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Harnessing Encrypted Data in Cloud for Secure and Efficient Image Sharing from Mobile Devices

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Media Data are Ubiquitous

- In 2014, millions of media data are generated in every minute.
  - ***INSTAGRAM*** users post 216,000 images;
  - ***WHATSAPP*** users share 347,222 images;
  - ***PINTEREST*** users pin 3,472 images;
  - ***YOUTUBE*** users upload 72 hours new videos;
  - ***VINE*** users share 8,333 videos;
  - …

**Data Never Sleeps 2.0, Domo Inc.*
http://www.domo.com/learn/data-never-sleeps-2

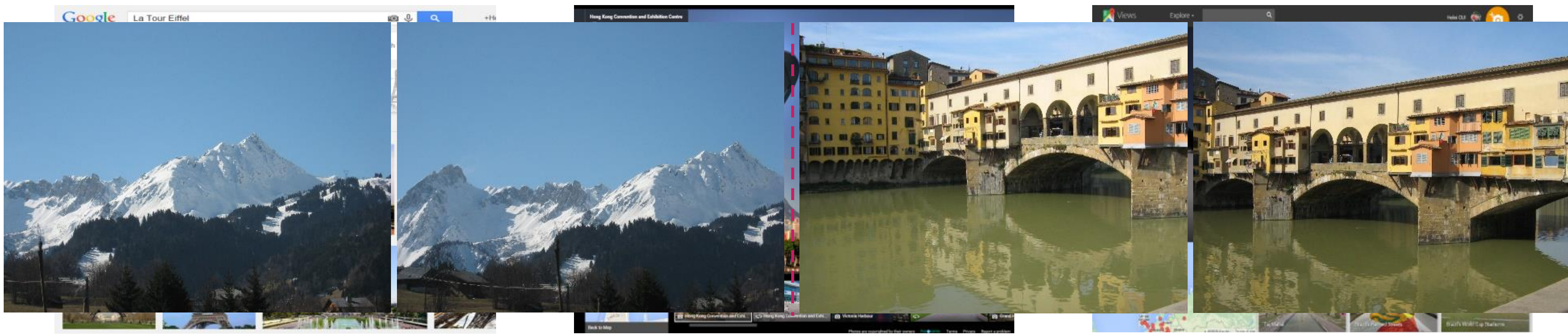
- Many applications utilize public cloud as backend.
  - for storage, processing, delivery, etc.

Computation, Storage, …

Exposing content-sensitive data to cloud raises privacy concerns.

And Meanwhile …

- Correlated images occur quite commonly in online image repositories.
  - Images with slightly different viewing angles, resolutions, or qualities.



- Various applications have already leveraged such correlations.
  - E.g., reduce media storage *[Zheng et. al AsiaCCS'2015]*, media transcoding *[Fan et. al ICASSP'2009]*, even image encoding *[Yue et. al TMM'2013]*, etc.

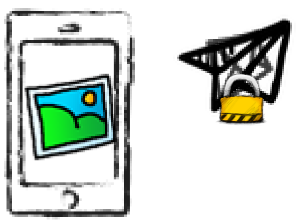
Can we securely leverage the image correlation to save the cost of original image transmission from mobile devices?

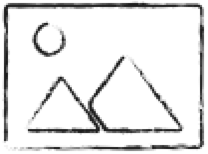
A demo of major steps

1. Secure digest generation;

2. Secure candidate selection;

3. Encrypted image reproduction.





Original image transmission could be saved.

Target scenario: You may want to securely share photos with friends, but the international data roaming can be expensive.

