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Advances in Noise Removal and Image Filtering using Fuzzy

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Abstract:- In this paper we give an overview of the advances made in image and video filtering using fuzzy logic, at our Fuzziness and Uncertainty Modeling Laboratory. The fact that fuzzy techniques have found an interesting application field in image and video filtering is not a surprise: detecting whether a pixel is corrupted by noise and assessing the degree to which such a pixel is corrupted are intrinsically fuzzy processes,that come along with uncertainty (is the pixel noisy or not?)and imprecision (how noisy is it?).This paper proposes an intelligent Furry lmqe Fdter (FIF)to remove impulse noise.The filter including two processes, the ImeUigenr Fuizy Number Deciding (mVD) pmcp~s and fuzzy inJkencc pmcess, to filter impulse noise from heavily corrupted images efiiciently.mVD can automatically decide the number of furzy number based on image features to overcome the drawbacks of Adoptive Weighted Furzy Mean (AWFM) filter that must be defined by domain expert Moreover,the fuzzy inference process refers the howledge base produced by IFND and fuzzy rule base that can improve the wealole ss of conventional filters in heavily corrupted condition.The intelligent FIF achieves better performance than the other filters based on the criteria of Mean Absolute Error (MAD,and Mean Square Error (MSE).By the experiments,FIF still keeps the high performance to filtering impulse noise from calor image.

Keywords:- Furzy number,AWFM filter,image processing, edge detection, impulse noise.

I. INTRODUCTION

Images and image sequences are among the most important information carriers in today's society, and have applications in a wide variety of fields (industrial, commercial,entertainment,medical,military,....).The power of images is that they can provide a lot of information in the blink of an eye.Due to bad acquisition,transmission or recording,the images are however often corrupted by noise.A preprocessing module to denoise the images then becomes necessary.For example,satellite images have to be denoised before ground structures can be detected,and surveillance images have to be denoised before face recognition algorithms can be applied.Inspired by the potential that fuzzy set theory has to offer in the field of image processing,our Laboratory works –

already for a decade–on the topic of image and video noise filtering.As noise detection is uncertain and noise removal is imprecise, fuzzy set theory and fuzzy logic turn out to be very valuable tools to develop new algorithms for image and video denoising.It has also been shown that so-called"fuzzy filters"outperform their classical counterparts,both in terms of numerical(e.g.,using Mean Square Error or Peak-Signalto-Noise-Ratio)and visual evaluation.We briefly review the basics of fuzzy set theory and fuzzy logic in Section 2.Sections 3 and 4 are devoted to a series of fuzzy filters,respectively for still images (grayscale and color)and image sequences(grayscale and color).In both cases we have developed filters for two very common noise types: impulse noise (where a fraction of the pixel values is replaced by either fixed noise values or random noise values) and gaussian noise (addititive noise);see Table I for an overview.These filters have been subject to comparative studies with other state-of-the-art filters, in order to demonstrate their value.Our goal here is not to give detailed technical explanations about the developed filters (16 in total),but to give the reader an overview of our work on this topic during the past decade (including comparative studies), and to show that fuzzy set theory and fuzzy logic are useful tools in image processing.

	Still gray	Still color	Video gray	Video color
fixed impulse	FIDRM	FIDRMC HFMRC HFC OWA		
random impulse	FRINR	HFC	FRINV-G	FRINV-C
gaussian	GOA FuzzyShrink	FCG OWA	FMDAF	FMDAF-RGB FMDAF-CR FMDAF-YUV

A Summary of the Different Fuzzy Filters for Noise Reduction That Were Developed In Our Laboratory.

However,the capability of conventional filters based on pure numerical computation 6 broken down rapidly when they are put in heavily noisy environment.There are many different methods of image processing we can get rid of noise.Median filter is the most used method [I],but it will not work efficiently when the noise rate is above 0.5. Yang and Tob [Z] used heuristic rules to improve the performance of traditional multilevel median filter.Russo and Ramponi [3] applied heuristic knowledge to build fuzzy rule based operators for smoothing, sharpening and edge detection.They can perform smoothing efficiently and preserving edges well. Choi and Krishnapuram [4] used a powerful robust approach to image enhancement based on fuzzy logic approach,which can remove impulse noise,smoothing out nowimpulse noise,and preserve edge well.Besides,there are still many methods for removing impulse noise [S-71.The common drawback of these methods is that they are sensitive to impulse noise when the noise rate becomes high.Weighted Fuzzy Mean (WFM) filter [8] has a better ability of image processing for high impulse noise.Especially when the noise is above 50% the traditional method for the image processing have no effect but WFM filter can still maintain a steady result. Adaptive Weighted Fuzzy Mem (A WFM) [SI filter can improve the WFM filter's incapability in a less noisy environment but still retain its capability of processing in the heavily noisy environment.The only defect of A WFMis that the number of fizy numbes are being decided by a domain expert and not generated automatically by the system, thus this paper proposes a method to automatically construct the fizy numbers for the intelligent IW.

