D3.2.2.1

Automatic image enhancement methods

Evaluation of Automatic Image Enhancement Methods for Reader Reporters' Images

Author(s): Henri Kivinen

Confidentiality: Consortium

Date and status: 10.12.2010 v0.7

This work was supported by TEKES as part of the next Media programme of TIVIT
(Finnish Strategic Centre for Science, Technology and Innovation in the field of ICT)

Version history:

Version	Date	State (draft/ /update/ final)	Author(s) OR Editor/Contributors	Remarks
0.1	18.11.2010	draft	Henri Kivinen	Structure of the deliverable
0.2	29.11.2010	update		
0.3	30.11.2010	update		
0.7	10.12.2010	update		Current form of the deliverable

Participants	Name	Organisation
Research partner	Henri Kivinen	**Aalto University**
	Mikko Nuutinen	**Aalto University**
	Pirkko Oittinen	**Aalto University**
Content provider	Santtu Parkkonen	**Sanoma News / Kaupunkilehdet**

Next Media
www.nextmedia.fi
www.tivit.fi

Executive Summary

In this study we evaluated different methods for automatic enhancement of images in the context of images taken by Vartti newspapers' readers. The majority of the images have been captured using mobile phones. Characteristic of mobile phone images is that they suffer from many types of distortions such as poor contrast, noise, motion blur and colour casts. In the application of the study, consumer supplied images are used in the web and in print. The web publishing workflow is fast-paced and the time allowed for computational improvement of any single image is very short preventing any human interaction. The current practice is to upload the incoming images automatically to the web site without any processing.
The goal of the study is to improve the quality of images at the web site. To achieve this, the research question addressed is to what extent can improvement be achieved by automatic processing in the computational time scale of a few seconds.

Enhancement algorithms for the study were selected based on a literature survey and compared with the state-of-the-art approach of adjusting colour channel histograms. The algorithms were applied to forty images, selected to represent the image mass of the application. The original and images were processed using four different algorithms and subjectively assessed by experts in the editorial staff of Vartti using the pair comparison method. The tests were accomplished at the workspaces of the participants who used their own computers and displays.

According to the results, the experimental algorithms led to statistically significant improvements in image quality.

Table of Contents

1 Introduction

Various factors have an effect on the visual quality of images captured by newspapers' readers. Technical limitations of users' cameras coupled with changing conditions in which users take photos results in visual quality which covers a wide range. Camera-related limitations arise as a combination of poor optics, noisy sensors, and modest processing capabilities of camera phones, which are the types of cameras commonly used by reader reporters.

Nevertheless, it is challenging to design a camera sensor and optics for mobile phone that can be used to take photos in conditions that range from bright daylight to shady indoor scenes with incandescent light or dark night scenes. Hence, it is most likely that the images have many distortions such as poor contrast, noise, motion blur, and color casts.

The distortions can be corrected manually or at least enhanced to correspond with a subjective perception of what an image could be at its best from an editor's perspective. Manual fine-tuning is however time consuming, and as the amount of image and video content is growing exponentially, there is an obvious need for automatic image enhancement. The research question addressed here is, to what extent is it possible to automatically enhance image quality in the case of camera phone images.

2 Methods for automatic image enhancement

In this study we focused on correcting colour balance and enhancing global and local contrast. This was the result of conclusions that was made according to literature review that directed to automatic methods for especially colour balance and contrast enhancement methods that will be presented in this chapter. Though we tested also robust denoising methods such as “Non local means” – and “K Nearest Neighbors” -filter, they are highly depended on their parameters. While it is possible to find manually working parameters for every image, automation would require solving complex parameterization problems or using learning systems.

Image enhancement methods that were selected in this study include two Retinex-based methods, one commercial method, and commonly used Auto-levels – method. In addition, we implemented “Automatic Color Equalization” – algorithm, which was developed by Rizzi et al. (2003). But computation time of ACE-algorithm was over 20 minutes (Intel Xeon Quad Core) per image (700x525), which is not conventional in this context. Nonetheless, we also implemented its boosted version (Gatta et al. 2006), but its output images included visible blocks in some cases due to its sub-sampling approach.

2.1 Basic histogram methods

One of the simplest and also very commonly used method for correcting colour balance and contrast in images is so called Auto-levels in the Photoshop. The Auto-levels is fast, and automatic for those images that have low dynamic range in at least on colour channel. Hence, it works well if one of the image’s colour channels has intensities that do not extend to both ends of its histogram. For example, in the captured image has a histogram which shows that the colour distribution is high in dark and light ends. Outcome of the Auto-levels – processing is presented in Figure 1, which shows only a minor visible difference.