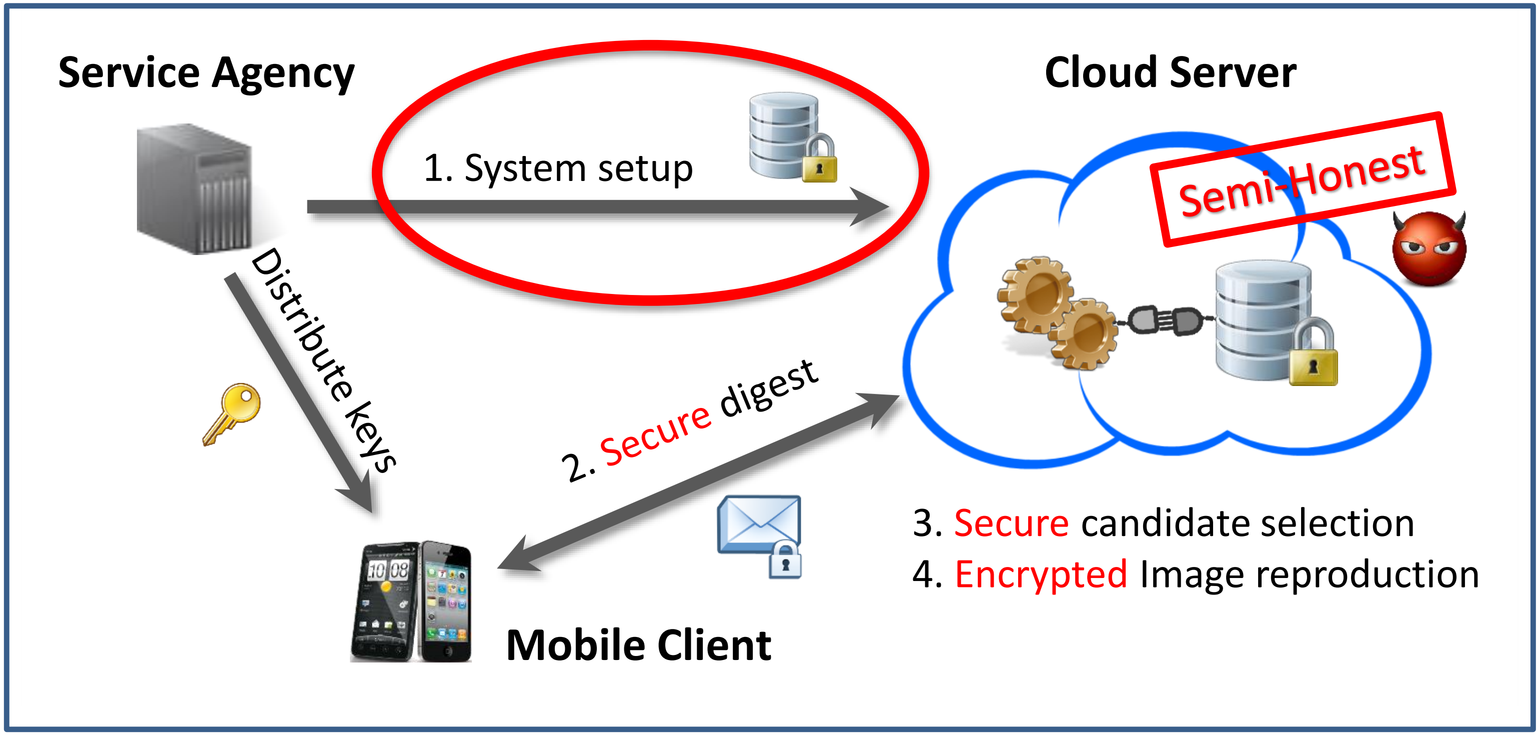
Two challenging subtasks:

- **Securely locate encrypted correlated image candidates.**
- **Secure image reproduction at cloud via encrypted candidates.**

The desirables:

- **Lightweight computation at client (usually mobile)**
- **Compact data transmission**
- **Security**

System Overview

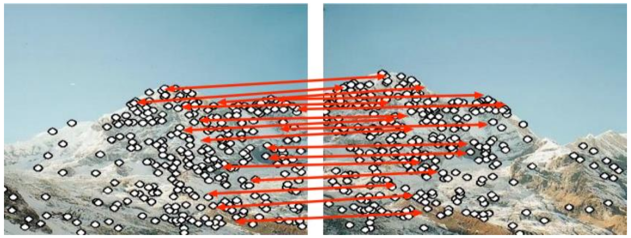


We assume the correlated image datasets are available at cloud.

