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The application of the weighted Distance Directional Filter for various colour spaces in the aspect of modern image quality metrics

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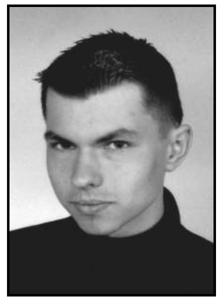

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Abstract

Some promising results obtained by the application of the weighted Distance Directional Filter (DDF) for the filtration of an impulse noise are presented in the paper. An interesting fact to emerge is that the trade-off between the Vector Median Filter and the Basic Vector Directional Filter, which is the essence of the DDF, not only depends on the colour space used during calculations but also on the weighting coefficients within the filter mask. These results may form the basis for further research to identify a closer relationship among the filter parameters in order to develop the fast adaptive version of the nonlinear weighted filter.

Keywords: weighted Distance Directional Filter, colour image filtering, image quality assessment.

Zastosowanie ważonego filtru odległościowo-kierunkowego w różnych przestrzeniach barw w aspekcie nowoczesnych wskaźników jakości obrazów

Streszczenie

W artykule zaprezentowane zostały rezultaty filtracji obrazów kolorowych uzyskane w wyniku zastosowania ważonego filtru odległościowo-kierunkowego w celu zredukowania szumu impulsowego. Interesujący jest fakt silnej zależności wyników zastosowania tego filtru, będącego połączeniem wektorowego filtru medianowego z wektorowym filtrem kierunkowym, zarówno od przestrzeni barw, jak również współczynników wagowych maski filtru. Wynikowe obrazy uzyskane po zastosowaniu filtracji w rożnych przestrzeniach barw zostały ocenione za pomocą kilku nowoczesnych porównawczych wskaźników jakości omówionych w rozdziale 3. W publikacji zamieszczono reprezentatywne wyniki oceny jakości z użyciem wskaźnika podobieństwa strukturalnego (SSIM). Ich analiza pozwala na określenie zależności pozwalających na modyfikację algorytmu filtracji w kierunku maksymalizacji wartości nowoczesnych wskaźników jakości obrazu o wysokim stopniu korelacji z ocenami subiektywnymi. Uzyskane wyniki mogą stanowić podstawę dalszych badań w celu dokładniejszego zbadania właściwości filtracji DDF oraz opracowania opartego na niej szybkiego adaptacyjnego algorytmu nieliniowej filtracji obrazów kolorowych.

Słowa kluczowe: ważony filtr odległościowo-kierunkowy, filtracja obrazów kolorowych, ocena jakości obrazów.

1. Introduction

The extension of many image processing algorithms from their greyscale versions to their colour equivalents is not always an easy task, image quality assessment and nonlinear (e.g. median) filtering being examples. The use of the typical definition of the median value for the vector values (three components of the colour for each pixel) requires the definition of a new quantity, used for sorting the vectors in order to find the 'median' one (where 'median' pixel should be interpreted as the most typical one within the mask). Nevertheless, such an assumption should be consistent with one of the most important features of the median filter: guaranteeing that only the colours present in the neighbourhood (dependent on the size of the filter mask) may be the result of the filter. For this reason an independent filtering of each channel should not be used.

2. Vector median filters and their modifications

Regardless of any new colours introduced into the resulting image, some types of the marginal ordering methods based on the independent filtration of each channel may be used for strongly de-correlated channels (e.g. "television" colour spaces with luminance and two channels of chroma).

A better solution, useful for the pixel (vector) ordering, necessary for the nonlinear multichannel image filtering, may be the application of the Vector Median Filter (VMF) proposed by Astola et al. [1]. This approach is based on the calculation of the aggregated distance between each pixel and the remaining ones within the current sliding window, usually using the Euclidean distance. This distance is treated as a measure of similarity to the other pixels within the mask, so the most typical pixel with the minimum aggregated distance is the result. Instead of using the most typical RGB colour cube, some other colour spaces may be used during the distance calculation [2]. A well-known extension of the VMF filter is the combination with the linear low-pass filter (Arithmetic Mean Filter – AMF) known as the Extended Vector Median Filter, which can be used for the elimination of a non-impulse or mixed noise. Further extension leads to the α-trimmed VMF where α elements with the lowest rank in the VMF are averaged by the AMF.