II. DECIDING PROCESS FOR RFMOVING IMPULSE NOISE

The characteristics of images are very suited to be represented by fuzzy numbers (81).Due to the extreme difference in the characteristics of the images,the simple adoption of fixed furzy numben cannot completely contain the characteristics of the full image.This section propose an Intelligent Fuzzy Number Deciding (IFND) process which can automatically decide the number of firzzy rumbas according to the histogram of the image. Now we define the fuzzy numberas follows: [Definition 11].The fuzzy sers used in the knowledge base of intelligent FIF are of the L R type fuzzy number [IO] formulated by the following equation:

$$f(x) = \begin{cases} L(\frac{m-x}{\alpha}), \text{ for } x \le m \\ R(\frac{x-m}{\beta}), \text{ for } x \ge m \end{cases} \quad ....(1)$$

Where G(y)=R(y)=max(O,l-y),andAx)on be represented23 atriplet [m,a,P] Figure 1 shows the filtering process of intelligent ITF.

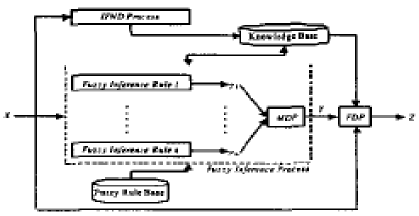

Fig. 1 The filtering process of intelligent fuzzy image filter.

The IFND process refers the input image features to produce the respective fuzzy numben into the knowledge base.The fuzzy inference process including fuzzy inference d e s and Middle Decision Process (MDP) uses the fuzzy rule base and knowledge base to perform the middle filtering.The Final Decision Process (FDP) will decide the final output of intelligent FIF.Figure 2 illustrates the process of generation offuzrynumbers for A W m and ITF.

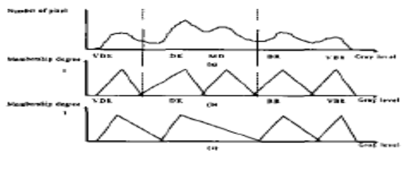

Fig. 2(a) The histogram of an image; (b) the generation process of *fuzzy numbers* for *AWFM* whose amount is fixed at 5; (c) the generation process of *fuzzy number* for intelligent *FIF* and its number of *fuzzy numbers* is not a fixed one.

Fig.2(a)shows the histogram of an image. Fig.**2**(b)is the generation process of *fizzy numbers* for AWEMwhose number is fixed at ***5.***Fig2 (c) is the generation process of fuzzy *numbers* for intelligent *FIF* and its number of fuzzy *numbers* is not fixed.

The algorithm for IFND process of intelligent FIF is as follows:

A. The algorithm for lFNDpmcess of intelligent FIF

Input: Noisocormpted image X , histogram
Outpt:Parametersset[m,a,p]oXf ;
Method:
Mliancevalue p ;
Stepl: Get the histogram of X .
Stepl.1: Get the start point X, of the histogram.
Stepl.2: Get the end point X, of the histogram.
StepZ: Get the mode Xde and it’s count X,.-.,.ofthe h i s t o w .
Step2.l: m, t XdF;
Step3: For XGRAYLEVEL + Xd,@ X,
Step3.1: order, + ~~XG”’”“L, , /Xd4”;<
Step3.2:order, c(XGRAYL€Y€~-X,)/(X-,- X-);
Step33: M t O
Step3.4: hirvrr +- oniprl -order2;
Step3.4.1: ifhisvm>pthen
Step3.4.1.1: b+XGRAYLEYEL;
Step3.4.1.2 M e M+l;
Step3.4.2: Else if (binrar2p & M=O)
Step3.4.2.1: XmOd+.X ,*-l, go to Stepl
Step3.4.3.1: Get the mode &ode_~ nLxt of the histogram between band b+M.
Step3.43.2 :; ,m+,&,2,
Step3.5: Get the graylevel of minimum count of histogram between Kade and
Step3.5.1:(r,t ml-(gaylevel of minimum count of histogram between
X_{mode} and X_{mode_Lnext} }.
Step3.5.2: $\beta_1 \longleftarrow$ { graylevel of minimum count of histogram between X_{mode} and X_{mode_Lnext} } - m_2 .
Step3.5.3: $X_{mode} \longleftarrow X_{mode\_Lnext}$, go to Step3.
Step4: For $XGRAYLEVEL \longleftarrow X_{mode}$ to X_{end};
Step4.1: $order1 \longleftarrow Val_{XGRAYLEVEL}/X_{mode\_value}$;
Step4.2: $order2 \longleftarrow (XGRAYLEVEL\ X_{end})/(X_{mode} - X_{end})$
Step4.3: $M \longleftarrow 0$
Stepl.4 bisvmt orderl -0rder2;
Stepl.4.1: If bisvm>pthen
Step4.4.l.l: b+ XGRAYLEm
Step4.4.1.2: M+ M+l;
Step4.4.2: Else if (bisvm5P & M4)
Step4.4.2.1: Xmde +Xm&+l, go to Step4.
Step4.43: Else if (bisvm2P & MZ 0)
Stepl.4.3.1: Get the mode &ale.aert of the histogram between b and b+M.
Step4.4.2.2 mi
Step4.5: Get the graylevel of mirimum coutt of histogram between and
Step4.5.1: a, t mi -(graylevel of minimum count of histogram between & aleand&a-mat).
Step4.5.2: fl,(graylevel of minimum count of histogram between Ynd and % dht1m I st@.5.3:xm*&xdem&&&.hat.
Step5: End

