Fingerprinting

Audio and Video Detection Systems

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Overview

Introduction

Fingerprinting

Content based fingerprinting:

- Algorithm that maps a multimedia object into a compact digital summary (set of hashes)

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  - Search engines (Shazam)
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Requirements

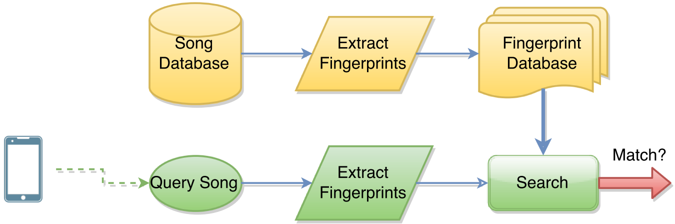
A fingerprint algorithm must be noise resistant and computationally efficient.

Table of Contents

Introduction

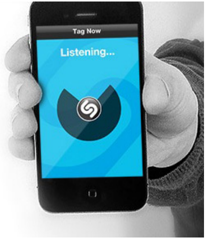

SHAZAM®
AT&T
11:32 AM
92%
Listening

Process


Song Database
Extract Fingerprints
Fingerprint Database
Query Song
Extract Fingerprints
Search
Match?

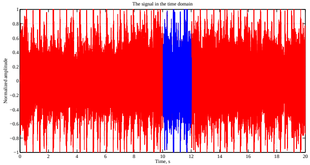
Goals

- The length of the recorded sample should not be more than 15 seconds long



Goals

- The length of the recorded sample should not be more than 15 seconds long
- The sample can come from any portion of the original audio track



Goals

- The length of the recorded sample should not be more than 15 seconds long
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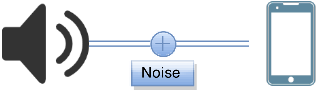
- Robust



Hashing

Transformations to the frequency domain

Fourier transform

Fourier transform: maps the signal $x(t) : \mathbb{R} \to \mathbb{C}$ into

$$X(f) = \int_{\infty}^{\infty} x(t) e^{-j2\pi ft} dt$$

which decomposes the function into its frequencies.

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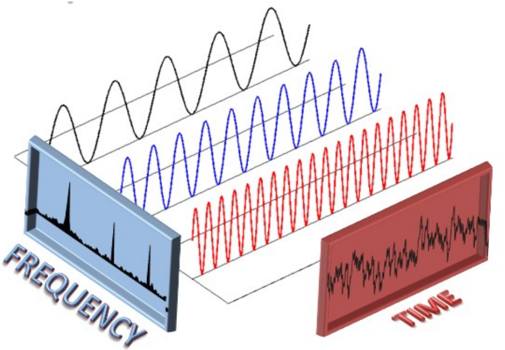

Short-time Fourier Transform

STFT is a Fourier-related transform used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time.

$$x(t) \xmapsto{STFT} X(\tau, f) = \int_{-\infty}^{\infty} x(t) w(t-\tau) e^{-j2\pi ft} dt$$

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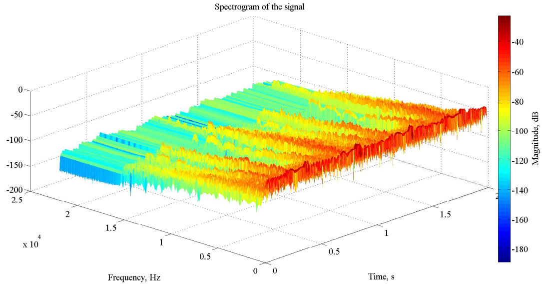
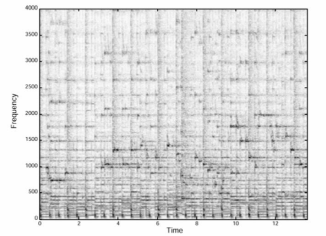


Constellation and Hashing



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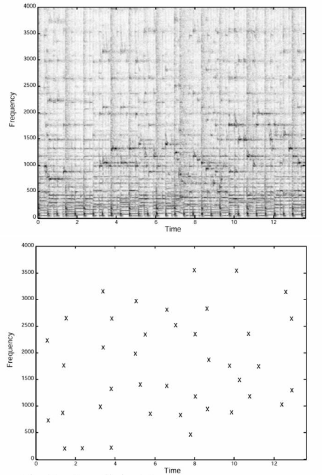

