Classification-based Color Constancy

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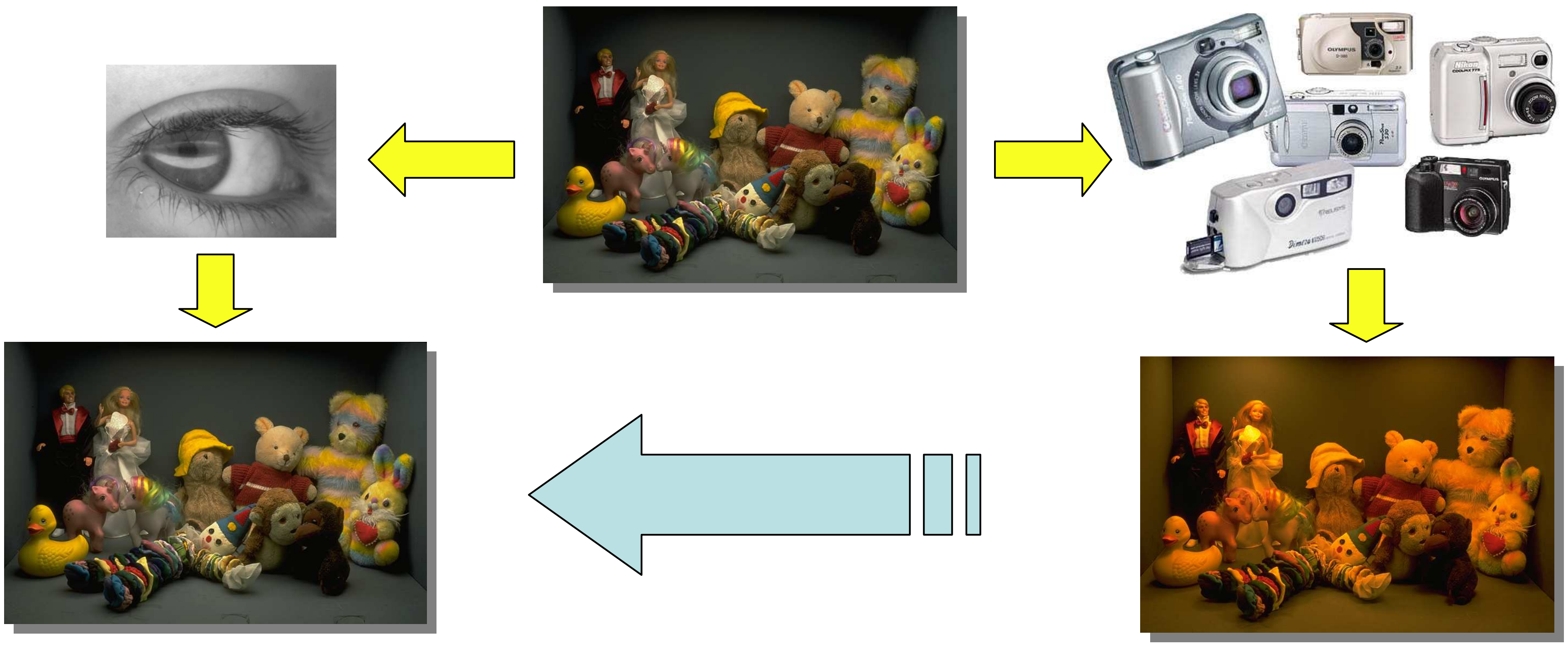
Color constancy on digital devices

The Human Visual System is (almost) able to compensate for illuminants (**color constancy**)