Figure 3 shows the graph representation of IFND process for intelligent FIF.By deciding the distance of orderl and d e r 2 , IFND can intelligent construct the fuzzy numbers for represenhng the image features.

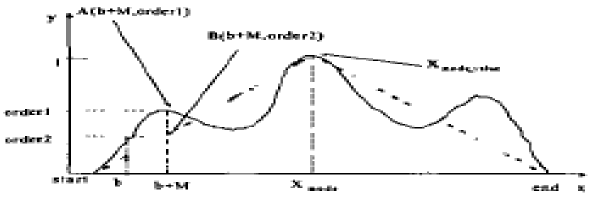

Fig. 3. The graph representation of *IFND process* for intelligent *FIF*. By deciding the distance of *order*1 and *order* 2, *IFND*can intelligent construct the *fuzzy numbers* to represent the image features.

III. FUZZY INFERENCE PROCESS FOR IMPULSE NOISE REMOVAL

Now we define the notations for fuzzy inference process. Let the corrupted image be denoted 23 x=[.r(i , ,>, i=r~o n , j = i t om],the middle result of fuzzy inference process be denotedas Y = [y (i . j) , i = i t o n , j = l tom].and the final result of intelligent fuzzy image filter be Z = [z (i , j),i = i r o n , j = 1 r o m].The fuzzy inference process of FIF is realized by the Sugenutyped inference approach[I I].The number of fuzzy rules is according to the result of IFND process, that is, it is various for different image.For example,if the number of fuzzy numbers produced by IFND is three,namely Dark (DO, Median (MD) and Bright (ER), then the fuzzy infeence mules are shown as follows.

Rule 1: f x (i - I , j-I) is OK, x(C1. j) is OK, xfi-I,j+l) is OK, x(i, j l) is OK, xfi, j) is OK, x(i,j+l) is OK, x(i+l. j-I) is DK, xfi+l. j) is OK.x(i+l, j+l) is DK

then

$$\bar{y}_1(i,j)=\frac{\sum_{k=-1}^{1}\sum_{l=-1}^{1} f_{DK}(x(i+k,j+l))\times x(i+k,j+l)}{\sum_{k=-1}^{1}\sum_{l=-1}^{1} f_{DK}(x(i+k,j+l))}$$

Rule2:if x(i4,jl)is MD,x(i-1,J) is MD,x(i-1,j+l)is MD,x(i,j-l)isMD,<i,j)is MD,x(i,fil)is MD,x(i+l, j-1)is MD, x(i+l, j)is MD,x(i + l ,p l) is MD then

$$\bar{y}_2(i,j)=\frac{\sum_{k=-1}^{1}\sum_{l=-1}^{1} f_{MD}(x(i+k,j+l))\times x(i+k,j+l)}{\sum_{k=-1}^{1}\sum_{l=-1}^{1} f_{MD}(x(i+k,j+l))}$$

Rule 3: ifx(i-1, j-1) is BR, x(i-I, j) is BR, x(i-I,p l) i s BR,x(i j-I) is ER, x(i j) isER,x(i,pl) is ER,x(i+l,j-I) is ER, x(i+l, j) is BR, rjitl, j + l)is ER then

$$\bar{y}_3(i,j)=\frac{\sum_{k=-1}^{1}\sum_{l=-1}^{1} f_{BR}(x(i+k,j+l))\times x(i+k,j+l)}{\sum_{k=-1}^{1}\sum_{l=-1}^{1} f_{BR}(x(i+k,j+l))}$$