Another possibility is the use of the directional filtering approach [3] represented by the Basic Vector Directional Filter (BVDF). In such cases the angular distance is defined as:

$$A_i = \sum_{j=0}^{N-1} \arccos\left(\frac{X_i \cdot X_j}{|X_i| \cdot |X_j|}\right) \tag{1}$$

and is used instead of the Euclidean one, where X stands for the three-components vectors in the chosen colour space (usually RGB). One of the simplest modifications of this technique is known as the Generalized Vector Directional Filter (GVDF). It is based on a cascading structure where the number of BVDF outputs with the minimum angular distances is filtered in the second stage using another ordering criterion.

A combination of both approaches leads to the Distance-Directional Filter (DDF) [4] with the following weighted ordering criterion:

$$\Omega_i = \left[\sum_{j=0}^{N-1} \arccos\left(\frac{X_i \cdot X_j}{|X_i| \cdot |X_j|} \right) \right]^{1-k} \cdot \left[\sum_{j=0}^{N-1} d\left(X_i, X_j\right) \right]^k \qquad (2)$$

where d stands for the Euclidean distance, and k denotes the parameter used for smooth changing in the filter type from VMF (k=1) to BVDF (k=0).

The above technique is known as reduced (aggregated) ordering because of the computation of a single ordering criterion based on the values taken from all of the channels. In such methods the lowest ranked pixel is chosen as the result while the outliers usually have much higher ranks.

Another approach to nonlinear colour image filtering is based on conditional ordering [5, 6] and is used typically in the HSV colour space. In these filters (known as VMED) the ordering is performed using the V component in the ascending order and the pixels with identical values are then sorted in the descending order using their saturation values, and then using a hue component for the pixels with the same S and V values. The middle element is chosen as the result but the main problem for smooth images with many flat areas (especially red) is the circular character of the hue channel [7].

3. Quality assessment

Reliable colour image quality assessment is not an easy task since many quality metrics are devoted to the assessment of greyscale images without taking into account the specificity of colour information [8]. Nevertheless, considering the character of the impulse noise filtered using the nonlinear filters, the most visible artefacts can also be easily observed in the greyscale versions of images. Their great influence on the overall image quality justifies the use of the greyscale image quality assessment methods in our experiments.

A typical 'classical' approach [9, 10] to image quality assessment is based on the Mean Squared Error (MSE) and similar metrics such as Peak Signal to Noise Ratio (PSNR). These techniques, representing full-reference methods and requiring a full knowledge of the ideal reference image, have been used for many years. Their main disadvantage is their poor correlation with subjective evaluations and the Human Visual System (HVS).

In recent years the dynamic progress in this field can be observed either by using no-reference [11] and reduced-reference [12] methods or proposing some new full-reference ones better correlated with human perception of various types of image distortions [13]. The main advantage of the first group is the lack of necessary knowledge of the reference image without any distortions. However, such "blind" methods are usually sensitive to only one or two types of distortions e.g. blur [14], JPEG blockiness or the presence of noise.

Taking into account the poor universality of no-reference methods and the availability of the reference images without any noise, the most useful methods for the assessment of the nonlinear filtering results appear to be the modern full-reference ones. The first method worth noting was published in 2002 by Wang and Bovik [15]. Known initially as the Universal Image Quality Index it was later expanded into Structural Similarity (SSIM) [16], which became possibly the most popular image quality assessment method of recent years. Both metrics have been defined for the single channel images only.

The local SSIM index is calculated within the sliding window (11×11 pixels Gaussian window is default but some modifications can also be made [17]) so the image quality map is obtained which is then averaged in order to calculate the overall SSIM index. The local index is calculated as the product of three components representing three common types of distortions: luminance distortions (l), contrast loss (c) and structural distortions (s) equivalent to mean, variance and correlation comparison respectively. Nevertheless, it can be presented in the shortened form as:

$$SSIM = \frac{\left(2 \cdot \overline{xy} + C_1\right) \cdot \left(2 \cdot \sigma_{xy} + C_2\right)}{\left(\overline{x}^2 + \overline{y}^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \qquad (3)$$

where the default values of small constants preventing division by zero for flat or dark areas of the image are $C_1=(0.01\times L)^2$ and $C_2=(0.03\times L)^2$ with L=255 as the maximum luminance level. The other symbols in the expression (3) represent mean values, variances and the covariance for the fragments of original and distorted images (x and y respectively).