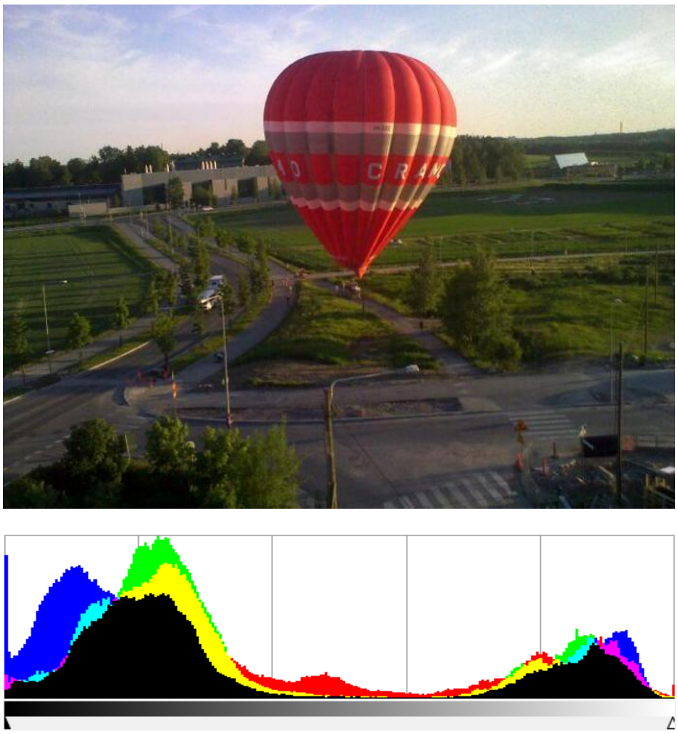

Figure 1 Original image (27) and its histogram.

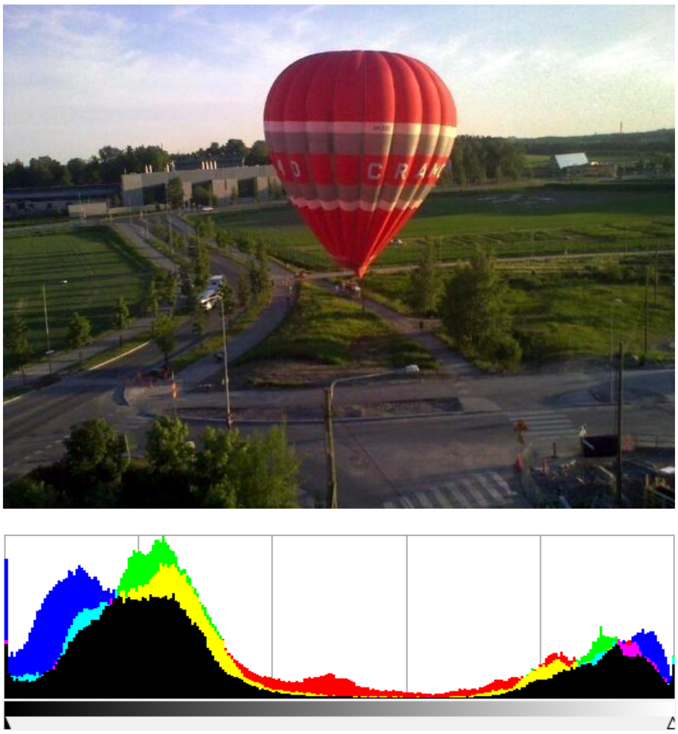

Figure 2 Auto-levels -processed image (27) and its histogram

This content-dependency results from Auto-levels –method's algorithm that uses minimum and maximum values of a histogram to calculate a gain-value, which is used to stretch the histogram to achieve the full dynamic range (Rahman et al.

2004). This can be seen from the histogram in Figure 2, and more clearly in Figure 3 and 4, where the algorithm stretches image's histogram according to its original histogram's minimum and maximum values.

