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Speech denoising using Diversity Enhanced Discrete Wavelet Transform and MAP filters associations

BADO Pascal[1]

Abstract: In this paper, we present new speech denosing methods based on some types of maximum a posteriori (MAP) filters applied in the wavelet domain. These methods take into account the statistical properties of the discrete wavelets transform (DWT) coefficients of speech signals. The experimental results are compared with those obtained in another paper published in this magazine, [1].
Keywords: wavelets, bishrink, MAP filters, Bayes, Wiener.

I. INTRODUCTION

The wavelets constitute a powerful tool for mathematical analysis which revolutionized the world of signal processing. The wavelets are functions with null average and finite energy. Their field of application is very large: compression, segmentation, denosing etc. The term denoising was introduced by David Donoho, [2]. He treated the case of signals perturbed by additive white Gaussian noise. The aim of this paper is the denoising of additively perturbed speech. Several speech denosing methods already exist. Some of them are based on the use of the wavelets transform, [1]. They differ by the type of filter used in the wavelets domain but all follows the Donoho's algorithm. It is based on the following three steps:

1. The computation of the wavelet transform, (WT),
2. The filtering of the obtained result,
3. The computation of the inverse wavelet transform, (IWT).

Donoho used the DWT. Another WT, namelly the diversity enhanced discrete wavelet transform, DEDWT, was preffered in [1].

For filtering in the DEDWT domain we will use in the following, MAP filters. Some of them will differ of the bishrink filter, used in [1]. The knowledge of the type of noise to be eliminated and of the probability density function (pdf) of the useful signal are essential for the second step of the denoising method. The success of the denosing procedure depends on the selection of the noise and useful signal pdfs. In the following, we present a speech denoising method which uses two types of MAP filters associations:

i) the bishrink filter and the Wiener filter on the one hand and
ii) the marginal MAP filter and the Wiener filter on the other hand.

The structure of this paper is the following. Section II consists in modeling the speech in order to estimate its pdf. Section III explains the proposed denoising method. Some variants, based on the use of different filters in the wavelets domain are described. The results obtained using these different variants are compared in section IV. The final section is dedicated to concluding remarks.

II. STATISTICAL MODELING OF THE SPEECH SIGNAL

The various MAP filters, which we will study and compare, require the knowledge of the pdf of the useful signal. In this section we will identify the pdf of speech on the basis of the comparison of the histogram of a speech signal with the elements of a family of usual pdfs. We consider the family of gamma generalized distributions, [3], defined for N random variables, $X = \{X_1, X_2, ..., X_N\}$ by:

$$f_X(x) = \frac{\gamma \beta^{\eta}}{2\Gamma(\eta)} |x|^{\eta\gamma - 1} exp\left(-\beta |x|^{\gamma}\right) \quad (1)$$

where $\Gamma(\eta)$ is the gamma function and η, β, γ are positive real-valued parameters; β is related to η and γ by:

$$\beta = \eta \frac{1}{\frac{1}{N}\sum_{i=1}^{N} |x_i|^{\gamma}} \quad (2)$$

For certain particular values of η and γ, the following models are found:

If : γ = 1, the (general) gamma pdf;
ηγ = 1, the generalized Gaussian pdf;
γ = 2 and η = 0.5, the Gaussian pdf;
γ = 1 and η = 1, the Laplacian pdf.

Analyzing this class and the histogram of speech signal, we can observe that this signal is close to the Laplacian pdf. This observation is highlighted in figure 1. The Laplacian pdf is defined by:

1. ENSIETA-Brest, France

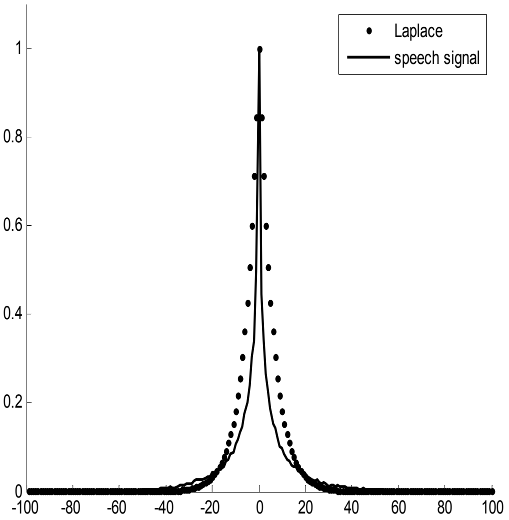

Fig. 1: The histogram of the speech segment feets well with a Laplacian distribution.

$$f_X(x)=\frac{1}{2b}exp\left(-\frac{|x-\mu|}{b}\right) \quad (3)$$

where *2b* is the variance and μ the mean. In the case considered in the experiment already reported the mean is null. The results obtained come to confirm the assumption that certain authors make in the treatment of the speech signals [1].

