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Speed-up Technique for a Local Automatic Colour Equalization Model

A. Artusi[1], C. Gatta[3], D. Marini[4], W. Purgathofer[2] and A. Rizzi[3]

[1]Department of Computer Science, Intercollege Nicosia (Cyprus)
[2]Institute of Computer Graphics and Algorithms, Vienna University of Technology
[3]Dipartimento di Tecnologie dell'Informazione, Università di Milano
[4]Dipartimento dell'Informazione e Comunicazione, Università di Milano

Abstract
In this paper we propose a speed-up technique for a local automatic colour equalization operator derived from a model of the human vision system. This method is characterized by local and global filtering effects, that simultaneously achieve different equalization tasks e.g. performing colour and lightness constancy, realizing dynamic image data driven stretching, controlling the contrast. We describe a way to quickly create a filtering mapping function to perform the global component of the mapping. This method is based on singular value decomposition (SVD) applied to sampled and filtered points in the input image. Then, the local information is added computing the basic algorithm on a neighbourhood of each input pixel. A slight quality loss is the price that we have to pay for a speed-up of more than two orders of magnitude of the basic algorithm. We present the results on several images and discuss the efficiency and the drawbacks of the speed-up technique.

Keywords: display algorithms, applications, image display

ACM CCS: I.3.3. Computer Graphics: *Speed-up Technique, Singular Value Decomposition (SVD), ACE, Local Filter, Colour Enhancement, Spatial Colour* I.4.1 Digitization and Image Capture: *Quantization, Sampling*

1. Introduction

For several reasons digital images can be acquired or synthetically generated with limited colour dynamics or with poor colour rendition. In order to solve the problem and correct colour in digital images, often a class of non-linear filtering algorithms characterized by data driven local effects and high-computational cost is used. Generally, local operators are able to produce better results than the global operators, but they are computing demanding and their use is precluded in the applications with critical time constraints.

In the context of automatic colour equalization, many works have been presented. Land and McCann [1] developed the Retinex approach that try to model the Human Visual System (HVS) colour perception. It assumes that colour sensation is based on the ratios of reflected light intesity in specific wavelength bands computed between adjacent areas of the image. In the next 40 years, variants of the Retinex approach have been implemented in software and in hardware [2–9] [10–14], showing a renewed research interest [15]. Several models of the HVS have been proposed so far (e.g. [16,17]), but very few of them are devised for image enhancement purposes.

Other approaches, not Retinex related, to the problem of the chromatic correction have been presented [18–23] [24–28] [29]. On one hand, all these approaches are not based on a clear and solid mathematical model. On the other hand, the problem can be seen as an acceleration of a mapping function between two different RGB colour spaces in image equalization. There are two possible approaches to perform this mapping function: heuristic models and physical models. The first one is used when no prior knowledge, concerning the mapping function, is available and reduces the implementation constraints. Instead, the second one does some assumptions on the shape of the mapping function and often impose constraints that limit the implementation of a speed-up technique.

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Figure 1: *Left: Original Image. Centre: Result using the original ACE algorithm; computational time 307 sec. Right: Result using the speed-up technique; computational time 3 sec. The speed-up factor is about of 102 times.*

In this paper, we want to show how using a heuristic model can help to easy implement a speed-up technique maintaining good performances in term of quality.

Recently has been presented a new approach called ACE [30,31], an alternative HVS model with local properties and consequently heavy-computational cost. In this paper, we present a speed-up technique applied to ACE. This technique is able to take into account both global as well as local information strongly reducing the computation costs. It is based on a quick filter-mapping function that performs the global component, then local component is extracted applying the basic algorithm on a neighbourhood of each input pixel. Then a linear combination of the global and local information is used to get the final output.

In Figure 1 results using the original ACE algorithm (centre) and the speed-up technique (right) are compared with the original image (left). In this case, slight visible differences are noticeable in the image obtained with the speed-up technique as compared to the image obtained with the original ACE algorithm. On the other hand the quality, when compared with the original image (left), is much improved and acceptable for many applications, with a filtering process speed-up of more than 100 times (from 307 to 3 sec).

In Section 2 a brief introduction about the equalization algorithm, called ACE, is presented. Descriptions of the basic idea, the related mathematical background and the implementation are presented in Section 3 and experimental results in Section 4. Conclusions and perspectives end the paper.

