Adaptive Matrices for Color Texture Classification

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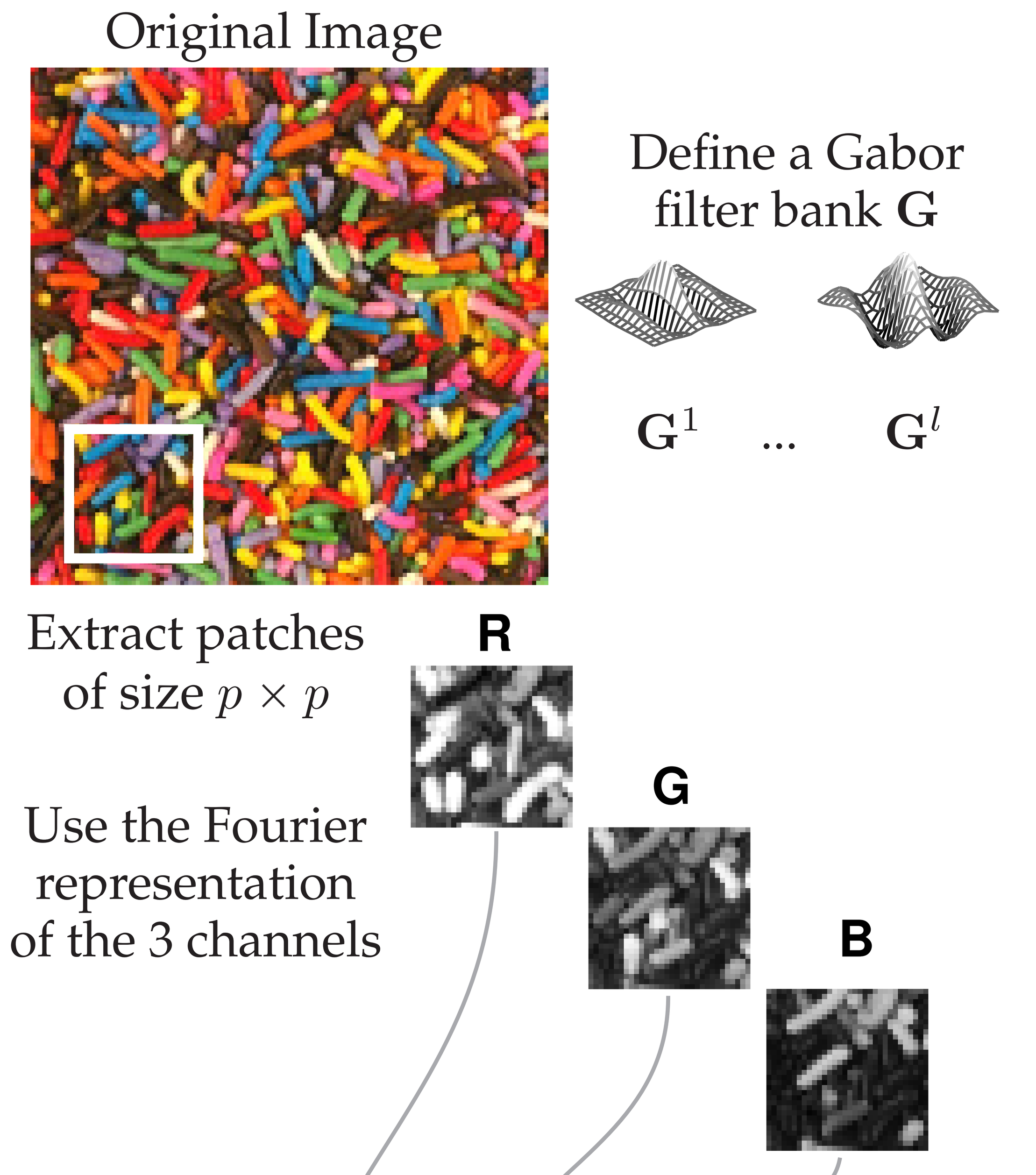
Contribution

Traditional texture analysis methods mostly concern gray scale images and their adaptation to the color domain is not always straightforward. We introduce a novel method for color texture classification and recognition based on Gabor filters that incorporates a data-driven adaptation of the system. Given a set of labeled color images and a bank of Gabor filters the goal is to learn a transformation of a color image to a single channel (intensity) image, such that the Gabor responses of the transformed images will yield the best possible classification.