Further extension of the SSIM metric leads to the Multi-Scale SSIM based on the idea of operating over a dyadic pyramid where the three components mentioned above are weighted using the exponents for each scale. The definition can be then expressed as:

$$\text{MS-SSIM} = \left(l_M\right)^{\alpha_M} \cdot \prod_{j=1}^{M} \left[\left(c_j\right)^{\beta_j} \cdot \left(\mathrm{s_j}\right)^{\gamma_j} \right] \qquad (4)$$

where M denotes the highest scale obtained after M-1 iterations of low-pass filtering and down-sampling the filtered image by a factor of 2. More details and the default values of the exponents can be found in the paper [18].

Another interesting idea based on similar assumptions is the use of the Visual Information Fidelity (VIF) using wavelet decomposition. It is worth noting that the same idea is used in the faster pixel domain version of that metric (VIFp), where the scales are used instead of the sub-bands. A general definition of the VIF metric can be presented as [19, 20]:

$$\mathrm{V}IF = \frac{\sum_{j=0}^{S} \sum_{i=0}^{M_j} I\left(c_{i,j}; f_{i,j}\right)}{\sum_{j=0}^{S} \sum_{i=0}^{M_j} I\left(c_{i,j}; e_{i,j}\right)} \qquad (5)$$

where S is the number of sub-bands, M_j stands for the number of blocks at j-th sub-band and $I(a;b)$ denotes the mutual information between a and b. The denominator and numerator are related to the information extracted by vision from the reference image and from the distorted one respectively. The mutual information is calculated between a block vector at a specified location in the reference image (c) and the perception (e) of that block by a human viewer with additive noise n, and the perception (f) of distorted block.

The experiments related to the nonlinear colour image filtration and the filter types proposed by various researchers are usually verified only by using some classical image quality assessment methods poorly correlated with subjective evaluations.

A similar problem concerns the evaluation of colour images using probably the only classical metric dedicated for colour images. Known as Normalised Colour Difference (NCD), it is calculated using CIE LAB or CIE LUV colour space and for this reason it is essential to verify the properties of some of the filtering algorithms by the use of presented modern approach as well as to modify some of them towards better quality of output images assessed by recently proposed metrics.

In order to verify the results obtained in the experiments all images have been assessed using all three presented metrics (SSIM, MS-SSIM and VIF) but in the paper only the SSIM results are presented for the clarity.

4. Experiments and results

The experiments conducted in this work consisted of using the central weighting approach for the Distance Directional Filter's mask with the additional change of the exponential parameter *k* in order to achieve better filtering results in comparison to the 'standard' unweighted filters. The filtering operations have been performed with the use of various colour spaces as well as a few versions of the weighting mask.

Taking into account the most typical applications the size of the mask has been chosen as 3×3 pixels in order to prevent a significant blur. The experiments have been conducted for the reference images without any distortions in order to find the quality loss for each method of filtration as well as for a set of images contaminated by a colour impulse noise.

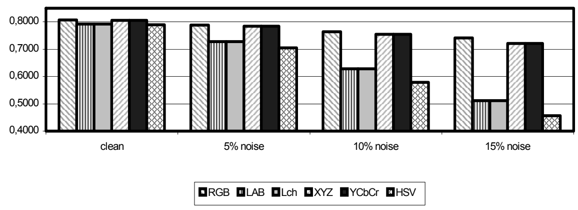


Fig. 1. SSIM values for the unweighted filter with the best values of parameter *k* (typical image)
Rys. 1. Wartości wskaźnika SSIM dla filtru nieważonego przy najlepszych wartościach parametru *k* (dla typowego obrazu)

