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# Statistically robust evidence of stochastic resonance in human auditory perceptual system

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**Abstract.** In human perception, exogenous noise is known to yield a masking effect, i.e. an increase of the perceptual threshold relative to a stimulus acting on the same modality. However, somehow counter-intuitively, the opposite mechanism can occasionally occur: a decrease of the perceptual threshold for a non-vanishing, *virtuous* amount of noise. This mechanism, called stochastic resonance, is deemed to provide important information about the role of noise in the human brain. In this paper, we investigate stochastic resonance in a detection task in the auditory modality. Normal-hearing participants were asked to judge the presence of acoustic stimuli of different intensity and superimposed to different levels of white noise. The matrix-like outcomes of a behavioural experiment were fitted by a two-dimensional, noise-dependent psychometric function. The fit revealed a statistically significant stochastic resonance in 43% of the experimental runs. We conclude that, in the auditory modality, stochastic resonance is a tiny effect that, under conventional circumstances, is largely overrun by standard masking.

**PACS.** 87.19.lc Noise in the nervous system – 43.66.Lj Perceptual effects of sound – 05.40.Ca Noise

## 1 Introduction

There is growing evidence that, under particular circumstances, the sensitivity of neural systems to weak signals can be enhanced by using an optimal amount of noise. As highlighted also in a very recent review [1], this phenomenon is known as stochastic resonance (SR) [2]. SR, first described in the framework of nonlinear physics, was demonstrated in a very wide range of research fields [3], all of them characterized by noise playing a non-detrimental role.

With regard to brain processes, a functional role of SR was documented in the human somatosensory system for balance control [4], the baroreflex system [5], and tactile sensitivity [6,7]. A model accounting for effects of SR in behavioural paradigms was discussed in [8]. This model relies on Signal Detection Theory (SDT) [9], the most successful model devised so far for the description of sensory and perceptual experiments. Evidence of SR has been shown in experiments addressing the visual modality [10–14], as well as in a cross-modal setup, in which visual perception improvement was driven by acoustic white noise [15]. Reference [16] provides a review of SR in sensory information processing.

SR in the human auditory system was observed at a physiological level [17], by investigating how transduction of mechanical stimulations into electrical signals depends on the amount of stochastic, mechanical fluctuations of hair cells. With regard to perception experiments, the first evidence of SR in the human auditory modality was described by Zeng et al. [18], in both normal hearing individuals and cochlear or brainstem implant recipients. Subjects were asked to detect the presence of a signal superimposed to a given level of white noise. By determining the perceptual threshold via a two-interval forced-choice adaptive staircase procedure (*three-down, one-up*, pointing at a correct detection rate of 79.4% [9,19]), a non-monotonic profile of perceptual threshold vs. noise intensity, with a minimum at a non-vanishing noise value, was reported. A similar experiment, though with normal hearing subjects only, was carried out by Long et al. [20]. The authors reported a somehow impressive improvement of human perception near the acoustic threshold. Finally, another recent work [21] addressed the role of different types of noise on acoustic perception, showing results similar to [18].

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All the works mentioned above claimed evidence of the occurence of SR in human acoustic perception. However, the statistical robusteness of these analyses appears to be questionable. In reference [18], the standard deviation relative to the data collected from the normal hearing subjects was one order of magnitude larger than the claimed threshold shift, whereas in reference [20] a quantification of the effect over the entire sample of subjects was lacking. In addition, the conspicuous threshold shift presented in [20] seems to be incompatible with the faint effect shown in [18]. With regard to [21], the statistical test used did not show SR unless data were heavily rearranged a posteriori.

A further, possibly decisive, concern regards the agreement between predictions, as discussed by Gong et al. [8], and experimental results. The analysis discussed in reference [8], which relies on SDT and agrees with experimental results achieved in the tactile sensory modality [6,7], rules out the possibility of observing SR whenever the correct detection rate overcomes 75%. This boundary level was clearly overcome in the works of references [18,20].

