J. Vis. Commun. Image R. 23 (2012) 143–149

Contents lists available at SciVerse ScienceDirect

J. Vis. Commun. Image R.

journal homepage: www.elsevier.com/locate/jvci

Fuzzy Directional (FD) Filter for impulsive noise reduction in colour video sequences

Alberto J. Rosales-Silva *, Francisco J. Gallegos-Funes, Volodymyr I. Ponomaryov

National Polytechnic Institute of Mexico, Mechanical and Electrical Engineering Higher School, Av. IPN S/N, UPALM SEPI Electronica, Edif. Z, Acceso 3, 3er Piso, Lindavista 07738, México D.F., Mexico

ARTICLE INFO

Article history:
Received 29 March 2010
Accepted 15 September 2011
Available online 20 September 2011

Keywords:
Fuzzy logic
Directional processing
Video colour sequences
Impulsive noise
Movement detection
Noise estimator
Spatio-temporal filtering
Processing time

ABSTRACT

This paper presents a novel Fuzzy Directional (FD) Filter for suppression of impulsive noise in colour video sequences. The proposed approach consists in the estimation of fuzzy levels to detect movement and noise presence in the neighbourhood frames, permitting to preserve the edges, fine details and chromaticity characteristics in colour images and video sequences. The new framework has been justified applying commonly used objective criteria, such as, Peak Signal to Noise Ratio (PSNR), Mean Absolute Error (MAE) and Normalized Colour Difference (NCD), as well subjective perception by human viewer showing better performance in comparison with known methods presented in the literature.

1. Introduction

There are known many algorithms that are employed for impulsive noise suppression in two dimensions (2D) [1–6]. A lot of efforts have been made on video sequence denoising, and many different approaches have been presented in the literature [7–10]. These approaches basically can be classified into three types: spatial denoising, temporal denoising and spatio-temporal denoising, mostly in Gaussian noise presence [7,8]. It is known that the principal difference between noise suppression in still images and video sequences, where the information from previous or/and may be future frames can be also available, consists of finding the efficient employment of several neighbour frames during processing, taking into account a possible motion between frames. Another problem is the movement or occlusion of camera that produces temporal changes, which together with spatial fine details, edges, and texture (2D spatial non-stationarities) hinder traditional techniques and demand to introduce novel adaptive frameworks [7–10].

Different vector based processing filters have been designed during last years in colour imaging. For instance, vector order statistics filters have demonstrated good performance in the noise removal [3–6]. The fuzzy filters are constructed by fuzzy rules to remove noise and to provide edge and fine detail preservation [1,9,10]. The output filter depends on the fuzzy rules and the defuzzification process, which combines the effects of applied rules to produce only an output value [1]. The vector directional filters employ the directional processing taking pixels as vectors, and obtaining the output vector that shows a less deviation of its angles under ordering criteria in respect to the other vectors [2,4].

The aim of this work is to design a novel scheme that permits to realize processing in 2D, as well as in 3D. The novel approach is based on fuzzy set theory and order vector statistics (directional) technique to detect the noise presence and movement levels permitting to suppress impulsive noise in RGB colour video sequences. The proposed 3D-FD filter employs a novel 2D-FD filter as a first (spatial) stage in previous $t-1$ frame of video sequence. In the second (temporal) stage of the algorithm, the filtering result from the first stage should be employed in processing of the current t frame of the video sequence. In the final stage, the current frame is filtered again with the 2D-FD filter according to the fuzzy rules based on direction information to suppress non-stationary noise left during the temporal stage of the procedure. Numerical simulations demonstrate that novel framework can outperform several filtering approaches in the processing of video colour sequences in terms of noise suppression, edges and small fine details preservation, and chromaticity properties.

2. 2-Dimension Fuzzy Directional (2D-FD) Filter

Let introduce *gradients* and *angle variance* as absolute differences to represent the level of similarity among different pixels. It helps to resolve two hypothesizes: the central pixel is a noisy one or it is a free noise pixel. Let calculate the gradient

* Corresponding author. Fax: +52 (55) 5729 6000x54622.
E-mail addresses: arosaless@ipn.mx (A.J. Rosales-Silva), fgallegosf@ipn.mx (F.J. Gallegos-Funes), vponomar@ipn.mx (V.I. Ponomaryov).