Method

We propose the Color Image Analysis LVQ (CIA-LVQ) extending the GMLVQ [3] scheme. This enables the learning of color texture.



$$\mathbf{x}^i = [\mathcal{F}(\mathbf{R}), \mathcal{F}(\mathbf{G}), \mathcal{F}(\mathbf{B})] \in \mathbb{C}^{p\cdot p\cdot 3}$$

with label y^i

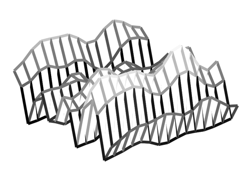
Color Image Analysis LVQ

CIA-LVQ

Initialize:

1. prototypes $\mathbf{w}^k \in \mathbb{C}^{p\cdot p\cdot 3}$ and labels $c(\mathbf{w}^k)$
2. transformation matrices $\Omega^k \in \mathbb{C}^{p\cdot p\cdot 3 \times p\cdot p}$

Define:

1. image descriptor: 

$$f_{\Omega^k}(\mathbf{v}, \mathbf{G}) : \mathbf{v} \to \mathbf{r}_k(\mathbf{v}) = \sum_l \mathbf{v}{\Omega^k}^\top * \mathbf{G}^l$$

2. distance: $d(\mathbf{x}^i, \mathbf{w}^k) = \| \, |\mathbf{r}_k(\mathbf{x}^i)|^2 - |\mathbf{r}_k(\mathbf{w}^k)|^2 \, \|^2$

Optimize:

the cost function

$$f_c(d) = \sum_i \frac{d(\mathbf{x}^i, \mathbf{w}^J) - d(\mathbf{x}^i, \mathbf{w}^K)}{d(\mathbf{x}^i, \mathbf{w}^J) + d(\mathbf{x}^i, \mathbf{w}^K)}$$

where
$$\mathbf{w}^J = \arg\min_j (d(\mathbf{x}^i, \mathbf{w}^j)) \text{ with } y^i = c(\mathbf{w}^J)$$
$$\mathbf{w}^K = \arg\min_j (d(\mathbf{x}^i, \mathbf{w}^j)) \text{ with } y^i \neq c(\mathbf{w}^K)$$

subject to $\mathbf{w}^L$ and Ω^L with $L \in \{J, K\}$

References

[1] Database VisTex of color textures from MIT. http://vismod.media.mit.edu/vismod/imagery/VisionTexture/vistex.html.

[2] A. Jain and G. Healey. A multiscale representation including opponent color features for texture recognition. *IEEE TIP*, 7(1):124–128, 1998.

[3] P. Schneider, M. Biehl, and B. Hammer. Adaptive relevance matrices in learning vector quantization. *Neural Computation*, 21(12):3532–3561, 2009.

Results

- Dataset: VisTex [1], 128×128 px images from the groups Bark, Brick, Tile, Fabric and Food.
- Experimental Setup: 15×15 px patches are randomly drawn from each image.
- The images in Fig. 1 (left) were used for the training and test sets.
- The training error is **10.6%** and the error on the test set **28%**.

