modified audio clip is audibly different or the attacks cause irritation to the listeners, the hashing technique should recognize such degree of changes and produce a different hash value from the original audio clip.

SUMMARY

[0029] Described herein is a technology for recognizing the content of digital signals. The technology determines one or more hash values for the original content of a digital signal.

[0030] This summary itself is not intended to limit the scope of this patent. For a better understanding of the present invention, please see the following detailed description and appending claims, taken in conjunction with the accompanying drawings. The scope of the present invention is pointed out in the appending claims.

BRIEF DESCRIPTION OF THE DRAWINGS

[0031] The same numbers are used throughout the drawings to reference like elements and features.

[0032] **FIG. 1** is a schematic block diagram showing an embodiment of an implementation of the present invention claimed herein.

[0033] **FIGS. 2A-2C** illustrate an implementation of the MCLT transform in accordance with an implementation of the present invention claimed herein.

[0034] **FIGS. 3A-1** and **3A-1** illustrate the time-frequency representation and the significance map, respectively, of given audio clip.

[0035] **FIGS. 3B-1** and **3B-1** illustrate the time-frequency representation and the significance map, respectively, of another audio clip.

[0036] **FIG. 4** is a flow diagram showing an illustrative methodological implementation of an implementation of the present invention claimed herein.

[0037] **FIGS. 5A-5C** illustrate some of the tasks performed by a statistic estimator in accordance with an implementation of the present invention claimed herein.

[0038] **FIG. 6** is a flow diagram showing an illustrative methodological implementation of an implementation of the present invention claimed herein.

[0039] **FIG. 7** is a flow diagram showing an illustrative methodological implementation of an implementation of the present invention claimed herein.

[0040] **FIG. 8** is a flow diagram showing an illustrative methodological implementation of an implementation of the present invention claimed herein.

[0041] **FIG. 9** is an example of a computing operating environment capable of implementing an implementation of the present invention claimed herein.

DETAILED DESCRIPTION

[0042] The following description sets forth one or more specific embodiments of an recognizer of audio-content in digital signals that incorporate elements recited in the appended claims. These embodiments are described with specificity in order to meet statutory written description, enablement, and best-mode requirements. However, the description itself is not intended to limit the scope of this patent.

[0043] Described herein are one or more exemplary implementations of a method and system of fusing portions of a print medium. The inventors intend these exemplary implementations to be examples. The inventors do not intend these exemplary implementations to limit the scope of the claimed present invention. Rather, the inventors have contemplated that the claimed present invention might also be embodied and implemented in other ways, in conjunction with other present or future technologies.

[0044] An exemplary embodiment of an recognizer of audio-content in digital signals may be referred to as an "exemplary audio recognizer."

[0045] Incorporation by Reference

[0046] The following co-pending patent applications are incorporated by reference herein (which are all assigned to the Microsoft Corporation):

[0047] U.S. patent application Ser. No. 09/390,271, entitled "A Technique for Watermarking an Image and a Resulting Watermarked Image" filed Sep. 7, 1999;

[0048] U.S. patent application Ser. No. 09/390,272, entitled "A Technique for Detecting a Watermark in a Marked Image" filed on Sep. 7, 1999;

[0049] U.S. patent application Ser. No. 09/316,899, entitled "Audio Watermarking with Dual Watermarks" filed on May 22, 1999;

[0050] U.S. patent application Ser. No. 09/614,660, entitled "Improved Stealthy Audio Watermarking" filed on Jul. 12, 2000;

[0051] U.S. patent application Ser. No. _____, entitled "Robust Recognizer of Perceptually Similar Content" filed on Apr. 24, 2001;

[0052] U.S. patent application Ser. No. _____, entitled "Derivation and Quantization of Robust Non-Local Characteristics for Blind Watermarking" filed on Apr. 24, 2001;

[0053] U.S. patent application Ser. No. 09/259,669, entitled "A System and Method for Producing Modulated Complex Lapped Transforms" filed on Feb. 26, 1999; and

[0054] U.S. patent application Ser. No. 09/421,986, entitled "System and Method for Hashing Digital Images" filed on Oct. 19, 1999.

[0055] The following U.S. patent is incorporated by reference herein: U.S. Pat. No. 6,029,126, entitled "Scalable Audio Coder and Decoder" issued on Feb. 22, 2000, and assigned to the Microsoft Corporation.

[0056] Introduction

[0057] Implementations, described herein, of the exemplary audio recognizer may be implemented (whole or in part) by an audio-content recognition system **100** and/or by a computing environment like that shown in **FIG. 9**.

[0058] An exemplary implementation is described herein as a technique for generally recognizing audio content of digital audio signals by hashing such signals to generate one or more hash values for each signal.

[0059] An exemplary implementation is described herein as a technique for identifying audio content of such signals by comparing identification hash values of signals. This exemplary implementation generates the same unique identifier (e.g., hash value) even though some forms of attacks have been done to the original digital audio signal, given that the altered signal is perceptually same to a human listener when comparing the altered signal with the original signal. However, if the altered signal is perceptually audibly different or the attacks cause irritation to the listeners, the hashing technique recognizes such degree of changes and produces a different hash value from the original signal.

[0060] An exemplary implementation is described herein as a technique for categorizing audio content of such signals by comparing categorization hash values of signals.

[0061] An exemplary implementation described herein is a technique that may be combined with techniques described in documents which are incorporated herein by reference.

[0062] Exemplary Applications

[0063] Implementations, described herein, of the exemplary audio recognizer are suitable for numerous applications, including the following (which are provided as examples and not as limitations): identification, searching & sorting in a database, semantic content categorization, and anti-piracy applications (such as watermarking). Some of the exemplary applications are discussed below:

[0064] Locating content in a database. Identification hash values may be stored and associated with specific audio content of a digital audio signal. When searching for such content, a search engine may look for a given hash value to locate the content. This is much more efficient that conventional techniques for searching for audio content in a database.

[0065] Semantic content categorization. This includes approximate matching of content between two digital audio signals. The hashing techniques of the exemplary embodiments have an intermediate hash value, which can be used to compare if two given items are similar. This hash value may also be called a categorization hash value.