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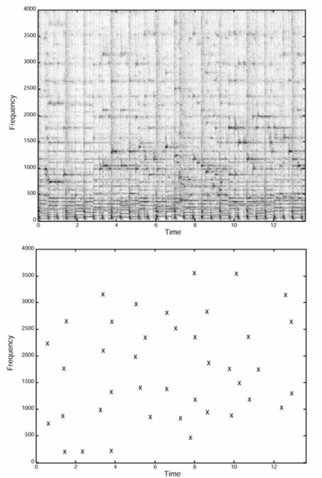

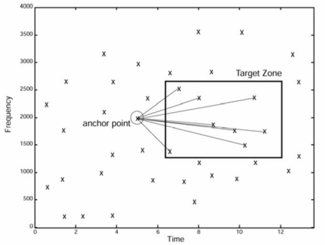

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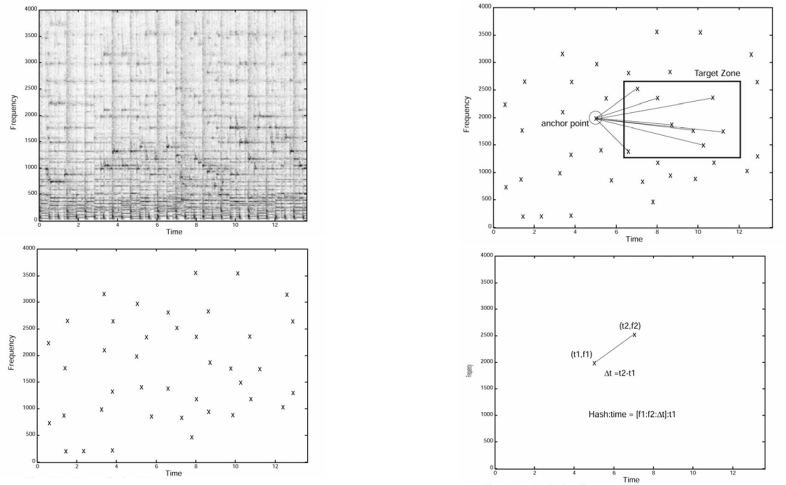

Hashing

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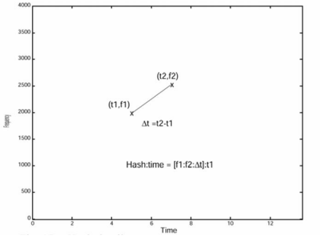

$$(f_1, f_2, \Delta t) \rightarrow \text{hash}$$

30 bits hash:

- 10 BITS frequency anchor
- 10 BITS frequency target
- 10 BITS time difference

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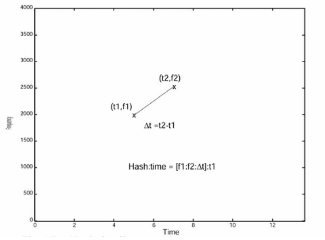

30 bits hash:

- 10 BITS frequency anchor
- 10 BITS frequency target
- 10 BITS time difference

Each hash is associated with the time offset:

$$\text{hash:offset} = (f_1, f_2, \Delta t) : t_1$$

Searching and Scoring

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We take all matching hashes of a given song and we plot their time offset

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DB song	Query song
h:t	h:τ

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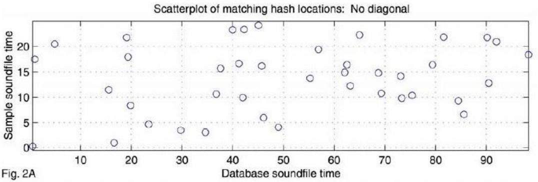


