Evaluation of image quality of the compression schemes JPEG & JPEG 2000 using a Modular Colour Image Difference Model.

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Image Quality

- Models of image appearance can be used to create multi – dimensional models of image quality
- The main aim is to derive a single metric of the over all image quality
- Replace human observations with weight image attributes with overall appearances of quality
- G. M. Johnson and M. D. Fairchild designed a framework for a colour image difference quality model which involves weighted sums of tonal balance, contrast and sharpness

Modular Image Difference Model

CIELAB → S-CIELAB → Modular Image Difference Model

+

Spatial properties of the eye (CSF) by spatial filtering pre-processing, before pixel-by-pixel colour difference calculation

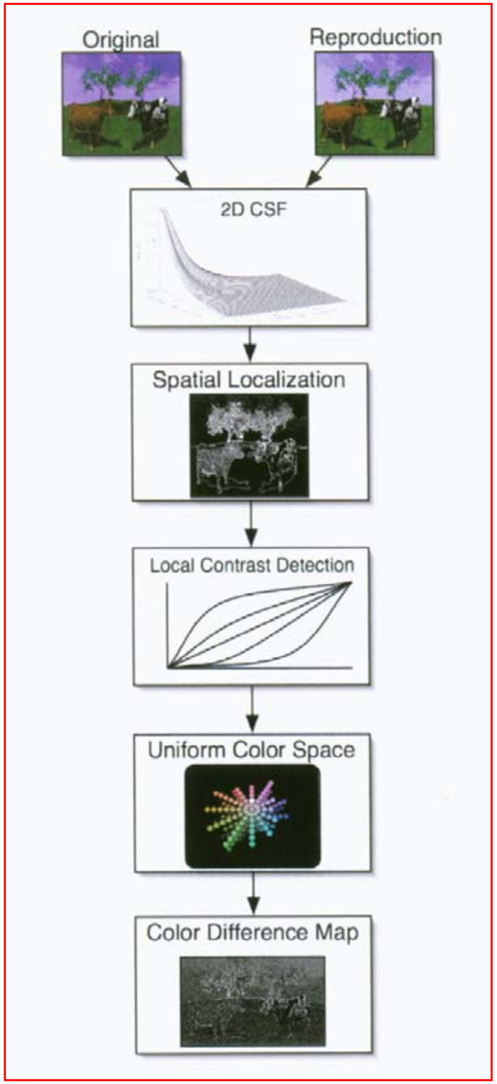
+

Independent pre-processing steps :

1. Spatial filtering
2. Spatial frequency adaptation
3. Spatial localisation
4. Local contrast
5. Colour difference map

Modular Image Difference Model

Flowchart:



(1). Spatial filtering

- It is performed on opponent colour channels representing a luminance channel and two chrominance channels (RED-GREEN and YELLOW-BLUE)
- Filtering was performed in the frequency domain as it is computationally easier and allows more control

(1). Spatial filtering

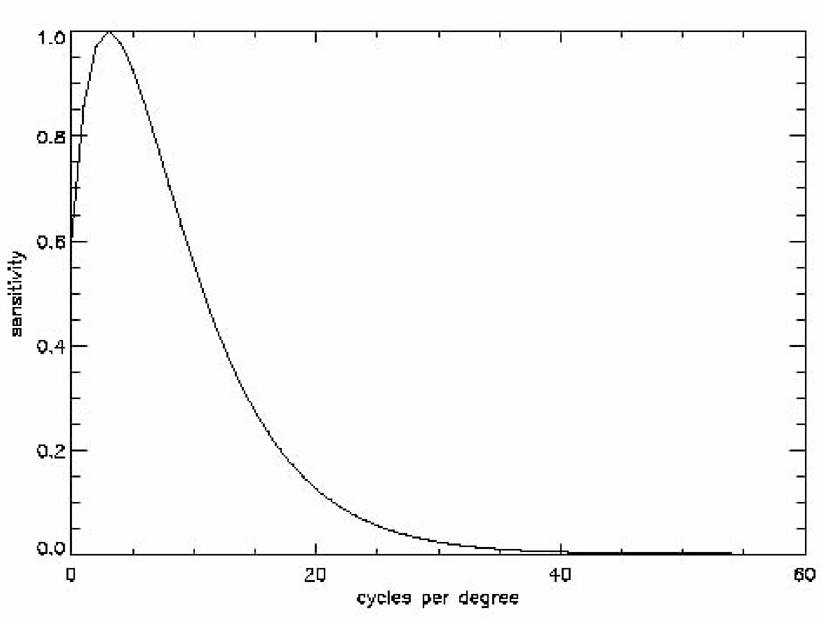
- $csf_{lum}(f) = a \cdot f \cdot e^{-b \cdot f}$

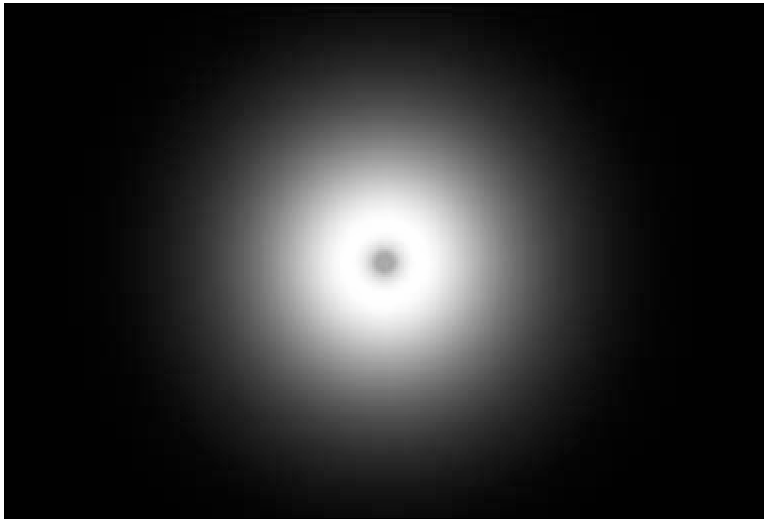
- $cfs_{chrom}(f) = a_1 \bullet e^{-b_1 f^{c_1}} + a_2 \bullet e^{-b_2 f^{c_2}}$