III. MAP FILTERS ASSOCIATIONS

In the previous section is given a model for the speech signal pdf. The aim of this section is the study of the pdf transformation realized by the DWT computation. The DEDWT is a colection of DWTs. First, we determine the connection between the pdfs of the input signal and of the wavelet coefficients. Second, the relation already obtained is verified by simulations.

A. The derivation of the wavelets transform coefficients pdf according to the speech signal pdf

Let us consider a random variable X with a pdf $f_X(x)$ and the change of random variable $Y=\alpha X$ with α a constant. The relation connecting the pdfs of X and Y is:

$$f_Y(x)=\frac{f_X(x)}{\left|\frac{dy}{dx}\right|}=\frac{f_X(\frac{y}{\alpha})}{|\alpha|}=\frac{1}{|\alpha|}f_X(\frac{y}{\alpha}) \quad (4)$$

If we consider the following relation between the random variables Z and the independent random variables $Y_k, k=\overline{1,K}$, $Z=\sum_{k=1}^{K}Y_k=\sum_{k=1}^{K}\alpha_k X_k$ with $\alpha_k \neq 0$ and $k=\overline{1,K}$, then:

$$f_Z(z)=f_{Y_1}(z)*f_{Y_2}(z)*\cdots*f_{Y_K}(z) \quad (5)$$

and if the random variables Y_k, $k=\overline{1,K}$, represent changes of the random variables $X_k, k=\overline{1,K}$, following the relations $Y_k=\alpha_k X_k$, then the pdf of the random variable *Z,* becomes:

$$f_Z(z)=\frac{1}{|\alpha|}f_{X_1}\left(\frac{z}{\alpha}\right)*f_{X_2}\left(\frac{z}{\alpha}\right)*\cdots*f_{X_K}\left(\frac{z}{\alpha}\right) \quad (6)$$

This relation can be used to compute the pdf of wavelet coefficients, $f_Y(y)$ of a process *X,* on the basis of the pdf of this process $f_X(x)$, if we consider that $X_1=X_2=\cdots=X_K=X$. In our case, the process *X* is a speech signal. So, the relation between the wavelet coefficients of a speech signal and its own pdf is:

$$f_Y(y)=\mathop{*}_{k=1}^{K}\frac{1}{|\alpha_k|}f_X\left(\frac{y}{\alpha_k}\right) \quad (7)$$

where α_k represent the coefficients of the filters (*h* or *g*) used for the computation of the wavelet transform. This relation can be applied to each filter of the DWT computation diagram, represented in figure 2. For the first iteration of the DWT, the pdf obtained after the first low-pass filter *h* is:

$$\overset{(7)}{\Rightarrow} f_U(u)=\mathop{*}_{k_1=1}^{K}\frac{1}{|h_{k_1}|}f_X\left(\frac{u}{h_{k_1}}\right)=\frac{1}{\prod_{k_1}^{K}|h_{k_1}|}\mathop{*}_{k_1=1}^{K}f_X\left(\frac{u}{h_{k_1}}\right)$$

$$\Rightarrow f_U(u)=P_h \mathop{*}_{k_1=1}^{K} f_X\left(\frac{u}{h_{k_1}}\right) \quad (8)$$

and $P_h=\frac{1}{\prod_{k_1}^{K}|h_{k_1}|}$.