2. ACE Basic Algorithm

The ACE algorithm is devised to simultaneously achieve the following image adjustments. It removes colour cast if present (e.g. due to un-calibrated devices or illuminant colour). It maximizes image dynamic range, exploiting in this way the image visual information content, simultaneously tuning the overall image contrast. In this section, we briefly describe the basic computation of ACE. For a more detailed description the reader can refer to [30,31].

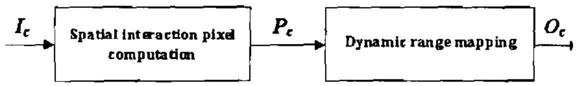


Figure 2: *ACE structure.*

ACE is composed of two stages: during the first stage it performs various adaptation mechanisms typical of the HVS, depending on chromatic and spatial properties of the input image (I) generating an intermediate image, that can be considered as a sort of *perceived image* (P). In order to make the image displayable, the second stage uses estimated *white* and *gray* to map the dynamic range of P into the available one.

This final stage implements two-global mechanisms, which are at the basis of the HVS adaptational mechanisms. The HVS normalizes the receptor's stimuli, maximizing towards a hypothetical white reference maximum [32]. We refer to this mechanism as *White Patch* (WP); it is usually correlated with the HVS *colour constancy* capability. The other mechanism, called *lightness constancy*, allows to stably perceive the world regardless its level of luminance. In terms of histogram properties of a digital image, this corresponds to a level distribution that has its centre mass around the middle value. We refer to this mechanism as *Gray World* (GW). It has to be recalled that these are only two-global simplifications of more robust and sophisticated local and global mechanisms.

ACE models those mechanisms in two stages, accounting their global effects in the second stage and their locality in first stage. Figure 2 shows the implementation scheme, where I is the input image, P is the intermediate image and O is the output displayable image while subscript c denotes the R,G,B chromatic channels.

The first stage produces an intermediate image P whose pixels i are transformed separately for each channel c as in Equation (1):

$$P_c(i) = \frac{\sum_{i,j\in I,j\neq i} r(I_c(i) - I_c(j))d(i,j)}{\sum_{i,j\in I,j\neq i} r_{\max} d(i,j)}. \quad (1)$$

The term $d(i, j)$ is a distance measure, and from experimetal results we noticed that euclidean measure or similar L2 distances, can be used alternatively without remarkable differences in the final results. The denominator is a normalization factor, introduced to avoid vignetting near the borders of the image, where $r_{\max}$ is the maximum value of the $r(\cdot)$ function:

$$r(\rho) = \begin{cases} -1, & \text{if } \rho \leq -1/slope \\ \rho \cdot slope, & \text{if } -1/slope < \rho < 1/slope. \\ 1, & \text{if } \rho \geq 1/slope \end{cases} \quad (2)$$

The variation of the $r(\cdot)$ function acts as a contrast tuner; the higher the slope is, the higher the contrast. In fact, $r(\cdot)$ functions range from linear to signum function, where values above 1 and below -1 are truncated (see Equation 2). To achieve satisfactory results in most of the images the *slope* should be around 5.

The aim of the second stage is to apply both GW and WP global corrections using the maximum value in P as an estimate of white and the middle value as an estimate of gray to map P into the available device dynamic range [0, D_{Max}], as shown in Equation (3),

$$O_c(i) = round[D_{\text{mid}} + s_c P_c(i)] \quad (3)$$

where D_{Max} is the available dynamic maximum value, $D_{\text{mid}} = D_{\max}/2$ and $s_c = D_{\text{mid}}/\max(P_c)$. Alternative mapping methods can be used to realize this second stage [33].

The algorithm has interesting properties: it is unsupervised and it works without any statistical or *a priori* information about the image. The major problem of ACE is its heavy-computational cost: $O(N^2)$, where N is the number of pixels. This strongly restricts the range of possible applications, thus a speed-up technique is needed.

3. The Speed-up Algorithm

One of the components of a local enhancer is a strategy to deal with local intensity ratios, which may correspond to surface reflectance changes, and reduce global differences, which may be associated with illuminations casts. A candidate speed-up strategy has to take into account the global as well as the local information in the original image. The basic idea is to realize a quick approximation of the global component of the original image and then to add its local component, computing the basic filter only on a small subset of the original image. For the global extraction, first the ACE algorithm is applied on a subset of the original image and the Singular Value Decomposition (SVD)[34] is used to extrapolate the ACE algorithm to the whole image. How the polynomial degree influence the results is showed in the Section 4. The local information is extracted applying ACE on a reduced neighbourhood of each input pixel. Finally, global and local information are recombined to have an output image comparable with the image obtained applying ACE in the traditional way (considering the whole image as neighbourhood).