[0066] This categorization hash value may be used to semantically classify audio content of audio works. Works of a similar nature tend to have categorization hash values that cluster together. Thus, these values are proximally near each other. This proximal range may be subjectively determined. For some semantic categories, the range may be large and for others it may be small.

[0067] The categorization hash can be computed incrementally. This means that if the exemplary embodiment may slide the window of the audio clip, one may compute the hash value on the new window from the old window without doing substantial reworking on the part that is common to old and new windows.

[0068] Anti-piracy search efforts. One may search for the pirated content of audio signals on the web, which might have been subjected to watermarking and/or malicious attacks, using a web crawler and a database of signal hash values.

[0069] Content dependent key generation (for watermarks): Since the watermarking technique must use secret keys, using the same key for millions of pieces of content may compromise the key. Thus, an exemplary embodiment may generate a hash value for an audio signal that may function as signal dependent keys. For an attacker without the knowledge of the secret key used, the hash value of a given content will be unpredictable.

[0070] Hashing

[0071] The use of hashing techniques, which map long inputs into short random-looking (i.e., uniformly distributed) outputs, are many and indeed wide-ranging: compilers, checksums, searching and sorting techniques, cryptographic message authentication, one-way hashing techniques for

digital signatures, time stamping, etc. These techniques usually accept binary strings as inputs and produce a fixed length ("L") hash value. These techniques use some form of random seeds (i.e., keys).

[0072] The hash values produced by such techniques are viewed as useful because they typically have following desirable characteristics:

[0073] Almost Uniformly Distributed —For any given input, the output hash value are uniformly distributed among the possible L-bit outputs.

[0074] Approximate Pairwise Independent—For two distinct inputs, the corresponding outputs are statistically almost independent of each other.

[0075] The hashing technique implemented by various systems and methods, described herein, is denoted as H. Given an input signal I, the hashing technique H produces a short binary string X, as follows:

$$H(I)=X$$

[0076] The hashing technique H has the following properties:

[0077] For any signal I_i, the hash of the signal, $H(I_i)$, is approximately uniformly distributed among binary strings of equal length.

[0078] For two distinct signals, I_1 and I_2, the hash value of the first signal, $H(I_1)$, is approximately independent of the hash value of the second signal, $H(I_2)$, in that given $H(I_1)$, one cannot predict $H(I_2)$.

[0079] If two signals I_1 and I_2 are perceptually the same or similar, the hash value of the first signal, $H(I_1)$, should equal the hash value of the second signal, $H(I_2)$.

[0080] The hashing techniques of the implementations, described herein, are similar in many respects to the hashing techniques described in some of the documents which are incorporated herein by reference. The hashing techniques, described herein, are particularly tailored to accommodate characteristics of the human auditory system and withstand various audio signal manipulation processes common to today's digital audio signal processing.

[0081] Perceptually Same and Perceptually Distinct

[0082] The exemplary audio recognizer treats two "perceptually same" audio signals as the same. Herein, a pair of digital audio signals are "perceptually same" when their identification hash values are the same (alternatively, substantially the same).

[0083] "Perceptually same" audio signals include those that sound as if they are they are substantially same to the human ear. As a first step in determining what it means to be perceptually same, one can use the standard Turing test used for formulating, for example, pseudo-randomness in cryptography. A listener is played two audio clips, one after another. Then the clips are played in random order and the listener should match up the clips. If the listener has no better than roughly a fifty-percent chance, the clips can be deemed perceptually same.

[0084] However, the use of the term is more general than that defined by the Turing test. Clips that have passed the Turing test may still be considered perceptually same when the listener is able to distinguish them only based on "slight and insubstantial differences." Regardless of such slight and insubstantial differences, the listener can clearly state that these clips "are the same audio clips for all practical purposes."

[0085] In contrast, a "perceptually distinct" digital goods is generally the converse of "perceptually same" digital goods. This may also be called "perceptually different" or "perceptually distinguishable".

[0086] Perceptually Similar

[0087] The exemplary audio recognizer treats two "perceptually similar" audio signals as different signals that should be categorized as similar. Herein, a pair of digital audio signals are "perceptually similar" when their categorization hash values are close in value (i.e., proximal). Signals that are "perceptually similar" may also be "perceptually same" if their identification hash values are the same.

[0088] Exemplary Hashing Technique of the Exemplary Implementations

[0089] The hashing technique of the exemplary implementations is an irreversible hashing function that operates on audio clips and yields a final hash value of a binary string of specified length. It also yields one or more intermediate has values. The hashing techniques of the exemplary implementations have the following criteria:

[0090] The hash values are almost uniformly distributed with high probability.

[0091] With high probability, the hash values for "perceptually audibly distinct" audio clips are different.

[0092] With high probability, the hash values for "perceptually audibly same" audio clips are the same.

[0093] Assume X denotes a particular audio clip, X' denotes a modified version of this clip which is "perceptually same" as X, and Y denotes a "perceptually distinct" audio clip. Assume L is the final length of the hash and H(.) represents a hashing function. The following is a performance measure on the hash values that are produced:

$$D(H(X), H(Y)) \triangleq \frac{\sum_{i=1}^{L} H(X_i) \otimes H(Y_i)}{L} \quad (1)$$

[0094] where $H(X_i)$ and $H(Y_i)$ are the values of H(X) and H(Y) respectively at the i^{th} location, and $\otimes$ stands for the XOR operation. Formula 1 is the ratio of the number of locations where H(X) and H(Y) are different to the total length of the hash.

[0095] The following are examples of a family of hashing functions, for use with the exemplary embodiments, with parameters: p, L (where $p \approx \frac{1}{2}^{L}$).

[0096] Randomization:

$$Pr[H(X) = \alpha] = p \approx \frac{1}{2^L}, \forall\, \alpha \in \{0, 1\}^L,$$

[0097] Perceptually distinct audio clips X, Y:

$$Pr[H(X)=\alpha | H(Y)=\beta] \approx Pr[H(X)=\alpha],\ \forall \alpha,\ \beta \in \{0,1\}^L,$$

[0098] Thus, H(X) is not equal to H(Y), with overwhelming probability

[0099] Perceptually same audio clips:

$$_{Pr}[H(X)=H(X')] \approx 1.$$

[0100] Therefore, apart from the randomization issue, the difference between identification hash values of audio clips may be represented as follows:

$$D(H(X),H(X'))=0, D(H(X),H(Y))>0, \quad (2)$$

[0101] for all possible different ("perceptually distinct") audio clips X, Y and for all possible "perceptually same" audio clips X, X'.