In the same way, the pdf obtained after the second high-pass filter *g* becomes:

$$\overset{(7)}{\Rightarrow} f_Y(y)=\mathop{*}_{k_2=1}^{K}\frac{1}{|g_{k_2}|}f_U\left(\frac{y}{g_{k_2}}\right)=\frac{1}{\prod_{k_2}^{K}|g_{k_2}|}\mathop{*}_{k_2=1}^{K}f_U\left(\frac{y}{g_{k_2}}\right)$$

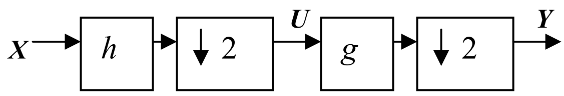

Fig. 2. The DWT first iteration computation diagram.

$$\Rightarrow f_Y(y) = P_g \overset{K}{\underset{k_2=1}{*}} f_U\left(\frac{y}{g_{k_2}}\right) \quad (9)$$

and $P_g = \frac{1}{\prod_{k_2}^{K} \left|g_{k_2}\right|}$.

Using the last two relations, we can compute the detail coefficients pdf after the first iteration:

$$\overset{(8),(9)}{\Rightarrow} f_Y(y) = P_g \overset{K}{\underset{k_2=1}{*}} P_h \overset{K}{\underset{k_1=1}{*}} f_X\left(\frac{y}{h_{k_1} g_{k_2}}\right)$$

$$\Rightarrow f_Y(y) = P_g (P_h)^K \overset{K}{\underset{k_2=1}{*}} \overset{K}{\underset{k_1=1}{*}} f_X\left(\frac{y}{h_{k_1} g_{k_2}}\right) \quad (10)$$

While proceeding in the same way, the following result is obtained for the second iteration:

$$f_Y(y) = P_g (P_h)^{K+K^2} \overset{K}{\underset{k_1=1}{*}} \overset{K}{\underset{k_2=1}{*}} \overset{K}{\underset{k_3=1}{*}} f_X\left(\frac{y}{h_{k_1} g_{k2} h_{k_3}}\right) \quad (11)$$

Finally, after the Nth iteration, the pdf of the detail coefficients becomes:

$$f_Y(y) = P \overset{K}{\underset{k_1=1}{*}} \overset{K}{\underset{k_2=1}{*}} \cdots \overset{K}{\underset{k_{N+1}=1}{*}} f_X\left(\frac{y}{h_{k_1} h_{k_2} \cdots h_{k_N} g_{k_{N+1}}}\right) \quad (12)$$

with $P = P_g (P_h)^{K+K^2+\cdots+K^N}$

We have proved in section II, that the pdf of the speech signal can be approximated with a Laplace law:

$$f_X(x) = \frac{1}{2b} \exp\left(-\frac{|x-\mu|}{b}\right).$$

So, if we compute the DWT of a speech signal, the model of the corresponding wavelet coefficients becomes:

$$f_Y(y) = P \overset{K}{\underset{k_1=1}{*}} \overset{K}{\underset{k_2=1}{*}} \cdots \overset{K}{\underset{k_{N+1}=1}{*}} F_1(y) \quad (13)$$

with:

$$F_1(y) = \frac{1}{2b} exp\left(-\frac{1}{b}\left(\left|\frac{y}{h_{k_1} h_{k_2} \cdots h_{k_N} g_{k_{N+1}}} - \mu\right|\right)\right)$$

If we compute the DWT of a zero mean white noise, which has a Gaussian distribution, whose formula is:

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{1}{2}\left(\frac{x}{\sigma}\right)^2\right),$$

the output pdf is given by:

$$f_Y(y) = P \overset{K}{\underset{k_1=1}{*}} \overset{K}{\underset{k_2=1}{*}} \cdots \overset{K}{\underset{k_{N+1}=1}{*}} F_2(y) \quad (14)$$

and:

$$F_2(y) = \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{1}{2\sigma^2}\left(\frac{y}{h_{k_1} h_{k_2} \cdots h_{k_N} g_{k_{N+1}}}\right)^2\right)$$

The central limit theorem stipulates that any sum of independent and identically distributed random variables will tend to be distributed according a normal law when their number tends towards the infinite [4]. Then we can affirm that the speech signal pdf converges towards a Gaussian after a certain number of convolutions, or equivalently after a certain number of DWT iterations. The problem is how fast this convergence is. In other words it is interesting to know if after a finite number of DWT iterations, the output pdf can be considered Gaussian. The number of convolutions required for one DWT iteration depends on the type of mother wavelets used, because a different number of coefficients K correspond to different types of mother wavelets. The smallest convolutions number per DWT iteration is obtained when the Haar wavelet mother is used. So, the smallest convergence speed is obtained using this mother wavelets. We have simulated the convergence process, using the Haar mother wavelets, for which we have the following values:

$$K = 2;\; h_1 = \frac{1}{\sqrt{2}};\; h_2 = \frac{1}{\sqrt{2}};\; g_1 = \frac{1}{\sqrt{2}};\; g_2 = -\frac{1}{\sqrt{2}}$$