Fig. 2A

Searching and Scoring

We take all matching hashes of a given song and we plot their time offset

DB song	Query song
h:t	h:τ

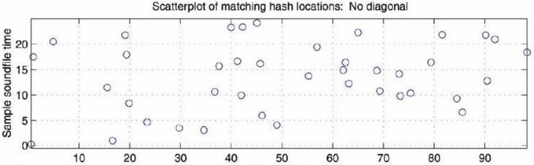


Fig. 2A

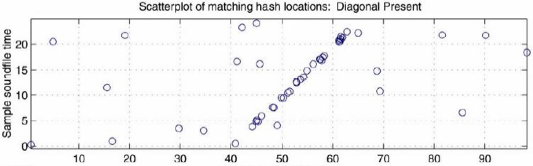
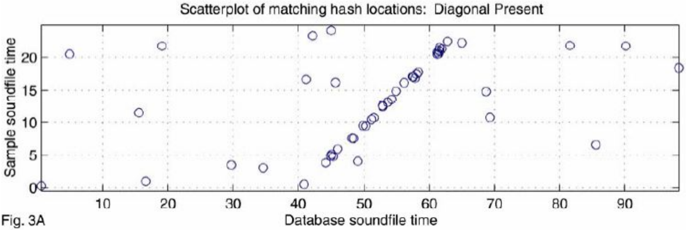


Fig. 3A

Scoring

- Matching features: $t_k = \tau_k + \text{constant}$



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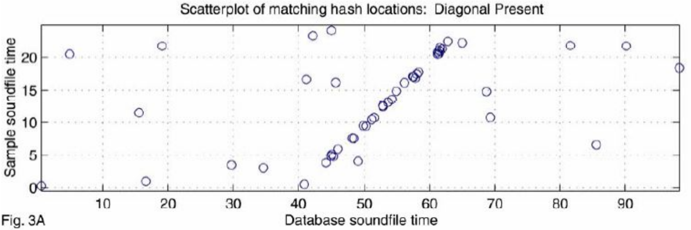
$$\Delta_k = t_k - \tau_k$$



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- Then we plot a histogram of these Δ_k

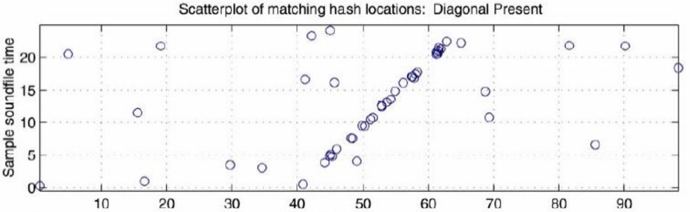


Fig. 3A

Scoring

Track that does not match the sample

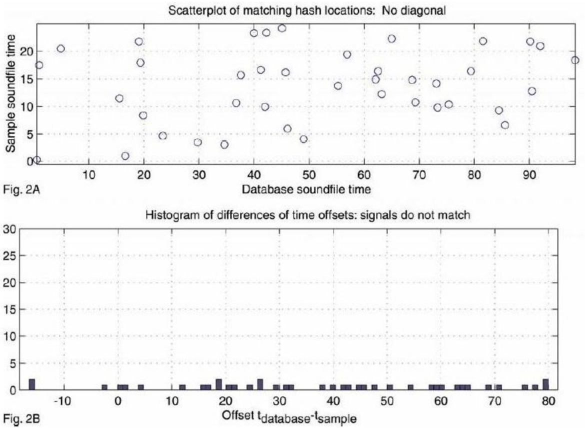


Figure : No diagonal in the scatter-plot.

Scoring

Track that matches the sample

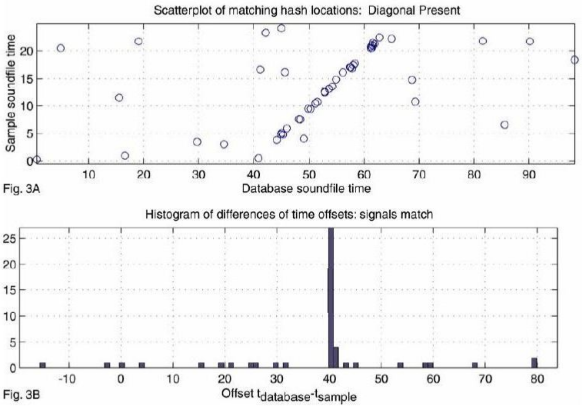
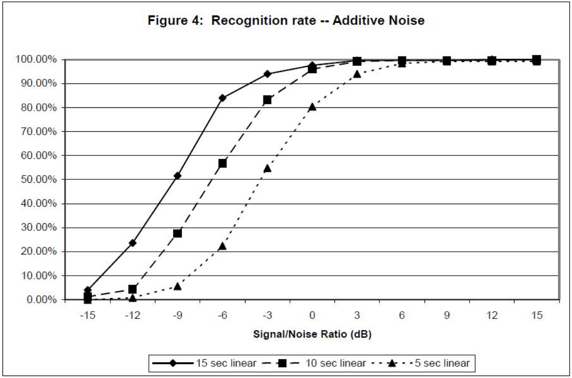