In the present paper we investigated SR in the auditory modality, carrying out an extensive analysis of sensory response in the presence of white noise on 11 normal-hearing subjects. We found SR in the auditory modality to be a tiny effect, largely masked by statistical fluctuations. Subjects were submitted to an experiment in which the task consisted in detecting an acoustic signal superposed to a varying amount of white noise. The role of noise in this experiment is therefore similar to that of other experiments that investigate SR in perception. Rather than using adaptive methods for the assessment of the sensory threshold, we used a straightforward "Yes-No" procedure to determine the functional dependence of the entire psychometric function on signal and noise intensity. Data were analyzed by means of a modified version of the Levenberg-Marquardt algorithm; this approach allowed us to fit the whole *threshold* – vs. – *contrast* (TvC) curve [22]. Thus, the evidence of SR can rely on a statistically significant degree of confidence (based on $\chi^2$) rather than on a simple visual inspection. Moreover, the predictions of reference [8] are not conflicting with our results.

The paper is organized as follows. In Section 2 we describe both the experimental setup and the phenomenological model devised to account for the effect of the noise on the acoustic perceptual threshold. Results, along with the details of the data analysis, are presented in Section 3. Finally, in Section 4, possible future perspectives are discussed.

## 2 Methods

The experimental setup is schematically shown in Figure 1. 11 normal-hearing participants were recruited to take part in the experiment (7 female, 4 male, age from 19 to 27, average 22, standard deviation 3); 9 subjects were naïve as to the purpose of the experiment. Participants were students or members of the University of Trento; they all provided informed consent before taking part in the experiment. Two different subjects performed the experiment two and three times, respectively. The experiment was conducted in a sound-attenuated room (Amplifon, Sispe Mod. G), located in the CIMeC's (Center for Mind/Brain Sciences) Psychophysics Laboratories in Rovereto (Italy). Acoustic stimuli were generated by means of C++ routines through an Audiophile 2496 PCI D/A converter (dynamic range 104 dB, dB relative to the full-scale) and presented monoaurally to the left ear of each participant through circumaural headphones (Sennheiser HD 580). Each acoustic stimulus consisted of a *signal* and a *noise* component of intensity $I_s$ and $I_n$, respectively. The signal was a 4000 Hz pure tone, whereas the noise was white Gaussian; henceforth, a stimulus will be identified by specifying the acoustic intensities, expressed in dB relatively to the full audio equipment range, of the noise and signal component as $(I_n, I_s)$. The stimulus duration was 400 ms. After each stimulus presentation, subjects were asked to judge whether or not they perceived the signal by pressing the 'S' or 'N' key on a computer keyboard, respectively. A new stimulus was presented 200 ms after the subject response.

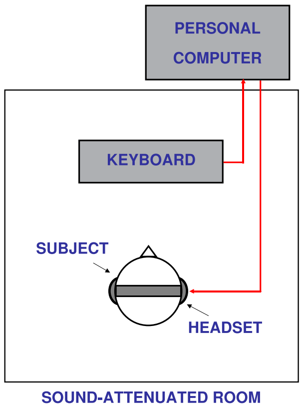


**Fig. 1.** (Color online) Schematic view of the experimental setup.

Given a noise level $I_n$, the psychometric function is assumed to be modelled by a Gaussian cumulative distribution function with mean $\mu$ and standard deviation $\sigma$. The mean $\mu$ is taken as the subjective perceptual threshold at that noise level. For each participant, to evaluate the masking effect, i.e. the increase of $\mu$ proportionally to $I_n$, and to detect SR, we assessed the TvC surface: this is defined as the probability of a "Yes" response as a function of the component intensities $(I_n, I_s)$ (see Fig. 2). To this purpose, on the strength of phenomenological considerations and in absence of any theoretical clue, we built a model for the TvC by considering a family of psychometric functions with constant standard deviation and noise-dependent perceptual threshold; in particular, we assumed the following hyperbolic profile for the threshold:

$$\mu(I_n) = \mu_0 + \frac{1}{2}\left[(1-k)(I_n - I_{nc})\right] + \frac{1}{2}\left[(1+k)\sqrt{(I_n - I_{nc})^2 + D^2}\right], \quad (1)$$

