NON-LINEAR LOW-LEVEL IMAGE PROCESSING IMPROVEMENT BY A PURPOSELY INJECTION OF NOISE

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Abstract: It is progressively realized that noise can play a constructive role in nonlinear formation processes. The starting point of the investigation of such useful noise effect has been the study of the Stochastic Resonance (SR) effect. The goal of this article is to propose a direct application of SR phenomenon in image processing, for the interest of SR in that domain is growing-up. As a prolongation of previous work already presented in the literature by author, we propose to quantitatively show that a purposely injection of a gaussian noise in a classical nonlinear image process, as image binarization, can play a constructive action. This work can also be interpreted as a first step for a better understanding of SR in image processing relating it to classical results obtained in a nonlinear signal processing framework for classical low-level image processing tool.

1 INTRODUCTION

It is progressively realized that noise can play a constructive role in nonlinear formation processes. The starting point of the investigation of such useful noise effect has been the study of the Stochastic Resonance (SR) effect. This paradoxical effect was first introduced some twenty years ago in the domain of climate dynamics, as an explanation for the regular recurrences of ice ages (Benzi et al., 1982). Following this, SR effect has been introduced in nonlinear signal processing to describe the mechanism of a constructive action of a white Gaussian noise in the transmission of a sinusoid by a nonlinear dynamic system governed by a double-well potential. From this time, the phenomenon of stochastic resonance has experienced large varieties of extensions with variations concerning the type of noise, the type of information carrying signal or the type of nonlinear system interacting with the signal-noise mixture (see for example (Gammaitoni et al., 1998) for a review in physics, (Harmer et al., 2002) for an overview in electrical engineering and (Chapeau-Blondeau and Rousseau, 2002) for the domain of signal processing). All these extensions of the original setup preserve the possibility of improving the processing of a signal by means of an increase in the level of the noise coupled to this signal. At the moment, new forms of useful noise effect, related to stochastic resonance, continue to be demonstrated. A recent specific domain of interest for the study of this useful noise effect is nonlinear image processing (see (Morfu et al., 2008) for instance).

The goal of this article is to propose a direct application of SR phenomenon in image processing, for the interest of SR in that domain is growing-up. As authors have already shown it in (Histace and Rousseau, 2006; Histace and Rousseau, 2010), a possible application field is nonlinear image restoration. Nevertheless, in order to have a better understanding of the process and the constructive action of noise, we propose to study a more simple image processing tool: Image binarisation.

The main layout of this article is the following: Second section proposes a presentation of the global framework of stochastic resonance non limited to image processing. Whereas such presentation has already been made in various articles, it bears important historical and conceptual significance. For this reason, we choose to remain it. Third section deals with application of SR phenomenon to image binarization. Finally, results will be concluded and discussed.

2 A COMMON FRAMEWORK FOR STUDY OF SR EFFECT IN NONLINEAR PROCESSING

Today, it is now widely assumed that a global framework for SR can be defined for all type of demonstrated effects (Chapeau-Blondeau, 2000).

Stochastic resonance involves four essential ele-

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ments: (i) an information-carrying or coherent signal s: it can be deterministic, periodic or non, or random; (ii) a noise η, whose statistical properties can be of various kinds (white or colored, Gaussian or non,...): (iii) a transmission system, which generally is nonlir ear, receiving s and η as inputs under the influenc of which it produces the ouput signal y; (iv) a per formance or efficacy measure, which quantifies som "similarity" between the output y and the coherent ir put s (it may be a signal-to-noise ratio, a correlatio coefficient, a Shannon mutual information, ...). Sl takes place each time it is possible to increase th performance measure by means of an increase in th level of the noise η. Historically, the developmen of SR have proceeded through variations and exter sions over these four basic elements. From the origi and as it has already been mentioned in previous sec tion, SR studies have concentrated on a periodic cc herent signal s, transmitted by nonlinear systems of dynamic and bistable type (McNamara and Wieser feld, 1989). This form of SR now appears simply as special form of SR. This primary form of SR will nc be entirely described in this article but a complete de scription can be found in (Chapeau-Blondeau, 200C for instance. For illustration, we propose to illustrat phenomenon of SR in the framework of image trans mission as it was formerly proposed in (Chapeau Blondeau, 2000). This example has the advantage c its simplicity which makes both theoretical and ex perimental analysis possible. Leaning again on th general scheme of SR phenomenon, author consider this time that the coherent information-carrying sig nal s is a bidimensional image where the pixels ar indexed by integer coordinates (i, j) and have inter sity $s(i, j)$. For a simple illustration, a binary imag with $s(i, j) \in \{0,1\}$ is considered for experiment. A noise $\eta(i, j)$, statistically independent of $s(i, j)$, linearly corrupts each pixel of image $s(i, j)$. The noise values are independent from pixel to pixel, and are identically distributed with the cumulative distribution function $F_\eta(u) = Pr\{\eta(i, j) \leq u\}$. A nonlinear detector, that it is taken as a simple hard limiter with threshold θ, receives the sum $s(i, j) + \eta(i, j)$ and produces the output image $y(i, j)$ according to:

$$\text{If } s(i,j)+\eta(i,j) > \theta \quad \begin{array}{ll} \text{then} & y(i,j)=1, \\ \text{else} & y(i,j)=0. \end{array} \tag{1}$$

When the intensity of the input image $s(i, j)$ is low relative to the threshold θ of the detector, i.e. when $\theta > 1$, then $s(i, j)$ (in the absence of noise) remains undetected as the output image $y(i, j)$ remains a dark image. Addition of the noise $\eta(i, j)$ will then allow a cooperation between the intensities of images $s(i, j)$ and $\eta(i, j)$ to overcome the detection threshold. The result of this cooperative effect can be visually appreciated on Fig. 1, where an optimal nonzero noise level maximizes the visual perception.

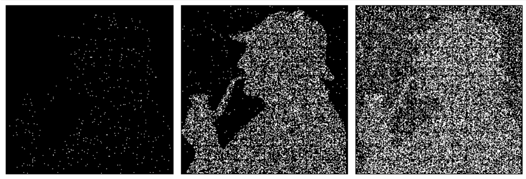

Figure 1: The image $y(i, j)$ at the output of the detector of Eq. (1) with threshold $\theta = 1.2$, when $\eta(i, j)$ is a zero-mean Gaussian noise with rms amplitude 0.1 (left), 0.5 (center) and 2 (right).

To quantitatively characterize the effect visually perceived in Fig. 1, an appropriate quantitative measure of the similarity between input image $s(i, j)$ and output image $y(i, j)$, is provided by the normalized cross-covariance defined in (Vaudelle et al., 1998) and given by:

$$C_{sy} = \frac{\langle (s - \langle s \rangle)(y - \langle y \rangle) \rangle}{\sqrt{\langle (s - \langle s \rangle)^2 \rangle \langle (y - \langle y \rangle)^2 \rangle}}, \tag{2}$$

where $\langle . \rangle$ denotes an average over the images.

C_{sy} can be experimentally evaluated through pixels counting on images similar to those of Fig. 1. Also, for the simple transmission system of Eq. (1), C_{sy} can receive explicit theoretical expressions, as a function of $p_1 = Prs(i, j) = 1$ the probabilty of a pixel at 1 in the binary input image $s(i, j)$, and as a function of the properties of the noise conveyed by $F_\eta(u)$ as mentioned in (Vaudelle et al., 1998).

Considering the above scenario, Fig. 2 shows variations of C_{sy} function of rms amplitude of the input noise η.

As one can see on Fig. 2, measure of cross-covariance as defined Eq. (2) identify a maximum efficacy in image transmission for an optimal nonzero noise level. This simple example is interpreted here as the first formalized instance of SR for aperiodic bidimensionnal input signal s (even if it is not clearly an image processing application).

We are now going to show that this kind of approach can be successfully transposed in a classical low-level image processing tool.

3 NOISE-AIDED IMAGE BINARIZATION

Let's consider image of Fig. 3. Let's now consider that our main goal is to binarize image of Fig. 3 in order to automatically extract barycenter of each coin.

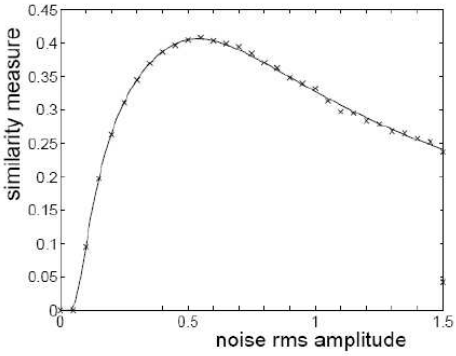

Figure 2: Input-output cross-covariance of Eq. (2) between input image $s(i,j)$ and output image $y(i,j)$, as a function of the rms amplitude of the noise $\eta(i,j)$ chosen zero-mean Gaussian. The crosses are experimental evaluations through pixels counting on images, the solid lines are the theoretical predictions ($p_1 = 0.6$) calculated by authors (Chapeau-Blondeau, 2000).