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doi:10.1016/j.jvcir.2011.09.007

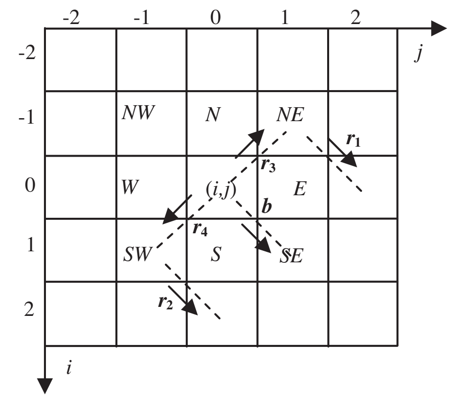

Fig. 1. Neighbourhood pixels, *basic (b) and related* (r1, r2, r3, r4) directions for *gradient and angle variance values.*

$G^{\beta}_{(k,l)} = |x^{\beta}_{C}(i,j) - x^{\beta}(i+k, j+l)|$, for each direction $\gamma = \{N, E, S, W, NW, NE, SE, SW\}$ with respect to the central pixel x^{β}_{c}, where $(i,j) = (0,0)$ represents a central pixel in a sliding window, β marks the colour planes in RGB space, and (k,l) represents each one of the mentioned directions with values $\{-1, 0, 1\}$ (see Fig. 1).

Similar to Refs. [10,11], let introduce not only one *basic gradient* for any direction, but also four *related gradients*, with (k,l) values $\{-2, -1, 0, 1, 2\}$. The *angle variance* is computed for each a channel in such a way, where we omit two of the three RGB channels in a colour frame. Functions G^{β}_{γ} and θ^{β}_{γ} show the gradient and angle variance values for each direction, respectively, and parameter γ marks a chosen direction.

For example, Fig. 1 exposes the employed pixels in the processing procedure in the *SE* direction for the *basic* and *related* components. The *basic gradient* value for *SE* direction is $G^{\beta}_{(1,1)} = G^{\beta}_{SE(b)}$ and the basic *angle variance* is calculated as follows:

$$\theta^{\beta}_{SE(b)} = \theta^{\beta}_{(1,1)} = \cos^{-1}\left[\frac{2\cdot 255^2 + x^{\beta}_{(0,0)}\cdot x^{\beta}_{(1,1)}}{\sqrt{2\cdot 255^2 + \left(x^{\beta}_{(0,0)}\right)^2}\cdot\sqrt{2\cdot 255^2 + \left(x^{\beta}_{(1,1)}\right)^2}}\right], \quad (1)$$

where $x^{\beta}_{(0,0)}$ and $x^{\beta}_{(1,1)}$ are the *basic* and *related* components agree to *SE* cardinal direction.

Four *related gradients* and *angle variance* values are given as follows: $T^{\beta}_{(0,2)} = T^{\beta}_{SE(r_1)}$, $T^{\beta}_{(2,0)} = T^{\beta}_{SE(r_2)}$, $T^{\beta}_{(-1,1)} = T^{\beta}_{SE(r_3)}$, and $T^{\beta}_{(1,-1)} = T^{\beta}_{SE(r_4)}$, where operator T can be a *gradient G* or *angle variance* θ.

The fuzzy sets and fuzzy rules form the knowledge base of a fuzzy rule-based reasoning system. Fuzzy rules are linguistic IF-THEN construction: "IF *A* THEN *B*", where *A* and *B* are the propositions containing linguistic variables *A* and *B*. After finding the fuzzy feature, we can form Linguistic IF-THEN rules.

Fuzzy membership function (*MF*) is a curve that defines how each point in the input space is mapped to a degree of membership between 0 and 1. We use here the Gaussian *MF* from the point of view of simplicity, convenience and efficiency.

Let introduce BIG and SMALL fuzzy sets, which permit to estimate the noise presence in a central pixel in a 5×5 sliding window (see Fig. 1). A big membership degree (≈ 1) in the SMALL set shows that the central pixel is free of noise, and a large membership degree in the BIG set shows that central pixel is noisy with large probability. The following Gaussian membership functions are used to calculate membership degrees for fuzzy *gradient* and fuzzy *angular deviation* values:

$$\mu\left(T^{\beta}_{\gamma}\text{BIG}\right) = \begin{cases} 1, & T^{\beta}_{\gamma} > med_1 \\ \exp\left\{-\left[\left(T^{\beta}_{\gamma} - med_1\right)^2 \Big/ 2\sigma^2_T\right]\right\}, & \text{otherwise} \end{cases} \quad (2)$$

$$\mu(T^{\beta}_{\gamma}\text{SMALL}) = \begin{cases} 1, & T^{\beta}_{\gamma} < med_2 \\ \exp\left\{-\left[\left(T^{\beta}_{\gamma} - med_2\right)^2 \Big/ 2\sigma^2_T\right]\right\}, & \text{otherwise} \end{cases} \quad (3)$$

where $\sigma^2_1 = 1000$, $med_1 = 60$, and $med_2 = 10$ for fuzzy gradients; and $\sigma^2_2 = 0.8$, $med_1 = 0.6$, and $med_2 = 0.1$ for fuzzy angular deviations. In order to find these values, we have realized intensive numerical simulations using a set of images and video sequences, some which are presented in Section 4 in wide range of noise intensity. Presented above values were found according to the optimal values of criteria PSNR and MAE.