In the next subsections, we describe the algorithmic details of the extraction of the global and local information of the original image. Then how to combine this information is presented.

3.1. Global information extraction

The general problem can be seen as defining a mapping function between two-different sets: the input RGB values of the original image and the RGB output values obtained with ACE. To speed-up this phase we have to apply ACE only on a subset of the original image. The subset is obtained by random sampling. We use this subset of input and output RGB values to create the mapping function between these two sets. It can be considered like a linear problem, in case of first-polynomial degree see Equation (4), where RGB_i are the subset input RGB values of the original image and RGB_o represent the output RGB values obtained with ACE applied on the subset. The elements a_{ij} represent the unknown coefficients that control the behaviour of the mapping function. Polynomials functions are used to defined the mapping function, and SVD is used to extract the unknown coefficients. Using polynomials functions of (not complete) second degree, the linear problem has the form as shown in Equation (5):

$$\begin{aligned} R_o &= a_{11} + a_{12}R_i + a_{13}G_i + a_{14}B_i \\ G_o &= a_{21} + a_{22}R_i + a_{23}G_i + a_{24}B_i \\ B_o &= a_{31} + a_{32}R_i + a_{33}G_i + a_{34}B_i \end{aligned} \quad (4)$$

$$\begin{aligned} R_o &= a_{11} + a_{12}R_i + a_{13}G_i + a_{14}B_i + a_{15}R_i^2 + a_{16}G_i^2 + a_{17}B_i^2 \\ G_o &= a_{21} + a_{22}R_i + a_{23}G_i + a_{24}B_i + a_{25}R_i^2 + a_{26}G_i^2 + a_{27}B_i^2 \\ B_o &= a_{31} + a_{32}R_i + a_{33}G_i + a_{34}B_i + a_{35}R_i^2 + a_{36}G_i^2 + a_{37}B_i^2 \end{aligned} \quad (5)$$

where index i represents the input image and index o represents the output image obtained with ACE algorithm. The coefficients a represent the unknown coefficients as described above.

Once the behaviour of the mapping function has been extracted it can be applied on the whole input scene.

Figure 3: *Child: Comparison of the results with the original image (left); considering the global information (centre) and considering global and local information (right).*

3.2. Local information extraction

Due to the sampling and the global characteristic of the mapping function, the proposed method could loose details in the final image. To solve this problem we have devised a local operator, described by Equation (6), to compensate for high-frequency loss. This equation is derived directly from Equation (1):

$$HF_c(i) = \frac{\sum_{i,j\in\Omega,j\neq i} r(I_c(i) - I_c(j))d(i,j)}{\sum_{i,j\in\Omega,j\neq i} r_{max}d(i,j)} \qquad (6)$$

where Ω is a circle of radius R, centered in the pixel i.

This formula is used to estimate the original high frequency content of the original algorithm. We choose to restrict the support of calculation to an Ω circular area centered in the pixel position, forcing the algorithm to work only on the high frequency. In this paper we have chosen $R = 3$ as a trade off between sharp results and time constraints.

The effect is to restore sharpness, as it can be seen in Figure 3. The image at the right is obtained adding the local information, extracted with the formula proposed in Equation (6), to the global one. We can see how the details are more visible in particular in the hair of the child, in the dog and in the ground (Figures 4 and 5).