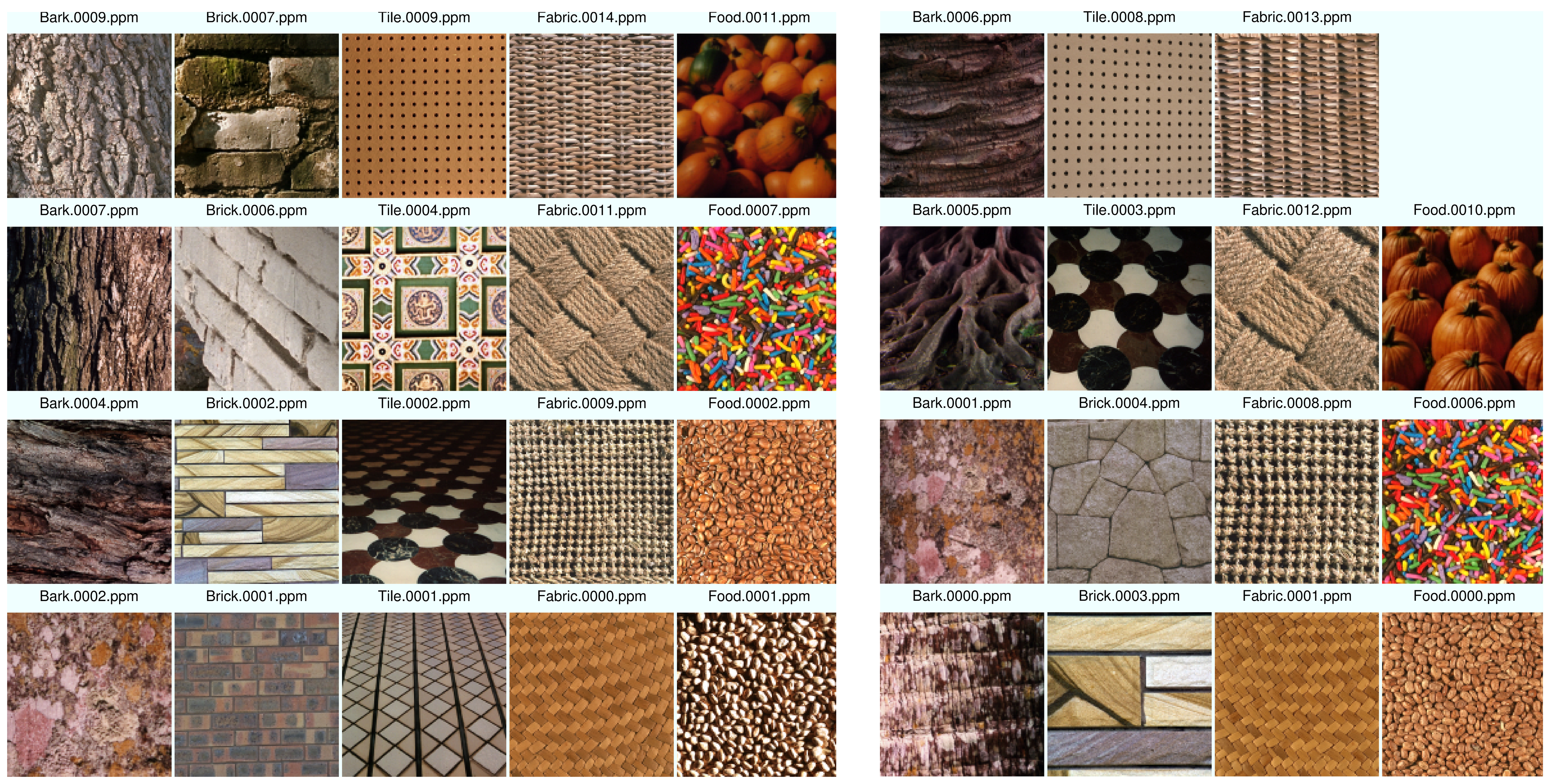


Fig. 1: Images used in the training, test (left) and the evaluation (right) sets.

- Evaluation set: Images in Fig. 1 (right), never presented during the training process.
- CIA-LVQ has an evaluation error of **28.8%**.
- We compare with: Opponent Color Features [2] (OCF) and the common approach of deriving textural information only from the luminance plane of images (RGB2GRAY) using a Nearest Neighbor (NN) classifier.
- The OCF/NN error is **43.1%** and the RGB2GRAY/NN error **61.9%**.