- f is represented in cycles per degree (cpd) of visual angle

- The functions are normalised to unity

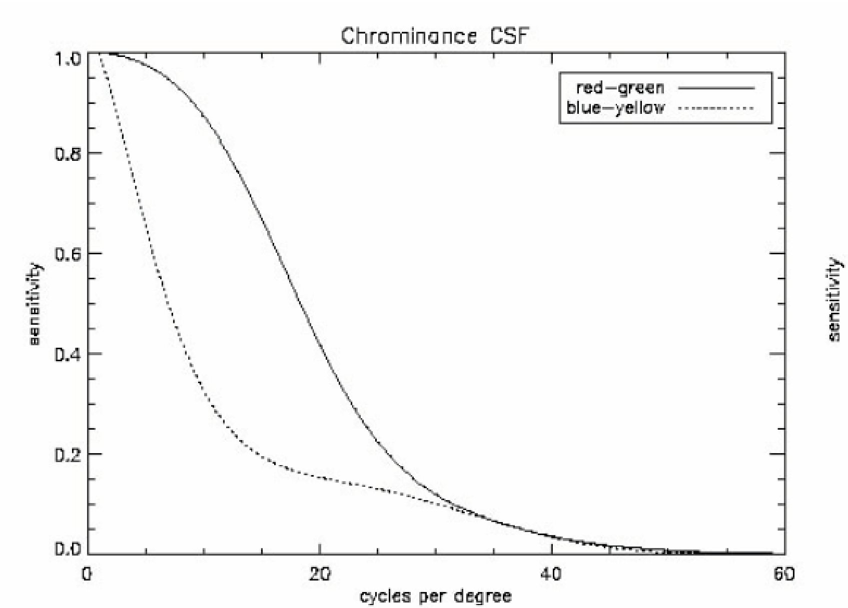
(1). Spatial filtering

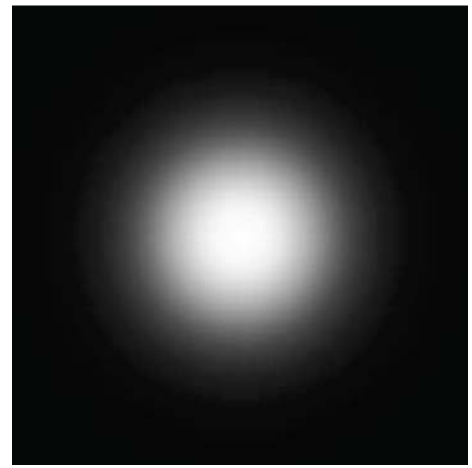




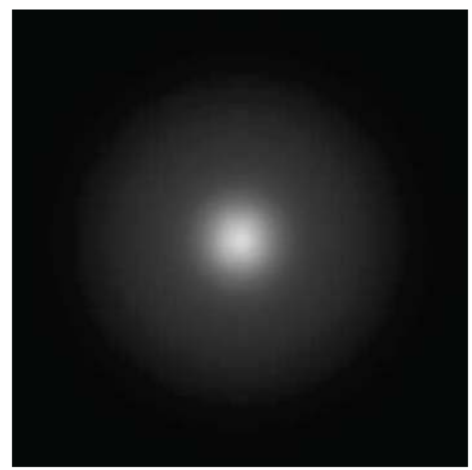
The above filter behaves as a band-pass filter for the luminance channel, peaking around 4 cycles-per-degree.

(1). Spatial filtering





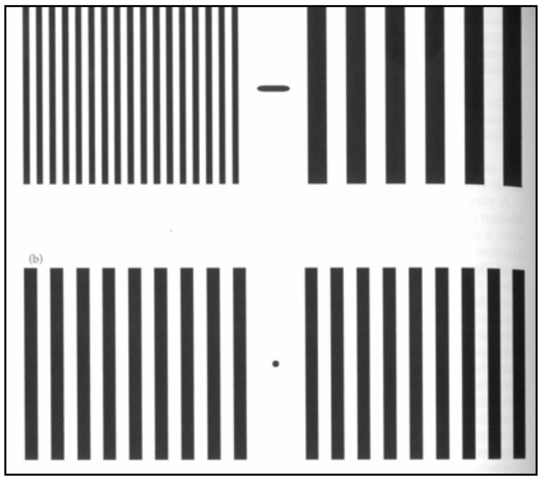
Chrominance a



Chrominance b

CSFs for the chrominance channels

(2). Spatial frequency adaptation



- Spatial frequency adaptation decreases sensitivity to certain frequencies based upon information present in the visual field

- This cannot be eliminated in real world viewing conditions
- Various models alter the nature of the CSFs upon:
    1. assumptions of the viewing conditions

  OR

  2. Information contained in the images themselves

(3). Spatial localisation

- The CS filters decrease the perceived differences for high frequencies
- HVS is considered to be very adept at distinguishing or localising, edges and lines → high frequencies
- Simple edge-enhancing filter, such as Sobel, can be applied
- However, it does not take into account the cycles/degree of the viewing situation

$$x_{dir} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$y_{dir} = \begin{bmatrix} -1 & 2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

(4). Local contrast detection

- A method for detection and enhancement of image contrast differences
- Series of gamma correction curves for each opponent channel are created based upon:
  1. Low frequency information of the channel
  2. Global contrast of the channel

(4). Local contrast detection

- The low frequency mask can be created by filtering each image with a low-pass Gaussian curve.

- The contrast curves can be generated by:

$$\boxed{gamma = max\left(\frac{input}{max}\right)^{2^{\left(\frac{median}{median-mask}\right)}}}$$

(4). Local contrast detection

- The low frequency mask can be created by filtering each image with a low-pass Gaussian curve.

- The contrast curves can be generated by:

$$gamma = \boxed{max}\left(\frac{input}{\boxed{max}}\right)^{2^{\left(\frac{\boxed{median}}{\boxed{median} - mask}\right)}}$$

(4). Local contrast detection

- The low frequency mask can be created by filtering each image with a low-pass Gaussian curve.

- The contrast curves can be generated by:

$$gamma = max\left(\frac{input}{max}\right)^{2^{\left(\frac{median}{median-\boxed{mask}}\right)}}$$

(4). Local contrast detection

- The mask can be computed by:
  1. Separating the image's different opponent channels (Lab)
  2. Blurring using a Gaussian low-pass filter
  3. Taking absolute input values for the chrominance channels.
- This is done because the chrominance channels have both positive and negative values
- Alternatively, different gamma curves can be created for positive and negative values

(5). Colour difference map

- The output of this procedure will be a map of colour differences that correspond to the ***perceived*** magnitude of error at each pixel position.
- The error map is often reduced to a more manageable dataset using statistics.
- Mean error [→] overall difference
- Max [→] threshold differences