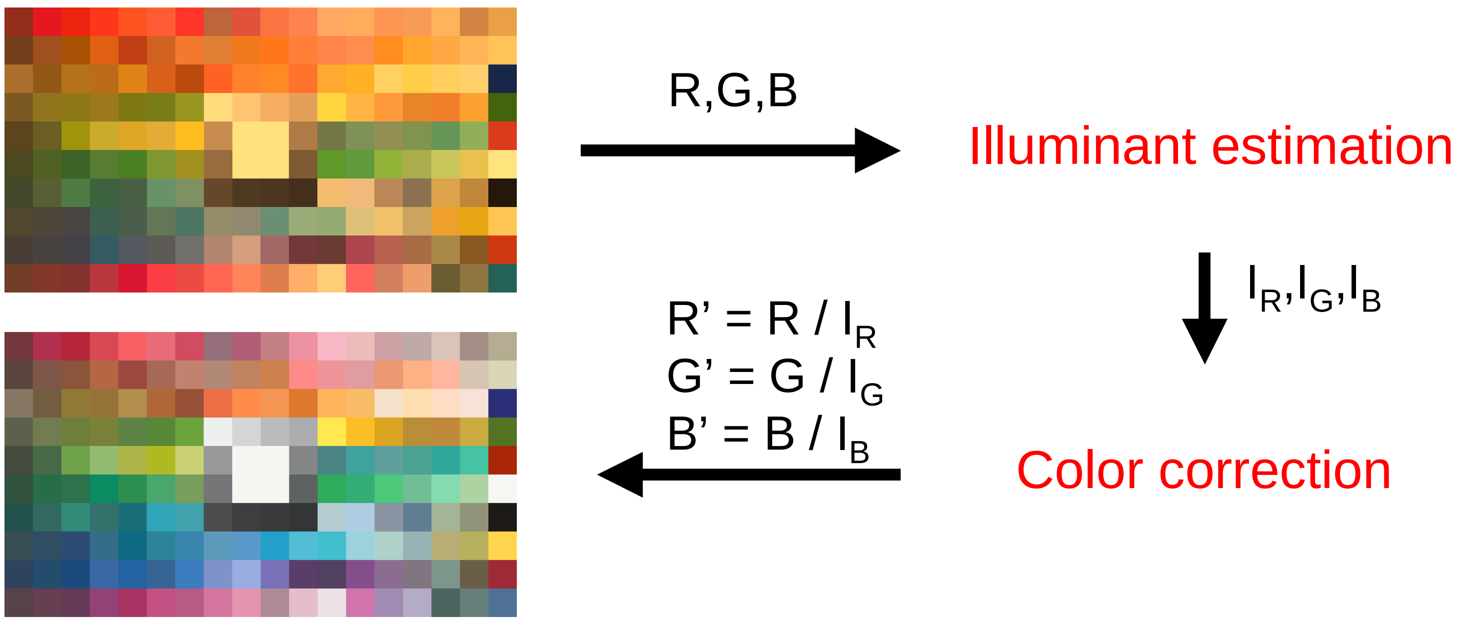
People expect Digital Imaging Acquisition systems to do the same

Computational color constancy tries to emulate this HVS feature on digital devices



Computational color constancy

- A popular approach adopts a two stage procedure:
  - the scene illuminant is estimated from the image data
  - image colors are then corrected on the basis of this estimate



Illuminant estimation

- An ill-posed problem
  - Algorithms usually exploit some assumptions about statistical properties of expected illuminants or of the objects reflectances