Figure 3: "coins" Image.

Classically, this task can be tackled by an automatic estimation of the optimal threshold corresponding to data to binarize. For instance, existing functions usually use Otsu's method (Otsu, 1979), which chooses the threshold to minimize the intraclass variance of the black and white pixels. Applying that kind of function to "coins" image leads to binarization results of Fig.4.

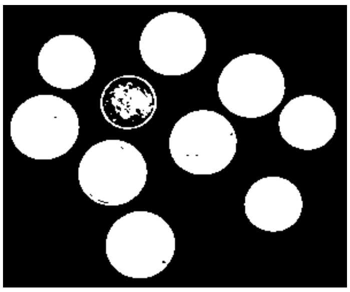

Figure 4: Binarized "coins" image using classical Otsu's method for automatic computation of optimal threshold level.

As one can notice, this approach is not satisfying since one coin (characterized by an average grey-level less important than other coins) will not be clearly detected during following processing steps. Empirical manual setting of the threshold can lead to more interesting results as shown Fig. 5.

Let's now consider, that existing method of Fig. 4 is a black box with no possibility to manually adjust threshold value to reach optimal result of Fig. 5.

Considering the classical framework of SR phenomenon, we now purposely corrupt original "coins" image with a white gaussian noise η of tunable standard deviation σ_η. Proposed process is then described by same equations as Eq. (1) with threshold θ corresponding to the value automatically computed thanks to Otsu's approach. In order to quantify the possible benefit of such addition, we choose to perform a measure of the normalized cross covariance of Eq. (2) between optimal result of Fig. 5 and obtained results for each value of σ_η. Result of this quantitative study is presented Fig. 6.

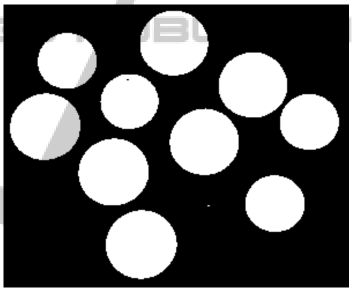

Figure 5: Binarized "coins" image using manual setting for threshold value.

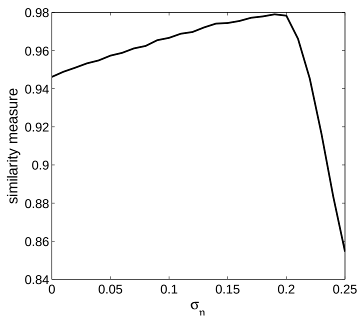

Figure 6: Normalized cross-covariance of Eq. (2) function of uniform purposely injected noise level σ_η.

As one can notice on Fig. 6, it is possible to reach an optimal value of the normalized cross-covariance for a non zero amount of noise. This is the classical signature of a SR phenomenon as demonstrated in previous section for nonlinear binary image transmission. One can also notice that the normalized cross-covariance fastly decrease once the optimal value is

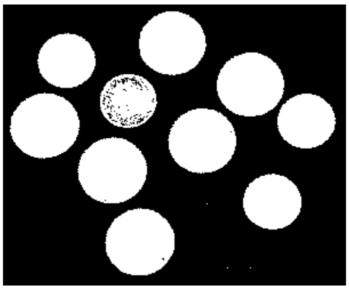

Figure 7: Optimal binarization result obtained for $\sigma_\eta = 0.19$.

reached: The large amount of corresponding noise, finally, completely degrade image information. Visually speaking, the optimal corresponding result presented Fig. 7 is very close from the optimal one of Fig. 5. Detection of the whole set of coins is now possible thanks to the purposely injection of η noise. Moreover, this experiment shows that it is now possible to adjust the inner threshold value of the binarization process thanks to an external tuning of noise level σ_η.

4 CONCLUSIONS

In this article, we show that the now well known SR phenomenon can find application in low-level image processing. More precisely, we show, thanks to a simple experiment, that a purposely injection of noise in a classical non tunable binarization process can lead to interesting results in term of optimal parameters setting. This is shown here as a proof of feasibility and more experiment will be made in order to clearly identify both theoretically and quantitatively the benefit of such an approach for more complex image processing tools as nonlinear image restoration for instance. This work can also be interpreted as a first step for a better understanding of SR in image processing relating it to classical results obtained in a nonlinear signal processing framework.

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