System Initialization

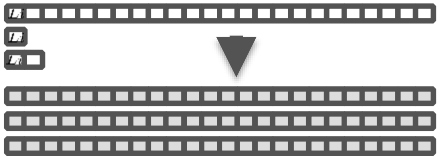
- Need to build an encrypted image database
  - to securely and efficiently locate the candidates.
  - use local feature (e.g., SIFT) and measure the closeness.
    - Adopted in many applications, e.g., object recognition.
    - More feature matches, more similar.

      [Brown et al. IJCV'2007]



- Initial attempt
  - Leverage searchable symmetric encryption (SSE)?
    - Use locality-sensitive hash (LSH) to hash the features, treat the hash values as keywords fed into SSE framework. *[Kuzu et al. ICDE'2012]*
    - But direct combination does not necessarily support large datasets.
      - E.g., thousands of features per image, and thousands of images.

One bad exemplary case of the encrypted inverted index



Secure & Efficient Searching Table

- We explore space efficient SSE *[Cash et al. NDSS'2014].*
  - Based on generic dictionary $\mathcal{D}$ (vertical design);
  - Treat each LSH keyword as an independent value;
  - Generate multiple key-value pairs, where key is converted from the LSH keyword, and the value contains the image/feature id.
- Padding can be avoided.
- Our construction:
  - For each feature f, compute LSH values:

    $\mathbf{v} = \{g_1(f)||1, \ldots, g_l(f)||l\}$, where $v_i = g_i(f)||i$;
  - For each v in $\mathbf{v}$:

    $K_1 \leftarrow P(Kv, 1||v)$, $K_2 \leftarrow P(Kr, 2||v)$;

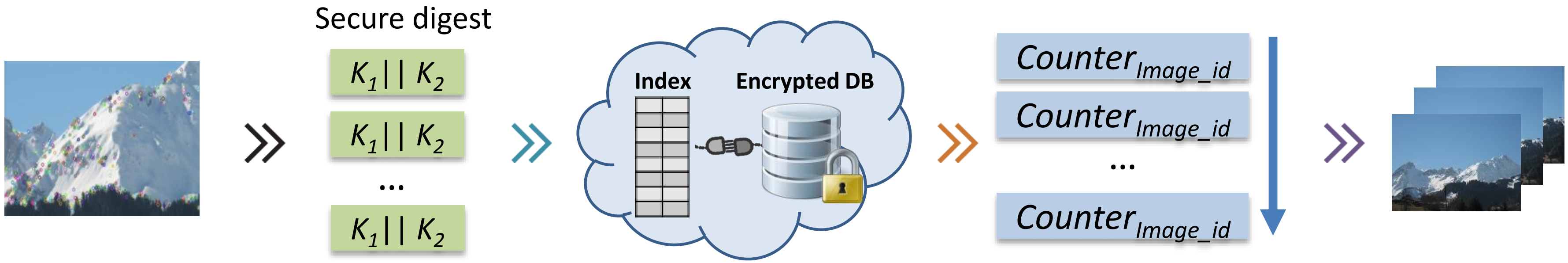
    $a \leftarrow F(K_1, c)$, $b \leftarrow Enc(K_2, f_{id})$;
  - $f_{id} = Image_{id} \,||\, feature_{id}$.