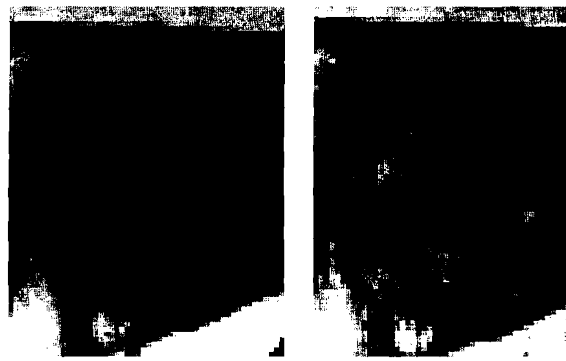


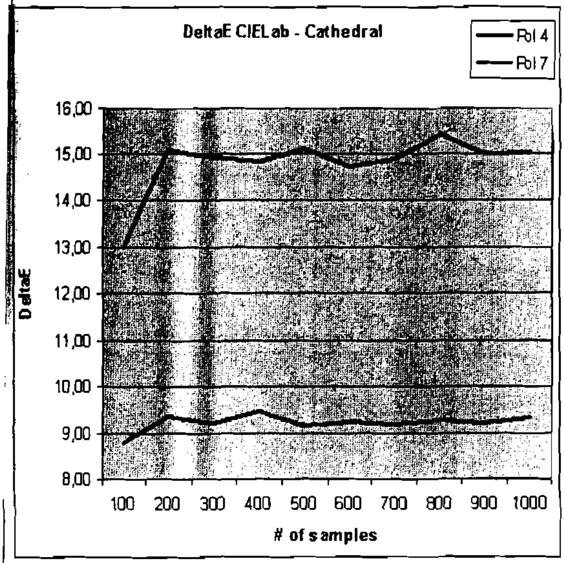
Figure 4: *Detail (hair) for the picture Child: Only considering the global information (left) and considering global and local information (right).*

Figure 5: *Detail (dog) for the picture Child: Only considering the global information (left) and considering global and local information (right).*

3.3. Combining global and local information

In this phase the problem is to set the strength of the high-frequency restoration. Since Equation (6) can modify highly the dynamic range of high-frequency content we must scale the HF_c contribution to ensure a balance between low- and high-frequency content. A precise solution can be computationally expensive, thus we decided to maintain the global part (low frequency) of the method and to add the local information (high frequency) by linearly combining them. Equation (7) is used to add the high-frequency content scaled by a constant α. Since HF_c has a mean value of zero, this procedure keeps the colour almost unchanged, while increasing the sharpness:

$$O_{FINAL,c}(i) = O_{GLOBAL,c}(i) + \alpha HF_c(i). \qquad (7)$$



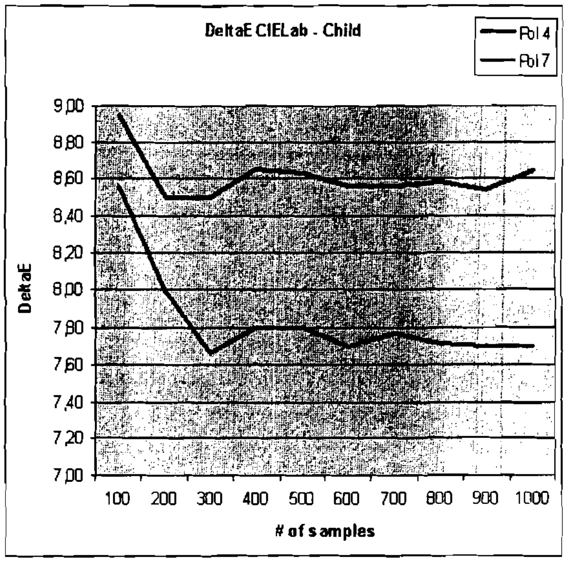


Figure 6: *CIELab colour error comparison between the first complete polynomial degree (four terms poly4) and the second not complete polynomial degree (seven terms poly7), varying the number of samples and using only the global information. Image Cathedral resolution 420 × 279 pixels, Image Child resolution 240 × 160 pixels.*

4. Experimental Results

The method has been tested on several natural and synthetic images giving good results. We report here test on four different images named *Cathedral*, *Child*, *Ferrari* and *Lake*, using the following PC configuration: 2 GHz Athlon with 1 Gbyte of memory RAM. We have conducted a series of tests to analyze the behaviour of the proposed approach varying the number of samples and the type of polynomial degree.

CIELab ΔE error metric is used to evaluate the results of our approach:

$$\Delta E = \sqrt{(L_i - L_o)^2 + (a_i - a_o)^2 + (b_i - b_o)^2} \quad (8)$$

where index i indicates the original values of the image obtained with the original algorithm ACE, and index o indicates the values of the image obtained with the acceleration technique (proposed approach).

A first series of tests, in order to analyze the quality performances using only the global extraction step as reported in Subsection 3.1, was conducted varying the number of samples and the polynomial degree.