Figure : Diagonal in the scatter-plot: cluster in the histogram.

Results

Results

- The algorithm performs well with significant levels of noise



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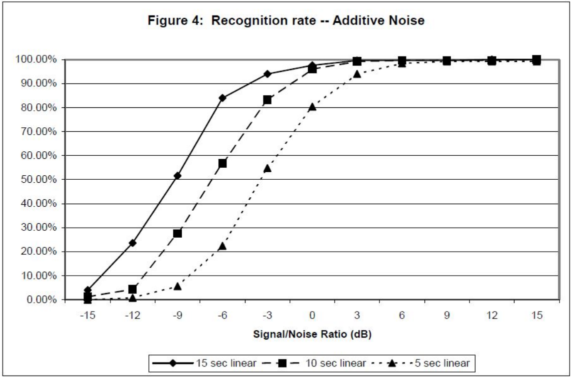

- For a database of 20 about thousand tracks the search time is in the order of 5 – 500 milliseconds.

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The purpose of this system is to detect copyrights violations.

A fingerprint should be

- Robust to content-preserving distortions
- Discriminant
- Easy to compute
- Compact

Image and Video Representations

- RBG

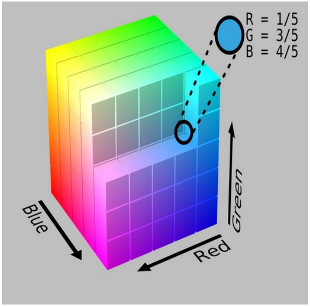
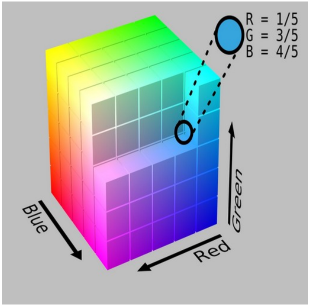


Image and Video Representations

- RBG
  - Colors represented as a combination of red, green and blue (3D-space)



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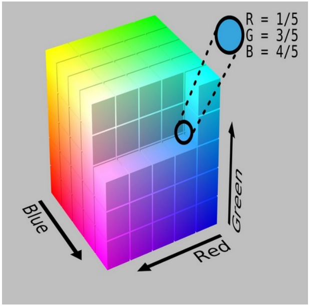

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- YUV

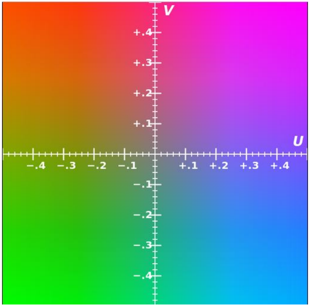

Image and Video Representations

- RBG
  - Colors represented as a combination of red, green and blue (3D-space)
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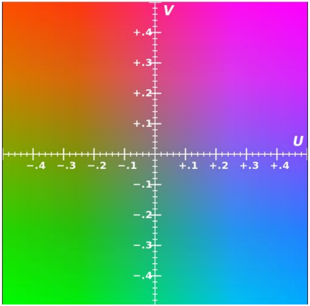
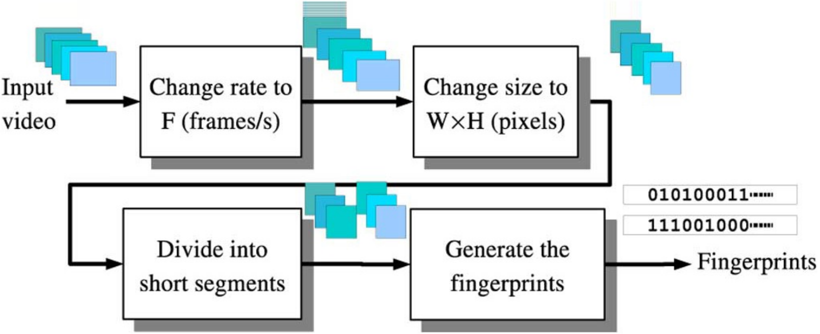
- YUV
  - Y is the luminance component, U and V are the chrominance components.