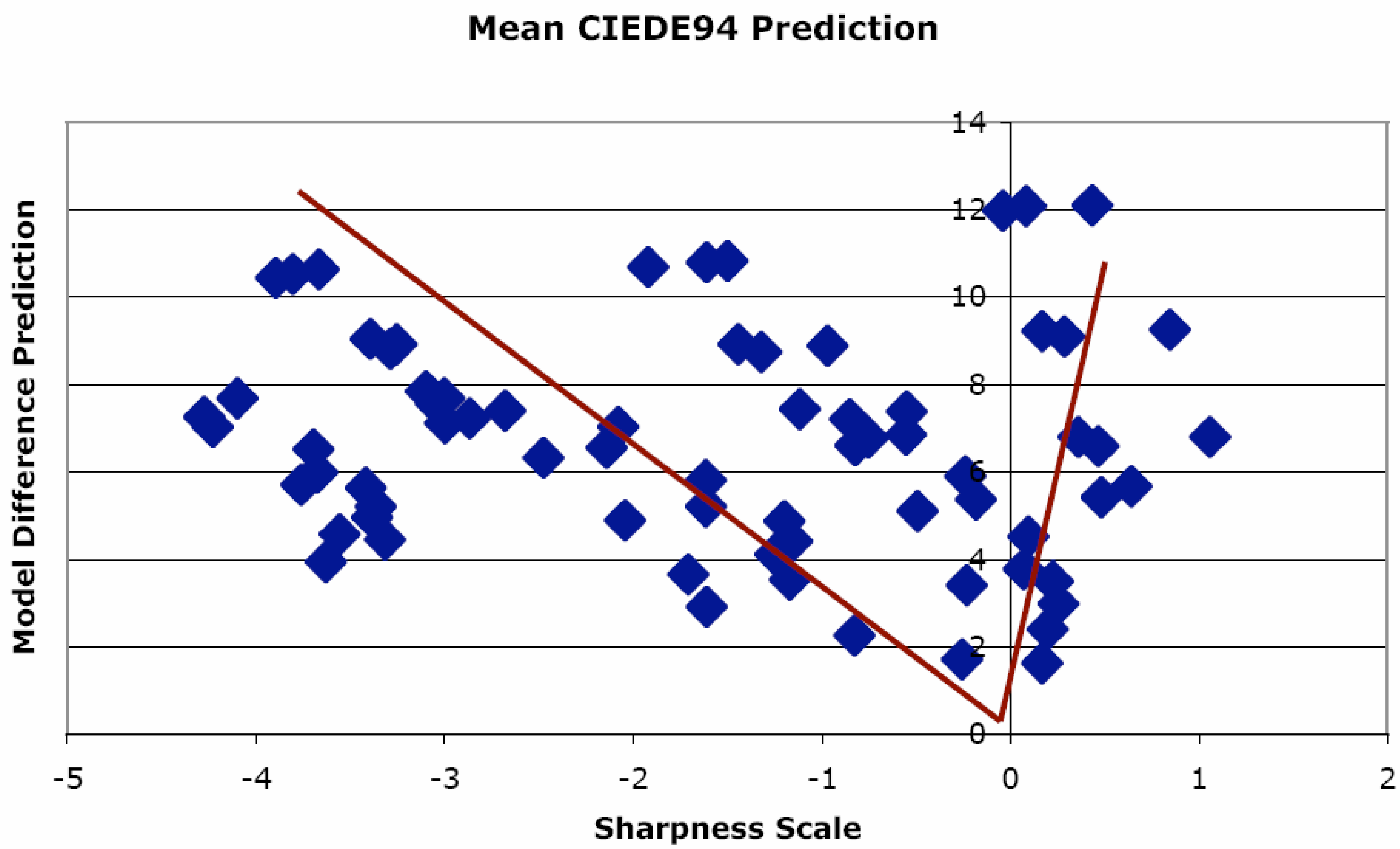
(5). Colour difference map

- More studies are currently held for the improvement of image statistics, as although they provide data reduction, they can be confusing in terms of masking other valuable information
- Standard deviation and standard deviation normalised by mean error appear to have a better success in experimental prediction

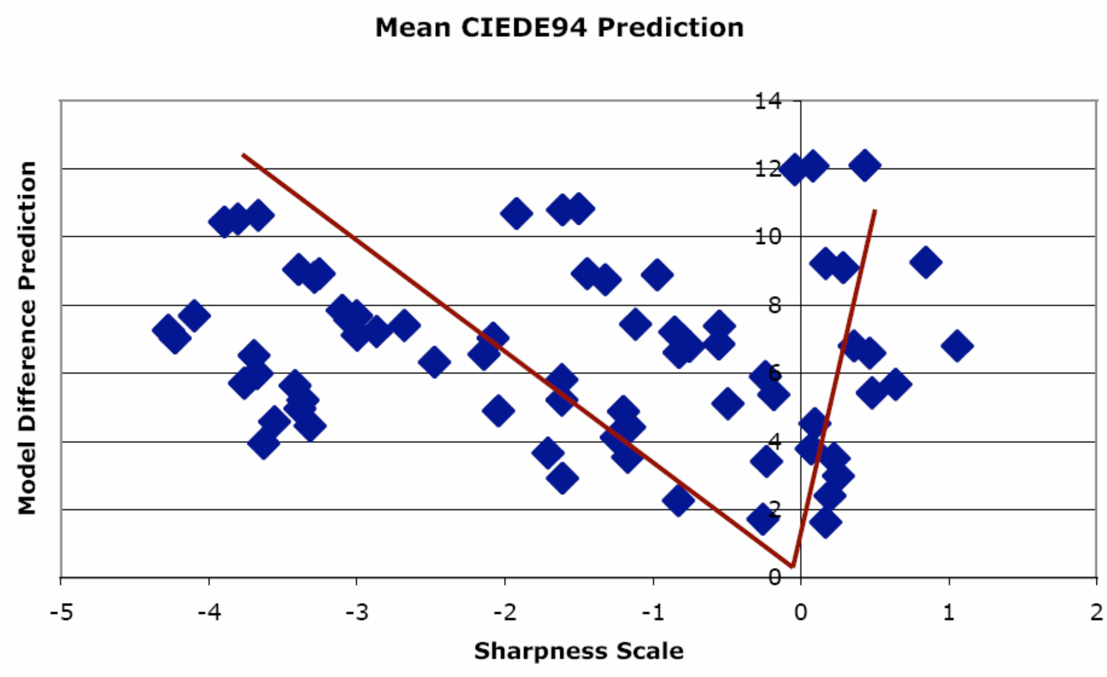
(6). Single metric

- This single metric can be obtained from the colour difference map
- This measure is then plotted against the subjective measures derived from psychophysical tests