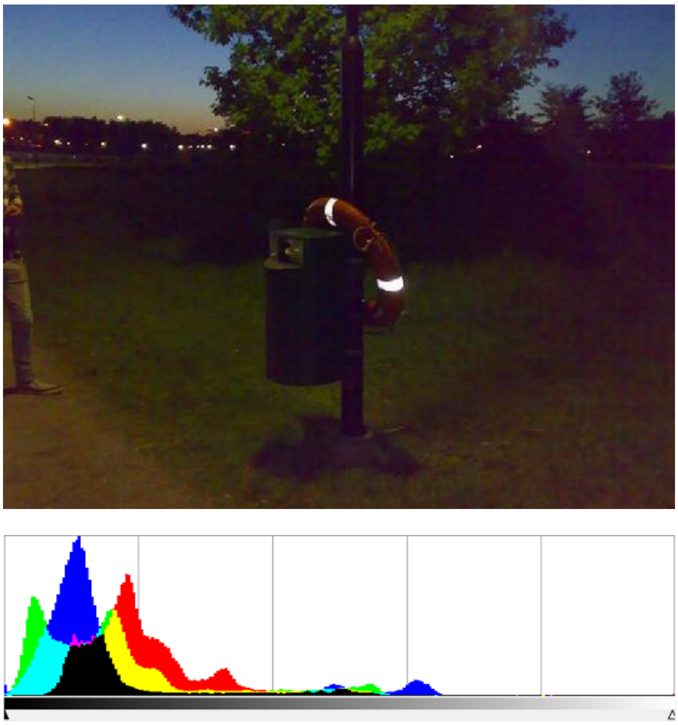

Figure 3 Original image (2) and its histogram.

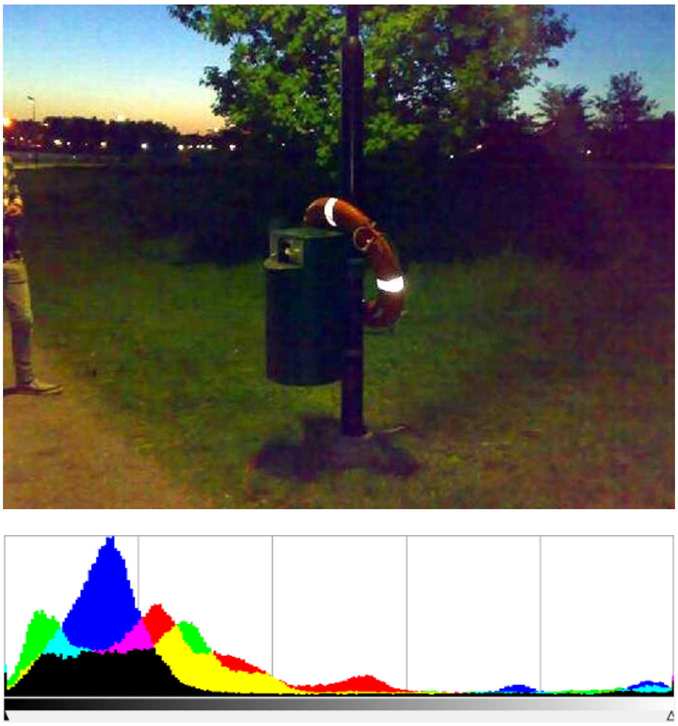

Figure 4 Auto-levels -processed image (2) and its histogram.

The Auto-levels is almost identical with the contrast stretch –algorithm. The only difference is that the Auto-levels –algorithm uses histogram clipping. This means that when the contrast stretch –algorithm defines the histogram maximum and minimum bins when there is at least one pixel in these bins, the auto-levels –method has a threshold value for the required number of pixels before a bin is defined as minimum or maximum. This has clear advantages in specific image contents.

2.2 Retinex-based methods

2.2.1 Retinex theory

Retinex theory is one of the first and perhaps also the most famous attemptto model and explain how the human visual system perceives colour. It was introduced by Land and McCann (1971) and has ever since evolved into various implementations.

According to experiments, Land and McCann discovered that colour perception is not only a light acquisition process, and that there are also other more complicated processes included. For example, the concept of colour constancy describes a phenomenon where human vision can adapt to global lighting of a scene such that object's reflectance is perceived equally even when the lightning changes.

The original model started from a concept of random walk computation. It was described by Land and McCann when they found out that one way to compute the lightness value of a pixel in an image can be calculated from a path of pixels ending at the current pixel. Hence, starting at random points, and averaging the products of ratios between intensity values in each path . (Bertalmío et al. 2009; Provenzi et al. 2005)

The basic assumption of the Retinex model is that the human visual system operates with three retinal-cortical systems. Each of the systems processes independently the low, middle, and high frequencies of visible electromagnetic spectrum. Also each of the independent processes represents of an image that determines a quantity of lightness. Thus, the perception of colour of each pixel in the image can be defined by superposition of triplet values computed by the Retinex. (Bertalmío et al. 2009; Provenzi et al. 2005)

The original experiments did not, however, involve digital images but included patches in 'Mondrian' pictures. It was suggested by Land himself (1977) that the Retinex theory can be used also to enhance images besides modelling colour perception. The assumption behind the application in this studystems from the idea that the Retinex should convert a generic picture of a scene into a more "natural" depiction. This means that the enhanced image should be closer to what a human observer, or photographer, would actually see while looking at the same scene (Bertalmío et al. 2009).

