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DENOISING TECHNIQUES ASPECTS

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Abstract: Denoising techniques for digital images represent a domain with a great amount of literature because still nowadays, denoising is a great challenge for the researchers. The published work presents different approached to this problem, each having its advantages and disadvantages. We present various types of methods used for image denoising.
Keywords: denoising techniques

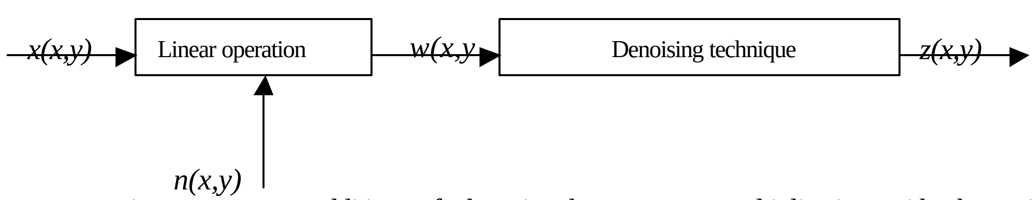
1. INTRODUCTION

Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted by noise. The wavelet based approach finds applications in denoising images corrupted by Gaussian noise. A quantitative measure of comparison is provided by the peak signal-to-noise ratio (PSNR).

Digital images are very important in real life applications such as satellite television, magnetic images, a.s.o. Data sets collected by sensors are greatly corrupted by noise. Imperfect instruments, problems concerning the acquisition data process and natural interference phenomena can degrade the data. Moreover, noise can be introduced by transmission and compression errors.

Noise reduction is a fundamental problem in image processing domain. Since the recent research activities in signal decomposition are basically driven by visual signal processing and coding applications, the properties of the visual system are examined and incorporated in the signal decomposition step. Most recently, the wavelet transform with a capability for variable-time frequency resolution has been advanced as an elegant multiresolution signal-processing tool.

A corrupted image is subjected to denoising techniques in order to obtain a clear image (denoised) $z(x, y)$.



The linear operation represents addition of the signal $s(x, y)$ or multiplication with the noise $n(x, y)$.

2. DENOISING ALGORITHMS CLASSIFICATION

For image denoising problem, there are two basic approaches:

a) **Spatial** filtering methods.
b) **Transformed** domain filtering methods.

a. Spatial filtering

Spatial filtering represents the traditional noise reduction scheme; in this case filters that can be classified into *linear* and *non-linear* filters.

Linear filters have the disadvantage that they destroy the lines and other thin details from an image, they diminish the contours and they have a very bad behaviour in the presence of the signal dependent noise. *Wiener filtering* requires information about spectra's noise and about the original signal and it behaves well if the base signal is smooth.

Non-linear filters are used to remove noise without its explicit identification. This type of filters imply low-pass filtering, making the assumption that noise occupy the most part of the frequency spectra. They perform well, removing noise to a certain degree, but they cause the loss of the image clarity.

b. Filters in the transformed domain

A classification of the filters in the transformed domain can be done according to the choice of the bases function.

Space-frequency filtering refers to the use of low-pass filters, using the Fast Fourier Transform. This type of methods is time-consuming and it depends on the cut-off frequency and on the filter transfers function.

Wavelet domain, beside time-frequency analyses, permits the best choice of a basis for a given signal, so one can introduce an optimisation factor in the fist step of the noise reduction algorithm. The other properties of the wavelet coefficients - fundamental properties of the wavelets (e.g. grouping the most significant coefficients, correlation between absolute value of the coefficients having the same spatial orientation from adjacent scales, a.s.o) - offer a diversity of processing the wavelet coefficients.

Filtering methods in the wavelet domain can be furthered classified into *linear* and *non-linear* methods. Linear filters, such as *Wiener filter* in the wavelet domain are very suitable when the noise present in a signal can be modelled as a Gaussian process and the accuracy measure is the *mean square error* (MSE). The researchers proposed *adaptive FIR Wiener* for noise reduction, where filtering is applied to each scale, and inter-scale filtering is not allowed.

Recently, the activity for image denoising is focused upon wavelet transform using *linear thresholding* methods. The procedure used for wavelet coefficients reduction is called *hard thresholding* and it was proposed by Donoho. This method generates artefacts in the processed image. To overcome this shortage, Donoho proposed *soft-thresholding* and Imola and Kamath proposed *semi-soft thresholding.*

The researchers study the optimal threshold choice, threshold that can be *adaptive* or *non-adaptive*.

In the case of *adaptive threshold*, Donoho and Johnstoned proposed the method called *SUREShrink,* which uses a hybrid between the universal threshold and SURE threshold. For *non-adaptive thresholding*, Donoho and Johnstone proposed the method called *VISUShrink*, which uses a non-adaptive universal threshold, which depends on the number of the available data. Because the chosen threshold can be too big - it depends on number of data - VISUShrink smoothes the image too much. SUREShrink method performs better than VISUShrink because it offers an optimal threshold for each coefficient.

The wavelet coefficients model exploits the multiresolution property of the wavelet transform. This technique identifies the correlation of the signal by observing the signal at different resolutions. It has excellent results, but it is very time-consuming, having big complexity. Wavelet coefficients can be modelled either *statistical* or *determinist*.