Key	Value
$a \leftarrow F(K_1, c)$	$b \leftarrow Enc(K_2, f_{id})$
…	…
…	…
…	…
…	…
…	…
…	…

Generic Dictionary

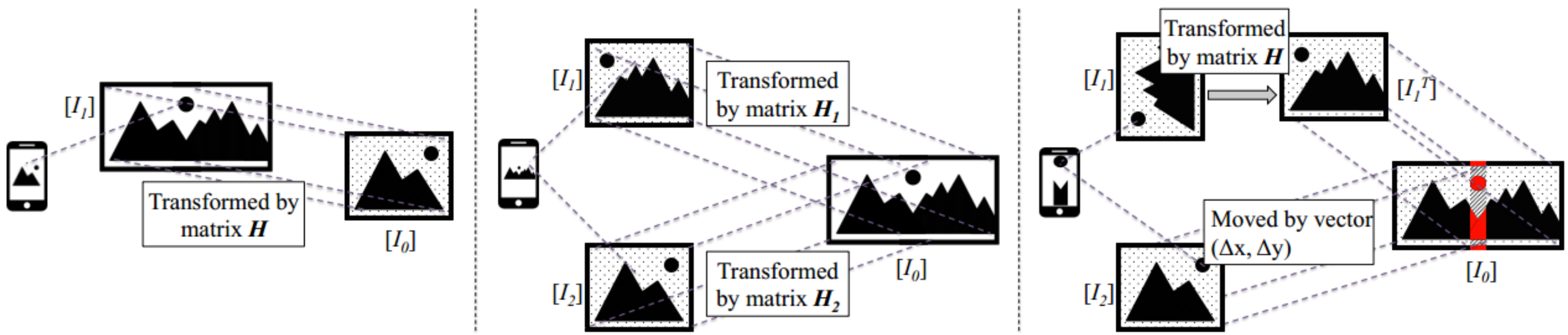
Candidate Selection

- Mobile client sends a compact secure digest ($\{K_1, K_2\}$):
  - Generated from the features of the image of interest;
  - For securely locating matched features at cloud.
- Voting-based ranking mechanism: the similarity between two images can be measured by the number of matched features.
  - More feature matches, more similar. *[Brown et al. IJCV'2007]*
  - Cloud locates the matched encrypted features ($f_{id} = Image_{id} \,||\, feature_{id}$).
  - Cloud ranks the frequency of $Image_{id}$ to get ***top-k*** candidates.



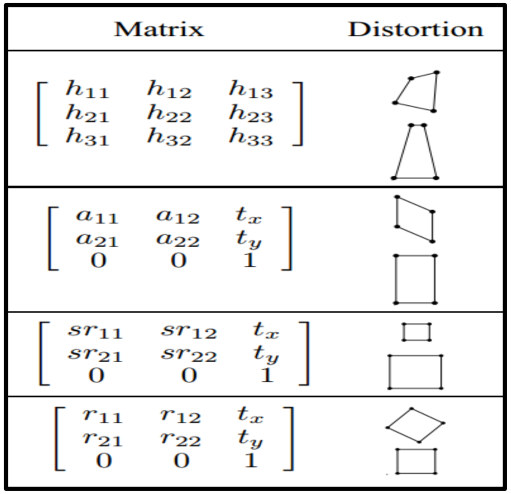
Encrypted Image Reproduction

- With the candidates, different possible ways to reconstruct the images can be supported:



(a) (b) (c)

- Need to instruct the cloud to reconstruct images from the candidates.
  - Usually it is a regular polygon area;
  - Can be measured by geometric transformation;
  - Denoted as a 3x3 matrix *H*.

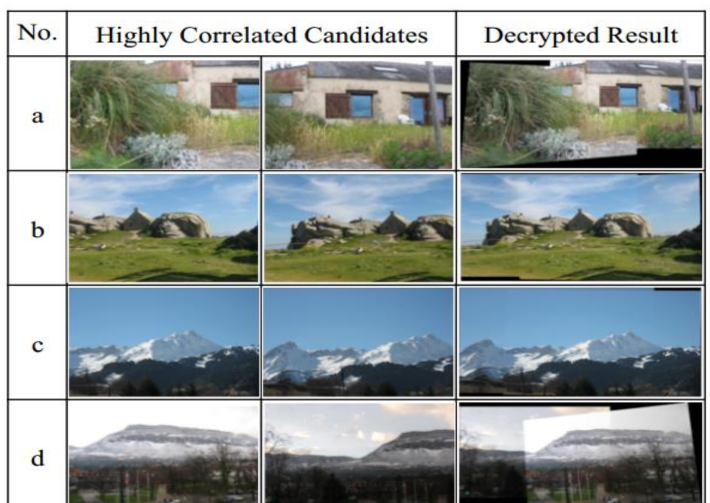


Encrypted Image Reproduction (Cont'd)