(7). Plotting

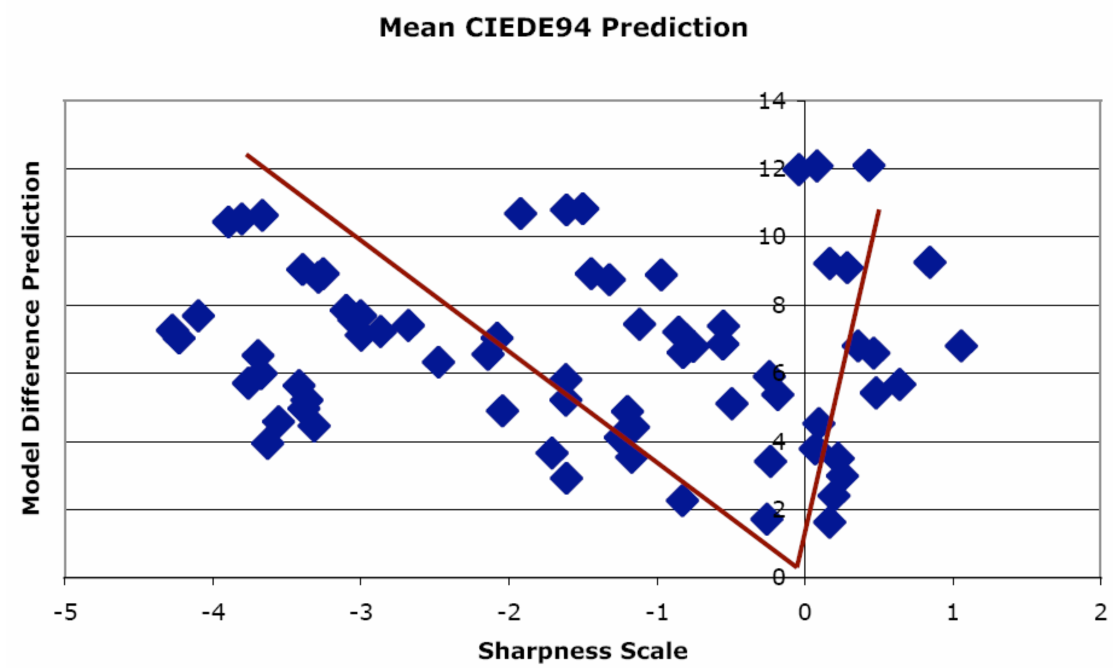

Mean CIEDE94 Prediction
Model Difference Prediction
Sharpness Scale
0
2
4
6
8
10
12
14
-5
-4
-3
-2
-1
0
1
2

(7). Plotting



- The plots have a distinctive “V” shape and that is because the subjective measures are signed (negative and positive) while the prediction are unsigned values

(7). Plotting



- All the points located on the left of the origin have been characterised as being worse at a specific attribute compared with the original image while the opposite goes for the points on the right of the origin

Method (1): preparation

- 10 test images were selected from Kodak-Photo CD. Different scene content, colourfulness, dynamic ranges.
- 1 tiff image + 8 compressed images per scene
- 4 in JPEG and 4 in JPEG2000 at compression ratios 20:1, 40:1, 60:1 and 80:1

Test Images


FIAT
Marlboro
arexons
MAGNETI MARELLI
SKF
WEBER
PIONEER
Agip


NEW YORK


85
15

Method (2): CSFs

- There were 3 different CSF implementations:

1. CSF without spatial frequency adaptation
2. CSF with “simple” spatial frequency adaptation (dividing by the number of frequencies present in the image)
3. CSF based on image dependent frequency adaptation (implementation is based on code provided by G. M. Johnson)

Method (3): sharpening

- The sharpening module was implemented using a spatial Laplacian filter instead of a Sobel filter as originally suggested

- *an extension of this module could be an edge – enhancing filter that would concentrate more on the frequency range of 22-30 cpd (G. M. Johnson)

Method (4):
masking & colour differences

- Masking was performed using the formula suggested, for each of the opponent channels of each image
- Colour differences were calculated using the CIEDE2000 colour difference formulas and they were applied on a pixel-by-pixel basis

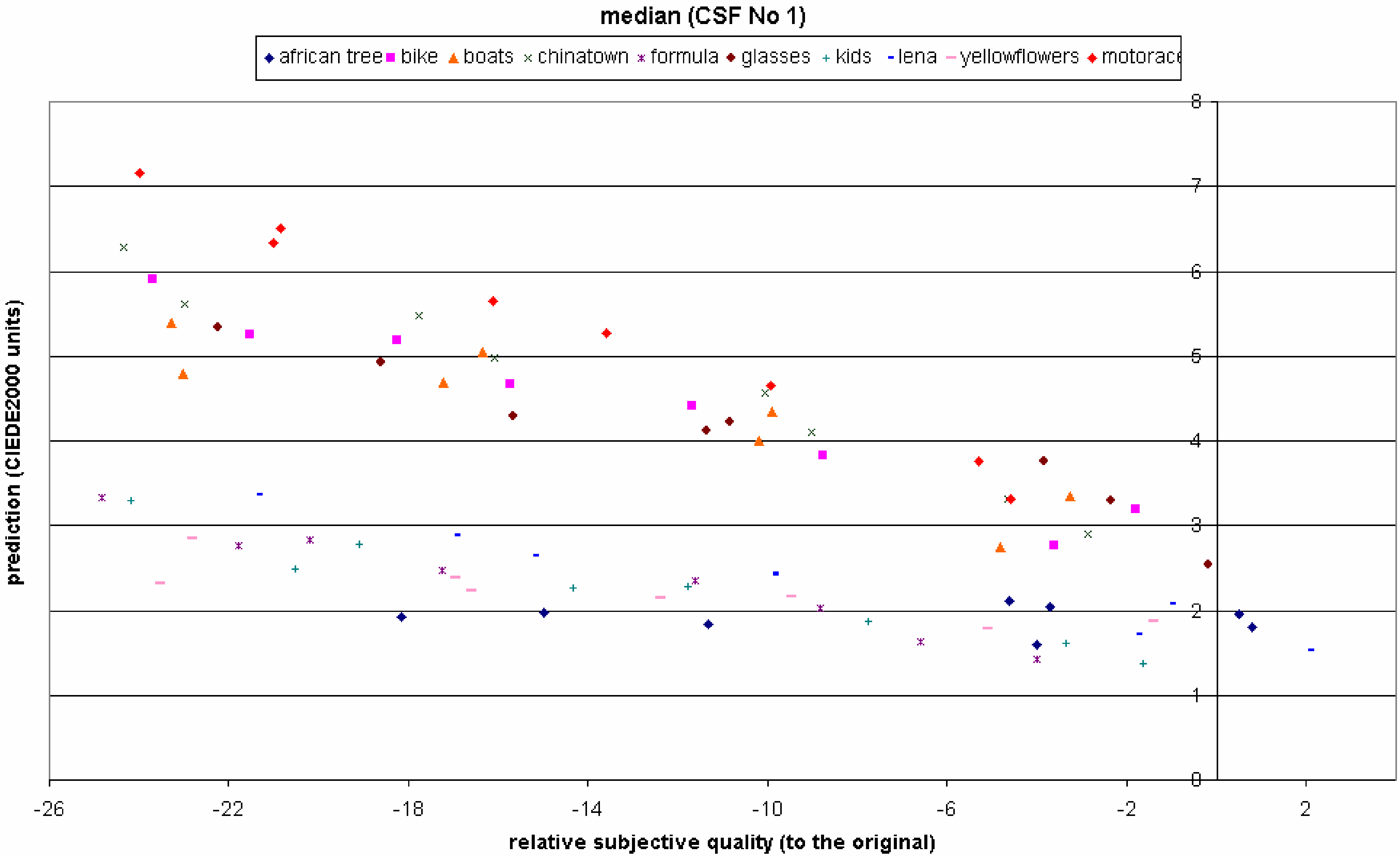
Method (5): final metric

- The final single metric was calculated by the evaluation of the median value of each error map
- The median was selected over other statistical measures calculated (max, mean, standard deviation, normalised standard deviation by mean error value) as it demonstrated the best fit for the specific data