[0102] Intermediate hash value. In the exemplary embodiments described herein, an intermediate hash value is calculated before the final (i.e., identification) hash value is calculated. The intermediate hash values are of length M, where M>L and have the following separation property:

$$D(H(X),H(X'))<0.2, D(H(X),H(Y))>0.40, \quad (3)$$

[0103] In the exemplary embodiments, M has a value within range of 5L to 10L. To determine the intermediate hash value, decoding stages of first order Reed-Müller codes employed with a specialized pseudo-norm. Given the intermediate hash, the exemplary embodiment uses some generic techniques (e.g., list-decoding procedures) to generate a binary string with desired properties.

[0104] For more information on generating intermediate hash values, see U.S. patent application Ser. No. _____, entitled "Robust Recognizer of Perceptually Similar Content" filed on Apr. _____, 2001.

[0105] Exemplary Audio Recognizer

[0106] **FIG. 1** shows the audio-content recognition system **100**, which is an example of an embodiment of the exemplary audio recognizer. The system **100** includes a transformer **110**, a statistics estimator **120**, an adaptive quantizer **130**, and an error-correction decoder **140**.

[0107] The transformer **110** obtains a digital audio signal **105** (such as an audio clip). It may obtain the signal from nearly any source, such as a storage device or over a network communications link. The transformer **110** puts the signal **105** in canonical form using a set of transformations. Specifically, the exemplary audio recognizer employs MCLT (Modulated Complex Lapped Transform) and obtain time-varying spectral characteristics, T_x **112**, of the audio clip.

[0108] The statistics estimator **120** applies a randomized interval transformation in order to extract audible statistics, μ_x **122**, of the signal. These audible statistics are expected to represent the audio signal in an irreversible manner while introducing robustness against attacks. For perceptually same audio clips, these statistics are likely to have close values (under suitable notions of metric) whereas for perceptually distinct audio clips they are far apart.

[0109] The adaptive quantizer **130** applies randomized rounding (i.e., quantization) to the outputs of the statistics estimator **120**. The adaptive quantizer produces outputs, q_x **132**, that are represented as binary vectors. Alternatively, the quantizer **130** may be non-adaptive.

[0110] The error-correction decoder **140** uses the decoding stages of an error correcting code to map similar values to the same point. The final output, h_x **142**, is produced by the decoder **140**. This final output is the final hash value. The decoder also produces an intermediate hash value. Alternatively, error-correction decoder **140** may be a randomized Vector Quantizater (VQ) or list-decoder, or other similar devices.

[0111] The decoder **140** produces intermediate hash values such that the normalized Hamming distance between intermediate hash values of perceptually distinct audio signals is greater than 0.40 and the normalized Hamming distance between intermediate hash values of perceptually similar audio signals is less than 0.20. Of course, these ranges are provided as examples only and not for limitation.

[0112] Each of aforementioned components of the audio-content recognition system **100** of **FIG. 1** is explained in greater detail below.

[0113] The Transformer **110** and MCLT

[0114] MCLT is a complex extension of MLT (Modulated Lapped Transform). MLT was introduced in and is used in many audio-processing applications, such as DolbyAC-3, MPEG-2. MCLT basis functions are found in pairs to produce real and complex parts separately. These basis functions are derived from MLT and they are phase-shifted versions of each other. It can be shown that they possess some intuitively pleasing properties such as perfect reconstruction and approximate shift invariance. The MCLT is a special case of 2× oversampled DFT (Discrete Fourier Transform) filter bank.

[0115] The MCLT is discussed more fully in U.S. patent application Ser. No. 09/259,669, entitled "A System and Method for Producing Modulated Complex Lapped Transforms," which is incorporated by reference herein.

[0116] **FIGS. 2A-2C** illustrate the MCLT scheme, like the one employed by the transformer **110** of the audio-content recognition system **100** of **FIG. 1**. **FIG. 2A** shows a timeline **210** of an input sequence of an audio signal (which is not shown). The sequence is broken into overlapping "blocks" (blocks **212-218**) along the timeline, so that neighboring blocks intersect by half.

[0117] As shown in **FIG. 2B**, the MCLT transform is applied, by MCLT transformer **230**, applied independently to each block (such as block "i") to produce spectral decomposition of size M. Assuming that the analysis and synthesis filters are of length **2M**, then the number of the frequency bands is M in the spectral domain.

[0118] **FIG. 2C** represents the combination of the spectral decomposition of the blocks in order to form the time-frequency decomposition, T_x. The MCLT transform of the blocks are combined into a matrix to obtain the time-frequency representation of an audio clip. For **FIG. 2C**, Let

M be the number of frequency bands and N be the number of the blocks and T, is the MCLT matrix and $T_x(i,j)$ is the MCLT value at location (i, j) where j=0, 1, . . . , N-1.

[0119] MCLT can be used to define a "hearing threshold matrix" H., which is the same size as T_x, such that if $T_x(i,j)>=H_x(i,j)$, then $T_x(i,j)$ is audible.

[0120] Randomized Interval Transformation (Statistics Estimation)

[0121] The following is the definition of the significance map S_x: $S_x(i, j)=1$, if $T_x(i, j)>=H_x(i, j)$; otherwise $S_x(i, j)=0$; where i=0, 1, . . . ,M-1 and j=0, 1, . . . , N-1.

[0122] **FIGS. 3A-1** and **3A-2** illustrate the time-frequency representation and corresponding significance map for an exemplary audio clip A. **FIGS. 3B-1** and **3B-2** illustrate the time-frequency representation and corresponding significance map for a different exemplary audio clip, clip B. Only the low-frequency portions of the time-frequency representations and the significance maps are depicted in these figures for the purposes of convenience.

[0123] As shown in **FIGS. 3A-1** and **3B-1**, there is a striking pattern in time-frequency representation of the audio clips. Furthermore, this pattern has a slowly varying structure—with respect to both time and frequency. The exemplary audio recognizer captures this existing structure in a compact fashion via randomized interval transformations (i.e., "statistics estimation").