With this assumption in mind we implemented two different versions of the Retinex for image enhancement. While there are numerous implementations of the Retinex in addition to random walk computations, etc., we chose the two due to their applicability to automatic image enhancement, especially for, simplicity, and thus, low computation time. In next sub-sections we briefly introduce Multiscale Retinex with color restoration, and similar method which uses only luminance channel.

2.2.2 Multiscale Retinex with color restoration

Multiscale Retinex algorithm (MSR) by Jobson et al. (1997b) is based on their previous work on single scale retinex (SSR). The SSR algorithm (Jobson et al. 1997a) is a simple implementation of the Retinex that was developed especially for more practical image processing. Their work was inspired by Land's most recent version of the Retinex where he described a centre/surround operator to replace the random walk computation. The centre/surround operator is similar to the difference-of-Gaussian function which is commonly used in natural vision science to model perceptual processes. Thus, as Land used a $1/r^2$ function for the operator, Jobson et al. used a Gaussian surround, which is defined as,

$$R_i(x,y) = \log I_i(x,y) - \log[F(x,y) * I_i(x,y)] \quad (1)$$

where $I_i(x,y)$ is the image distribution in the ith colour channel, * is the convolution operator, $F(x,y)$ its surround function, and $R_i(x,y)$ is the output of Retinex. Jobson et al. noticed, however, that the method will produce better results by using three scales for the Gaussian function. Hence, smaller scales resulted to images with good dynamic range compression, while larger scales provided better tonal rendition. Combination of three scales, small, intermediate, and large, provided them both.

The Retinex processing still had problems with images having regional and global gray-world violations, i.e., spatially averaged relative spectral reflectance are not equal in three colour spectral bands of the image. This is a consequence of processing an image by each channel independently, and it is shown as desaturation in the image. Jobson et al. (1997b) corrected this by using a colour restoration function, which is defined as,

$$C_i(x,y) = \beta\left\{\log[\alpha I_i(x,y)] - \log\left[\sum_{i=1}^{S} I_i(x,y)\right]\right\} \quad (2)$$

where β is a gain constant, and α controls strength of nonlinearity of the restoration. Final version of the MSRCR is then written as,

$$R_{MSRCR_i}(x,y) = G[C_i(x,y)\{\log I_i(x,y) - \log[I_i(x,y) * F_n(x,y)]\} + b] \quad (3)$$

where G and b are final gain and offset values.

2.2.3 Luminance based multiscale retinex

In addition to using only the luminance channel, the Luminance based multiscale Retinex (LB_MSR)–method differs from MSRCR also in how it handles convolution results (Tao & Asari 2004). First, the luminance channel for color image is defined as,

$$I(x,y) = R \times \frac{R}{R+G+B} + G \times \frac{G}{R+G+B} + B \times \frac{B}{R+G+B} \qquad (4)$$

Whereas the original MSR function for all channels is,

$$R_{MSR2}(x,y) = \frac{1}{3}\left[\log \frac{I(x,y)}{I(x,y) * F_1(x,y)} + \log \frac{I(x,y)}{I(x,y) * F_2(x,y)} + \log \frac{I(x,y)}{I(x,y) * F_3(x,y)}\right] \qquad (5)$$

which can be written as

$$R_{MSR2}(x,y) = \frac{1}{3}\left[\log \frac{I(x,y) \cdot I(x,y) \cdot I(x,y)}{\left(I(x,y) * F_1(x,y)\right) \cdot \left(I(x,y) * F_2(x,y)\right) \cdot \left(I(x,y) * F_3(x,y)\right)}\right] \qquad (6)$$

where $F_i(x,y)$ is a Gaussian with three different scale and $I(x,y)$ is the luminance values of original image.