Original image

Gray world

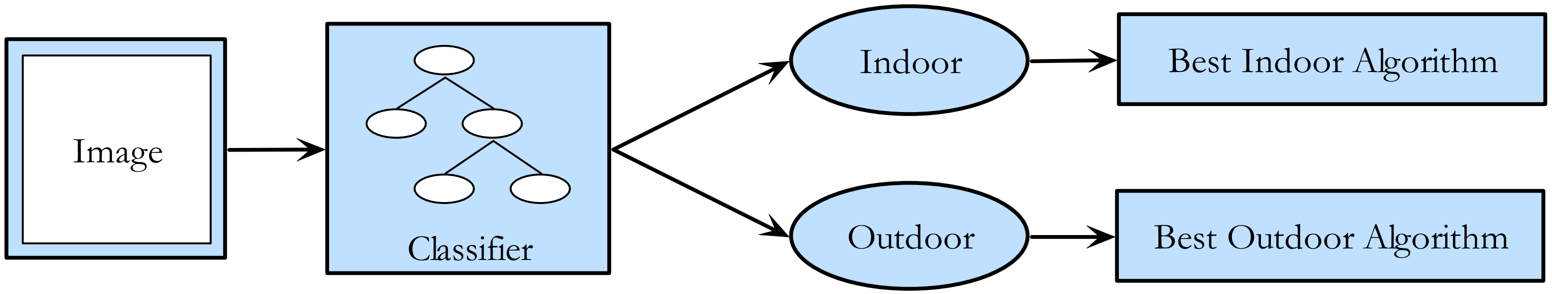
White Point

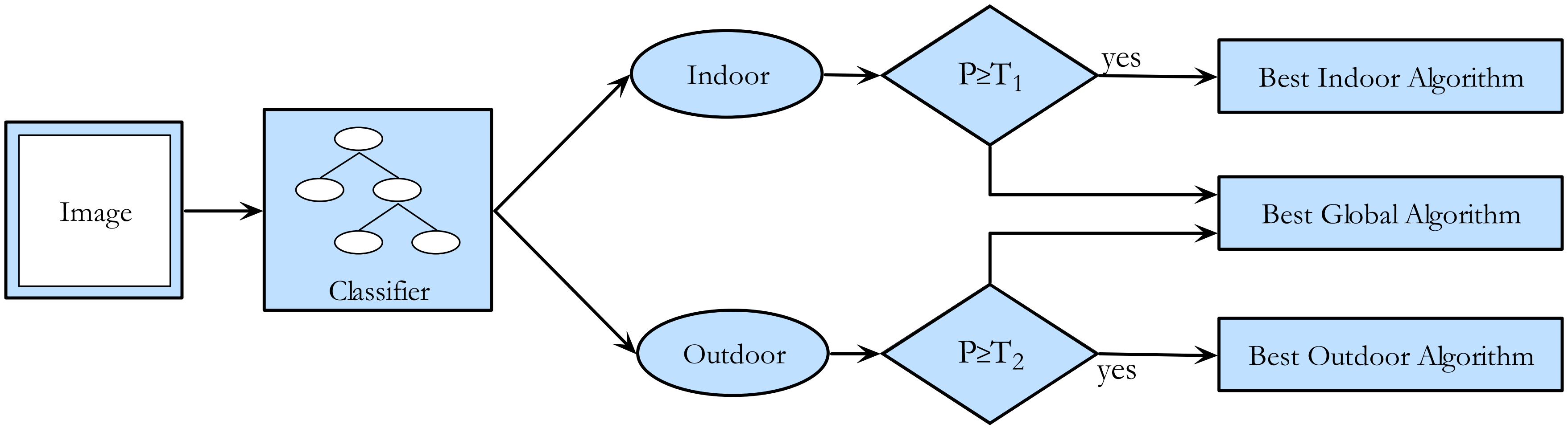
Our approach

- Improve illuminant estimation by taking into account **automatically extracted** information about the content of the images
  - We considered indoor/outdoor classification because
    - Indoor/outdoor images present different content
    - Are usually taken under different illumination conditions

Our approach

- We have designed different strategies for the selection of the most appropriate algorithm (or combination of algorithms) for each class





Dataset

- The Ciurea and Funt image database
  - 15 video clips at 15 fps
  - More than 11000 frames
  - A gray sphere is used to estimate the illuminant color
  - Video summarization techniques are used to select 1135 uncorrelated images




F. Ciurea, B. Funt, “A Large Image Database for Color Constancy Research,” Proc. IS&T/SID 11th Color Imaging Conf., pp. 160-164, 2003.