To determine if the central component is noisy, the following novel fuzzy rules based on gradient values and angle deviations are employed:

> **Fuzzy Rule 1** introduces the membership level of pixel x^{β}_{c} in the set BIG for γ direction

IF (G^{β}_{γ} is BIG AND $G^{\beta}_{\gamma(r_1)}$ is SMALL AND $G^{\beta}_{\gamma(r_2)}$ is SMALL AND $G^{\beta}_{\gamma(r_3)}$ is BIG AND $G^{\beta}_{\gamma(r_4)}$ is BIG) AND (θ^{β}_{γ} is BIG AND $\theta^{\beta}_{\gamma(r_1)}$ is SMALL AND $\theta^{\beta}_{\gamma(r_2)}$ is SMALL AND $\theta^{\beta}_{\gamma(r_3)}$ is BIG AND $\theta^{\beta}_{\gamma(r_4)}$ is BIG), **THEN** the fuzzy gradient-angular value $G^{\beta}_{\gamma}\theta^{\beta}_{\gamma}$ is BIG, where $(A \text{AND} B) = A\cdot B$, and $(A)\text{AND}(B) = \min(A, B)$.

> **Fuzzy Rule 2** presents the noisy factor gathering eight fuzzy gradient-directional values, obtained from the Fuzzy Rule 1, that are calculated for each direction:

IF ($G^{\beta}_{N}\theta^{\beta}_{N}$ is BIG OR $G^{\beta}_{S}\theta^{\beta}_{S}$ is BIG OR $G^{\beta}_{E}\theta^{\beta}_{E}$ is BIG OR $G^{\beta}_{W}\theta^{\beta}_{W}$ is BIG OR $G^{\beta}_{SW}\theta^{\beta}_{SW}$ is BIG OR $G^{\beta}_{NE}\theta^{\beta}_{NE}$ is BIG OR $G^{\beta}_{NW}\theta^{\beta}_{NW}$ is BIG OR $G^{\beta}_{SE}\theta^{\beta}_{SE}$ is BIG) **THEN** the noisy factor r^{β} is BIG, where $(A\text{OR}B) = \max(A, B)$.

The noisy factor r^{β} is obtained as the maximum fuzzy weighted value found for any cardinal direction and is employed as a threshold to distinguish between a noisy pixel and a free noise one. This value was selected as the maximum fuzzy weighted value to determine the noise level present in the sample to process, this noise level was obtained by the fuzzy value in the BIG fuzzy set representing the noise level of the sample to be processed and that a value of ≈ 1 is indicative that the central pixel is corrupted.

If the noisy factor $r^{\beta} \geqslant 0.3$ (where value 0.3 was chosen according to the optimal PSNR and MAE criteria values found in numerous experiment with a set of images and video sequences), the filtering procedure employs the fuzzy gradient-angular values as weights (indicating that the component pixel is noisy); in opposite case, the output pixel is presented as unchanged central pixel: $y^{\beta}_{output} = x^{\beta(j)}_{\gamma}$ (indicating that the component pixel is free from noise). The parameter r^{β} is used with a threshold to distinguish: whether a pixel is corrupted or noise-free according to the fuzzy values obtained for each cardinal direction. In first case, the fuzzy weights are used in the standard negator function $\sigma(x) = 1 - x$, $x \in [0,1]$ and are defined as $\rho\left(G^{\beta}_{\gamma}\theta^{\beta}_{\gamma}\right) = 1 - G^{\beta}_{\gamma}\theta^{\beta}_{\gamma}$, where $G^{\beta}_{\gamma}\theta^{\beta}_{\gamma} \in [0,1]$. In this way we obtain a fuzzy value that shows us the value of noise-free level for use by the noise suppression algorithm.

Finally, the algorithm of Fuzzy Directional Filter is realized as follows:

1. Calculate the fuzzy weights by use an ordering procedure in the magnitude of the pixel values for each component including central component pixel (*i,j*): $x^{\beta}_{\gamma} = \left\{x^{\beta}_{SW}, \ldots, x^{\beta}_{(i,j)}, \ldots, x^{\beta}_{NE}\right\}$, where $x^{\beta(1)}_{\gamma} \le x^{\beta(2)}_{\gamma} \le \cdots \le x^{\beta(9)}_{\gamma}$ implies that the fuzzy weights are satisfied to next: $\rho\left(G^{\beta F}_{\gamma}\theta^{\beta F}_{\gamma}\right)^{(1)} \le \rho\left(G^{\beta F}_{\gamma}\theta^{\beta F}_{\gamma}\right)^{(2)} \le \cdots \le \rho\left(G^{\beta F}_{\gamma}\theta^{\beta F}_{\gamma}\right)^{(9)}$.