At this point Tao & Asari noticed it is possible to reduce noise and still compress the dynamic range if the denominator of log function in (6) is changed from multiplication to summation,

$$R_{MSR2}(x,y) = \frac{1}{3}\left[\log \frac{I(x,y) \cdot I(x,y) \cdot I(x,y)}{I(x,y) * \left(F_1(x,y) + F_2(x,y) + F_3(x,y)\right)}\right] \qquad (7)$$

2.2.4 Implementation issues

Parameters of both Retinex-based methods were equal to what their authors used with their tests. However, we noticed that lower scale values for Gaussians were more suitable for the test images, because in some cases larger scale blurred the image too much losing visual information. In the papers, the MSRCR-algorithm originally used scale values of 15, 80, and 250, and the LB_MSR with values of 5, 20, 240. We used values from 1 to 3. It was also noted by Jobson et al. (1997b) that the scale values are not critical if reasonable coverage from local to near global is found.

Also what we discovered was that the use of Auto-levels –processing before the Retinex provided better results in terms of visual quality. It seems that this way it is possible to make use of the capabilities of both methods where one fails and other succeeds. This was not, however, evaluated with subjective tests due to practical limitations.

Currently we have implemented all the algorithms with Java, while MSRCR has also C++ -version built on Windows 7, which is much faster: less than a second per image. Later on we will also provide a web service[1] where it is possible to enhance given image.

3 Evaluation of methods

To answer the question is it possible to automatically enhance images we conducted subjective tests. During the tests, employees of Vartti Newspaper compared a set of reader reporters' images that where corrected with implemented methods.

3.1 Test images

The set of images consisted of forty (40) different contents that were selected from Puskaradio -service[2] (former Vartti.fi) where the readers' images are published. Size of the images was 700 x 525. The selection was done partly such that images where from different periods and seasons during 2009 and 2010, but also such that there where both low and high quality images. As we needed to test also that implemented methods would not attenuate images of higher quality.

All the images, original and processed will be published in our web site[3] later on.

3.2 Subjective test arrangements

As was mentioned earlier, evaluation of the enhancement methods was carried out by subjective comparisons of a number of images processed with different algorithms. The tests were conducted as pair comparison where eight (8) observers compared one image pair at a time until all pair combinations had been evaluated. Pair comparison of forty images has a total of 400 pairs, as in,

$$pairs = n \cdot \frac{m \cdot (m-1)}{2} \tag{4}$$

where n is the number of images and m is the number of different methods to evaluate.

The reason for such a high number of different images rises from fact that image processing has been and still is very content-dependent, and there are many challenges left to overcome it on full scale. Therefore it is necessary to test as many image contents as possible/feasible. After the tests it was noted that it was somewhat burdensome due to repetitive task and the workload, and also due to

[1] http://nextmedia.tml.hut.fi/imgEnhance/
[2] http://omakaupunki.hs.fi/paakaupunkiseutu/puskaradio/viestit/mms/
[3] http://nextmedia.tml.hut.fi

technical problems in the test application. Average time for conducting the pair comparison test was 67 minutes, while median was 39 minutes.

The web application[4] for the pair comparison was implemented with Java using the Apache Wicket[5] -framework, which is running on Apache Tomcat[6] (version 6.02) web server. It was noted that the Wicket –framework suited well for such a simple user interface as our pair comparison test. In addition we used simple Javascript code on client-side to resize test images according to the resolution of each user's display. This made it possible to run the test even with smartphones, albeit most of the displays had a resolution of 1280x1024.

4 Results

4.1 Pair comparison analysis and results

As was previously mentioned, the subjective tests were accomplished with pair comparison tests. For the analysis of pair comparison results we applied the law of comparative judgement by Torgerson (1952). In Torgerson's multidimensional scaling method, the distances between each pair of stimuli, or images in this case, are located on a distance continuum. If we assume that the human response to preferential quality difference between images is normally distributed and this distribution has a constant standard deviation, the comparative judgements can be converted to an interval scale in terms of this standard deviation. (Torgerson 1952; Edinger 2000)

The scaling method has four steps. First, the comparison results are accumulated into a matrix so that the element in the matrix is increase by one, if the observer prefers image enhancement method listed at the top row, and if the observer prefers a method listed along the side, the value of the element is left unchanged. Also, the values above the diagonal are calculated by subtracting from the number of judgements the corresponding element below the diagonal. The resulting matrix is presented in Table 1. Field numbers in the table are: (0) Original, (1) Auto-levels, (2) MSR Luminance, (3) MSRCR, and (4) Commercial.

Table 1 Cumulative observer judgement for test image (1).