Starting from a Laplace pdf we obtain for the first and the second iterations, the detail wavelet coefficients pdf curves presented by figure 3 and figure 4. It can be observed that the curve of figure 4 is close to a Gaussian. So, we can assume that using Daubechies mother wavelets (all those mother wavelets have a higher corresponding K value), the pdf of the wavelet coefficients of a speech signal can be considered Gaussian, after some iterations of the DWT. So, the starting conditions, used for the MAP filter construction, that will be presented in the following, concerning the distribution of the wavelet coefficients, cannot be kept unchanged throughout the entire denoising process in the wavelets domain. For different iterations different models for the distribution of the wavelet coefficients of the clean speech must be considered.

B. Histograms of DWT coefficients of the speech signal

The aim of this section is to give a practical verification of the theoretical results obtained in the previous section. We have calculated and represented the histograms of the DWT coefficients of the same segment of speech signal used in section II, in order to study their pdfs. The histograms are represented on figure 5. The Laplace distribution is heavy tailed. Its speed of descent towards zero is smaller then the speed of descent towards zero of a Gaussian distribution. Analyzing figure 5, it can be observed that the speed of descent towards zero of the curves increases with the level of decomposition. This means that the pdf of the DWT coefficients converges asymptotically towards a Gaussian. Intermediate simulation results proved that the difference between the speeds of descent towards zero of the curves corresponding to the fourth and the fifth iteration is not important; so we could think that convergence is reached after four iterations. This conclusion is in agreement with the results of the previous section.

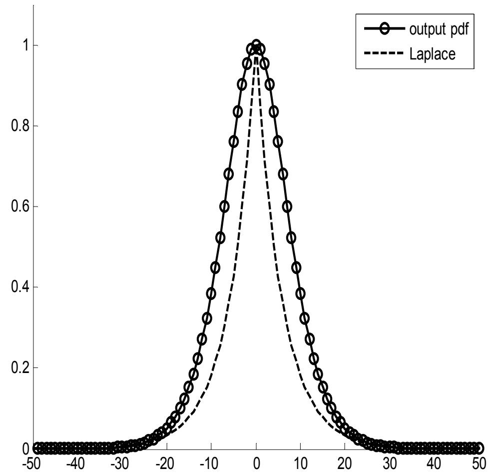

Fig. 3: A comparison of the input (Laplacian) distribution with the output distribution after the first iteration.

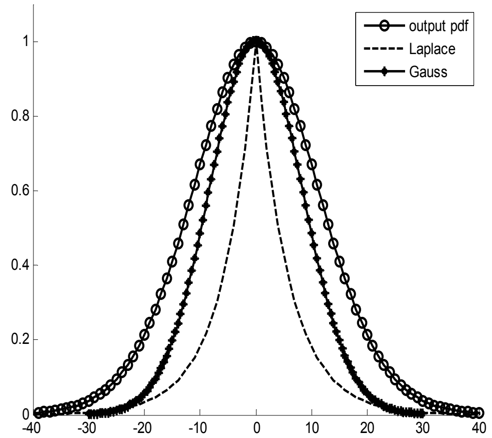

Fig. 4: A comparison of the input (Laplacian) distribution with the output distribution after the second iteration and with the Gaussian distribution.

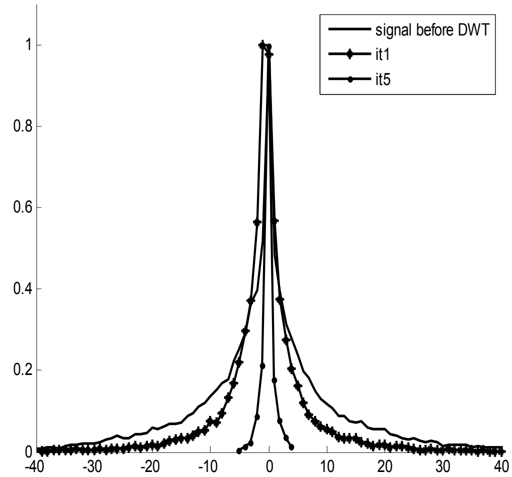

Fig. 5: A comparison of the histograms of the speech signal before the calculation of the DWT and those of the DWT coefficients after the first and the fifth iteration.