In Figures 6 and 7, ΔE CIELab errors, are reported for the proposed approach using only the global information varying the polynomial degree and the number of samples. An improvement can be noticed when the polynomial degree increases, while increasing the number of samples has an ambiguous performance. Best performances are obtained with 400 samples. Despite this fact, the visual comparison of the images obtained with the complete first-polynomial degree (four terms) and the image obtained with the not complete second-polynomial degree (seven terms), shows an annoying blue spot in the sun, see Figure 8. From these results, we can see that the better performance in term of pleasantness is obtained with the complete first-polynomial degree (four terms).

The reason of that can be related to the over-fitting problem that we have when redundant information, introduced by the sampling phase, is used to reconstruct the original-mapping function. This information introduces noise that can disturb the reconstruction of the mapping function. In this case a polynomial function with low degree is less sensible to the noise introduced by the redundant information.

The next step is, as described in Subsection 3.3, to combine the extracted global and local information. Preliminary experiments show that the most suitable value for the parameter α is 0.1, and we used this value in all our experiments. In Figures 9 and 10 ΔE CIELab errors are reported, for the complete first-polynomial degree (four terms) and varying the number of samples. In these graphs we compare the colour errors obtained using only the global information and the combination of both global and local information. The introduction of local information improves the performances in terms of colour error of the speed-up technique.

In Figure 11 a comparison is also reported between the original image (left), the image obtained applying the complete ACE (centre) and the image obtained with the speed-up

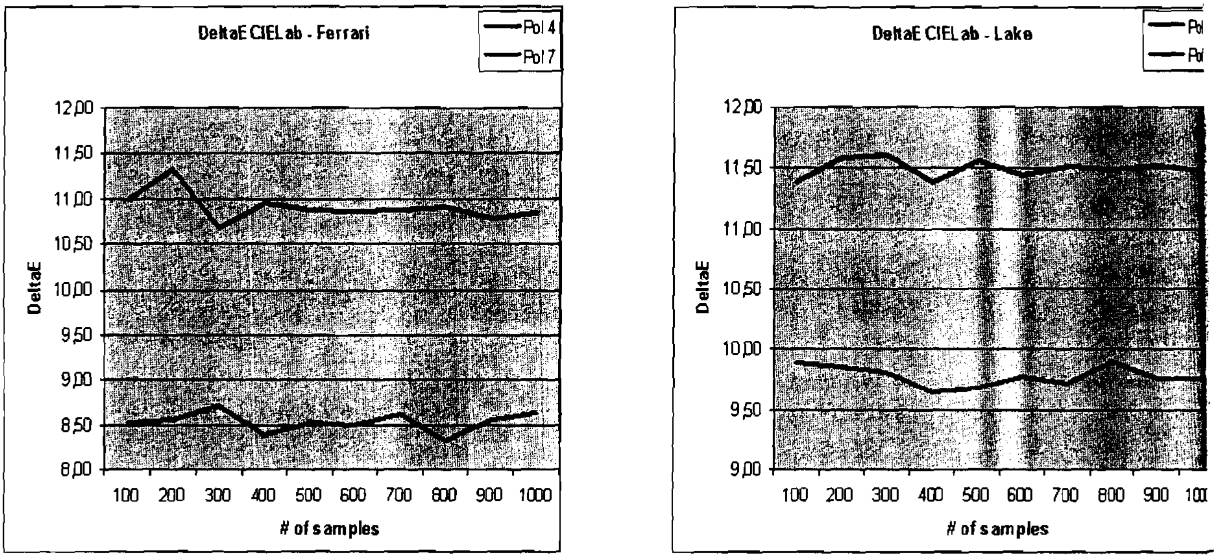


Figure 7: *CIELab colour error comparison between the first complete polynomial degree (four terms poly4) and the second not complete polynomial degree (seven terms poly7), varying the number of samples and using only the global information. Image Ferrari resolution 240 × 235 pixels, Image Lake resolution 360 × 235 pixels.*