	0	1	2	3	4
0	-	4	8	7	6
1	4	-	6	8	7
2	0	2	-	5	4
3	1	0	3	-	4
4	2	1	4	4	-
Sum.	**7**	**7**	**21**	**24**	**21**

[4] http://nextmedia.tml.hut.fi/ImageComparison
[5] http://wicket.apache.org/
[6] http://tomcat.apache.org/

Second step is formation of a matrix in which each element is the corresponding element in divided by a number of judgements (eight observers). The division gives a proportion of times that a method at the top was preferred over a method listed along the side. The resulting matrix is presented in Table 2. Third step is to transform the values in to the units of normal deviate. This value is an estimated preferential difference between scale values of two image enhancement methods and corresponds to an area under normal distribution curve for a proportion value. The estimates of the interval scale values are evaluated by averaging the values in the columns. The matrix of preference scale values and corresponding interval scale values is presented in Table 3.

Table 2 Proportions of judgements for test image (1).

	0	1	2	3	4
0	0	0.5	1	0.875	0.75
1	0.5	0	0.75	1	0.875
2	0	0.25	0	0.625	0.5
3	0.125	0	0.375	0	0.5
4	0.25	0.125	0.5	0.5	0

Table 3 Preference scale values for test image (1).

	0	1	2	3	4
0	0.00	0.00	2.33	1.15	0.67
1	0.00	0.00	0.67	2.33	1.15
2	0.00	-0.67	0.00	0.32	0.00
3	-1.15	0.00	-0.32	0.00	0.00
4	-0.67	-1.15	0.00	0.00	0.00
Avg.	-0.36	-0.36	0.54	0.76	0.36

Finally, perceptual difference between pairs is calculated as an absolute value of difference between the preference scale values. These values of perceptual difference for all the test images are presented in Table 4. Here we coloured with light green cells that have highest value in its row, and with light blue values that are negative. Thus, the negative values mean that observers preferred original image over enhanced images. Higher absolute values mean that observers were more consisted with their judgements.

Table 4 Perceptual differences between image enhancement methods compared to original image.

Image	0 vs 1	0 vs 2	0 vs 3	0 vs 4
1	0.00	0.90	1.12	0.73
2	0.33	1.12	0.53	0.56
3	0.24	0.27	0.60	0.76
4	0.30	1.69	0.76	-0.10
5	0.29	0.75	0.95	-0.53
6	-0.25	-0.19	-0.19	0.00
7	-0.12	0.14	0.74	-0.62
8	0.30	0.93	0.77	0.97
9	0.50	0.62	1.02	1.09
10	0.60	1.43	1.16	0.94
11	0.27	1.16	0.57	1.43
12	0.04	1.43	1.07	0.00
13	-0.13	0.66	-0.06	0.00
14	0.19	0.77	0.85	-0.40
15	-0.25	0.49	0.59	0.28
16	0.54	0.95	0.76	0.40
17	0.10	0.56	0.93	0.56
18	0.60	1.13	1.26	0.66
19	0.97	0.59	0.16	0.90
20	0.06	1.29	0.59	-0.23
21	0.47	1.02	0.95	0.53
22	0.13	0.06	-0.13	-0.39
23	0.37	1.16	1.16	0.10
24	0.34	-0.15	-0.25	0.78
25	0.56	1.30	0.84	0.10
26	0.07	0.49	0.96	0.30
27	0.36	1.19	1.45	0.90
28	-0.29	0.56	0.46	0.26
29	0.79	1.45	1.46	0.46
30	0.60	0.62	0.86	0.52
31	0.16	1.02	1.12	0.32
32	0.56	1.39	1.48	0.29
33	0.40	1.53	1.29	0.48
34	-0.13	0.26	0.87	0.13
35	0.53	0.12	0.86	0.06
36	0.11	0.24	0.76	1.07
37	0.01	0.34	0.67	0.48
38	0.33	0.53	0.53	0.27
39	0.30	0.23	0.83	0.93
40	0.04	0.53	0.90	-0.33

The summary of the results is presented in Figure 5, where light green column shows a percentage of image contents that had a positive perceptual difference. We defined image as perceptually enhanced if over half of the observers preferred it over original image. Consequently we do not consider the range of scale values. For example, for an image enhancement method to be acknowledged as fully automatic it would certainly require that a lot more than half of the observers prefers its output. This, however, was not tested in our evaluation. It was enough that the image processing would not deteriorate the images.