[0124] The statistics estimator **120** estimates statistics reflect characteristics of the signal **105**. In order to achieve this purpose, the estimator **120** carries out estimation of statistics in the time-frequency plane. The estimator **120** exploits both local and global correlations. Correlations exist both along frequency axis and along the time axis. The estimator **120** may, for example, employ one or two exemplary approaches. Approach I operates along the frequency axis for each block (i.e., exploits correlations along the frequency axis for a given block). Approach II operates along the time axis for each frequency subband; and therefore, it exploits correlations along time.

[0125] Methodological Implementations of Approach I and Approach II:

[0126] **FIG. 4** show methodological implementations of both Approach I and Approach II, which is performed by the estimator **120** of the audio-content recognition system **100** (or some portion thereof). These methodological implementations may be performed in software, hardware, or a combination thereof.

[0127] The methodology of Approach II is very similar to Approach I. The main difference is that in Approach I correlations along frequency are exploited instead of correlation along time while in Approach II correlations along time are exploited instead of correlation along frequency.

[0128] At **410** of **FIG. 4**, for each block, the estimator **120** determines if there exist sufficiently many entrees exceeding the hearing thresholds. If not pass to the next block, else collect the "significant" coefficients into a vector of size $M' \leq M$. More generally, the columns of T_x are used in Approach I and the rows of T_x are used in Approach II.

[0129] At **412**, the estimator **120** performs a randomized interval transformation. **FIG. 5A** illustrates the concept of randomized "splitting" at a single level. At a single level of randomized splitting of a vector **510** (in either the frequency or time domain depending upon the Approach), first a randomization interval **520** (i.e., randomization region) is found that is to be symmetric around the midpoint **522**. The ratio of the length of the randomization interval to the length of the whole vector **510** is the randomization tuning parameter for splitting. This may be a user-specified value.

[0130] **FIG. 5A** shows that a random point **524** is chosen within this interval **520**. This random point **524** is the point to do the splitting; as a result, two "chunks" are formed. Then this procedure is carried out a specified number of times-each time is a "level" of the splitting. The level is a function of M' and the expected number of coefficients desired within the smallest chunk. Hence, the expected number of coefficients that are within the smallest chunk is a user-specified parameter and determines the "level" for each block. As an example, in **FIG. 5B**, the recursive splitting is carried out twice, hence level=2.

[0131] At **414** of **FIG. 4**, the first order statistics at each level for each chunk are estimated once the split points are randomly found. As an example, consider **FIG. 5B**. At second level of splitting, there are a total of four chunks (chunks **541**, **542**, **543**, **544**), and the estimator **120** collects the arithmetic means of these four chunks (alternatively, other statistical values can be collected, such as variance). Then the estimator **120** proceeds to the first level of splitting, and the estimator **120** computes the arithmetic means at that level-namely, arithmetic means of chunks **545** and **456** in **FIG. 5B**). Finally, at the zeroth level, the estimator **120** performs the arithmetic mean computation for the whole vector **510** (namely, chunk **547**). All of these arithmetic means are collected in a statistics vector.

[0132] At **416**, the process returns back to the beginning of the loop at **405** and repeat the steps of blocks **410-416** until all blocks have be processed. After all blocks have been processed, the loop ends at **418**.

[0133] **FIG. 5C** illustrates the difference of Approach I **560** and Approach II **570** on the time-frequency representation **550** of an audio signal.

[0134] In Approach I, the estimator **120** estimates the statistics for each time block. With Approach I, the result of the estimator **120** is a statistics vector μ_f to denote the estimated means along the frequency axis.

[0135] In Approach II, the estimator **120** estimates the statistics for each frequency subband. With Approach II, the result of the estimator **120** is a statistics vector ft to denote the estimated means along the time axis.

[0136] Although both Approaches I and II of the exemplary embodiment are designed to estimate the first order statistics at this point, an alternative embodiment may include an estimation of any order statistics. In tests, it has been observed that first order statistics yield better results than second order statistics at this point. Regardless of which approach is employed (Approach I or II), the function of the adaptive quantizer **130** and the error correction decoder **140** is the same.

[0137] Another exemplary embodiment employs a third approach, Approach III, which combines Approaches I and II. In this approach, statistics are estimated based on random

rectangles in the time-frequency plane. The shape of these rectangles may be adjusted to capture the appropriate characteristics.

[0138] Input Adaptive Quantization

[0139] The adaptive quantizer **130** produces discrete level of outputs given the statistics vector as the input. Meanwhile, the adaptive quantizer **130** effectively increases robustness properties of the hashing techniques (employed by the exemplary audio recognizer) and augments the amount of randomization.

[0140] In signal processing, the traditional way of producing discrete level of outputs from continuous level of inputs is termed as "quantization." Assume Q is the number of quantization levels (i.e., the cardinality of the set of discrete level of outputs). Also assume $\mu(j)$ denote the j^{th} element of a given statistics vector/and $\mu'(j)$ denote its quantized version. In conventional quantization schemes, the quantization rule is completely deterministic and given by

$$\Delta_i \leqq \mu(j) < \Delta_{i+1} \Rightarrow \mu'(j) = i, i = 0,1, \ldots, Q-1,$$

[0141] where the interval $[\Delta_i, \Delta_{i+1})$ is termed as i^{th} quantization bin. With the description herein of the exemplary embodiment, the focus is on the location of quantization bins rather than the reconstruction levels. In traditional quantization schemes in signal processing, the reconstruction levels are significant since quantization is usually applied as a part of a compression scheme. However, apart from the indexing issues, the reconstruction levels are not of significance for the exemplary embodiment described herein. Therefore, without loss of generality, the reconstruction levels are assumed to be given by integer indexes from the set $\{0,1, \ldots, Q-1\}$.