- Computing *H* is to eliminate false positive and estimate geometric transformation:
  - Directly compute *H* at cloud in ciphertext domain is not practical.
    - E.g., fully homomorphic encryption.
  - Mobile client can efficiently compute *H*:
    - Candidate size is small (e.g., < 5);
    - Feature descriptors are small (76 KB for 500 features);
    - The result *H* is very compact, 36 bytes.

H #1000 features (ms)	*H* #500 features (ms)
64	24

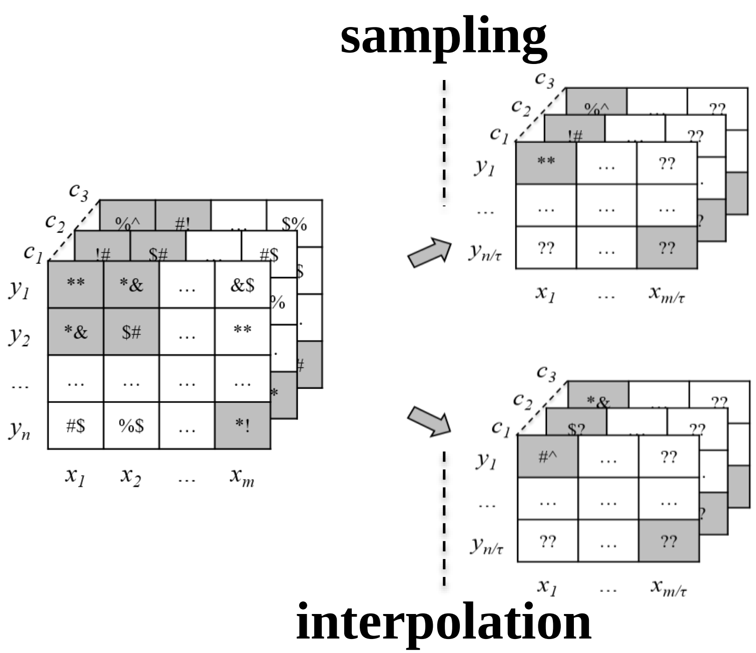
**Test on iPhone 6.*



**Examples of newly generated image without cropping.*

Two Approaches

- Knowing *H*, existing image processing techniques can be adopted in pixel/patch level.



Manipulate the position of each pixel,
e.g., replace, select, removal, etc.
Symmetric Encryption
e.g., AES, Blowfish.

Require computation on pixels.
Semi-homomorphic Encryption
e.g., Paillier cryptosystem.
(we have discussed how to pack multiple values to reduce the stroage space.)

Security Analysis

- Image content and features are protected in encrypted forms with semantic security along the service flow.
- Interaction in <u>*candidate selection*</u>, following the security framework of SSE *[Curtmola et.al CCS'2006]*
  - Simulation based security definition:
    - Real world: conduct real protocol **Ω** for candidate selection;
    - Ideal world: apply ideal function $\mathcal{F}$ to simulate the service flow.

Adversary should not be able to differentiate the real interactions from Ω and the simulated outputs by applying $\mathcal{F}$.