C. *Filters associations*

We have just shown that the starting conditions concerning the distribution of the wavelet coefficients cannot be kept unchanged throughout the entire denoising process in the wavelets domain. This is why we propose an association of filters: a first-one when the pdf of the wavelet coefficients is supposed Laplacian and a second association when this law becomes Gaussian. In this section we were particularly interested in the choice of the second filter. If we consider y a noisy wavelet coefficient, w the true coefficient and n the noise, [5], we can write that:

$$y = w + n \tag{15}$$

The classical MAP estimator for (15) is:

$$\hat{w}(y) = \underset{w}{\arg\max}\, P_{w|y}(w|y) \tag{16}$$

Using Bayes rule, one gets:

$$\begin{aligned} \hat{w}(y) &= \underset{w}{\arg\max}\left[P_{y|w}(y|w)\cdot P_w(w)\right] \\ \Rightarrow \hat{w}(y) &= \underset{w}{\arg\max}\left[P_n(y-w)\cdot P_w(w)\right] \end{aligned} \tag{17}$$

Equation (17) is equivalent to:

$$\hat{w}(y) = \underset{w}{\arg\max}\left[\ln P_n(y-w) + \ln P_n(w)\right] \tag{18}$$

If the signal and the noise have both a Gaussian pdf, then:

$$P_n(n) = \frac{1}{\sigma_n\sqrt{2\pi}} exp\left(-\frac{1}{2}\left(\frac{n}{\sigma_n}\right)^2\right) \tag{19}$$

and

$$P_w(w) = \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{1}{2}\left(\frac{w}{\sigma}\right)^2\right) \tag{20}$$

With the aid of the last two relations, the argument of the right hand side of (18) becomes:

$$ln\,P_n(y-w)+ln\,P_w(w)=$$

$$ln\left(\frac{1}{\sigma_n\sqrt{2\pi}}\right)-\frac{(y-w)^2}{2\sigma_n^2} \quad (21)$$

$$+ln\left(\frac{1}{\sigma\sqrt{2\pi}}\right)-\frac{(w)^2}{2\sigma^2}$$

To maximize (21), the following equation is solved:

$$\frac{d\left[ln\,P_n(y-w)+ln\,P_w(w)\right]}{dw}=0 \quad (22)$$

Using (21) it becomes:

$$2\frac{(y-w)}{2\sigma_n^2}-2\frac{(w)}{2\sigma^2}=0$$

or:

$$-w\left(\sigma_n^2+\sigma^2\right)+\sigma^2 y=0$$

So, the solution of the MAP equation is in this case:

$$\hat{w}=y\frac{\sigma^2}{\sigma^2+\sigma_n^2} \quad (23)$$

This relation corresponds to the zero order Wiener filter whose impulse response is:

$$h[n]=\frac{\sigma^2}{\sigma^2+\sigma_n{}^2}\delta[n]$$

Then the second filter to be considered is necessarily the Wiener filter. For the first filter, we have two possibilities:

a) If we do not take into account the inter-scale dependency of the wavelet coefficients, for the first iterations, where the coefficients of the DWT of the speech signal follows a Laplace law, one obtains:

$$P_w(w)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\sqrt{2}\frac{|w|}{\sigma}\right) \quad (24)$$

Supposing that the wavelet coefficients corresponding to the noise n are Gaussian distributed, the MAP equation becomes:

$$ln\,P_n(y-w)+ln\,P_w(w)=$$

$$ln\left(\frac{1}{\sigma_n\sqrt{2\pi}}\right)-\frac{(y-w)^2}{2\sigma_n^2}+ln\left(\frac{1}{\sqrt{2}\sigma}\right) \quad (25)$$

$$-\frac{\sqrt{2}|w|}{\sigma}$$

The solution of (22) is in this case:

$$\sigma w(y-w)-\sqrt{2}\sigma_n^2|w|=0$$

or:

$$\sigma\,sgn(w)(y-w)-\sqrt{2}\sigma_n^2=0$$

This equation has two possible solutions:

If $w>0$, the solution is:

$$\hat{w}=y-\sqrt{2}\frac{\sigma_n^2}{\sigma}$$

If $w<0$, the solution is:

$$\hat{w}=y+\sqrt{2}\frac{\sigma_n^2}{\sigma}$$

We can notice that if $y>\sqrt{2}\frac{\sigma_n^2}{\sigma}$ then $w>0$, and the solution of the MAP equation is:

$$\hat{w}=y-\sqrt{2}\frac{\sigma_n^2}{\sigma}$$

If $y<-\sqrt{2}\frac{\sigma_n^2}{\sigma}$ then $w<0$, and the solution of the MAP equation becomes:

$$\hat{w}=y+\sqrt{2}\frac{\sigma_n^2}{\sigma}$$

Therefore, if $|y|>\sqrt{2}\frac{\sigma_n^2}{\sigma}$, the solution of the MAP equation can be written in the following compact form:

$$\hat{w}=sign(y)|y|-\sqrt{2}sign(y)\frac{\sigma_n^2}{\sigma} \quad (26)$$

If we define:

$$(g)_+=\begin{cases} g, & \text{if } g>0 \\ 0, & \text{otherwise} \end{cases},$$

the relation (26) can be written in the final form:

$$\hat{w}=sign(y)\left(|y|-\sqrt{2}\frac{\sigma_n^2}{\sigma}\right)_+ \quad (27)$$

The right hand side of equation (27) is the classical soft shrinkage function. This is the input-output relation of the MAP filter still called soft-thresholding filter. It requires to estimate σ_n^2, the noise variance and the standard deviation σ of the useful signal. The estimate of the noise variance is done by using the sequence of the details obtained after the DWT first iteration and the estimate of the standard deviation of the useful signal coefficients is done locally in a moving window. In short, if the scale inter-dependency of the DWT coefficients is not considered, the filter which should be used is the soft-thresholding filter with local threshold. In the following, this filter will be called marginal MAP filter.

b) On the other hand if the estimate takes into account two successive iterations, we can write: $w=(w_1, w_2)$ and the pdf proposed by Levent Sendur and Ivan W. Selesnick [3] for the wavelet coefficients, is:

$$P_w(w)=\frac{3}{2\pi\sigma^2}exp\left(-\frac{\sqrt{3}}{\sigma}\sqrt{w_1^2+w_2^2}\right) \quad (28)$$

Let us find the MAP estimator corresponding to the model given in (28), if the noise is again considered to be Gaussian distributed.

If we define $f(w)=\log(P_w(w))$, then (18) becomes:

$$\hat{w}(y)=$$

$$\underset{w}{arg\,max}\left[-\frac{(y_1-w_1)^2}{2\sigma_n^2}-\frac{(y_2-w_2)^2}{2\sigma_n^2}+f(w)\right] \quad (29)$$

This is equivalent to solve the system composed by the following two equations, if $f(w)$ is assumed to be strictly convex and differentiable:

$$\frac{y_1-\hat{w}_1}{\sigma_n^2}+f_1\left(\hat{w}\right)=0 \quad (30)$$

and:

$$\frac{y_2-\hat{w}_2}{\sigma_n^2}+f_2\left(\hat{w}\right)=0 \quad (31)$$

where f_1 and f_2 represent the derivative of $f(w)$ with respect to w_1 and w_2, respectively. Taking into account the relation (28), it can be written:

$$f(w)=log\left(\frac{3}{2\pi\sigma^2}\right)-\frac{\sqrt{3}}{\sigma}\sqrt{w_1^2+w_2^2} \quad (32)$$

and the solutions of the system already mentioned are:

$$f_1(w)=-\frac{\sqrt{3}w_1}{\sigma\sqrt{w_1^2+w_2^2}} \quad (33)$$

and:

$$f_2(w)=-\frac{\sqrt{3}w_2}{\sigma\sqrt{w_1^2+w_2^2}} \quad (34)$$

Solving (30) and (31) by using (33) and (34), the MAP estimator can be written as:

$$\hat{w}_1=\frac{\left(\sqrt{y_1^2+y_2^2}-\frac{\sqrt{3}\sigma_n^2}{\sigma}\right)_+}{\sqrt{y_1^2+y_2^2}}\cdot y_1 \quad (35)$$

This relation gives place to the use of a filter called bishrink filter.

