

# **Currency Recognition on Mobile Phones**

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### Goal

# Method Overview

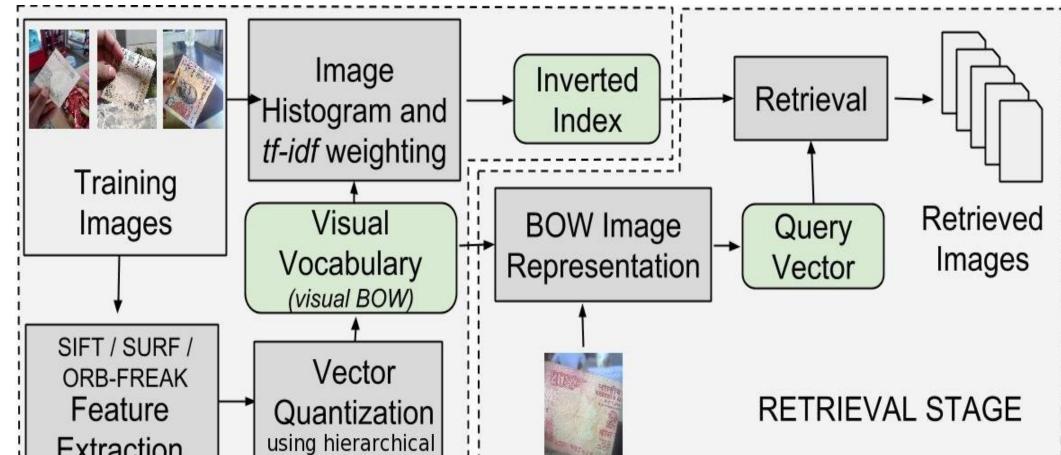
Recognizing currency bills in cluttered scenes and challenging situations on a low-end mobile phone. This mobile application is intended for robust, practical and easy use by the visually impaired.



## Motivation and Challenges

#### **B.** Instance Retrieval

Classification of bills in the image uses an instance retrieval pipeline: 1. Building a visual vocabulary -The set of clusters of features obtained from standard forms the visual descriptors, vocabulary of images. 2. Image Indexing using Text **Retrieval Methods -** Each image is



- We formulate the recognition problem as a task of fine-grained instance retrieval that can run on mobile devices.
- The real-world usage by the visually impaired introduces challenging queries in terms of the image quality, the portion of the bill visible, illumination and clutter.
- Strong restrictions in the memory, application size, and processing time.
- A thin index structure is used to make the application efficient and compact.

# Method Overview

#### • High-level control flow diagram

1. The app once started does not need any input from (App Start ) Image Capture Image Currency the user. Recognition 2. It takes a picture when the Ambiguous Result phone is held stable for some time. **Final Decision** Exit Tap on Audio Output 3. The app processes the image and gives audio feedback.

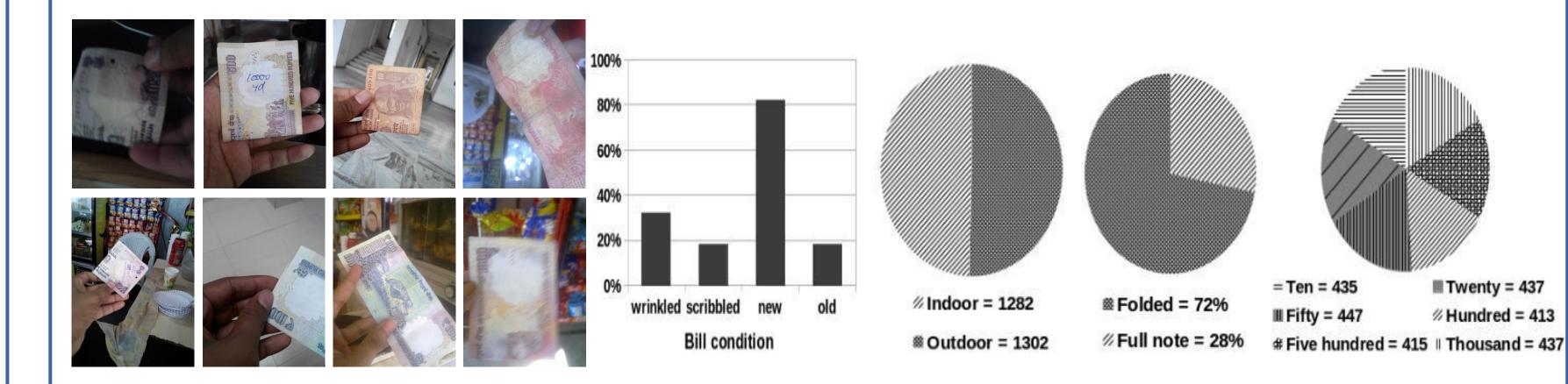
represented by a histogram of visual words followed by *tf-idf* weighting.

	K-means		Test Ir	nage
OFFLINE	TRAINING			U
		]	 	

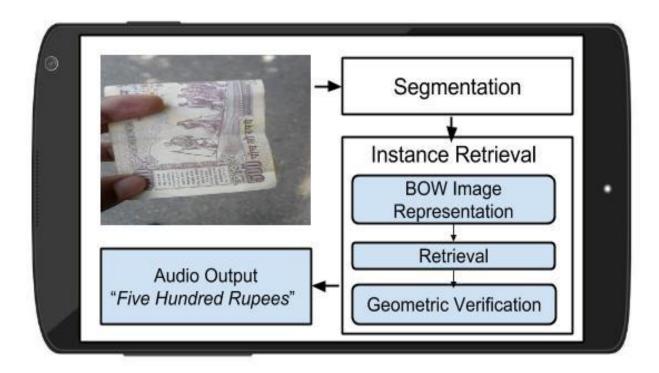
- **3. Retrieval Stage -** Each test image histogram is compared to the training set via cosine similarity. The ten most similar images are retained.
- 4. Spatial re-ranking To ensure spatial consistency of keypoints, we use geometric verification (GV) by fitting the fundamental matrix.
- 5. Classification Each retrieved image votes for its image class by the number of spatially consistent keypoints. The class with the highest vote is returned as the result.