Real table $\mathcal{D}$

Key	Value
a	b
…	…
…	…

Real Ω

Ideal $\mathcal{F}$

Simulated table $\mathcal{D}'$

Key	Value
a'	b'
…	…
…	…

Security Analysis

Real table $\mathcal{D}$

Key	Value
a	b
…	…

Simulated table $\mathcal{D}'$

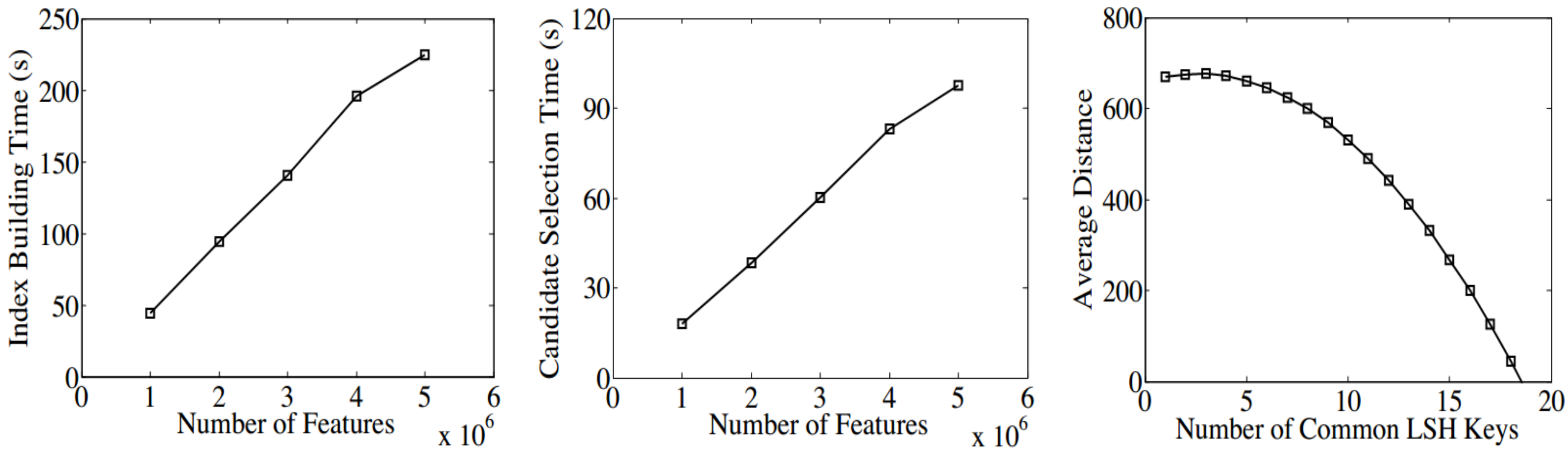
Key	Value
a'	b'
…	…

- Quantify the leakage functions (L_1, L_2) in candidate selection:
  - L_1: (N, [**f**], |[**f**]|), where N is the number of key-value pairs;
  - L_2: ({**t**}$_{\mathbf{q}}$, {f_{id}}, {[**f**]}), where **q** is the number of adaptive queries.
- Simulate a query on a simulated searching table:
  - Generates random strings to simulate secure digest **t'**;
  - Returns identical number of feature packages **r'** from L_2;
  - Achieve (L_1, L_2)-secure against adaptive attacks in random oracle model:
    - Replace the PRF with the random oracle H_1: $P(K, v) := H_1(K \| v)$;
    - The encryption algorithm Enc, on input K, f_{id}, chooses a random $r \in \{0,1\}^{\lambda}$, and outputs $(r, H_2(K \| r) \oplus f_{id})$, where H_2 is another random oracle.

Experiment Evaluation

- AWS server "c3.4xlarge"
- iOS 8.1 SDK
- Java 1.7 SDK
  - Java Cryptography Architecture
- OpenCV 2.4.10
- INRIA Holiday dataset
  - 1491 images, where numbers of images contain with overlapped areas
- MIRFLICKR-25K
  - select 10,000 images

Efficient and Effective Searching Table



- Both the index building time and candidate selection time are in linear to the size of dataset.
- The more common LSH keywords the two features share, the more similar they are.
  - **Overall accuracy can be guaranteed.**

Encrypted Image Reproduction is Fast

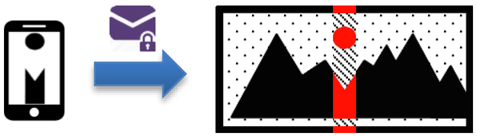
No.	Result (pixel)	Overlapped (pixel)	Symmetric (ms)	Asymmetric (ms)
a	3,764,466	783,600	47.62	15.52
b	5,583,891	2,465,688	87.1	43.17
c	7,699,860	4,519,680	132.9	74.28
d	11,517,444	2,310,528	143.5	49.82

- The time cost of symmetric key based approach is positively correlated with the result size;
- But for the other one, it is positively correlated with the overlapped size.