Image classification

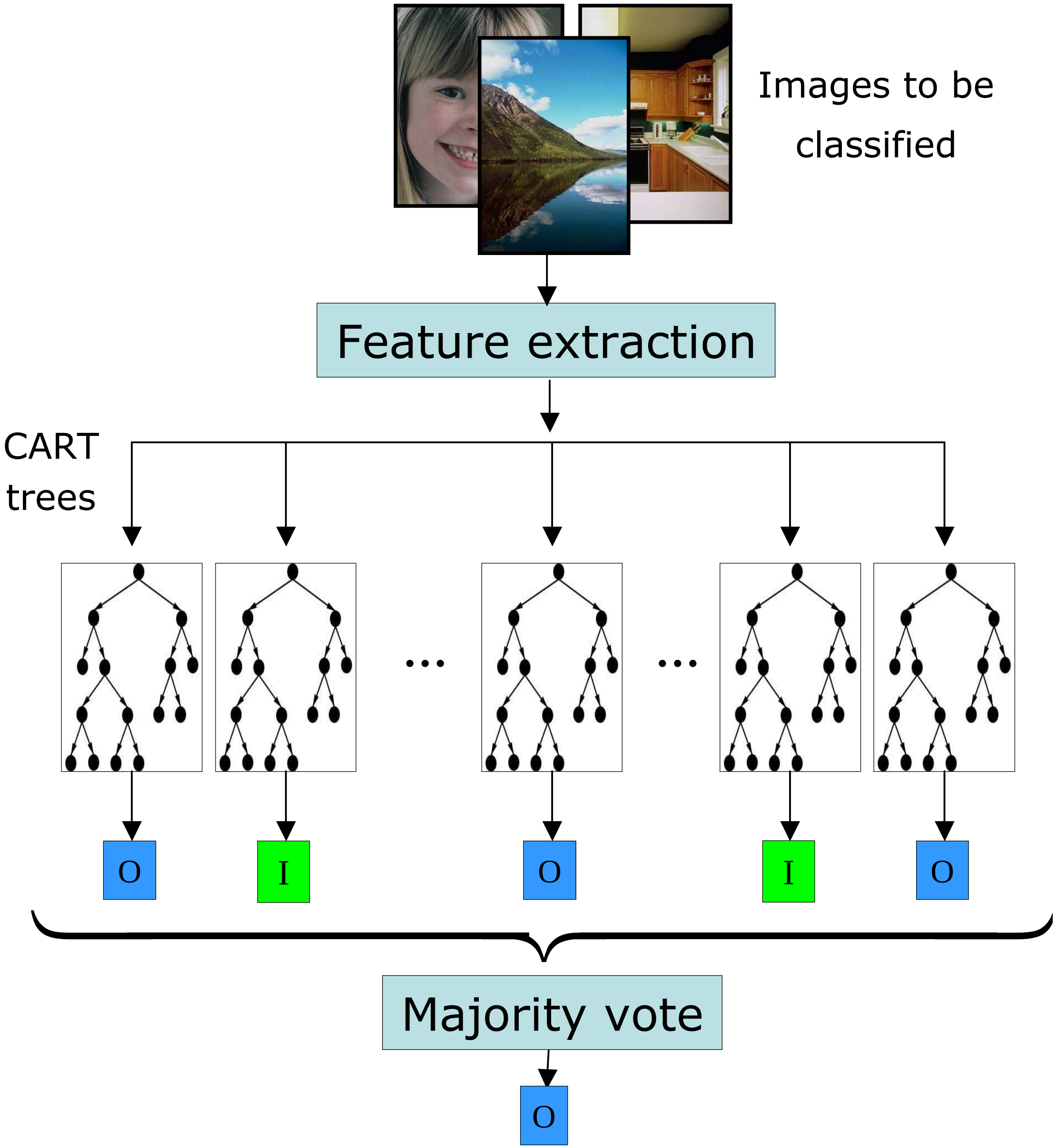


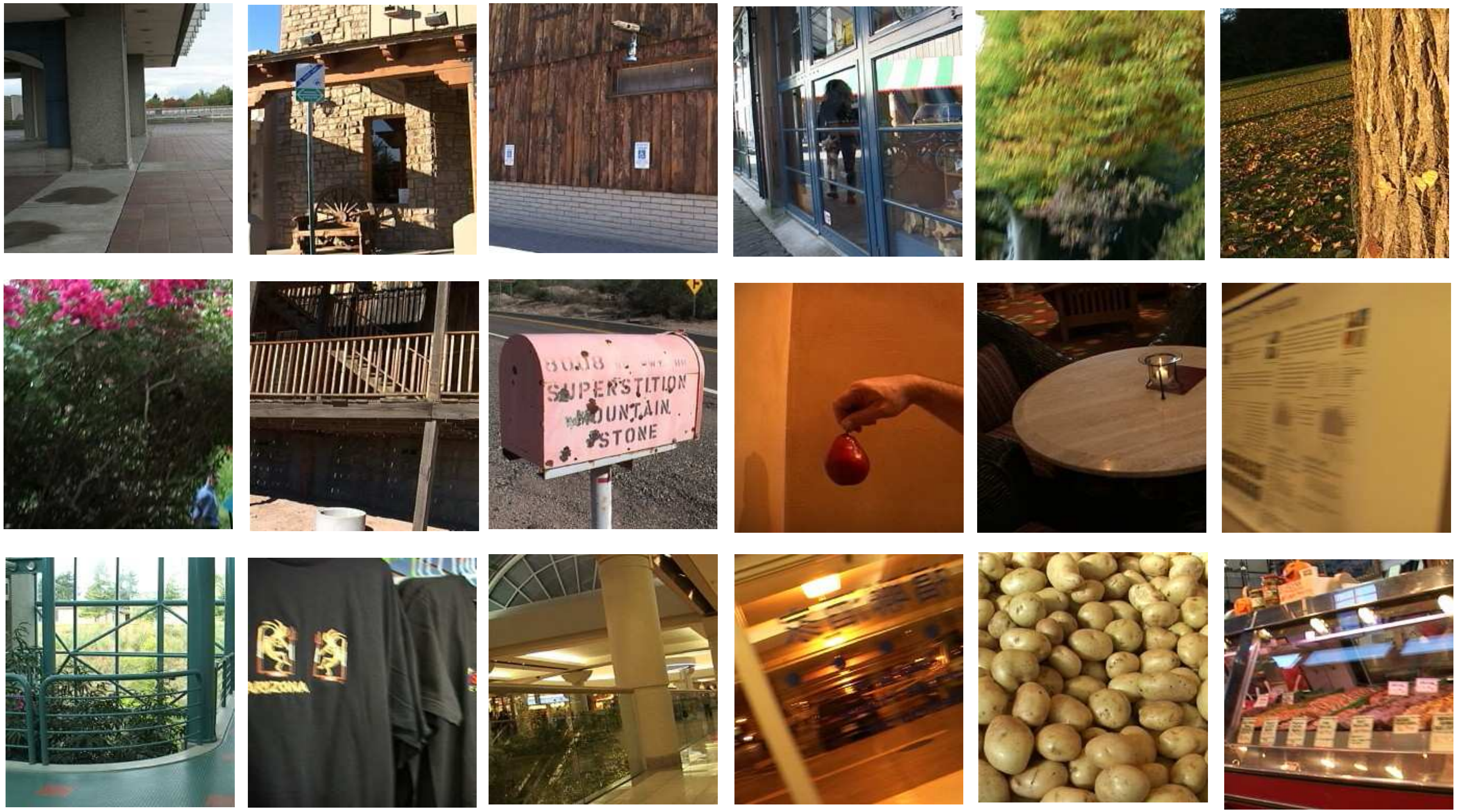
Image description

- Images are described by a set of low-level visual features
  - General purpose (i.e. not specifically related to indoor/outdoor classification)
  - Easy (and fast) to compute
- Feature vectors of 107 components are used
  - Color moments in the YCbCr color space (7 x 2 x 3)
  - RGB Histogram (27 bins)
  - Edge direction histogram (18 bins)
  - Wavelets statistics (10 x 2)

Image classification

- A forest of 50 trees has been trained using bootstrap replicates of a training set composed by 6785 images downloaded from the web (2105 indoor and 4680 outdoor)
  - No enhancement procedure (such as white balancing) has been applied to the images
- We obtained a classification accuracy of
  - 93.1% on an independent validation set
  - 85.1% on the Ciurea and Funt dataset

Some misclassified images



Color constancy algorithms

- We considered the framework proposed by Van de Weijer et al.

$$\left(\iint |\nabla^n \boldsymbol{\rho}_\sigma(x,y)|^p \, \mathrm{d}x\mathrm{d}y \right)^{\frac{1}{p}} = k\mathbf{I}$$

