Authenticated Content-Based Image Retrieval

GUO Shangwei

June 21, 2018

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Framework of CBIR

HKBU Database Group

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- BOW Coding + Inverted File

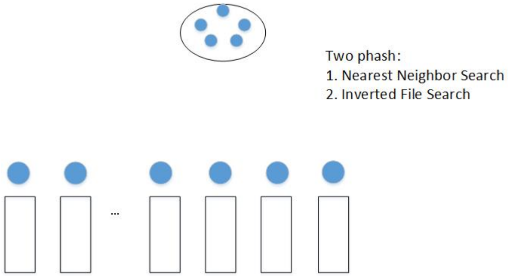
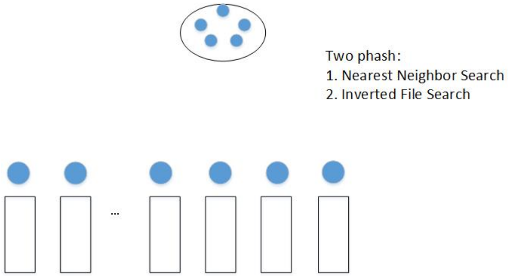


Figure 1: The CBIR framework we use

Framework of CBIR

- BOW Coding + Inverted File



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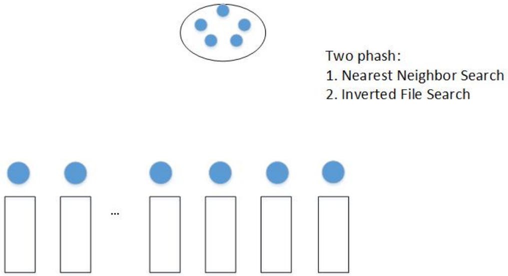

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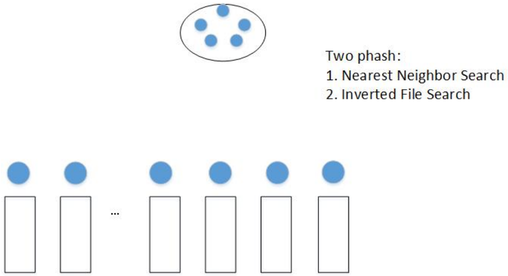

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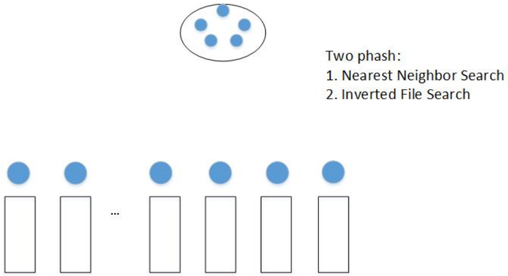

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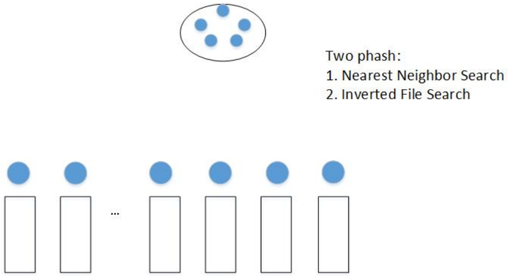

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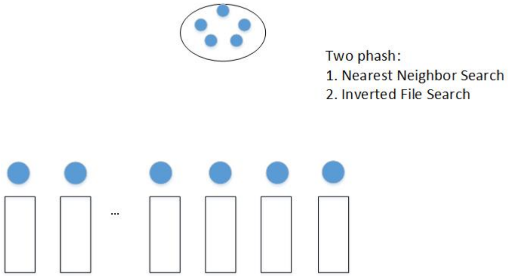

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  - Authentication algorithms for both BOW coding(ANN) and similarity search

Problem Definition

- Entries: DO, SP and Client

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  - Client can verify the integrity of query results SP claims to return

Approximate k-means(AKM)

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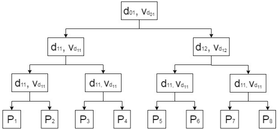

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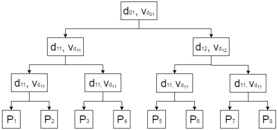

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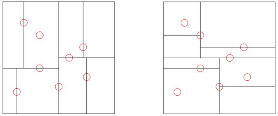

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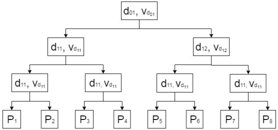

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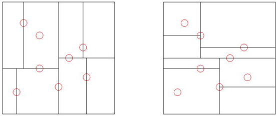

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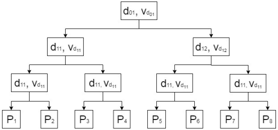

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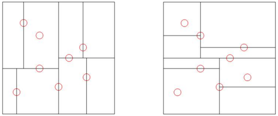

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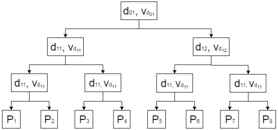

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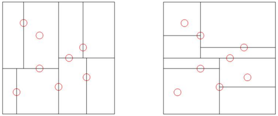

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- Approximate NN Search
  - When searching the trees, a single priority queue is maintained across all the randomized trees so that search can be ordered by increasing distance to each bin boundary.
  - The degree of approximation is determined by examining a fixed number of leaf nodes, at which point the search is terminated and the best candidates returned.