Bandwidth Saving

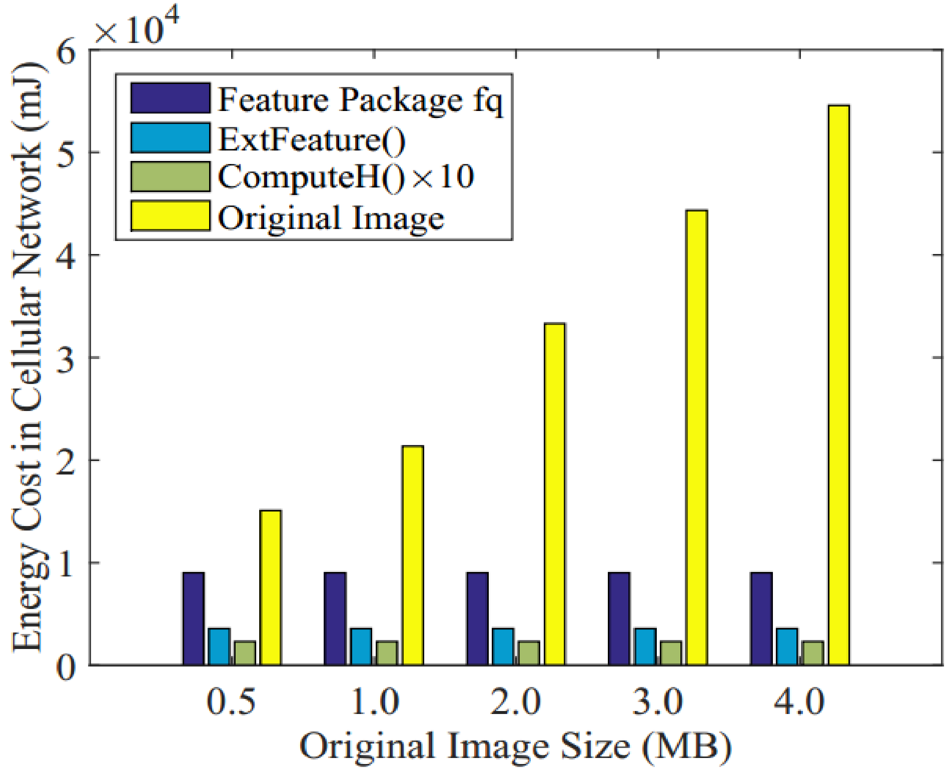
No.	t (KB)	r (KB)	H (Byte)	Result （KB）	Overall Saving
a	31.25	380	36	2309.6	82.2%
b	31.25	380	36	2494.2	83.5%
c	31.25	456	36	2105.6	76.9%
d	31.25	456	36	5548.3	91.2%
***Avg.**	**31.25**	**304**	**36**	**2764.8**	**87.8%**

- Up to 90% can be saved, compared with the original image size (~2.7MB) in JPEG.
  - Assuming sufficient amount of highly correlated images available at cloud.
  - Mainly depends on the *top-k* candidates.



**Avg. is estimated by the setting (l =5, m = 200, k = 4), and the result size is 2.7 MB.*

Energy Saving (in full version)



- Our design can indeed bring the energy saving, when considering all computations and data transmission.
  - Can be saved from **1.5X** to over **5X**.

**Test on Google Nexus 5 by using the App, Power Tutor 2 Pro.*

Conclusion and Future Works

- Summary:
  - Our system securely leverages the image correlation to save the bandwidth and energy cost of original image transmission from mobile devices.
- Future works:
  - Further reduce the bandwidth, e.g., increase the feature quality to decrease the number of the features.
- Thank you! Questions?

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