J. van de Weijer, T. Gevers, A. Gijsenij, "Edge-based Color Constancy," *IEEE Trans. on Image Processing*, 16(9), pp. 2207–2214, 2007

- We selected six, widely used, algorithms
  - Gray World (GW): $n = 0$, $p = 1$, $\sigma = 0$
  - White Point (WP): $n = 0$, $p = \infty$, $\sigma = 0$
  - Shades of Gray (SG): $n = 0$, $\sigma = 0$
  - General Gray World (gGW): $n = 0$
  - Gray Edge (GE1): $n = 1$
  - Second Order Gray Edge (GE2): $n = 2$
- Some algorithms require a tuning for the parameters p and σ

Color constancy algorithms

- We considered also two combining algorithms:
  - Least Mean Squares (LMS): the output of the six algorithms are linearly combined (weights need to be estimated)
  - No2Max: the two estimations with the highest distance from the others are discared. The remaining four are averaged (S. Bianco, F. Gasparini, R. Schettini, "A Consensus Based Framework For Illuminant Chromaticity Estimation," J. of Electronic Imaging, 17, pp. 023013-1–9, 2008)

Experimental results

- A training set of 300 images has been used to determine the optimal parameters of the algorithms (via pattern search)
  - On the two classes
  - On the whole training set

	Indoor Images		Outdoor Images		Whole Training	
	Median	WST	Median	WST	Median	WST
GW	4.91	3	7.86	0	5.62	1
WP	11.83	0	2.81	2	7.76	0
SG	**4.31**	**6**	2.81	2	5.56	1
gGW	4.32	**6**	2.81	2	5.57	1
GE1	5.40	1	3.72	1	5.45	1
GE2	5.57	1	**2.48**	**7**	5.47	1
N2M	5.13	3	2.83	2	5.02	6
LMS	4.58	5	2.71	2	**4.50**	**7**

Experimental results

- On the 835 images of the test set (331 indoor 504 outdoor)
  - Content Independent Strategy (CI): algorithms tuned on the whole training set
  - Content Dependent Parameterization (CDP): class specific parameters, chosen on the basis of the output of the classifier

	CI strategy		CDP Strategy	
	Median	WST	Median	WST
GW	5.95	0	5.95	0
WP	5.48	3	5.48	3
SG	5.80	0	4.08	**4**
gGW	5.80	0	5.39	1
GE1	4.47	5	4.32	3
GE2	4.65	5	**3.94**	**4**
N2M	4.79	4	4.01	**4**
LMS	**4.18**	**7**	4.05	**4**

Experimental results

- Algorithm selection
  - Class-Dependent Algorithms (CDA): for each class the best algorithm (and its corresponding parameters) is selected
  - Class-Dependent Algorithms with Uncertainty Class (CDAUC): introduction of the uncertainty class. Images falling in that class are processed by the algorithm that has proved to be the best class-independent algorithm.

Strategy	Underlying algorithms	Median	WST
CI	LMS, general purpose parameters	4.18	0
CDP	GE2, indoor and outdoor parameters	3.94	1
CDA	SG for indoor and GE2 for outdoor	3.78	1
CDAUC	SG ind., GE2 out., LMS uncertain	**3.54**	**3**

Experimental results

- Image misclassification approximately doubles angular errors
  - 4.85 vs. 9.79 on indoor images
  - 2.31 vs. 5.07 on outdoor images
- How much improvement is expected using a better classifier?
  - We obtained a median angular error of 3.48 degrees using an “optimal” classifier
  - An error of 5.63 has been obtained using a “random” classifier

Summary of the experiments

- If no knowledge of the image content is exploited (CI strategy), combining methods perform better than the single ones
- The algorithms that can be tuned on the basis of image contents benefit by the classification process
- For the specific classes, combining methods do not seem to be the best choice
- Illuminant estimation can be improved by using different algorithms (or a different set of parameters) for indoor and outdoor images (CDP and CDA strategies)
- The introduction of an uncertainty class (CDAUC strategy), further improves the results

Future work

- Collection of a large dataset with high content and illuminant variability
- The results can be improved using additional classes?
- And using additional algorithms?
- How knowledge about the acquisition device can be incorporated in the framework?