Authenticated AKM

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1. Framework of CBIR
2. Authenticated AKM
3. Authenticated Inverted File

Authenticated AKM

- Merkle random kd-trees: Just apply Merkle tree

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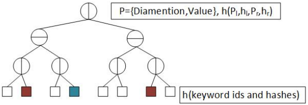
- Challenge: There are too many queries. It is inefficient if SP generates a VO for every query and then client verifies its integrity
- Generate and verify VO in batches

VO Generation



VO: P[P[P[leafH leafN] P[leafH leafN]] P[(Pl nodeH) P[leafN leafH]]]

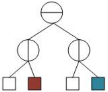
Figure 4: VO generation

Algorithm 1: Generate VO

Input: Location set L of leaf nodes, node P, VO;

if P is a leaf node **then**
    if P in L **then**
        VO $\leftarrow P$;
        return
    else
        VO $\leftarrow hash(P)$;
        return
    end if
end if
VO $\leftarrow P$;
VO $\leftarrow [$;
if P_l leafs $\cap L \neq \varnothing$ **then**
    GeneVO(L, P_l, VO);
else
    VO $\leftarrow P_l$;
end if
if P_r leafs $\cap L \neq \varnothing$ **then**
    GeneVO(L, P_r, VO);
else
    VO $\leftarrow P_r$;
end if
VO $\leftarrow]$;
return VO

Verification



VO: P[P[leafH leafN] P[leafH leafN]]

Figure 5: VO verification

Algorithm 2: Verify VO (computation of hash can be done synchronously)

Input: Queries Q_i, VO, lists H_i, current list locations, thresholds;

while VO still has entries **do**
  if P is an internal node **then**
    Split lists $H_{si} \leftarrow \varnothing$;
    for H_i **do**
      if The current threshold in H_i is smaller than the corresponding threshold **then**
        Split;
      else
        Location + 1;
      end if
    end for
    if The current thresholds in H_i are smaller than the corresponding thresholds **then**
      Current list locations + 1;
    else
      return Error;
    end if
  end if
  if [**then**
    VerifyVO(Q_{i_s}, VO, H_{i_s}, current list locations, thresholds);
  end if
  if] **then**
    return
  end if
end while
return

Verification

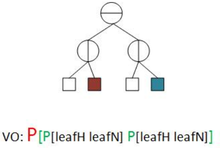


Figure 6: VO verification

Algorithm 3: Verify VO

Input: Queries Q_i, VO, lists H_i, current list locations, thresholds;

if P is leaf node **then**
  if The current thresholds in H_i are smaller than the corresponding thresholds **then**
    Current list locations + 1;
  else
    return Error;
  end if
end if
if P is leaf hash **then**
  if The current thresholds in H_i are greater than the corresponding thresholds **then**
    Current list locations + 1;
  else
    return Error;
  end if
end if

Check Leaf Nodes

- Challenge: False positive leaf nodes need to be checked

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- Just reveal part of keyword for authentication

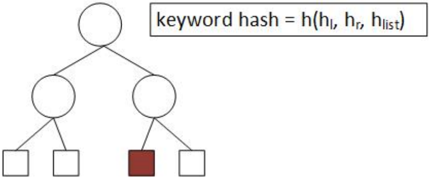

Figure 7: Keyword and its corresponding hash

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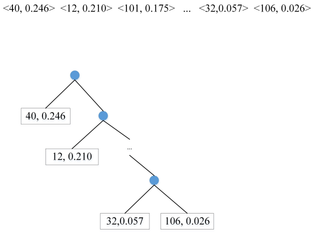

Figure 8: Impact sorted

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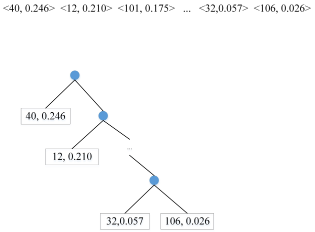

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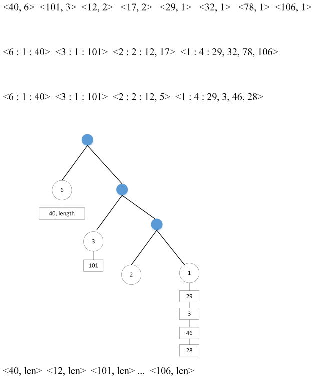

Figure 9: Frequency sorted

Authenticated Inverted File

- Combine Impact-Ordered and Frequency-Ordered

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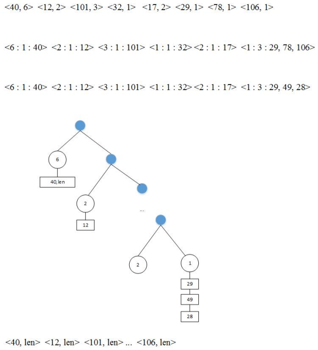

Figure 10: Combine impact-ordered and frequency-ordered 1

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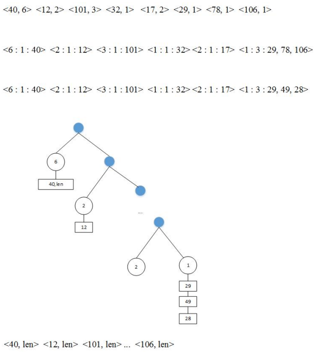
- Combine Impact-Ordered and Frequency-Ordered



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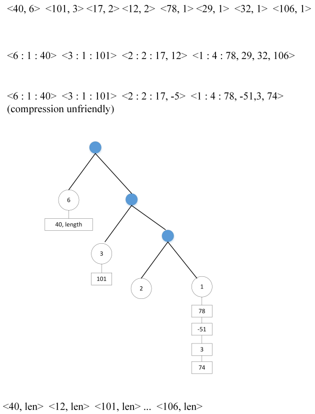

Figure 11: Combine impact-ordered and frequency-ordered 2

Other Issues

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