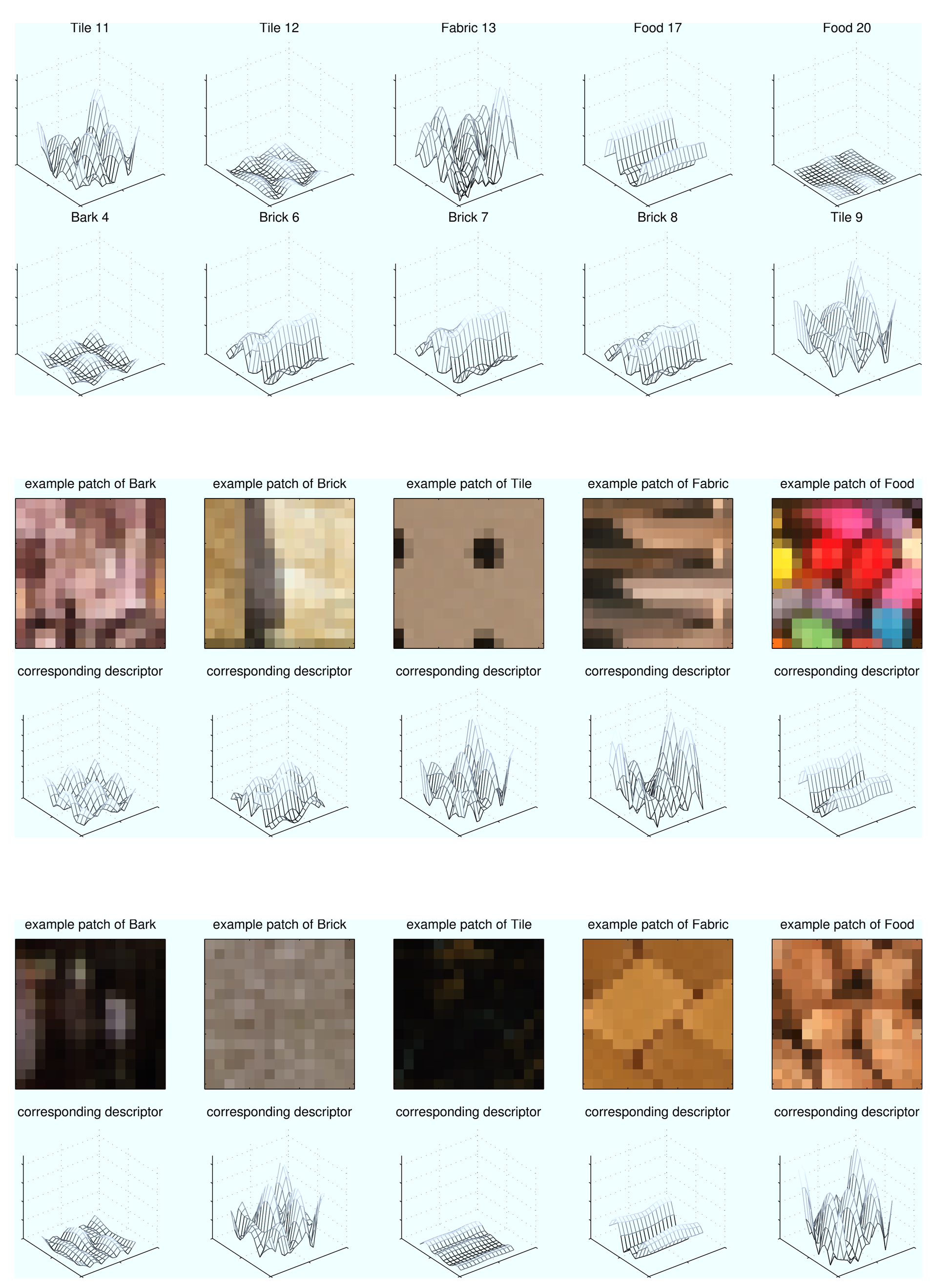


Fig. 2: Descriptors of prototypes used for classification (top), alongside examples of correctly (middle) and wrongly (bottom) classified image patches and their descriptors.