Statistical model of wavelet coefficients is based upon some interesting properties of the wavelet transform, such as multi-scale correlation, local correlation. There are two statistical methods that exploit the statistical properties of the wavelet coefficients relying on the probabilistic model: *Joint Probabilistic Model* and *Marginal Probabilistic Model*.

Joint Probabilistic Model like HMM – *Hidden Markov Model* (J. Romberg, H. Choi) and GSM – *Gaussian Mixture Scale* (Strela), are efficient to capture the inter-scale dependencies and to estimate the necessary parameters from noisy observations. Jansen and Bulthel proposed another approach called HMT, which has the disadvantage to be very complex during the training stage.

The marginal probabilistic model is based on the marginal distribution of the wavelet coefficients. One uses *GMM model* (*Gaussian Model*) and *Generalized Gaussian Model* (*GGD*) to model the wavelet coefficients. Although GGD is more precise, GMM is widely used. M. Michak and P. Moullins proposed a methodology where the wavelet coefficients are supposed to be random independent Gaussian variables. They use the MAP (maximum posteriori probability) rule to estimate the marginal variance of the coefficients. All the above methods require noise estimation, which is very difficult in real applications.

Non-ortonormal transforms by using *undecimated wavelet transform* (UDWT) are good for signal decomposition ensuring a better visual resolution. Burrus, Cohen and Mallah give excellent papers in this domain. The combination between translation invariance (Chen) and multiwavelets offers better results for the Lena image in MSE (mean square error) terms.

Recently, a new method called ICA (*Independent Component Analyses*) draws attention in the field of *adaptive transforms*. An exceptional merit of ICA is that it doesn't use the assumption that the signal is a Gaussian or the noise has Gaussian distribution, which is good for mixed noise removal.

3. CONCLUSIONS

An ideal noise reduction procedure requires a priori information about noise. The majority of the current denoising techniques use the assumption that images are corrupted by Gaussian noise, with is not true in real applications. The algorithms use visual qualitative measures and quantitative measures such as PSNR (peak signal-to-noise ratio), SNR (signal-to-noise ratio). The majority of the algorithms assume that noise variance and the noise model are known and they compare their performances with other algorithms. In the case of using the wavelet transform, the choice of the primary scale and the choice of the wavelet analyses have a great importance concerning the success of the thresholding procedure. Some papers do not specify either the decomposition level or the used wavelet.

In the future, the researcher will focus on robust statistical models for the non-orthogonal wavelet coefficients based on inter-scale and intra-scale correlations. These methods will be effectively applied for image denoising and compression.

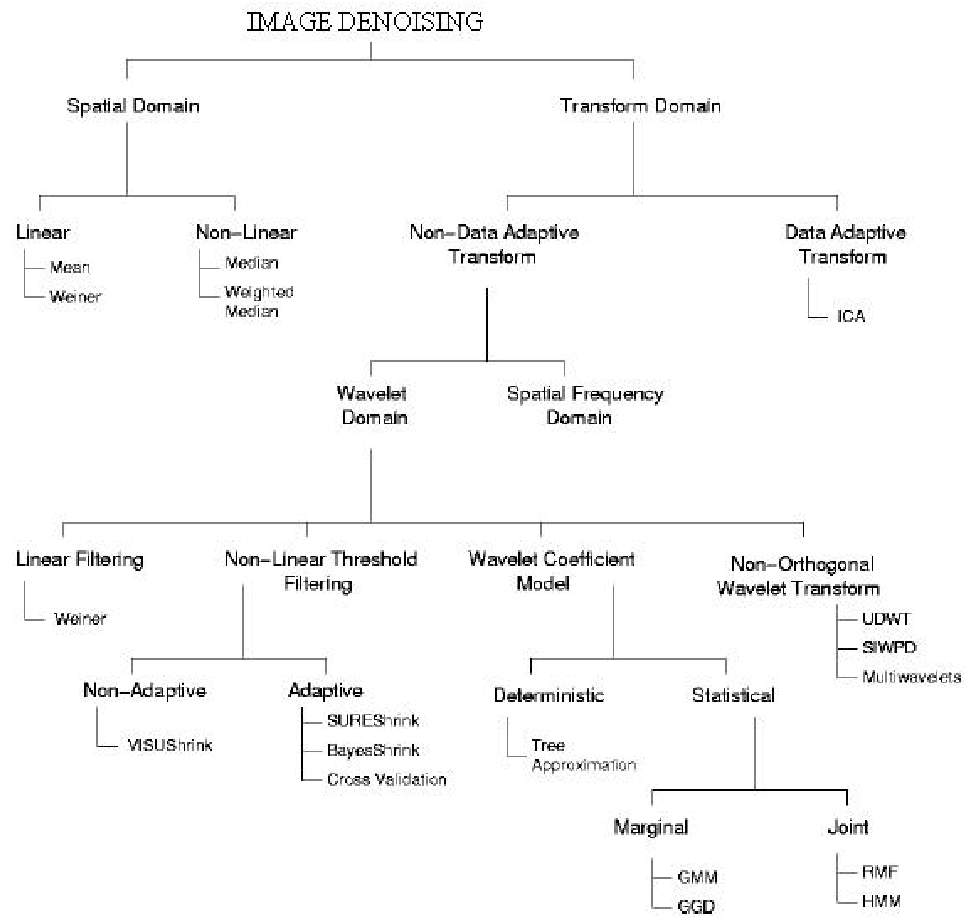


Fig. 1 Image denoising techniques

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