Therefore we can see from that MSR Luminance –method (2) had the highest percentage of images that were perceptually enhanced, while commercial method failed to processes a quarter of the images. In addition we also compared the methods by calculating a percentage in which a method had the highest scale difference of all methods. In this comparison it can be noted that the MSRCR was clearly the best performing image enhancement method.

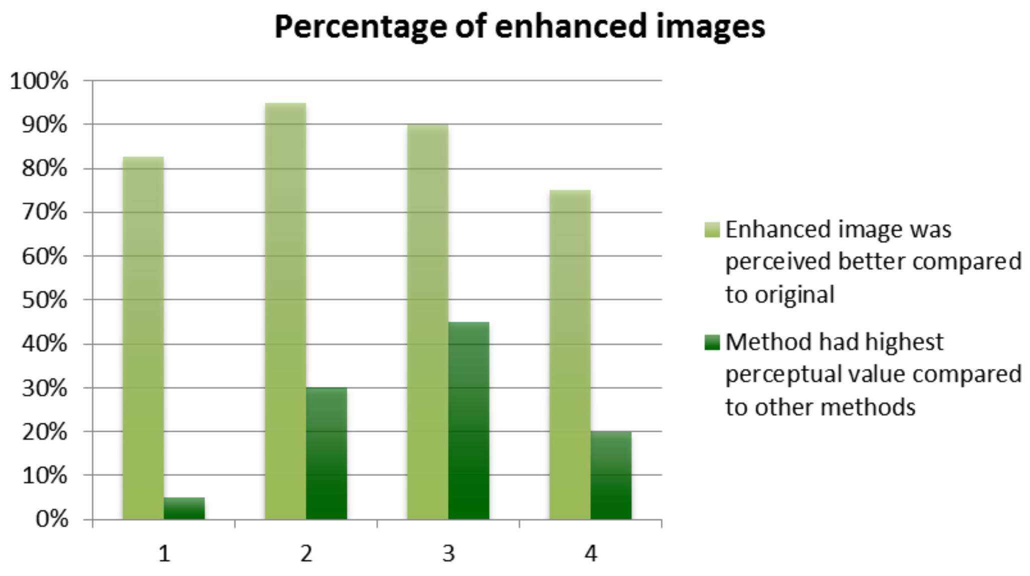

Figure 5 Percentage of image contents on which processed version was preferred over original version (light green). Percentage of image contents where corresponding image enhancement method had highest value (dark green). (0) Original, (1) Auto-levels, (2) MSR Lum., (3) MSRCR, and (4) Commercial method.

Is it then possible to state that the MSRCR –method performs automatic image enhancement? It depends. If it is enough that most of the observers, or viewers, prefer the outcome, then the answer is yes. However, if we look at Figure 6 one it can be noticed that some of the methods resulted in higher variance between judgements. As we calculated observer-wise percentage of each method’s share of all the comparisons, and according to standard deviation, we calculated 95% confidence interval for each method. This shows that observers where not concur with all the images. Nevertheless, according to t-test for averages (Table 5) we can state that the difference between the original and both Retinex-based methods is well below 0.05, and therefore, statistically significant. While the difference between averages of the Retinex-based methods, was not statistically significant.

The same non-significance exists between the Auto-levels and commercial method as well.

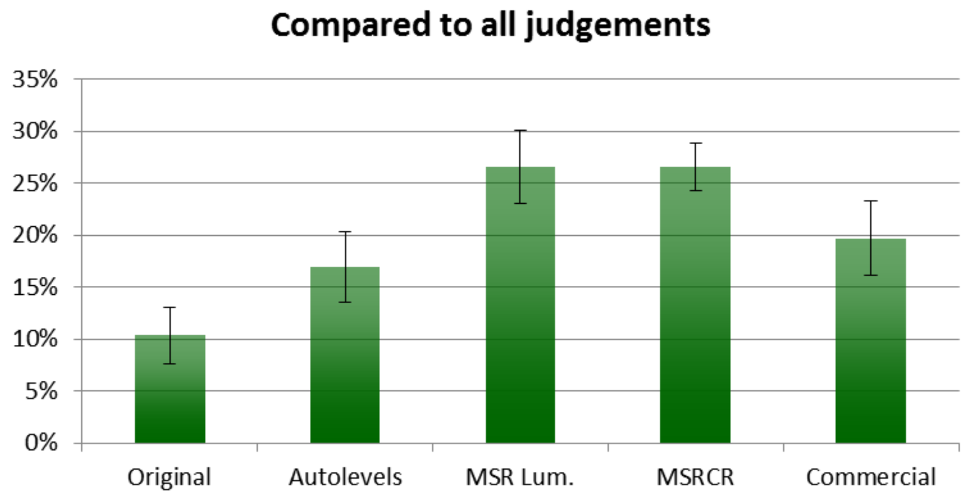

Figure 6 Average observer-wise percentages of positive judgements for each method with 95% confidence interval.