Method (6):
correlation with psychophysical test results

- Interval scaling results from psychophysical tests performed on the same set of images were obtained from E. Allen
- The relative quality differences between the original and the compressed images were calculated for all scenes

Results

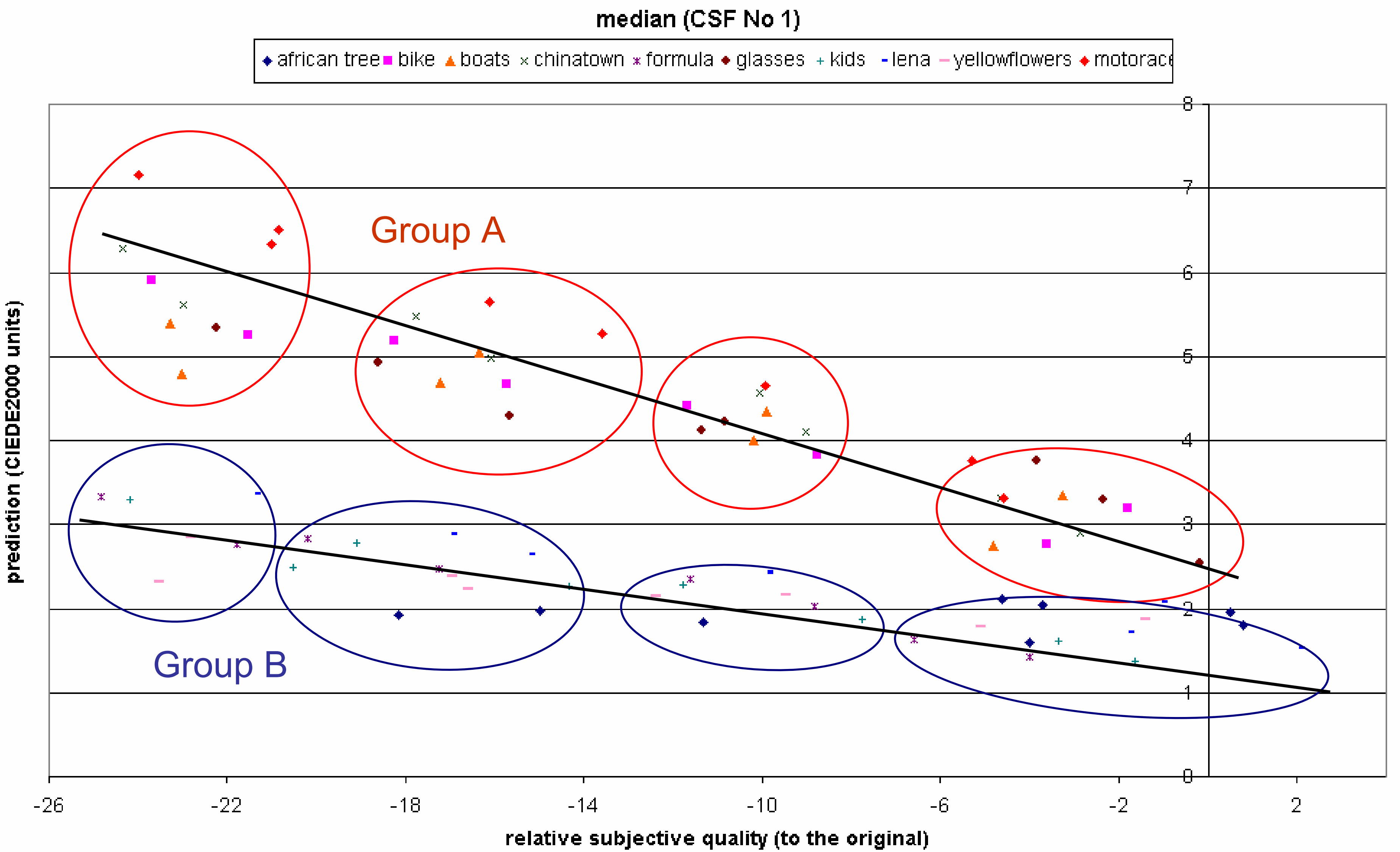

median (CSF No 1)
african tree
bike
boats
chinatown
formula
glasses
kids
lena
yellowflowers
motorace
prediction (CIEDE2000 units)
0
1
2
3
4
5
6
7
8
-26
-22
-18
-14
-10
-6
-2
2
relative subjective quality (to the original)

Observations on CSF No1

- There is definite *clustering* for images compressed with ratios 20:1, 40:1, 60:1 and 80:1, both for JPEG and JPEG2000
- There is *grouping* for certain images:

Group A	Group B
Bike, boats, chinatown, glasses, motorace	Formula, yellowflowers, kids, lena, african tree