[0142] Typically, the input statistics vector comes from a distribution that is highly biased at some points. To account for this "colored" nature of the statistics distribution, the exemplary embodiment employs an "adaptive quantization" scheme, which takes of possible arbitrary biases at different locations of the distribution of the statistics. In particular, the exemplary embodiment uses a normalized histogram of it as the distribution of the statistics. A normalized histogram is usually very resistant against "slightly inaudible" attacks, thus such an adaptive scheme does not really bring a burden in terms of robustness. Furthermore, a normalized histogram approximates the p.d.f. (probability density function) of the marginal density functions of $\mu(j)$ are the same for all j, and the approximation error diminishes as the size of μ tends to in infinity. Thus, within the exemplary embodiment $\{\Delta_i\}$ is designed such that

$$\int_{\Delta_{i-1}}^{\Delta_i} p_\mu(t)\,dt = \frac{1}{Q}, \; i = 0, 1, \ldots, Q-1.$$

[0143] where p_μ stands for the normalized histogram of the input statistic vector μ. The intervals $[\Delta_i-1, \Delta_i)$ determine the quantization bins. Furthermore, define the "central points", $\{C_i\}$, such that

$$\int_{\Delta_{i-1}}^{C_i} p_\mu(t)\,dt = \int_{C_1}^{\Delta_i} p_\mu(t)\,dt = \frac{1}{2Q}, \; i = 0, 1, \ldots, Q-1.$$

[0144] Now around each Δ_i, we introduce a randomization interval $[L_i,U_i]$ such that

$$\int_{L_i}^{\Delta_i} p_\mu(t)\,dt = \int_{\Delta_1}^{U_i} p_\mu(t)\,dt, \;\; i = 0, 1, \ldots, Q-1,$$

[0145] In other words, the randomization interval is symmetric around Δ_i for all i and we also impose the constraint that $C_i \leqq L_i$ and $U_i \leqq C_{i+1}$. The exact location of these randomization intervals are determined by "Randomization Factor",

$$\text{Randomization Factor} = \frac{\int_{L_i}^{\Delta_i} p_\mu(t)\,dt}{\int_{\Delta_{i-1}}^{\Delta_i} p_\mu(t)\,dt}, \; i = 0, 1, \ldots, Q-1$$

[0146] where "randomization factor" is a parameter that determines the amount of randomization at the output of quantization and is a user-specified number that can clearly take values in the range [0,½]. This the p.d.f.-adaptive randomized quantization rule of the exemplary embodiment:

$$L_i \leq \mu(j) \leq U_i \Rightarrow \mu'(j) = \begin{cases} i \text{ with probability } \dfrac{\int_{L_i}^{\mu(j)} p_\mu(t)\,dt}{\int_{L_i}^{U_i} p_\mu(t)\,dt} \\ i-1 \text{ with probability } \dfrac{\int_{\mu(j)}^{U_i} p_\mu(t)\,dt}{\int_{L_i}^{U_i} p_\mu(t)\,dt} \end{cases}$$

and

$$C_i \leq \mu(j) \leq L_i \Rightarrow \mu'(j) = i-1 \text{ with probability } 1,$$

$$U_i \leq \mu(j) < C_{i+1} \Rightarrow \mu'(j) = i \text{ with probability } 1$$

[0147] Under such a randomized quantization rule, if $L_i \leqq \mu(j) \leqq U_i$, then $E[\mu'(j)]=\Delta_i$. This choice of the "Randomization Factor" offers a trade-off: As this factor increases, the amount of randomization at the output increases, which is a desired property; however, this also increases the chances of being vulnerable to attacks and modifications especially because in that case the security of the system relies, to a great extent, on keeping the randomization key as a secret. Thus, choosing a suitable range for "Randomization Factor" is a delicate issue. In the exemplary embodiment, a user-specified input parameter determines this issue. With such user-specified input parameter, the user may balance the degree of randomization desired against security concerns to achieve a customized result.

[0148] Error Correction Decoding

[0149] Once the exemplary embodiment has the quantized statistics, the next step is to convert these values into a binary bit stream (i.e., digital signal) and shorten the length of the overall stream in such a way that "perceptually same" audio clips are mapped to binary strings that are close to each other and "perceptually distinct" audio clips are mapped to binary strings that are far away from each other.

[0150] In order to achieve this purpose, the exemplary embodiment employs first order Reed-Müller codes at this point. Those who are skilled in the art understand and appreciate that other error correction schemes as well as possibly randomized Vector Quantization techniques may be employed and remain within the spirit and scope of the claimed invention.

[0151] Reed-Müller codes are a class of linear codes over GF(2) that are easy to describe and have an elegant structure. The generator matrix G for the first order Reed-Müller code of blocklength 2^m is defined as an array of blocks:

$$G = \begin{bmatrix} G_0 \\ G_1 \end{bmatrix}$$

[0152] where G_0 is a single row consisting of all ones and G_1 is a matrix of size m by 2^m. G_1 is formed in such a way that each binary m-tuple appears once as a column. Thus, the resulting generator matrix is of size m+1 by 2^m. More details on error correcting codes and Reed-Müller codes by found in *Theory and Practice of Error Control Codes* (1983) by R. Blahut.

[0153] Although there exist computationally efficient techniques for decoding with Reed-Müller codes (decoding with majority logic), the exemplary embodiment is using an exhaustive search on the input word space for the sake of simplicity. Unlike traditional decoding schemes that use Hamming distance as the error metric, the decoding scheme of the exemplary embodiment uses an error measure, which is termed as "Exponential Pseudo Norm" (EPN). It is more suitable than traditional error metrics (such as Hamming distance) for multimedia (image and audio) hashing problems.

[0154] Assume x_D and y_D are two vectors of length L such that each component of these vectors belongs to the set {0,1, . . . ,Q-1} where $\log_2 Q$ is a positive integer. Similarly, assume x and y are binary representations of the vectors x_D and y_D respectively, where each decimal component is converted to the binary format by using $\log_2 Q$ bits. The lengths of x and y are therefore going to be both L $\log_2 Q$. EPN is defined between the binary vectors x and y as

$$EPN(x, y) \triangleq \sum_{i=1}^{L} K^{|x_D(i) - y_D(i)|},$$

[0155] where $x_D(j)$ and $y_D(i)$ denote the ith elements of the vectors x_D and y_D respectively. EPN (x, y) is actually a function of Q and K as well; however, for the sake of having a clean notation the exemplary embodiment are embedding these values in the expression and simply assuming that these values are known within the context of the problem.