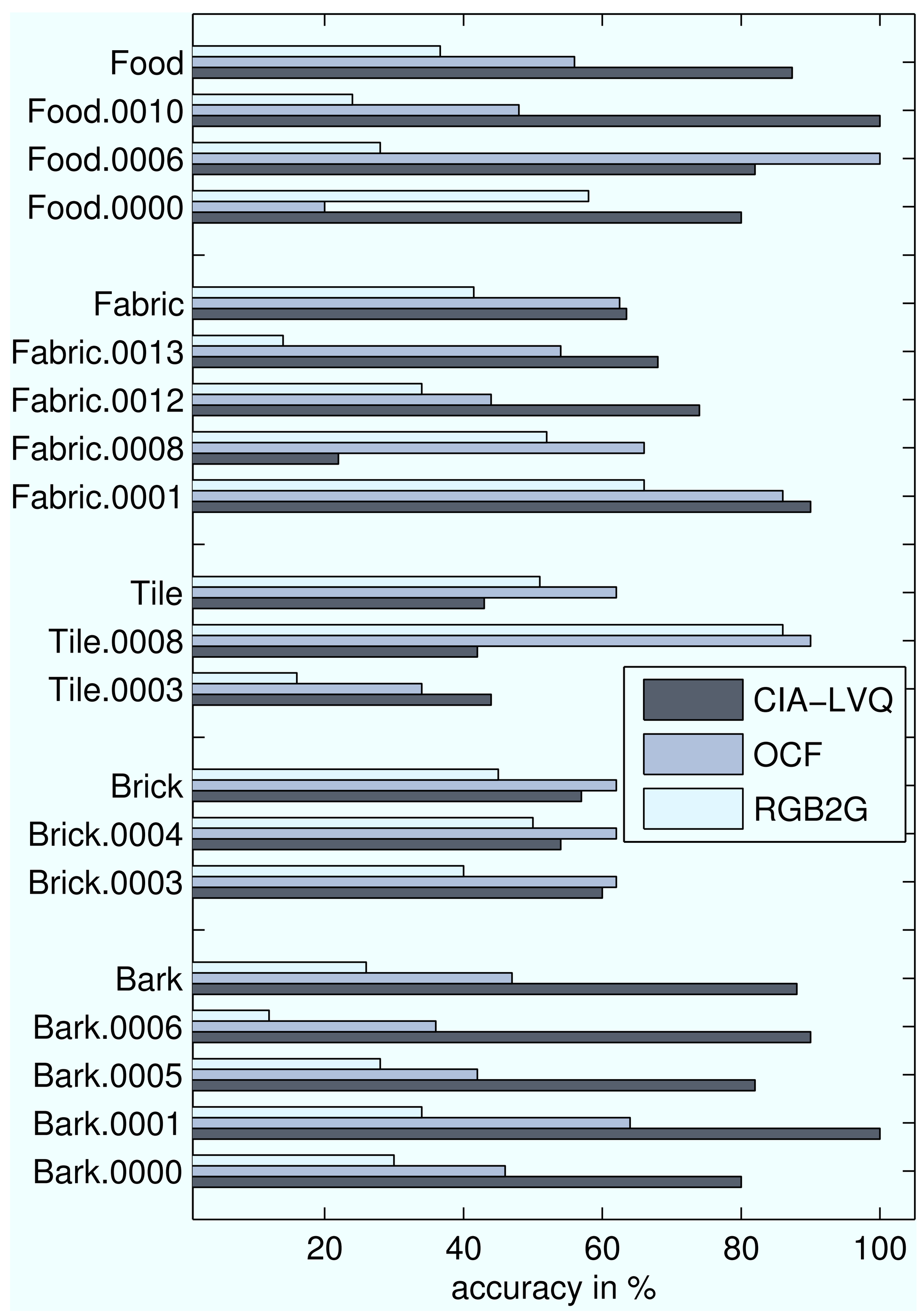


Fig. 3: Classwise and individual image accuracies

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