Results

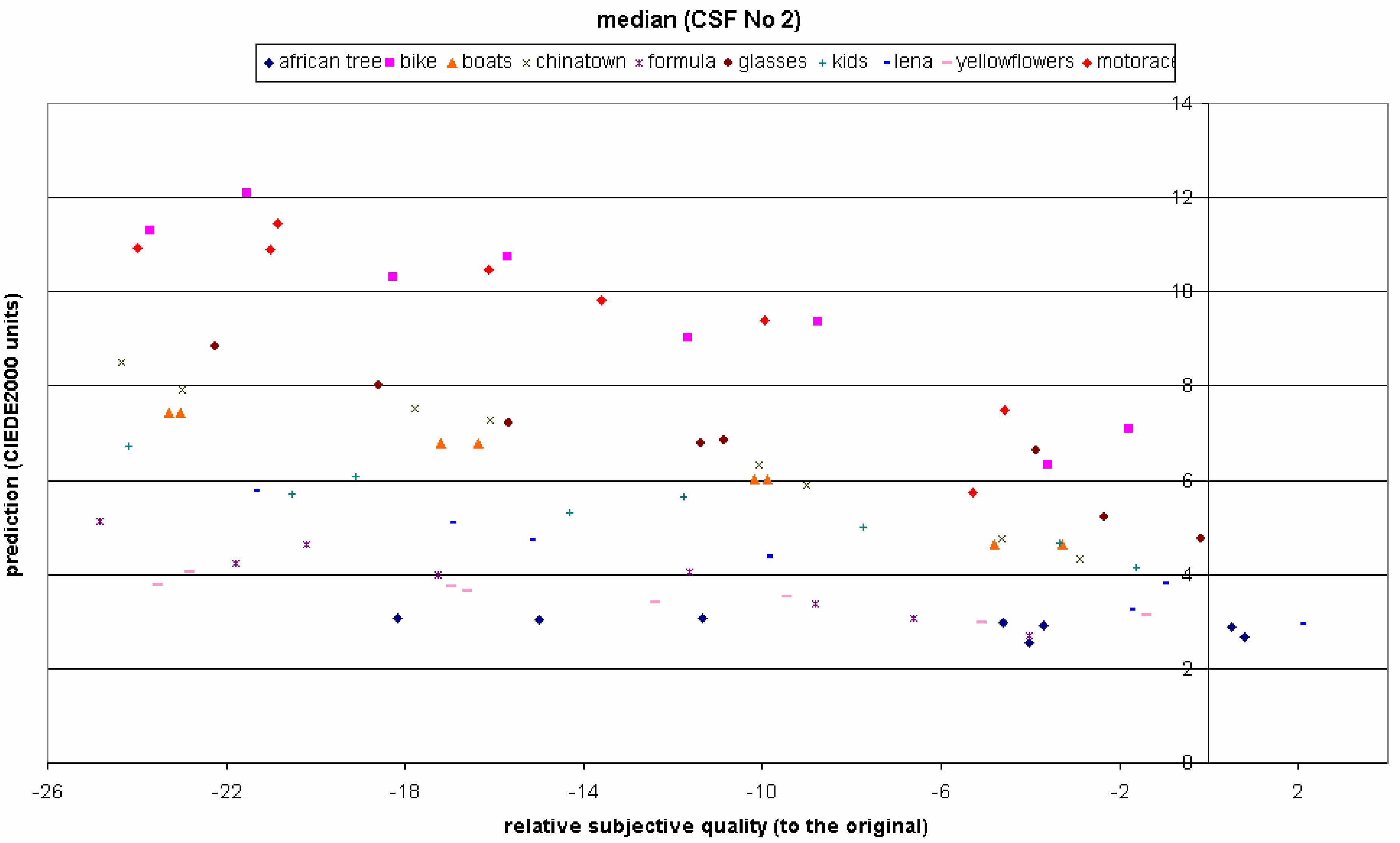

median (CSF No 1)
african tree
bike
boats
chinatown
formula
glasses
kids
lena
yellowflowers
motorace
Group A
Group B
prediction (CIEDE2000 units)
relative subjective quality (to the original)
0
1
2
3
4
5
6
7
8
-26
-22
-18
-14
-10
-6
-2
2

Observations on CSF No1

The correlation coefficients for the data set were calculated for all the points and for the individual observed groups and the results agree with the visual observations

Grouping	***Correlation coefficients***
All	0.3241
Group A	0.8329
Group B	0.6731

Results

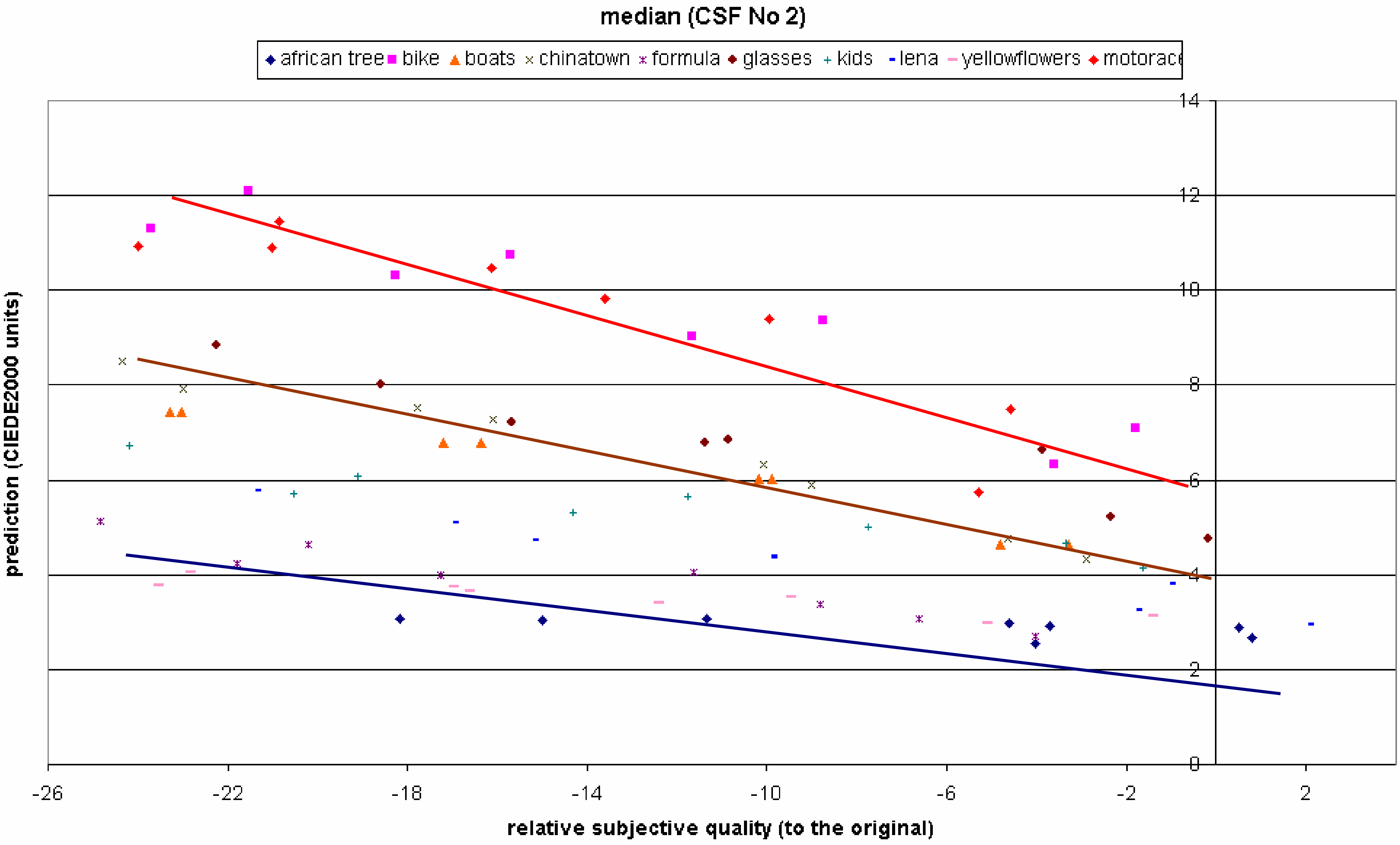


median (CSF No 2)
african tree
bike
boats
chinatown
formula
glasses
kids
lena
yellowflowers
motorace
prediction (CIEDE2000 units)
relative subjective quality (to the original)
0
2
4
6
8
10
12
14
-26
-22
-18
-14
-10
-6
-2
2