The MDP is implemented by a weighted average approach for the three intermediate *fupy* inference results,that is

$$y(i,j)=\frac{\sum_{r=1}^{3} w_r\times \bar{y}_r(i,j)}{\sum_{r=1}^{3} w_r} \qquad ....2$$

where each weight wr is 1 if the anom of associated intermediate inference result y,(i, j)and the fizzy estimaior result [SI is minimum;otherwise it is zero.Let x(i, 1) -A< 1) = S(i, j),then we define the fizzy detecton for evaluating the amplitudes of positive impulse noise and negative impulse noise as follows.[Definirion 21 The fuzzy derecton FLIP,,(.) and FD,,(.) [7] are the mechanisms to detect the amplitudes of positive impulse noise b o s andnegative impulse noise i n e g of the whole smeared image,respectively.If

$$\sum_{i=1}^{N_1}\sum_{j=1}^{N_2} f_{LR\_I\_D\_pos}(\delta(i,j))\neq 0 \quad \text{and} \quad \sum_{i=1}^{N_1}\sum_{j=1}^{N_2} f_{LR\_I\_D\_neg}(\delta(i,j))\neq 0,$$

then they are realized by invoking the following formulas:

$$FD_{pos}(X)=\frac{\sum_{i=1}^{N_1}\sum_{j=1}^{N_2} |\delta(i,j)|\times f_{LR\_I\_D\_pos}(\delta(i,j))}{\sum_{i=1}^{N_1}\sum_{j=1}^{N_2} f_{LR\_I\_D\_pos}(\delta(i,j))} \quad (3)$$

$$FD_{neg}(X)=\frac{\sum_{i=1}^{N_1}\sum_{j=1}^{N_2} |\delta(i,j)|\times f_{LR\_I\_D\_neg}(\delta(i,j))}{\sum_{i=1}^{N_1}\sum_{j=1}^{N_2} f_{LR\_I\_D\_neg}(\delta(i,j))} \quad (4)$$

Where and I-D-neg are the fuzzy intervals for detecting positive and negative impulse noise respectively,and X=[x(i,j)]l,+,is the received image. Otherwise, s-pos=o 2nd <-neg=O A fizzy signal space [7] is a signal space whose partitions are decided by fuzzy intervals.The partitions include fuzzy uncorrupted subspace,fuzzy positive subspace,fuzzy negarive subspace and f w z y undecided subspace by the fuzzy uncompted interval, fuzzy posirive interval,fizzy negative interval, and the fuzzy undecided interval respectively.Then the FDP decides the final filtering result z(i, j)according to the following fuzzy i n k m e rules:

Rule FDPI: Ifthe distance ofxfi, j) and yfi, j) ir located in fizy uncorrupted subspace, then thefinal ourputzfi, j) =x(i, j).

Rule FDPZ: If the distance ofx(i, j) and yfi, J] is locared in fuzzy undecided subspace then thefindouptzfi, J] =yo, j).

RuleFDP3: If the distance ofx(i, j) and yo, j) is located in fwzy positive subspacr; then the final mrput z(i.1) = x(i, j) - 5p...

Rule FDP4: If the distance ofx(i. j) and yfi, j) is located in fuzzy negative subspace; then the finaloutputzlij) = x(i, j

IV. RESULTS

There are many different methods for removing impulse noise from corrupted images [1-61],But when the noise rate becomes high,the performance of these filters is broken down rapidly.In this paper,we implement four different algorithms including A WFM jilter,Medimfilrer, Selection medianfilrer (SMF)[121 and FiF filter to filter the heavily corrupted image.The experiments are performed on the image "Lenna" corrupted by additive impulse noise.

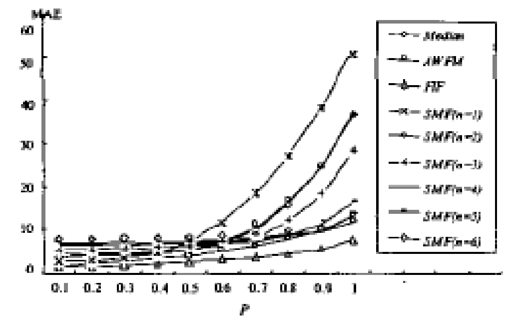

Fig. 4 The MAE curves for median filter, *AWFM, FIF,* and *SMF,* where *n* is the filtering mask for *SMF.*

Figure 4 sbJws the MAE curves for the four methods, where n is the filtering mask for SME Besides, we also compare our method with the other filters including WFM, RCRS, CWM, WO$ and Sfark filters. Figure 5 shows the curves of all compared filters for the MAE criterion