Preprocessing

Preprocessing



Discrete cosine transform

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- It is a widely used tool in image and video processing and compression!
- It is possible to extract some relevant information from the frequency representation

Discrete cosine transform
Formula

The two-dimensional DCT of an M-by-N matrix A is defined as follow:

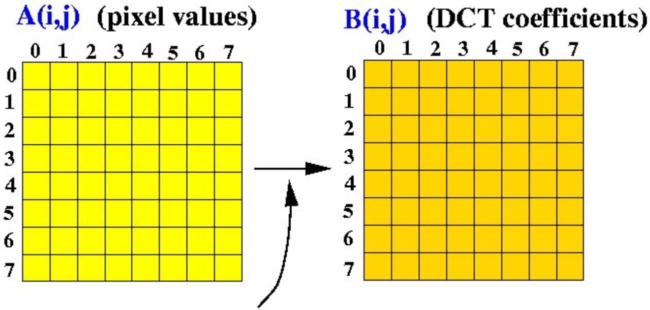
$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos \frac{\pi(2m+1)p}{2M} \cos \frac{\pi(2n+1)q}{2N}$$

$$\alpha_p = \begin{cases} \frac{1}{\sqrt{M}}, & p = 0 \\ \sqrt{\frac{2}{M}}, & 1 \leq p \leq M-1 \end{cases} \qquad \alpha_q = \begin{cases} \frac{1}{\sqrt{N}}, & q = 0 \\ \sqrt{\frac{2}{N}}, & 1 \leq q \leq M-1 \end{cases}$$

where $0 \leq p \leq M-1$ and $0 \leq q \leq N-1$ are the matrix indexes.

Discrete cosine transform

Example



$$B(k_1,k_2) = \frac{1}{4} C(k_1)C(k_2) \sum_{i=0}^{7} \sum_{j=0}^{7} A(i,j) \cos\left[\frac{\pi \times k_1}{2 \times 8}(2i+1)\right] \cos\left[\frac{\pi \times k_2}{2 \times 8}(2j+1)\right]$$

$$C(k) = \frac{1}{\sqrt{2}} \quad \text{if } k = 0$$

$$C(k) = 1, \text{ otherwise}$$

3D-DCT

3D Discrete cosine transform

3D-DCT is a DCT applied to a 3-dimensional matrix.

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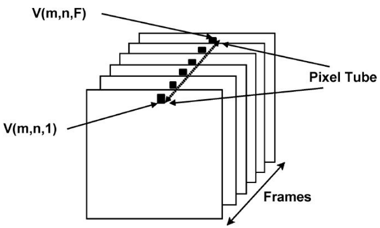
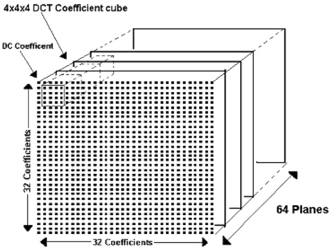
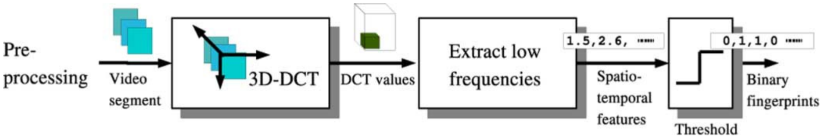
Time domain