[0156] Q is the number of quantization levels, and K is the "exponential constant" that determines how EPN penalizes large distances more. The results are approximately insensitive to the value of K if it is chosen to be large enough. Since part of the aim of the exemplary embodiment is to clearly distinguish between close and far values in the decimal representations of binary strings, EPN is suitable for incorporations into the hashing techniques of the exemplary embodiment.

[0157] Examples of methodological acts performed by the error correction decoder **140** are as follows:

[0158] Divide the quantized data into chunks of length that is user-specified.

[0159] Convert them into binary format by using $\log_2$ Q bits for each component, where Q is the number of quantization levels.

[0160] Form the generator matrix of first order Reed-Müller code where the length of the codewords is as close as possible to the length of the binary representation of the chunks.

[0161] For each possible input word (there are a total of 2^{m+1} possible input words for a generator matrix of size m+1 by 2^m), generate the corresponding output word.

[0162] Find the EPN between each corresponding output word and the quantized data.

[0163] Pick up the input word that yields the minimum amount of EPN.

[0164] Methodological Implementation of the Exemplary Audio-Content Recognizer

[0165] **FIG. 4** shows an illustrative methodological implementation of the exemplary audio-content recognizer performed (wholly in part) by the audio-content recognition system **100** (or some portion thereof). This methodological implementation may be performed in software, hardware, or a combination thereof.

[0166] Audio-Content Identification Methodological Implementation

[0167] **FIG. 6** illustrates an audio-content identification methodological implementation of the exemplary audio-content recognizer. At **610** of **FIG. 6**, the exemplary audio-content recognizer retrieves a subject audio clip from a database of audio clips or some other source of such audio signals. Once a subject clip is chosen, the exemplary audio-content recognizer, at **612**, transforms it, in accordance with the transformation performed by the transformer **110**, described above.

[0168] At **614** of **FIG. 6**, the exemplary audio-content recognizer estimates statistics of the transformed clip, in accordance with the estimation performed by the statistics estimator **120**, described above. At **616**, the exemplary audio-content recognizer adaptively quantizes the estimated statistics of the transformed clip, in accordance with the quantization performed by the adaptive quantizer **130**, described above. At **618**, the exemplary audio-content recognizer performs error-correction decoding on the results of

the adaptive quantization, in accordance with the decoding performed by the decoder **140**, described above.

[**0169**] At **620** of **FIG. 6**, it determines the hash values based upon the result of the above steps. The hash values include an intermediate hash value (i.e., categorization hash value) and a final hash value. These hash values are recognition representations of the audio content of the original audio clip. That is because these hash values may be used to recognize (and even identify) the audio content within an audio clip.

[**0170**] At **622** of **FIG. 6**, the resulting hash values are displayed and stored. These values are stored in a database in association with the original subject clip from which the values were calculated.

[**0171**] Piracy Detection Methodological Implementation

[**0172**] **FIG. 7** illustrates a piracy detection methodological implementation of the exemplary audio-content recognizer. At **756** of **FIG. 7**, the exemplary audio-content recognizer retrieves a hash value of a selected audio clip. More particularly, it retrieves the final hash value (i.e., identification hash value) of such clip from a database of audio clips or some other source of such clips.

[**0173**] **FIG. 7** also shows the audio-content identification method of **FIG. 6** at block **752**. The method **752** calculates a final hash value of an audio clip **750** that is suspected of being a copy of the selected clip retrieved by block **756**. At **754**, the exemplary audio-content recognizer retrieves the calculated final hash value of the suspect audio clip **750** from the audio-content identification method of block **752**. Of course, this can be reversed so that the method **752** provides the hash value of the selected clip while block **752** provides the hash value of the suspected clip.

[**0174**] At **758**, the exemplary audio-content recognizer compares the hash values of the two clips (suspect clip **750** and selected clip of **756**) to determine if they substantially match. Substantially matching means that the two hash values are close enough in value to reasonably conclude that the two clips have the same hash values within a margin of error.

[**0175**] If the result of such comparison is no substantial match, then the exemplary audio-content recognizer indicates, at **760**, that the suspect clip **750** is not a substantial copy of the selected clip of **756**. In other words, no piracy is detected if the final hash values of compared clips do not substantially match. At **764**, this process ends.

[**0176**] However, if the result of such comparison is a substantial match, then the exemplary audio-content recognizer indicates, at **762**, that the suspect clip **750** is a substantial copy of the selected clip of **756**. In other words, piracy is detected if the final hash values of compared clips substantially match. At **764**, this process ends.

[**0177**] Audio Content Categorization Methodological Implementation

[**0178**] **FIG. 8** illustrates an audio content categorization methodological implementation of the exemplary audio-content recognizer. At **816** of **FIG. 8**, the exemplary audio-content recognizer retrieves a hash value of a selected audio clip. More particularly, it retrieves the intermediate (i.e., categorization) hash value of such clip from a database of audio clips or some other source of such clips.

[**0179**] In dashed box **805**, **FIG. 8** also shows an alternative way of getting an intermediate hash value of the selected clip. This is by processing the clip using the audio-content identification method of **FIG. 6** at block **812**. The method **812** calculates an intermediate (i.e., categorization) hash value of the selected clip. At **814**, the exemplary audio-content recognizer retrieves the calculated intermediate hash value of the selected audio content-base clip **810** from the audio-content identification method of block **812**.

[**0180**] At **820**, the exemplary audio-content recognizer uses the intermediate hash value of the selected clip to group such clip with others of similar (i.e., proximal) intermediate hash values. In other words, based upon the intermediate hash value of a given clip, the exemplary audio-content recognizer groups the given clip with other clips having similar intermediate hash values. Thus, the hash values of all is clips in a given grouping are clustered together (i.e., proximal each other). Although these groupings are somewhat objectively determined, the subjective nature of the content of clips within a grouping will be similar to that of the content of others within the grouping.

[**0181**] The exemplary audio-content recognizer uses the categorization hash value of the selected clip to group such clip with others of similar (i.e., proximal) categorization hash values. In other words, based upon the categorization hash value of a given clip, the exemplary audio-content recognizer groups the given work with other works having similar categorization hash values. Thus, the hash values of all works in each grouping are clustered together (i.e., proximal each other). Although these groupings are primarily objectively determined, the subjective nature of the content of works within a grouping will be similar to that of the content of others within the grouping.