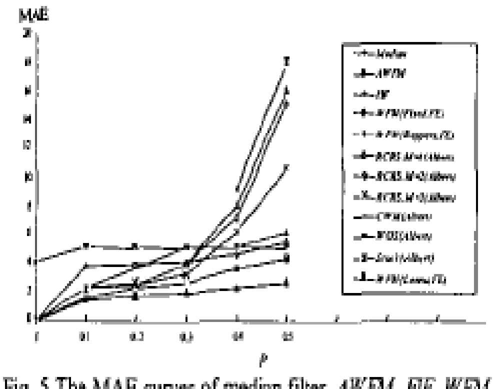

Fig. 5 The MAE curves of median filter, *AWFM, FIF, WFM, RCRS, CWM, WOS*and *stack* filters.

Notice that the MAE curves of RCRS. CWM, *WO$* and *Stack* filters are obtained by learning from a 512 by 512, 8 bitsipixel image of“Albert”, and then filtering a 512 by 512, 8 bitsipixel image of “Lenna” [5]. However, in our experiment, the “Lenna” image is sized 256 by 256 pixels with the same gray level resolution. Since it is difficult to judge the performance of image removal processing algorithm based solely quantitative analysis, we show some filtered results for subjective evaluation.

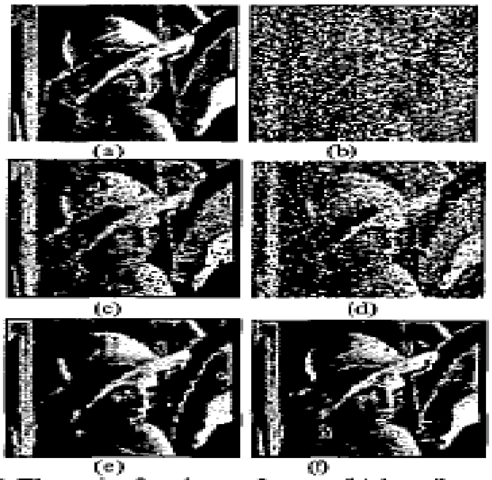

Fig. 6(a) The noise-free image Lenna; (b) heavily corrupted image by 90% additive impulse noise; (c) result of *AWFM*; (d) result of *median* filter, (e) result of *SMF*, and (e) result of *FIF*.

Figure 6 shows the "Lenna" image corrupted by 90% additive impulse noise and the filtered results. Figure 6(a) to Figure 6(f) show the noisefree image, heavily corrupted image, result ofAWFM, result of median filter, result of SME and result of FIF, respectively.

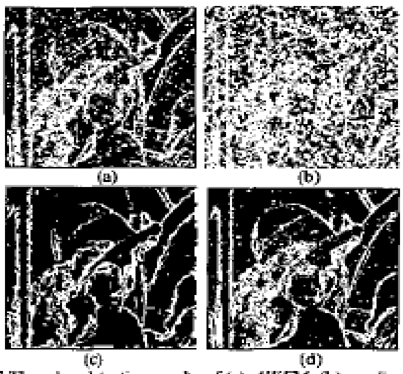

Fig. 7 The edge detection results of (a) *AWFM*; (b) *median* filter; (c) *SMF*, (d) and *FIF*.

Figure 7 shows the edge detection results of AWFM, *median* filter, SMF, and FIF, respectively. We also apply the four filters to color image processing. Figure 8 shows the filtering results of color image "Lenna".

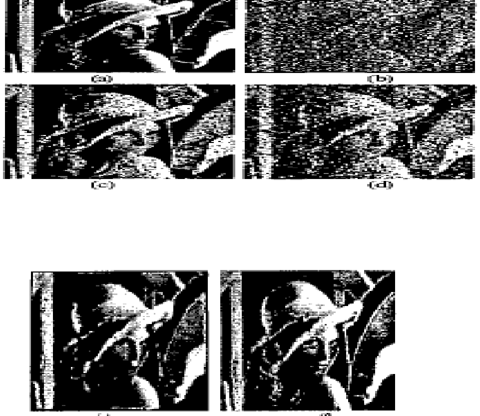

Fig. 8(a) The noise-free color image Lenna; (b) heavily corrupted color image by 90% additive impulse noise; (c) result of *AWFM*; (d) result of *median* filter; (e) result of *SMF*, and (f) result of *FIF*.

Figure 8(a) to Figure 8(f) show the noise-free color image, heavily corrupted color image, result of AWFM, result of median filter, result of SME and result of FIF, respectively.