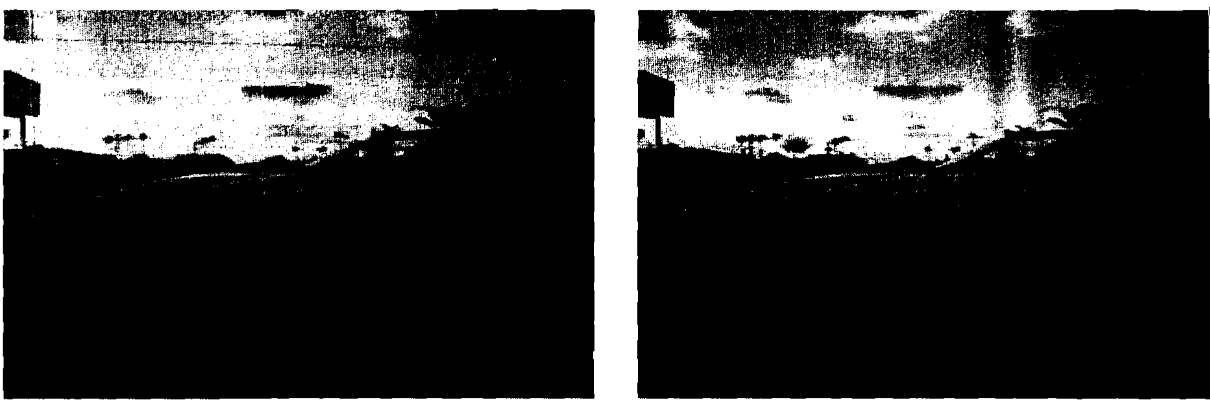


Figure 8: *Fearrari: Comparison between the images obtained with the first complete polynomial degree (four terms poly4)(left) and the second not complete polynomial degree (seven terms poly7) (right). In the image on the right a blue spot on the sun is visible.*

technique (right) for the image *Cathedral*. In Figure 12 the same comparison is reported for the image *Ferrari*.

Finally we performed some experiments to evaluate the improvement, introduced by our speed-up technique, in terms of time, compared to the original ACE algorithm.

The results are summarized in Table 1. The time is reported in seconds applying a complete first-degree polynomial (four terms) and using 400 samples for all four images used in our experiments.

The time performances show that applying the speed-up technique we are able to reduce the computation time drastically by more than two orders of magnitude.

5. Conclusions and Perspectives

We have presented a speed-up strategy for a local automatic colour equalization model called ACE, showing its ability in terms of time performance and perceived quality of the final result.

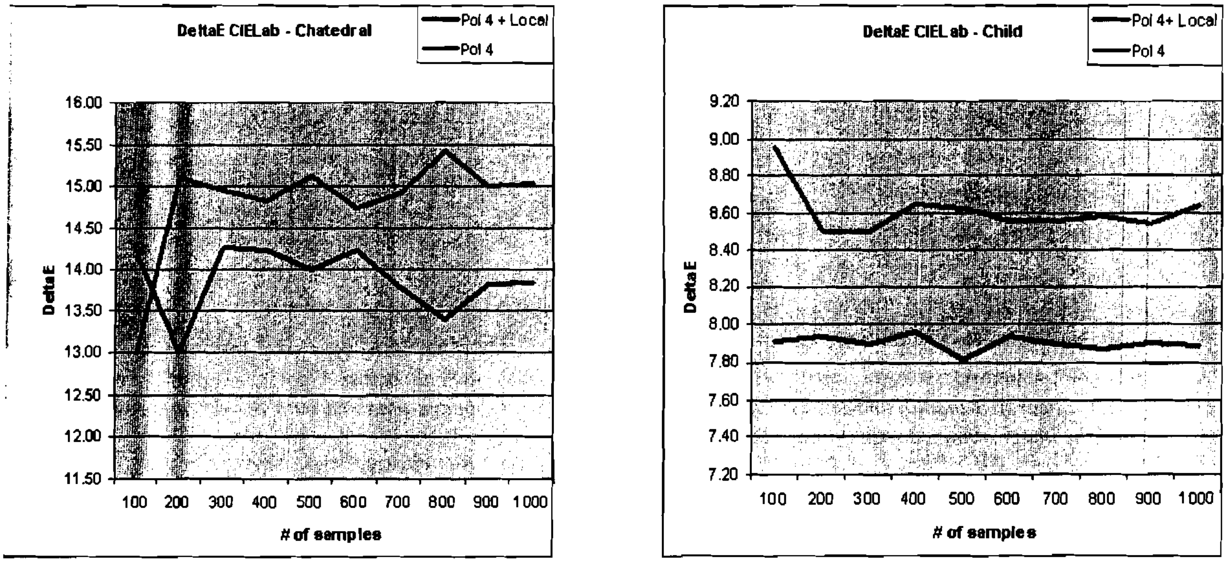


Figure 9: *CIELab colour error comparison between the first complete polynomial degree (four terms poly4) using only the global information, and using both local and global information. Image Chatedral resolution 420 × 279 pixels, Image Child resolution 240 × 160 pixels.*