[**0182**] The boundaries between groupings are determined manually or automatically. Manually, a person selects the boundary between groupings using the natural clustering seen after many clips have been categorized. Automatically, a system mathematically selects the boundary between groupings to be some point between (perhaps halfway) the centers of the groupings. Of course, other such techniques may to used to determine boundaries. These techniques may be fully automatic, fully manual, or some combination.

[**0183**] At **822**, the exemplary audio-content recognizer stores the categorization results in a database. At **824**, the process ends.

[**0184**] Exemplary Computing System and Environment

[**0185**] **FIG. 9** illustrates an example of a suitable computing environment **900** within which an exemplary audio recognizer, as described herein, may be implemented (either fully or partially). The computing environment **900** may be utilized in the computer and network architectures described herein.

[**0186**] The exemplary computing environment **900** is only one example of a computing environment and is not intended to suggest any limitation as to the scope of use or functionality of the computer and network architectures. Neither should the computing environment **900** be interpreted as having any dependency or requirement relating to

any one or combination of components illustrated in the exemplary computing environment **900**.

[**0187**] The exemplary audio recognizer may be implemented with numerous other general purpose or special purpose computing system environments or configurations. Examples of well known computing systems, environments, and/or configurations that may be suitable for use include, but are not limited to, personal computers, server computers, thin clients, thick clients, hand-held or laptop devices, multiprocessor systems, microprocessor-based systems, set top boxes, programmable consumer electronics, network PCs, minicomputers, mainframe computers, distributed computing environments that include any of the above systems or devices, and the like.

[**0188**] Exemplary audio recognizer may be described in the general context of computer-executable instructions, such as program modules, being executed by a computer. Generally, program modules include routines, programs, objects, components, data structures, etc. that perform particular tasks or implement particular abstract data types. Exemplary audio recognizer may also be practiced in distributed computing environments where tasks are performed by remote processing devices that are linked through a communications network. In a distributed computing environment, program modules may be located in both local and remote computer storage media including memory storage devices.

[**0189**] The computing environment **900** includes a general-purpose computing device in the form of a computer **902**. The components of computer **902** can include, by are not limited to, one or more processors or processing units **904**, a system memory **906**, and a system bus **908** that couples various system components including the processor **904** to the system memory **906**.

[**0190**] The system bus **908** represents one or more of any of several types of bus structures, including a memory bus or memory controller, a peripheral bus, an accelerated graphics port, and a processor or local bus using any of a variety of bus architectures. By way of example, such architectures can include an Industry Standard Architecture (ISA) bus, a Micro Channel Architecture (MCA) bus, an Enhanced ISA (EISA) bus, a Video Electronics Standards Association (VESA) local bus, and a Peripheral Component Interconnects (PCI) bus also known as a Mezzanine bus.

[**0191**] Computer **902** typically includes a variety of computer readable media. Such media can be any available media that is accessible by computer **902** and includes both volatile and non-volatile media, removable and non-removable media.

[**0192**] The system memory **906** includes computer readable media in the form of volatile memory, such as random access memory (RAM) **910**, and/or non-volatile memory, such as read only memory (ROM) **912**. A basic input/output system (BIOS) **914**, containing the basic routines that help to transfer information between elements within computer **902**, such as during start-up, is stored in ROM **912**. RAM **910** typically contains data and/or program modules that are immediately accessible to and/or presently operated on by the processing unit **904**.

[**0193**] Computer **902** may also include other removable/non-removable, volatile/non-volatile computer storage media. By way of example, **FIG. 9** illustrates a hard disk drive **916** for reading from and writing to a non-removable, non-volatile magnetic media (not shown), a magnetic disk drive **918** for reading from and writing to a removable, non-volatile magnetic disk **920** (e.g., a "floppy disk"), and an optical disk drive **922** for reading from and/or writing to a removable, non-volatile optical disk **924** such as a CD-ROM, DVD-ROM, or other optical media. The hard disk drive **916**, magnetic disk drive **918**, and optical disk drive **922** are each connected to the system bus **908** by one or more data media interfaces **925**. Alternatively, the hard disk drive **916**, magnetic disk drive **918**, and optical disk drive **922** can be connected to the system bus **908** by one or more interfaces (not shown).

[**0194**] The disk drives and their associated computer-readable media provide non-volatile storage of computer readable instructions, data structures, program modules, and other data for computer **902**. Although the example illustrates a hard disk **916**, a removable magnetic disk **920**, and a removable optical disk **924**, it is to be appreciated that other types of computer readable media which can store data that is accessible by a computer, such as magnetic cassettes or other magnetic storage devices, flash memory cards, CD-ROM, digital versatile disks (DVD) or other optical storage, random access memories (RAM), read only memories (ROM), electrically erasable programmable read-only memory (EEPROM), and the like, can also be utilized to implement the exemplary computing system and environment.

[**0195**] Any number of program modules can be stored on the hard disk **916**, is magnetic disk **920**, optical disk **924**, ROM **912**, and/or RAM **910**, including by way of example, an operating system **926**, one or more application programs **928**, other program modules **930**, and program data **932**. Each of such operating system **926**, one or more application programs **928**, other program modules **930**, and program data **932** (or some combination thereof) may include an embodiment of a digital audio signal hashing unit, a watermark encoder, transformer, a statistics estimator, an adaptive quantizer, an error-correction decoder, and a hasher.

[**0196**] A user can enter commands and information into computer **902** via input devices such as a keyboard **934** and a pointing device **936** (e.g., a "mouse"). Other input devices **938** (not shown specifically) may include a microphone, joystick, game pad, satellite dish, serial port, scanner, and/or the like. These and other input devices are connected to the processing unit **904** via input/output interfaces **940** that are coupled to the system bus **908**, but may be connected by other interface and bus structures, such as a parallel port, game port, or a universal serial bus (USB).

[**0197**] A monitor **942** or other type of display device can also be connected to the system bus **908** via an interface, such as a video adapter **944**. In addition to the monitor **942**, other output peripheral devices can include components such as speakers (not shown) and a printer **946** which can be connected to computer **902** via the input/output interfaces **940**.