Observations on CSF No2

- There is grouping of images but not especially tight clustering
- “motorace” and “bike” are significantly separated from other images
- “kids”, “boats”, “chinatown” and “glasses” seem to be forming another group
- Last group is formed by “lena”, “african tree”, “formula” and “yellowflowers”
- Although the clusters are not tight, the areas of the same compression ratio appear again

Results

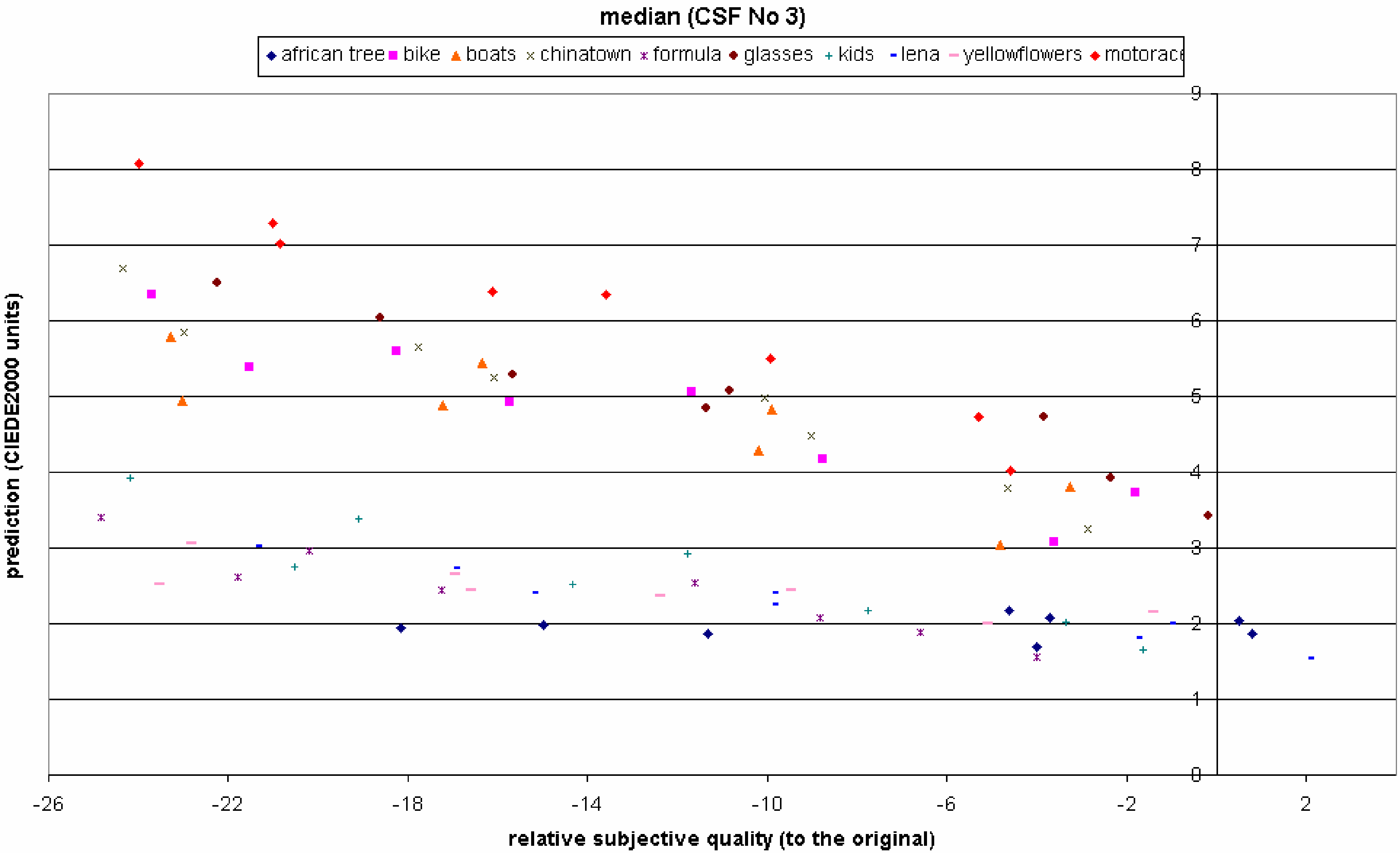

median (CSF No 2)
african tree
bike
boats
chinatown
formula
glasses
kids
lena
yellowflowers
motorace
prediction (CIEDE2000 units)
relative subjective quality (to the original)
0
2
4
6
8
10
12
14
-26
-22
-18
-14
-10
-6
-2
2

Observations on CSF No2

The calculated correlation coefficients for this data set are in agreement with the visual observations:

Grouping	*Correlation coefficients*
All	0.2465
Motorace & bike	0.844
Chinatown, glasses, boats & kids	0.6742
Formula, tree, lena & yellow flowers	0.4805