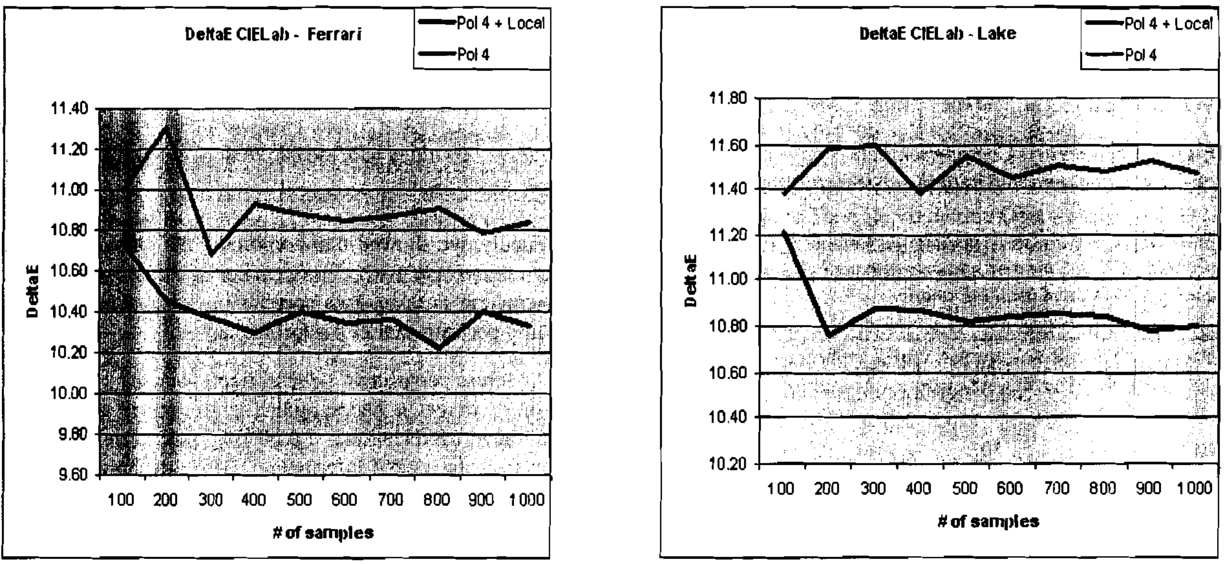


Figure 10: *CIELab colour error comparison between the first complete polynomial degree (four terms poly4) using only the global information, and using both local and global information. Image Ferrari resolution 240 × 235 pixels, Image Lake resolution 360 × 235 pixels.*

ACE can be used for 2D image enhancement or as a final perceptual rendering tool in a 3D image syntehsis pipeline [35].

This strategy is based on the separation of global and local information of the original image. In order to maintain the semplicity and reducing the constraints, that otherwise will limit the speed performances of the technique, a SVD is used to extract global information, while local information is extracted applying the original ACE algorithm on a reduced neighbourhood of each input pixel. The strategy

Figure 11: *Cathedral: Comparison between the original image (left), the image obtained with the original ACE algorith (centre) and the image obtained with the speed-up technique (right).*

Figure 12: *Ferrari: Comparison between the original image (left), the image obtained with the original ACE algorithm (centr and the image obtained with the speed-up technique (right).*

Table 1: *Comparison of the time performances (seconds) of the original ACE with the new speed-up technique that uses only global and both global and local information.*

Algorithm	Child 240 × 160	Cathedral 420 × 279	Ferrari 240 × 235	Lake 360 × 235
ACE	307	3044	495	1399
Global (1)	2	8	3	5
Global + Local (2)	3	10	4	7
Speed-up factor (1)	154	381	165	280
Speed-up factor (2)	102	304	124	200

is designed in order to be integrated easily in the original ACE algorithm, it can also be applied on alternative local operators.

This technique shows how an acceleration of more than two orders of magnitude of the original operator is possible. The experimental results also show that increasing the polynomial degree does not guarantee a final pleasantness of the output image.

Finally, we showed that combining the global and loca information only 10%, corresponding to $\alpha = 0.1$, of the local information is taken into account in order to improve th quality performance of the technique.

As future perspective, several improvements can be don in order to get a better quality performance of the cur rent speed-up technique, e.g. testing a different techniqu to extract the global information. Also a technique able t avoid the separation of global and local information, an able to learn the behaviour of the local operator, can b studied.

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