[**0198**] Computer **902** can operate in a networked environment using logical connections to one or more remote computers, such as a remote computing device **948**. By way of example, the remote computing device **948** can be a personal computer, portable computer, a server, a router, a

network computer, a peer device or other common network node, and the like. The remote computing device **948** is illustrated as a portable computer that can include many or all of the elements and features described herein relative to computer **902**.

[**0199**] Logical connections between computer **902** and the remote computer **948** are depicted as a local area network (LAN) **950** and a general wide area network (WAN) **952**. Such networking environments are commonplace in offices, enterprise-wide computer networks, intranets, and the Internet.

[**0200**] When implemented in a LAN networking environment, the computer **902** is connected to a local network **950** via a network interface or adapter **954**. When implemented in a WAN networking environment, the computer **902** typically includes a modem **956** or other means for establishing communications over the wide network **952**. The modem **956**, which can be internal or external to computer **902**, can be connected to the system bus **908** via the input/output interfaces **940** or other appropriate mechanisms. It is to be appreciated that the illustrated network connections are exemplary and that other means of establishing communication link(s) between the computers **902** and **948** can be employed.

[**0201**] In a networked environment, such as that illustrated with computing environment **900**, program modules depicted relative to the computer **902**, or portions thereof, may be stored in a remote memory storage device. By way of example, remote application programs **958** reside on a memory device of remote computer **948**. For purposes of illustration, application programs and other executable program components such as the operating system are illustrated herein as discrete blocks, although it is recognized that such programs and components reside at various times in different storage components of the computing device **902**, and are executed by the data processor(s) of the computer.

[**0202**] Computer-Executable Instructions

[**0203**] An implementation of an exemplary audio recognizer may be described in the general context of computer-executable instructions, such as program modules, executed by one or more computers or other devices. Generally, program modules include routines, programs, objects, components, data structures, etc. that perform particular tasks or implement particular abstract data types. Typically, the functionality of the program modules may be combined or distributed as desired in various embodiments.

[**0204**] X Exemplary Operating Environment

[**0205**] **FIG. 9** illustrates an example of a suitable operating environment **900** in which an exemplary audio recognizer may be implemented. Specifically, the exemplary audio recognizer(s) described herein may be implemented (wholly or in part) by any program modules **928-930** and/or operating system **928** in **FIG. 9** or a portion thereof.

[**0206**] The operating environment is only an example of a suitable operating **8** environment and is not intended to suggest any limitation as to the scope or use of functionality of the exemplary audio recognizer(s) described herein. Other well known computing systems, environments, and/or configurations that are suitable for use include, but are not limited to, personal computers (PCs), server computers, hand-held or laptop devices, multiprocessor systems, microprocessor-based systems, programmable consumer electronics, wireless phones and equipments, general- and special-purpose appliances, application-specific integrated circuits (ASICs), network PCs, minicomputers, mainframe computers, distributed computing environments that include any of the above systems or devices, and the like.

[**0207**] Computer Readable Media

[**0208**] An implementation of an exemplary audio recognizer may be stored on or transmitted across some form of computer readable media. Computer readable media can be any available media that can be accessed by a computer. By way of example, and not limitation, computer readable media may comprise "computer storage media" and "communications media."

[**0209**] "Computer storage media" include volatile and non-volatile, removable and non-removable media implemented in any method or technology for storage of information such as computer readable instructions, data structures, program modules, or other data. Computer storage media includes, but is not limited to, RAM, ROM, EEPROM, flash memory or other memory technology, CD-ROM, digital versatile disks (DVD) or other optical storage, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, or any other medium which can be used to store the desired information and which can be accessed by a computer.

[**0210**] "Communication media" typically embodies computer readable instructions, data structures, program modules, or other data in a modulated data signal, such as carrier wave or other transport mechanism. Communication media also includes any information delivery media.

[**0211**] The term "modulated data signal" means a signal that has one or more of its characteristics set or changed in such a manner as to encode information in the signal. By way of example, and not limitation, communication media includes wired media such as a wired network or direct-wired connection, and wireless media such as acoustic, RF, infrared, and other wireless media. Combinations of any of the above are also included within the scope of computer readable media.

Conclusion

[**0212**] Although the invention has been described in language specific towards digital audio signals, it is to be understood that the invention defined in the appended claims is not necessarily limited to digital audio signals. Rather, it may apply to other digital signals (e.g., images, multimedia, video, film, data, information, text, etc.)

[**0213**] Although the invention has been described in language specific to structural features and/or methodological steps, it is to be understood that the invention defined in the appended claims is not necessarily limited to the specific features or steps described. Rather, the specific features and steps are disclosed as preferred forms of implementing the claimed invention.

1. A computer-implemented method for hashing a digital signal, comprising:

transforming the digital signal into a digital signal transform;

randomly dividing the digital signal transform into multiple chunks, each chunk containing signal data;

averaging, for each of the chunks, the signal data to produce corresponding chunk averages;

generating, based in part on the chunk averages, an exponential distribution having multiple distinct quantization levels;

randomly rounding each of the chunk averages to one of the quantization levels to produce rounded values; and

hashing a composite of the rounded values.

2. A computer-implemented method as recited in claim 1, wherein the transforming is performed according to a MCLT technique.

3. A computer-implemented method as recited in claim 1, wherein the averaging comprises computing a variance of the signal data in cases where the chunk average is approximately zero.

4. A computer-implemented method as recited in claim 1, wherein the hashing comprises processing the rounded values to produce an intermediate hash value such that for perceptually distinct digital signals, the intermediate hash values differ approximately 60% of the time and for perceptually same digital signals, the intermediate hash values agree in all but approximately 20% of the time.

5. A computer-implemented method as recited in claim 1, wherein the hashing comprises processing the rounded values using a Reed-Müller error correction code decoder.

6. A computer-implemented method as recited in claim 1, wherein the hashing comprises processing the rounded values using a Reed-Müller error correction code decoder with an exponential pseudo-random norm.

7. A computer-implemented method as recited in claim 1, wherein the hashing produces an intermediate hash value, further comprising reducing a size of the intermediate hash value via an error correction process.

8. A computer-implemented method as recited in claim 1, wherein the digital signals are selected from a group consisting of digital audio signals, digital video signals, digital music signals, digital image signals, and digital multimedia signals.

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