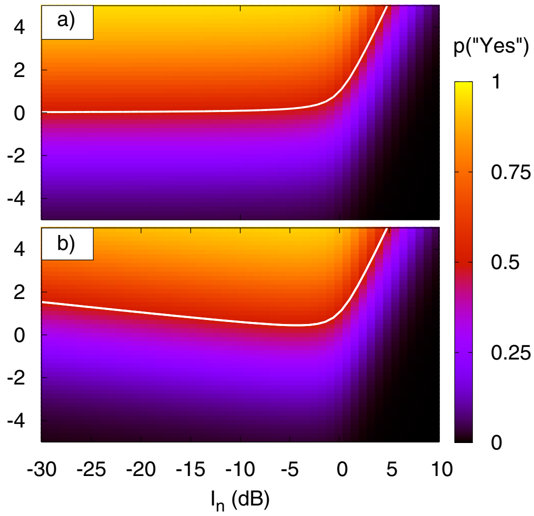


**Fig. 2.** (Color online) A color map of the TvC function; each white solid line corresponds to the profile of $\mu(I_n)$. The surface parameters are $\mu_0 = 0$ dB, $I_{nc} = 0$ dB, $\sigma = 3.0$ dB, and $D = 2.0$ dB. In a), $k = 0$ and the TvC shows no SR. In b) $k = 0.05$; the profile shows a minimum, i.e. a clear evidence of SR.

where $\mu_0$ is the subjective threshold in absence of external noise, $I_{nc}$ represents the critical noise intensity at which the masking effect starts to take place, $k$ corresponds to the slope of the negative asymptote, and $D$ is proportional to the distance between the focus of the hyperbola and the point of coordinates $(I_{nc}, \mu_0)$; this last parameter avoids the discontinuity in $(I_{nc}, \mu_0)$, conventionally used in the scientific literature (see, for example, Ref. [22]).

In Figure 2 a color map of our model for the TvC is presented. For $I_n > I_{nc}$, the thresholds is expected to linearly increase with the noise intensity on an absolute scale [22]. Since here the intensities are expressed in dB, the slope of the rightmost asymptote ($I_n \to \infty$) is unitary. On the contrary, the leftmost asymptote slope $k$ is a free parameter for the fit procedure. Under standard circumstances, i.e. if the unique effect of the noise is masking, the parameter $k$ would vanish. Moreover, there is no reason to expect negative values for $k$. On the other hand, a positive value of the parameter $k$ would correspond to a negative slope for the asymptote, yielding a minimum of equation (1) for $I_n \sim I_{nc}$. As SR is expected to occur if there is a minimum of the function $\mu = \mu(I_n)$ for a non-vanishing $I_n$ value, a positive $k$ value would be a sign of SR. The position of the minimum for $k > 0$, i.e. $I_n \sim I_{nc}$, is in agreement with what is suggested in previous works [8,18,20,21].

In order to optimally fit the model, we measured the TvC function on a suitable set of intensity values $(I_n, I_s)$: for each experimental run, the 2-dimensional region of interest was chosen by taking the point $(I_{nc}, \mu_0)$ as a reference. To this purpose, prior to the main experimental phase, we first measured the psychometric function without noise in order to obtain $\mu_0$. Then, we repeated the procedure by adding an amount of noise equal $\mu_0 + 30$ dB: we empirically found that, once this noise value was set, the resulting new threshold $\mu_1$ laid within the masking region. Since the slope in the masking region is unitary, disregarding SR effects ($k = 0$) and considering $D = 0$, it is easy to see that the critical noise value $I_{nc}$ can be estimated as $2\mu_0 + 30 - \mu_1$. To speed-up this preliminary measurement and thus circumvent the need for a break before the main experimental session, we developed an adaptive procedure that, starting from a set of 3 signal intensities (each presented 4 times), rapidly converged to the subjective psychometric parameters by choosing step-by-step new signal intensities according to a maximum likelihood estimation (MLE). The average duration of this preliminary measurements was 6(1) min.