### Experiments and Results

**Dataset** <sup>#</sup> – 2584 images captures the possible use cases of a visually impaired user.



#### • A conceptual schematic of the back-end



#### A. Segmentation

- Image Segmentation reduces processing time and improves accuracy.
- It not only cuts down the data to process but also the likelihood of irrelevant features by eliminating much of the background.
- We use GrabCut, which involves energy minimization based on iterative graph cuts.
- The cost function for this is:

$$E(x,y) = -\sum_{i} \log p(y_i|x_i) + \sum_{(i,j)\in\mathcal{E}} S(y_i,y_j|x)$$

where  $\chi_i$  is the colour of the *i*<sup>th</sup> pixel and  $y_i$  is +1 if the pixel belongs to the object, otherwise -1.  $S(y_i, y_i | x)$  favours neighbor pixels with similar color to have the same label.

Images from the dataset with bills in varying illumination and background.

#### Various statistics that reflects the dataset's comprehensiveness.

#### Results

**1. Results of mobile adaptation** (a) Storage and memory requirements (b) Time analysis

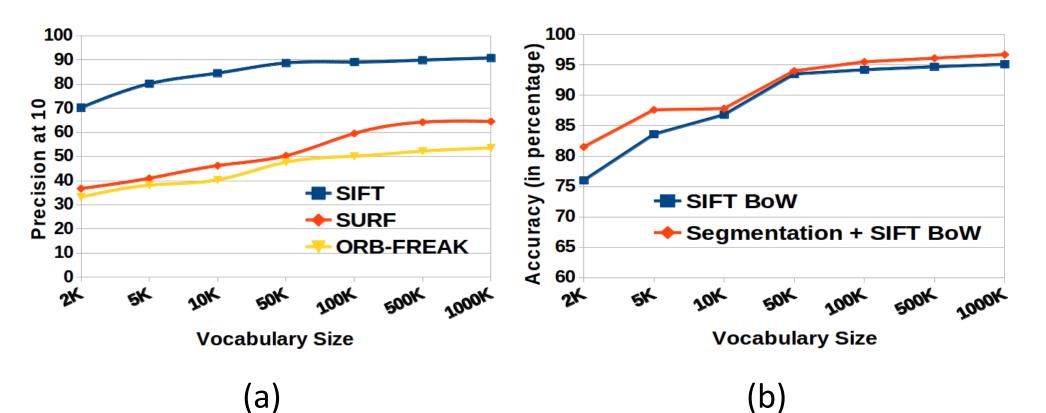
	AM use (on average) overted index ocabulary (10K) eypoints location	Size
RAM u Inverte (a) Vocabu Keypoi	RAM use (on average)	23.5MB
	nverted index Vocabulary (10K) Keypoints location	20.5MB
	5.3MB	
	Keypoints location	11MB
	Annotations	6.9KB

	Module	SIFT BoW+GV Time in seconds			
	wodule	without segmentation	with segmentation		
	Segmentation	-	0.27 s		
	SIFT keypoints detection	0.25 s	0.25 s		
(b)	SIFT descriptor extraction	0.27 s	0.13 s		
	Assigning to vocabulary	0.01 s	0.01 s		
	Inverted index search	0.12 s	0.12 s		
	Spatial re-ranking	0.61 s	0.31 s		
	Total Recognition Pipeline	<b>1.26</b> s	1.09 s		

**2. Classification Accuracy** using SIFT, SURF and ORB-FREAK each as the feature, with segmentation, for various sizes of the vocabulary.

Footuro	Vocabulary Size						
Feature	<b>2</b> K	5K	10K	50K	100K	500K	1000K
SIFT	81.2%	87.6%	87.8%	93.9%	96.1%	96.3%	96.7%
SURF	68.7%	71.4%	72.8%	79.6%	84%	92%	92.4%
ORB-FREAK	49.8%	55.8%	56.6%	65.2%	66.1%	69.3%	71.1%

**3.** (a) Precision at 10 with segmentation. (b) Comparison between accuracy of SIFT BoW + GV and segmentation + SIFT BoW + GV.



#### • Segmentation results



## Conclusions

- Succeeded in developing a system that recognizes bills reliably, and ported the system to a mobile environment.
- With limited processing power and memory, the system still achieves high accuracy and low reporting time.
- Segmentation is particularly helpful for retrieval.
- Easily adaptable to other currencies, while maintaining performance.

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### References

- 1. Jayaguru Panda, Michael S. Brown, and C. V. Jawahar. Offline mobile instance retrieval with a small memory footprint. ICCV, 2013.
- 2. C. Rother, V. Kolmogorov, and A. Blake. GrabCut: interactive foreground extraction using iterated graph cuts. SIGGRAPH, 2004.
- 3. J. Sivic and A. Zisserman. Video Google: A text retrieval approach to object matching in videos. ICCV, 2003.
- 4. Xu Liu. A camera phone based currency reader for the visually impaired. ASSETS, 2008.

<sup>#</sup>Android App, Code and Data are available on Project Web Page

http://researchweb.iiit.ac.in/~suriya.singh/Currency2014ICPR/

**Centre for Visual Information Technology** http://cvit.iiit.ac.in

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