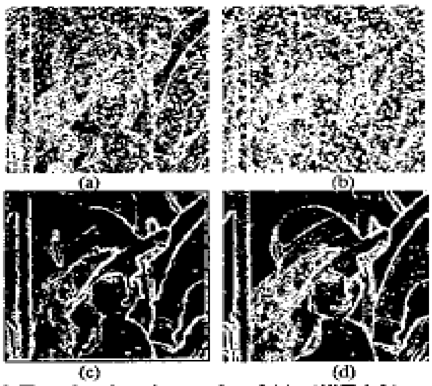

Fig. 9 The edge detection results of (a) *AWFM*; (b) *median* filter; (c) *SMF*; and (d) *FIF*, for color image Lenna

Figure 9 shows the edge detection results of *AWFM*, *medim* filter, *SMF;* and FIF, for color image "Lenna" respectively. Finally, the comparisms of MAE and MSE for the gray level image "Lenna" and its color image version are shown in Table 1 and Table 2, rerpectively.

TABLE 1. THE COMPARISONS OF MAE AND MSE FOR THE GRAY LEVEL IMAGE LENNA .

Lenna (gray)	MAE	MSE
AWFM	9.018	5949.229
Median	25.433	14060.117
SMF (n = 6)	9.933	5211.489
FIF	5.618	4039.953

TABLE 2. THE COMPARISONS OF MAE AND MSE FOR THE COLOR IMAGE LENNA.

Lenna (color)	MAE	MSE
AWFM	25.623	13822.328
Median	46.769	19911.936
SMF (n=6)	19.726	7306.864
FIF	13.857	7067.876

V. FUZZY SET THEORY AND FUZZY LOGIC

A crisp set in a universe X is characterized by an X−{0, 1} mapping,where 1 indicates that an element belongs to the set and 0 indicates it doesn't.A fuzzy set A in a universe X is characterized by an X − [0, 1] mapping μA, called the membership function [1],where μA(x) indicates the degree to which the element x in X belongs to the set A or satisfies the property expressed by the set A.In other words,fuzzy sets allow membership degrees between 0 and 1 and thus a more gradual transition between "belonging to" and "not belonging to".This makes fuzzy sets very useful for the processing of human knowledge, where linguistic values (e.g. large, small, . . .) are used. For example,a difference in gray level is not necessarily small or not small, but can be small to some degree.A possible embership function of the fuzzy set small is given in Figure 10.The extension from crisp to fuzzy sets comes along with an extension of the underlying binary logical framework to fuzzy logic.In fuzzy logic,expressions can be true or false to a

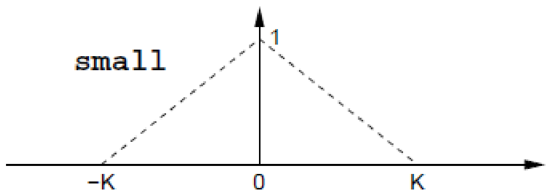

Fig.10.A possible membership function of the fuzzy set small (the parameter K can be chosen by the user,depending on the application.)

The closer an element is to 0, the higher its membership value is. certain degree, and consequently we should be able to connect such expressions (with the logical NOT, AND, OR, . . .) using fuzzy logical operators that extend their binary counterparts.This can be achieved by using fuzzy logical operators,such as negators (NOT),conjunctors (AND) and disjunctors (OR). Formally [2],a negator N is a decreasing [0, 1] − [0, 1] mapping that satisfies N(0) = 1 and N(1) = 0,a conjunctor C is an increasing [0, 1]×[0, 1]−[0, 1] mapping that satisfies C(0, 0) = C(1, 0) = C(0, 1) = 0 and C(1, 1) = 1,and a disjunctor D is an increasing [0, 1]×[0, 1]−[0, 1] mapping that satisfies D(1, 1) = D(1, 0) = D(0, 1) = 1 and D(0, 0) = 0.
The boundary conditions ensure that these fuzzy operators are real extensions of the binary NOT,AND and OR. Popular examples are Ns(a) = 1 − a, CM(a, b) = min(a, b) and CP (a, b) = a · b, DM(a, b) = max(a, b) and DP (a, b) = a + b − a · b,respectively,with a, b 2 [0, 1].Having fuzzy sets to model linguistic values and fuzzy logic to reason with them, fuzzy rules can be used to model human reasoning and to derive new (imprecise) knowledge from given (imprecise) knowledge.An example of a fuzzy rule is an expression of the form IF((p is P AND q is Q) OR (r is NOT R)),THEN (s is S),with P,Q,R,S fuzzy sets (modeling linguistic values)and p, q, r, s elements from the corresponding universes.The degree S(s) to which "s is S" (e.g., to which a pixel is considered noisy) is given by the degree to which the antecedent of the rule (i.e., the IF-part) is true.This degree is given by S(s)=D(C(P(p),Q(q)),N(R(r))),using a disjunctor D,a conjunctor C and a negator N.With the above tools we are able to create a mathematical model for human reasoning with imprecise knowledge.