In the main experimental session we defined a $NM$ grid in the $(I_n, I_s)$ plane; the grid steps were 2.5 dB and 1 dB for the noise and signal components, respectively. In addition, for each of the $N$ noise values, 3 stimuli with vanishing signal intensity were added to the grid in the perspective of further investigation; these stimuli are not included in the present analisys. The resulting set of $N(M + 3)$ stimuli were randomized; each stimulus was presented 4 times. We suitably centered the grid around the point $(I_{nc}, \mu_0)$ for each experiment. With regard to the signal component, the value $M = 11$ was chosen, and the grid was centered around $\mu_0$. With regard to the noise component, different configurations were used: the number of noise values investigated varied from $N = 11$ (6 runs), to $N = 12$ (2 runs), $N = 14$ (3 runs), and $N = 15$ (3 runs); $I_{nc}$ was positioned within 65% and 80% of the noise intensity range. Given the different $N$ values, the total number of presented trials was 616, 672, 784 and 840, respectively. The average duration of the whole experiment was 25(5) min.

Results can be summarized by a $NM$ histogram $R_{n,s}$ corresponding to the number of "Yes" responses given for each stimulus on the grid; the possible values for each bin are $0, 1, 2, 3, 4$. We fit the results by means of a chi-square ($\chi^2$) test: as a matter of fact, although the distribution events within a single bin is binomial and the number of events for each bin is only 4, we can use the $\chi^2$ test because of the large number of bins involved in the fit ($NM \geq 121$) [23]. We calculated the $\chi^2$ merit function by comparing each entry of $R_{n,s}$ with the expected value $r_{n,s}$, obtained from the TvC model and normalized so that $\sum_{n,s} R_{n,s} = \sum_{n,s} r_{n,s}$. To minimize the $\chi^2$, we used a Levenberg-Marquardt algorithm, suitably modified to take into account the modified statistics (binomial rather than Gaussian).

## 3 Results and discussions

Table 1 shows the values of $k$ for each experimental run. The right column reports the probability $p$ of the null hypothesis $k = 0$, given the measured $k$ value and its error, computed by means of the $\chi^2$ distribution.

The fit procedure yields new values of $I_{nc}$, $\mu_0$, and $\sigma$. To distinguish these values from those determined during the preliminary measurement of the two psychometric functions (with and without noise), we will henceforth

**Table 1.** Values of the parameter $k$ estimated by the fit of the TvC on the histograms $R_{n,s}$ for each participant; the numbers close to the subject's name are the number of different experiments run on that subject. The error on the last significant digit, correspondent to the standard deviation, is reported in parenthesis. The probability that $k = 0$, calculated according to the $\chi^2$ distribution, is shown. There is a single result with negative $k$. The other data are grouped according to whether the null hypothesis $k = 0$ is higher than $1-68.3\% = 31.7\%$. Four experimental runs are highlighted by an asterisk: as explained in the main text, these experiments show a strong discrepancies of the values of $I_{nc}$, $\mu_0$ as well as a large value of $\sigma$.

| Subject | $k$ | $p(k = 0)$ % |
|---|---|---|
| MC | 0.14(5) | 0.4 |
| DT1 | 0.27(1) | 2.0 |
| AV1 | 0.10(5) | 3.2 |
| RS | 0.03(2) | 16.1 |
| AV2 | 0.6(5) | 20.2 |
| AV3 | 0.2(2) | 30.3 |
| RT | 0.04(6) | 57.0 |
| DG* | 0.1(2) | 67.9 |
| MF* | 0.4(9) | 70.2 |
| AL* | 0.2(7) | 76.6 |
| SD | 0.01(5) | 77.4 |
| LN* | 1(2) | 82.7 |
| DT2 | 0.00(6) | 99.5 |
| EZ | –0.01(2) | 54.8 |

**Table 2.** A resume of the occurence of SR in the sample of subjects: the SR is present if $k$ is significantly larger than zero.