Table 5 Results of t-test for average percentages.

Methods	p-value
0 vs.1	0.00019
0 vs. 2	0.00033
0 vs. 3	0.00014
0 vs. 4	0.00608
1 vs. 2	0.01000
1 vs. 3	0.00287
1 vs. 4	**0.20738**
2 vs. 3	**0.49344**
2 vs. 4	0.01816

5 Conclusions

According to the results we can state that low quality images, such as images that are taken with camera phones, can be automatically enhanced with current methods. These methods enhance contrast on both global and local levels, and fixes color casts. But there are still distortions such as noise and motion blur which are difficult to correct automatically.

In addition, it is commonly known that especially higher level image quality is biased on subjective level. Thus, quality of an image enhancement outcome, manual or automatic, is also depended on who is viewing it. Basically this problem stems from fact that we do not yet know how the perceived image quality is related to lower and higher level adaptation-processes of human visual system.

Besides perceptual issues we should also examine the image quality from journalistic perspective, in which the image quality can also have an information-based factor. Meaning that when a picture is always a depiction of a scene, this representation is always an estimation of what the scene holds in terms of visual objects. This representation could however consist of information that is not visible if we concentrate only on visual image quality. For example, in some cases the shadows might contain the most valuable information in picture.

Of course this is not an issue in professional photography where skilled photographers take photos with best available cameras, which differs quite a lot from reader reporters' and their consumer level cameras. Even though it is very likely that consumers will have constantly evolving arsenal of new tools for taking better pictures, and thus, the need is for higher level image enhancement methods, which adapts to user's preferences and for a specific need for the outcome of enhancement.

For the next year (2011) our plans include transition from the still images to videos, where low level quality issues are still valid even after the technical capabilities of camera phones have found their saturation point.

References

Bertalmío, M., Caselles, V. & Provenzi, E. (2009) *Issues About Retinex Theory and Contrast Enhancement.* International Journal of Computer Vision, vol. 84, 1. pp. 101-119.

Buades, A., Bartomeu, C. & Morel, J. M. (2005) *A Non-local Algorithm for Image Denoising.* Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), vol. 2 (2005), pp. 60-65.

Edinger. J. R. (2000) *Scaling Subjective Impressions of Quality*. IS&T NIP16: International Conference on Digital Printing Technologies. pp. 37-382.

Gatta, C., Rizzi, A. & Marini, D. (2006) *Local linear LUT method for spatial colour-correction algorithm speed-up.* IEE Proceedings. Vision, Image and Signal processing, vol. 153, 3. pp. 357-363.

Jobson, D. J., Rahman, Z. & Woodell, G. A. (1997a) *Properties and Performance of a Center/Surround Retinex.* IEEE Transactions on Image Processing, vol. 6, 3. pp. 451-462.

Jobson, D. J., Rahman, Z. & Woodell, G. A. (1997b) *A Multiscale Retinex for Bridgin the Gap Between Color Images and the Human Observation of Scenes.* IEEE Transactions on Image Processing, vol. 6, 7. pp. 965-976.

Land, E. H. (1977) *The Retinex Theory of Color Vision.* Scientific American, vol. 237, 6. pp. 108-128.

Land, E. H. (1986) *An alternative technique for the computation of the designator in the retinex theory of color vision.* Proceedings of the National Academy of Sciences of the United States of America, vol. 83, 10. pp. 3078-3080.

Tao, A. & Asari, V. (2004) *Modified luminance based MSR for fast and efficient image enhancement.* Applied Imagery Pattern Recognition Workshop, 2003. Proceedings. 32nd.

Torgerson. W. S. (1952) *Multidimensional Scaling: I. Theory and Method*. Pyschometrika. 17. 4. pp. 401-419.

Provenzi, E., De Carli, L. & Rizzi, A. (2005) *Mathematical definition and analysis of the Retinex algorithm.* Journal of the Optical Society of America, B, vol. 22, 12. pp. 2613-2621.

Rizzi, A., Gatta, C. & Marini, D. (2003) *A new algorithm for unsupervised global and local color correction.* Pattern Recognition Letters, vol. 24, 11. pp. 1663-1677.