VI. FUZZY FILTERS FOR STILL IMAGES

The main advantage of fuzzy filters is that they allow us to work and to reason with linguistic information, just as experts do (approximate reasoning);see the scheme in Figure 11.Our work on image denoising started with the so-called GOA filter [3].The filter is designed for the removal of Gaussian noise in grayscale images,and uses fuzzy rules to detect the degree to which the gradient in a certain direction is small.The idea is that a small gradient is caused by noise,while a large gradient is caused by image structure;see Table II for an example.Fuzzy rules are also applied to calculate the correction term that is used for the denoising;the contribution of neighbouring pixels depends on their gradient values.The results of the GOA filter were very good,and demonstrated the usefulness of fuzzy logic for the construction of noise reduction filters.In order to confirm these good results we
carried out extensive comparative studies of existing classical and fuzzy filters,including the mean filter,the adaptive Wiener filter [4],fuzzy median (FM) [5],the adaptive weighted fuzzy mean (AWFM1 and AWFM2) [6], [7],the iterative fuzzy filter (IFC),the modified iterative fuzzy filter (MIFC),and the extended iterative fuzzy filter (EIFC) [8].

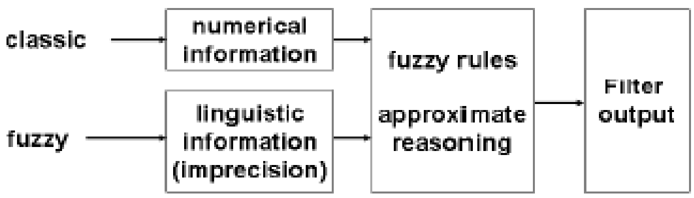

Fig. 11. Fuzzy filters not only use numerical information to filter out the noise in images, but can also work with linguistic information. Furthermore, fuzzy logic allows us to reason with this linguistic information and enables us to better approximate human reasoning.

IF $\nabla^F_{NW}(i,j)$ is small and $\nabla_{NW}(i,j)$ is positive THEN ϵ is positive

Table 3

A Fuzzy Rule That Models The Following Reasoning (See [3] For Details):If The Fuzzy Gradient Of A Pixel(I,J)In The North-West (Nw) Direction Is Small And Its Actual Gradient (The Difference Between The

Pixel And Its Neighbour In The Direction Nw) Has A Positive Value,Then The Correction Term C For That Pixel Has A Positive Value. The Fuzzy Gradient Is Calculated Using Gradient Values Of The Pixel(I,J)And Its Neighbours Perpendicular To The Considered Direction;It Is Used To Differentiate Between Gradient Values Caused By Noise And Gradient Values Caused By An Edge In The Image.

A second filter for the reduction of gaussian noise from grayscale images was presented a few years later [9]. This FuzzyShrink-filter can be seen as a fuzzy variant of an existing probabilistic shrinkage method, and was developed in the wavelet domain. The filter outperformed fuzzy non-wavelet methods, such as the histogram adaptive fuzzy filter (HAF) [10], the EIFC filter, the smoothing fuzzy control based filter (SFCF) [11], the decreasing weight fuzzy filter with moving average centre (DWMAV) [12], the adaptive fuzzy switching filter (AFSF) [13], the fuzzy similarity filter (FSB) [14], and the AWFM. It also was comparable with other recent but more complex wavelet methods, including the bivariate wavelet shrinkage method [15], the feature-based wavelet shrinkage method from [16] and the probabilistic shrinkage method [17].After the succesfull GOA filter for gaussian noise, we developed the Fuzzy Impulse noise Detection and Reduction Method (FIDRM [18]) for the removal of fixed impulse noise in grayscale images. The filter followed a similar approach.