IV. EXPERIMENTAL RESULTS

Section III enables us to consider two associations of possible filters:

1. In the case where the inter-scale dependency of the DWT coefficients is not considered, for the first iterations, we use the marginal MAP filter and for the last iterations, we use the Wiener filter. We called this association of filters, the MAP_Wiener filter.
2. When we take into account the inter-scale dependency of the coefficients of two successive iterations, the association that we called Bishrink_Wiener is used.

We simulated the denoising method proposed and compared the signal to noise ratio (SNR) enhancement obtained for these two associations of filters for the marginal MAP filter and for the bishrink filter, proposed in [1], called in the following Bishrink_f, for different values of the input SNR. The results are represented on figure 6.

A first conclusion obtained analyzing this figure is that the Bishrink_Wiener gives a better result than the bishrink filter and the Bishrink_f filter. This comes to confirm the theoretical results obtained in section III, highlighting the importance of commutation between models, especially when the inter-scale dependency is considered. Afterwards, there is not any difference between the MAP_Wiener filter and the marginal MAP filter. The two corresponding curves are identically. So, if the inter-scale dependency is not considered, the commutation between models is not required. These curves have the larger increasing speed, reason that makes us think that for the speech signals, the inter-scale dependency between the DWT coefficients of two consecutive iterations can be neglected in the denosing process.

We have repeated the experiments with colored noise. It was generated by filtering a zero mean white Gaussian noise with the aid of a first order IIR low-pass filter. We have simulated two such filters, having different cut-off frequencies. We have obtained each time practically the same results like those represented in figure 6. So, the denoising method proposed in this paper, is robust against the nature of the power spectral density of the perturbing noise. This is, of course, an important advantage of the proposed denoising method. It can be also observed that the proposed method has an excellent performance for low input SNRs. At – 5 dB, its SNR gain is of 10 dB.

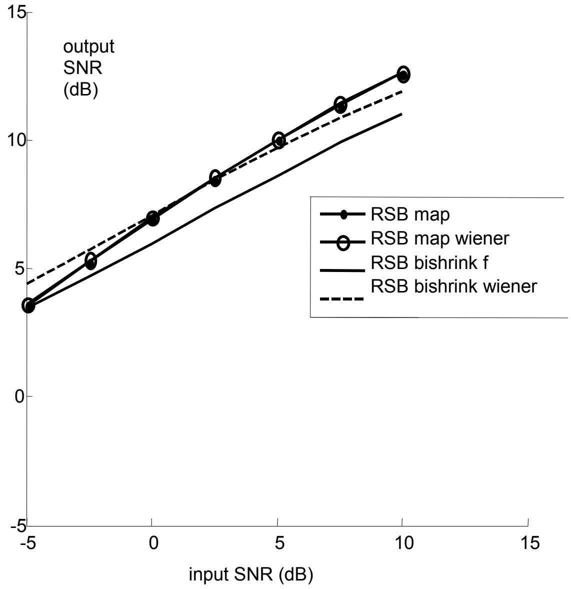

Fig. 6: Comparison of the output SNR for various MAP filters.

V. CONCLUSION

In this article, we proposed new methods of speech enhancement. At the beginning, on the basis of the statistical properties of the speech signals and those of the DWT coefficients, we showed that it is necessary to combine different MAP filters at different DEDWT decomposition levels for an efficient denoising. Combining different types of filters, deduced in this paper, we have built two MAP filters associations. To follow, we have tested, by simulation, these associations. The results obtained by comparing the output SNR, are better than those of the Bishrink filter and those of the Bishrink_f filter, used in [1]. So, the method proposed is better than the noise spectral subtraction method or the pure statistical denoising method, that has inferior SNR improvements, versus the association DEDWT-Bishrink_f, like is proved in [1]. Moreover, these results show that the association that does not take into account the inter-scale dependency of the DWT coefficients is the best for denoising speech signals. The method proposed is efficient especially for low input SNR signals (see figure 6). This is the reason why it can be used in applications where the quality of speech is very bad. For example, the proposed denoising method can be applied for the enhancement of the robustness of a Voice Activity Detector. When the SNR of the speech is high enough, the distortion introduced by the proposed denoising method is important, being better to avoid its utilization in applications where a high quality of the speech signal is required.

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