Results



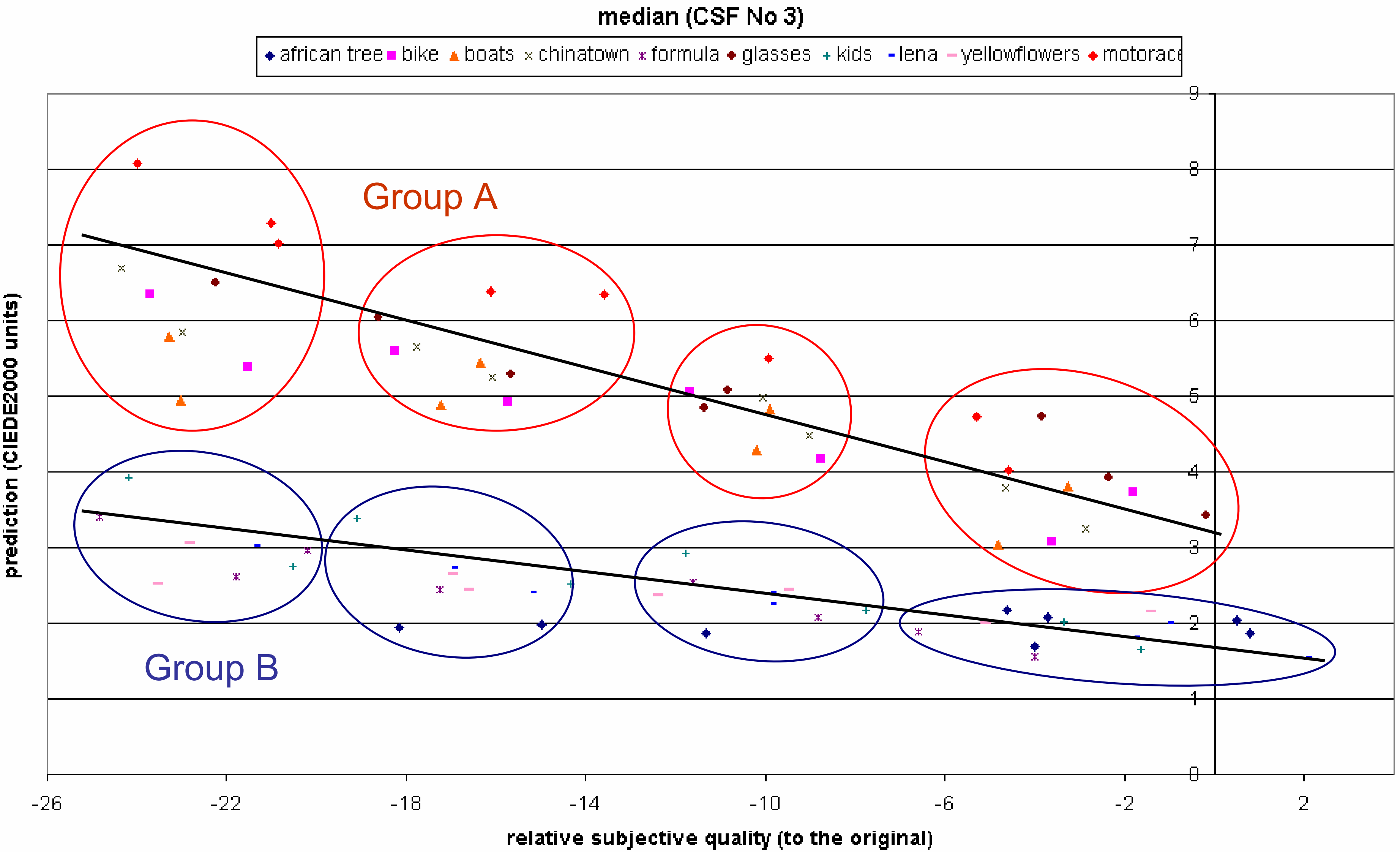
median (CSF No 3)
african tree
bike
boats
chinatown
formula
glasses
kids
lena
yellowflowers
motorac
prediction (CIEDE2000 units)
relative subjective quality (to the original)
0
1
2
3
4
5
6
7
8
9
-26
-22
-18
-14
-10
-6
-2
2

Observations on CSF No3

- Clusters and separate groups appear in this implementation of spatial frequency adaptation
- The groups are again:

Group A	Group B
Bike, boats, chinatown, glasses, moto	Formula, yellowflowers, kids, lena, african tree

Results



median (CSF No 3)
african tree
bike
boats
chinatown
formula
glasses
kids
lena
yellowflowers
motorace
Group A
Group B
prediction (CIEDE2000 units)
relative subjective quality (to the original)
0
1
2
3
4
5
6
7
8
9
-26
-22
-18
-14
-10
-6
-2
2

Observations on CSF No3

The calculated correlation coefficients for the third data set are:

Grouping	***Correlation coefficients***
All	0.2579
Group A	0.7133
Group B	0.6412

Observations on all plots

- A “V” shape resulting from G. M. Johnson and M. D. Fairchild’s experiment did not appear when plotting these values
- With the exception of “tree40”, “tree20” and “lena20k”, all compressed images were characterised as having less quality when compared with the original
- This was expected as artefacts of compressed images are not visually accepted by observers

Observations on all plots

- As expected, colour difference predictions were greater for images of less subjective quality
- This results in the negative slope seen in the relevant plots

More observations…

- There is a scene dependency factor, affecting the distribution of the images on the above plots (separate groups)
- More information on the images is needed in order to derive more accurate conclusions on that grouping
- Image statistics were applied on the specific set of images

Image statistics

	mean	median	mode	variance	skewness	entropy
african tree	79.6081	73	60	1192.8	0.013	6.7244
bike	65.0478	60	4	2459.7	1.3459	7.1729
boats	105.3255	105	21	5091.8	0.333	7.5801
chinatown	105.9272	81	56	4448.9	0.6417	7.7137
formula	77.9055	72	4	2956.1	1.0947	7.1875
glasses	159.3687	177	236	4515.1	-0.7277	7.7212
kids	94.7588	53	249	6263.8	0.9826	6.9924
lena	103.3443	107	109	2621.6	0.0455	7.5154
yellowflowers	82.5954	81	81	778.724	1.4524	6.26
motorace	80.595	58	14	5050.3	1.141	7.4615

Image statistics

- There were no obvious correlations between the image statistic values and the grouping of the specific images
- Therefore, no extra information for this grouping was extracted

Image statistics

- Dr. S. Triantaphillidou has developed an image quality measure that depends on the *“busyness”* of the image
- This provides a measure of detail by calculating the proportion of busy areas to non-busy areas

Image statistics

- The results from this measure for the relevant pictures were:

	"busyness"	*Rank*
Group A		
Bike	83.65	13
Boats	60.29	10
Chinatown	84.60	14
Glasses	44.20	5
Motorace	89.25	15
Group B		
African tree	2.38	1
Formula	32.73	2
Kids	40.48	4
Lena	50.10	8
Yellow flowers	35.41	3

Image statistics

- It seems that all the *"busy"* images are forming Group A while the less *"busy"* ones are included in Group B, with the exception of the image "glasses".

	"busyness"	*Rank*
Group A		
Bike	83.65	13
Boats	60.29	10
Chinatown	84.60	14
Glasses	44.20	5
Motorace	89.25	15
Group B		
African tree	2.38	1
Formula	32.73	2
Kids	40.48	4
Lena	50.10	8
Yellow flowers	35.41	3

Image statistics

- As seen, all the *"busy"* images are forming Group A while the less *"busy"* ones are included in Group B, with the exception of the image "glasses".

	"busyness"	***Rank***
Group A		
Bike	83.65	13
Boats	60.29	10
Chinatown	84.60	14
Glasses	44.20	5
Motorace	89.25	15
Group B		
African tree	2.38	1
Formula	32.73	2
Kids	40.48	4
Lena	50.10	8
Yellow flowers	35.41	3

Observations

- It seems that “busy” images correspond to greater colour difference predictions
- This may be due to the creation of more compression artefacts in areas of greater detail resulting in more colour differences in these areas

Recommendations for future development

- Aiming at the creation of a new model based on the combination of the model suggested by G. M. Johnson & M. D. Fairchild and the model suggested by Dr. S. Triantaphillidou
- Incorporation of an extra processing step in the calculation of *"busyness"* that would apply a specified CSF on the images

Thank you
for your attention