Frequency domain



Fingerprinting using 3D-DCT



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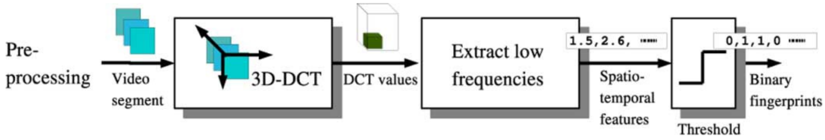
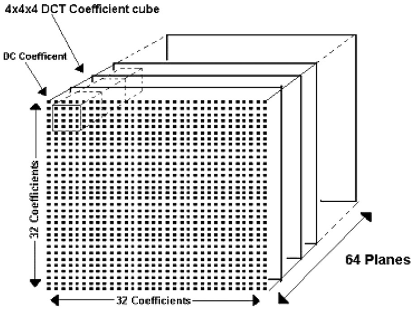
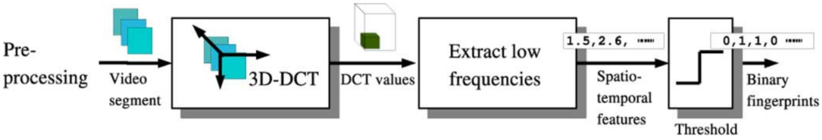
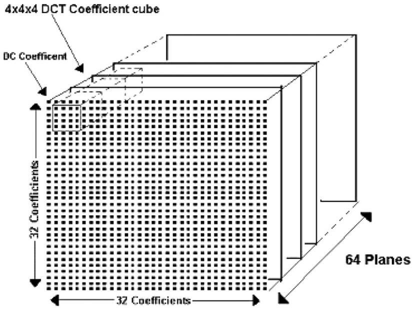




Fingerprinting using 3D-DCT





Binary fingerprints are derived by thresholding the low-frequency coefficients of the transform; the threshold is the median value of the selected coefficients.

Fingerprinting using TIRIs

TIRI

Temporally Informative Representative Image

A TIRI contains spatial and temporal information of a short segment of a video sequence.

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Temporally Informative Representative Image

A TIRI contains spatial and temporal information of a short segment of a video sequence.

$$I'_{m,n} = \sum_{k=1}^{J} w_k I_{m,n,k}$$

where $I_{m,n,k}$ is the luminance value of the (m,n)th pixel in a set of J frames and w_k is a weighting factor.

TIRI

Weighting factor

Experiments were made with different w: constant, linear, exponential.

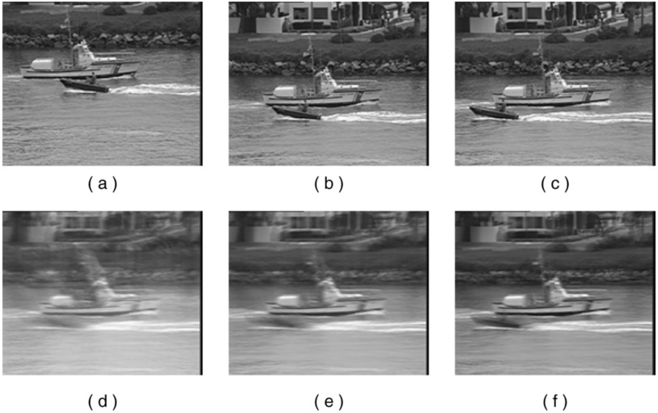
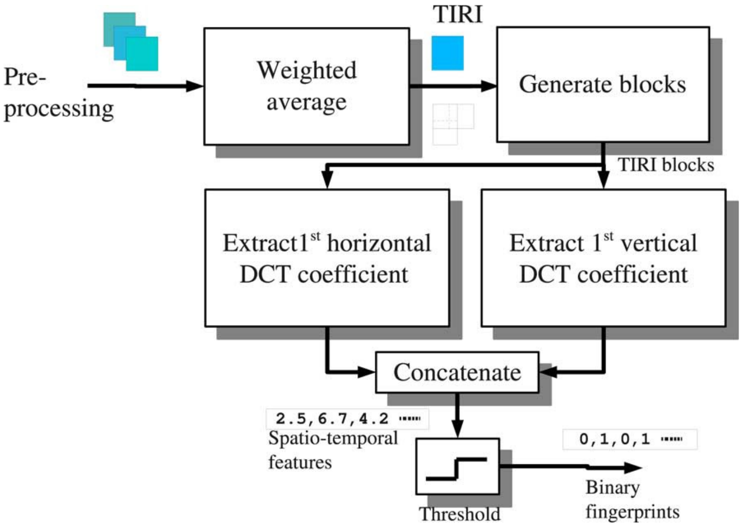