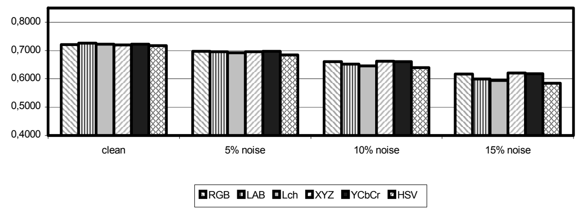


Fig. 2. SSIM values for the unweighted filter with the best values of parameter *k* (image with many details)
Rys. 2. Wartości wskaźnika SSIM dla filtru nieważonego przy najlepszych wartościach parametru *k* (dla obrazu z dużą ilością szczegółów)

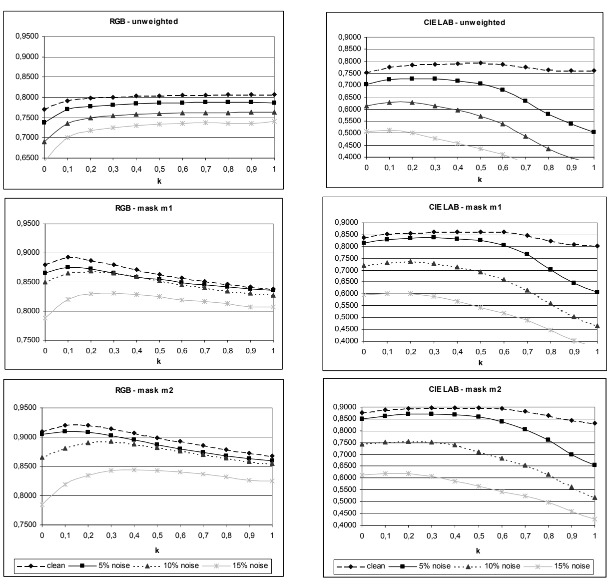


Fig. 3. SSIM values for various masks in RGB and CIE LAB colour spaces dependent on parameter *k* (typical image)
Rys. 3. Wartości wskaźnika SSIM dla różnych masek w przestrzeniach barw RGB oraz CIE LAB w zależności od parametru *k* (dla typowego obrazu)

The implementation of the weighted mask has been considered as the approach most similar to the greyscale median filter where the higher weight increases the chance of choosing the respective pixel as the result. Analysing the algorithms of the colour filtration the weights within the mask may be treated as divisors so that corresponding pixels with higher mask values reduce their values of respective aggregated distances in comparison to the standard filtering.

Another problem related to the application of various colour spaces is related to the circular character of the hue component present in the HSV or Lch colour spaces. In this case the 'zero point' is chosen arbitrarily as the red colour so pixels with similar colours may be treated as outliers if their hue values are close to 0 or 1 (assuming the normalized hue range from 0 to 1). In order to eliminate the influence of such an effect, the 'switching hue' method has been used, where the difference between two hue values is calculated twice (in the left and right direction of the hue circle) and the smaller difference is chosen for further calculations.

All the computations have been made using some standard test images and the representative results are presented in figures. The values of the image quality metrics have been computed for the greyscale versions of the filtered images and their good correlation with subjective assessment can also be verified by exemplary images presented in Figs. 4 and 5.

The comparison of the quality metrics' values for the results obtained for the unweighted DDF with the best value of the parameter *k* (changing from 0 to 1 by 0.1) using various colour spaces for a typical image is presented in Fig. 1. Lower quality obtained for the CIE LAB, CIE LUV and HSV colour spaces are caused mainly by their nonlinearity. Nevertheless, for the image containing a lot of details (e.g. well known test image „Mandrill") the quality differences are not as large (Fig. 2) and the results obtained for a high levels of noise may be even better than for a typical image with similar contaminations. The values of PSNR, MS-SSIM and VIF metrics lead to similar conclusions, also for the weighted filters, so they are not included in the paper.

Much more interesting results can be observed analysing the influence of the amount of noise on the value of the parameter *k* leading to the best results as well as the impact of the slenderness of the weighting mask. In our experiments two masks were used: the flatter one (*m*1) with central weight 1.5 times higher than the corner ones and the slender one (*m*2) with the normalised central weight equal to 2. The SSIM values obtained for those masks together with the unweighted filter are presented in Figs. 3 and 6. Analysis of the results obtained using the other quality metrics leads to similar conclusions related to the possibility of an adaptive choice of the parameter *k* depending on the estimated amount of noise and the colour space used during the filtration procedure.