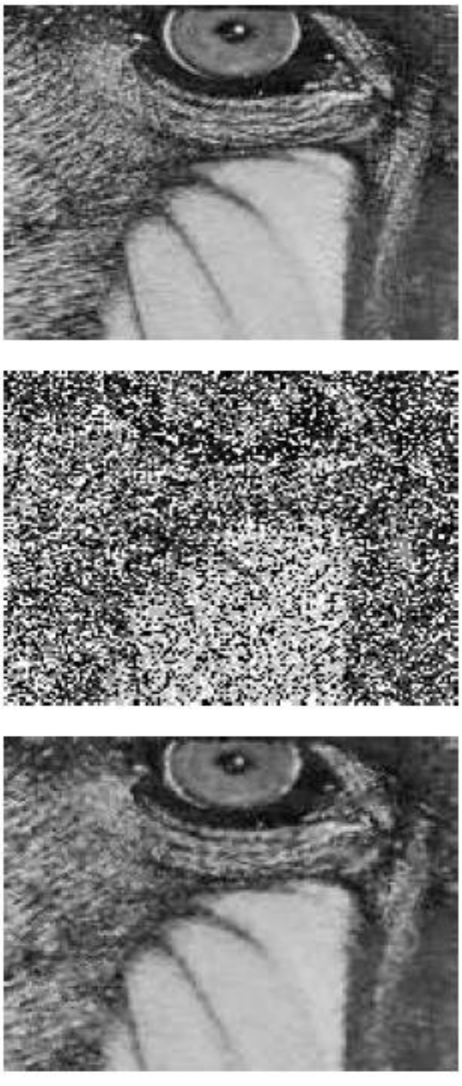

Fig. 12. Noise removal from the Mandrill image:

Top = part of the original image,middle=image contaminated with 50% impulse noise (salt & pepper noise), bottom = denoised result with the FIDRM filter as the GOA filter, as it used gradient values to detect and remove the noise. The visual results are quite spectacular, as shown in Figure 12. Again, extensive experiments confirmed the state-of-the-art results of the filter. The filter could easily be extended to color images by applying the filter on each of the color bands separately. The results for color images were relatively good [19],but the disadvantage of this approach is that correlations between color bands are neglected and small color artefacts are introduced.This inspired us to construct other filters, specifically to remove impulse noise from color images, and led to the FIDRMC and HFMRC filters.The FIDRMC filter consists of two separated steps:the detection phase and the filtering phase.The detection phase is applied separately to each color component,where fuzzy rules are used to determine whether a pixel pigment is corrupted with impulse noise or not.After the detection phase the filter only focuses on those pixel pigments which have a non-zero membership degree in the fuzzy set “impulse noise”.In the filtering phase we also take into account the color information of a certain neighbourhood around a given central pixel [20].The HFMRC filter follows a different approach and uses the histograms of the color component differences to detect and filter the fixed impulse noise [21].The HFMRC filter was later upgraded to the more complex HFC filter [22] that could also tackle randomly valued impulse noise in color images. Previously,our FRINR filter already achieved the goal of removing randomly valued impulse noise in grayscale images [23].The detection phase of the FRINR filter consists of two units that are both used to define corrupted impulse noise pixels.The first unit investigates the neighbourhood around a pixel to conclude whether the pixel can be considered as impulse noise or not,while the second unit uses fuzzy gradient values to determine the degree to which a pixel can be considered as impulse noise and the degree to which a pixel can be considered as noise free. For the comparative studies, several other filters were considered. A first group of filters are grayscale filters that were extended to application on color images (see previous comparative studies),and a second group of filters are vector filters that were designed specifically for color images.It concerns the fuzzy vector rank filter (FVRF) [24],the fuzzy credibility color filter (FCCF) [25] and the adaptive vector median filter (AVMF) [26]. Regarding the removal of gaussian noise from color images, we developed the FCG filter [27].In contrast to most other methods, the first subfilter of the FCG filter distinguishes between local variations due to noise and local variations due to image structures (such as edges) by using the color component distances instead of component differences.The second subfilter is used as a complementary filter which especially preserves differences between the color components.Filters in the comparative study include the hidden Markov tree method (HMT) [28], the 3D-DFT method [29], the Bayesian least squares - Gaussian scale mixture filter (BLS-GSM) [30], the bivariate shrinkage method,the chromatic filter proposed in [31],and the total least square filter (TLS) [32].

VII. CONCLUSION

The power of fuzzy filters is that they can model human (approximate) reasoning, using linguistic variables in the reasoning process. Fuzzy set theory and fuzzy logic provide the tools, and comparative studies demonstrate that fuzzy filters can outperform classical approaches. We certainly do not want to claim that fuzzy set theory is “the way to go”, but where applicable it can lead to an improvement of image processing results.

In this paper, we have proposed an intelligent fuzzy image filter for additive impulse noise removal. The intelligent FIF contains two processes, IJWD process and fuzzy inference process, to perform the efficient recovery task. IFND process can generate the fizzy numbers of the specified image automatically and store them into the knowledge base. Then the fwzy infemence process refers the knowledge base and fuzzy rule base to execute the fuzzy inference. Furthennore, the FDPwill decide the final output by the decision rules.For image detection, we adopt the Sobel operator to work with the filters. n e experimental results show that FIF achieve the most efficient for removing heavily corrupted additive impulse noise. In the future, we will refine this method to make it can deal with various noise models such as Gaussian impulse noise. Besides, the edge detection algorithm for noise image will also be developed.

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