Figure : (d) $w_k = 1$ (costant), (e) $w_k = k$ (linear), (f) $w_k = 1.2^k$ (exponential)

TIRI-DCT


Pre-
processing
Weighted
average
TIRI
Generate blocks
TIRI blocks
Extract1st horizontal
DCT coefficient
Extract 1st vertical
DCT coefficient
Concatenate
2.5,6.7,4.2 ......
Spatio-temporal
features
Threshold
0,1,0,1 ......
Binary
fingerprints

Searching

Searching requirements

After the fingerprint is extracted, the database is searched for the closest fingerprint.

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Nearest neighbor problem

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Hamming distance

The process used to create binary fingerprints allow us to use the Hamming distance as a metric of similarity.

Inverted-File-Based Similarity search

$$\underbrace{0110001}_{1^{st}\ \text{word}}\ \underbrace{0010110}_{2^{nd}\ \text{word}} \dots\ \underbrace{1110001}_{(n-1)^{th}\ \text{word}}\ \underbrace{0010101}_{n^{th}\ \text{word}}$$

$m =$ word length

$$n = \frac{L}{m}$$

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$$n = \frac{L}{m}$$

Position of a word in a fingerprint

	1	2	3	...	n-1	n
1	1, 44, 250	10, 14, 99	21, 250			
2	2, 86	5, 170, 241				
⋮				⋱		
⋮						
2^m				...	61, 26	4

Inverted-File-Based Similarity search

To find a query fingerprint in a database:

- The fingerprint is divided into *n* words (of *m* bits)

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To find a query fingerprint in a database:

- The fingerprint is divided into *n* words (of *m* bits)
- The query is compared with fingerprints that starts with the same word.
- If the Hamming distance is below a certain threshold, the match is found.

Position of a word in a fingerprint

	1	2	3	...	n-1	n
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2	2, 86	5, 170, 241				
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Inverted-File-Based Similarity search

To find a query fingerprint in a database:

- The fingerprint is divided into n words (of m bits)
- The query is compared with fingerprints that starts with the same word.
- If the Hamming distance is below a certain threshold, the match is found.
- Otherwise the procedure is repeated with the second word and so on.

Position of a word in a fingerprint

	1	2	3	...	n-1	n
1	1, 44, 250	10, 14, 99	21, 250			
2	2, 86	5, 170, 241				
⋮				⋱		
2^m				...	61, 26	4

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- If no match is found, then the cluster that is the second closest to the query is examined, then the third and so on

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F-score It is the harmonic mean of precision and recall:

$$F = 2\frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

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Attack	F-score	
	3D-DCT	TIRI-DCT
Noise	1.00	0.99
Brightness	1.00	0.99
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Speed

- TIRI-DCT is more than 3 times faster than 3D-DCT
- Approximate search algorithms are much faster than the exhaustive search when the error rates are low. Cluster-based approach is faster.

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- It yields a high average true positive rate of 97.6% and a low average false positive rate of 1%.

YouTube testing

Results of Scott Smitelli tests:

Modification Performed	Result
Song reversed	Pass
Pitch was lowered 6%	Pass
Pitch was lowered 5%	Fail
Pitch was raised 5%	Fail
Pitch was raised 6%	Pass
Time was expanded 6%	Pass
Time was expanded 5%	Fail
Time was compressed 5%	Fail
Time was compressed 6%	Pass
44% noise, 56% song	Fail
45% noise, 55% song	Pass

Modification Performed	Result
Volume was reduced 48 dB	Fail
Volume was reduced 18 dB	Fail
Volume was reduced 6 dB	Fail
Volume was increased 6 dB	Fail
Volume was increased 18 dB	Fail
Volume was increased 48 dB	Fail
Slow down 4%	Pass
Slow down 3%	Fail
Speed up 3%	Fail
Speed up 4%	Fail
Speed up 5%	Pass

Questions?