Comparing the results presented in Figs. 1 and 4 the importance of the colour space can be noticed for the typical images, which are easier to filter and contain more information related to lower frequencies. Analysing the effects of filtration shown in Figs. 2 and 5 it can be noticed that the influence of the chosen colour space is seriously reduced.


noisy image filtered in RGB (*m2*)

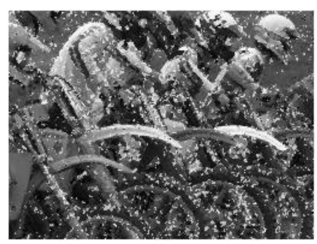
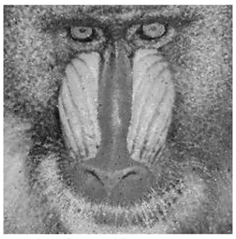

noisy image filtered in HSV (*m1*)

Fig. 4. Comparison of a typical image filtered using various colour spaces with different masks
Rys. 4. Porównanie typowego obrazu po filtracji w rożnych przestrzeniach barw z użyciem różnych masek

noisy filtered in RGB (*m2*)



noisy filtered in HSV (*m1*)

Fig. 5. Comparison of an image with many details filtered using various colour spaces with various masks

Rys. 5. Porównanie obrazu z dużą ilością szczegółów po filtracji w rożnych przestrzeniach barw z użyciem różnych masek

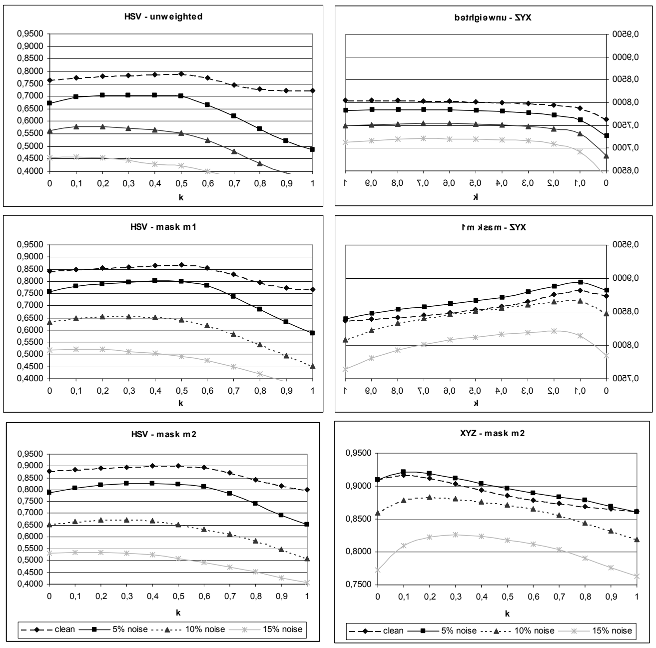


Fig. 6. SSIM values for various masks in HSV and CIE XYZ colour spaces dependent on parameter *k* (typical image)

Rys. 6. Wartości wskaźnika SSIM dla różnych masek w przestrzeniach barw HSV oraz CIE XYZ w zależności od parametru *k* (dla typowego obrazu)

Another interesting problem is the proper choice of the parameter *k*, which defines the importance of the vector and directional parts of the filter. Not only is such a choice dependent on the colour space but also on the amount of noise. In some colour spaces for a given mask the best results for the images without any noise (or similarly with a little noise) are obtained for *k* close to 0 while for the images corrupted by a 15% impulse noise the best choice is about 0.4 or 0.5 (e.g. RGB mask m2). For some other colour spaces (e.g. CIE LAB) better results for the clean images are obtained for *k* about 0.5 and for noisy images the optimal value of parameter *k* decreases.

5. Summary

These results, regardless of their preliminary character, could form the basis of future work towards definitions of some adaptive colour image filtering methods utilising various colour spaces and the estimated amount of noise. Analysing the results an interesting direction for further work seems to be the dynamic change between the VMF and BVDF filters depending on the local image statistics, which can also be useful for the fast video analysis and filtering purposes [21]. Nevertheless, such an approach requires the definition of a more accurate relationship between the amount of noise and the proper value of the parameter *k* with more experimental research.

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