| Condition | Occurrence | Occurrence rate |
|---|---|---|
| $k > 0,\quad p(k = 0) \leq 31.7\%$ | 6 | 43 |
| $k > 0,\quad p(k = 0) > 31.7\%$ | 7 | 50 |
| $k <= 0,\quad p(k = 0) \leq 31.7\%$ | 0 | 0 |
| $k <= 0,\quad p(k = 0) > 31.7\%$ | 1 | 7 |

rename the former values as $I_{nc}^{pre}$, $\mu_0^{pre}$, and $\sigma^{pre}$, respectively. In order to test the reliability of the fit procedure, we computed for the parameters $I_{nc}$ and $\mu_0$ the deviation between the values estimated during the preliminary measurement and with the fit procedure, averaged over the entire sample of experimental runs. The results are $\langle|I_{nc} - I_{nc}^{pre}|\rangle = 4 \pm 17$ dB and $\langle|\mu_0 - \mu_0^{pre}|\rangle = 55 \pm 15$ dB. The latter result is significantly, and unexpectedly, different from zero. However, by ruling out the four worst cases, i.e. the experimental runs showing the maximum deviation of $\mu_0$ ($DG$, $MF$, $AL$ and $LN$), we obtained $\langle|I_{nc} - I_{nc}^{pre}|\rangle = 4 \pm 1.5$ dB and $\langle|\mu_0 - \mu_0^{pre}|\rangle = 1.6 \pm 1.5$ dB. Similar results were obtained with regard to $\sigma$: the average of this parameter over the entire sample is $20 \pm 35$ dB; however, by ruling out the four experimental runs mentioned above, one gets an average of $4 \pm 1$ dB. The rest of the sample can be considered homogeneous.

Table 2 shows the absolute and relative occurence of the SR effect in the sample of experimental sessions. In the majority of cases the parameter $k$ assumes a positive value; however, this positiveness is statistically significant only in the 43% of the experimental runs. In addition, the improvement of the stimuli detection is small in comparison with the shift of the perceptual threshold caused by the masking effect.

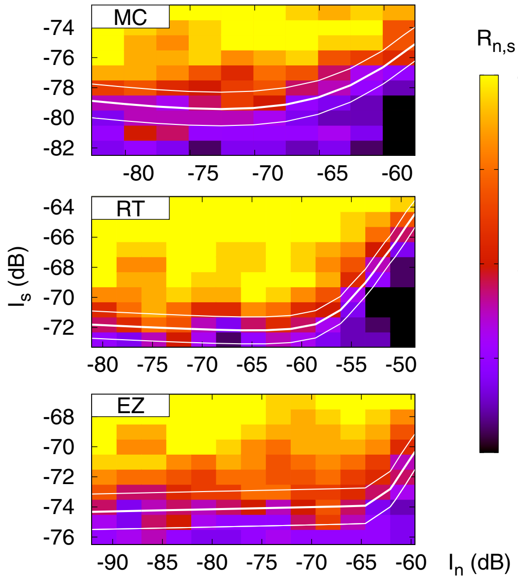


**Fig. 3.** (Color online) Color map of the $R_{n,s}$ matrix for three different experimental runs. On each map, the corresponding profiles of $\mu(I_n) + \sigma/3$ (top-line), $\mu(I_n)$ (middle-line) and $\mu(I_n) - \sigma/3$ (bottom-line), obtained by fitting the data with the model, are shown.

Figure 3 shows three color maps of the experimentally-determined $R_{n,s}$ matrix as well as the profiles of $\mu(I_n)$ and $\mu(I_n) \pm \sigma/3$. For the subject $MC$, the profile of $\mu(I_n)$ shows a pronounced minimum below the onset of the masking effect, which can be interpreted as evidence of SR. On the contrary, both subject $RT$ and subject $EZ$ show either a less detectable minimum or a flat profile. In all the three cases, the occurrence of the masking effect is evident.

## 4 Conclusions

We reported a statistically robust method, based on $\chi^2$ statistics, to demonstrate the occurrence of SR in psychophysical experiments. When applied to the context of signal and noise in the auditory modality it reveals that SR does exist, however it is less consistent with respect to what has previously been reported in the literature. This finding has two main implications. First, it reveals that SR in the auditory modality is a small effect, easily masked by fluctuations of the perceptual threshold. This conclusion provides some serious constraints to the suggested applications of auditory SR for earing-aid devices or prosthesis (such as cochlear implants). Second, it calls for a re-examination of the SR effect in vision and somatosensation using our statistically robust methodology. This could help clarify whether the difference in SR size between audition and the other sensory modalities reflects different methodological approaches or instead some fundamental difference between the various perceptual systems.

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## References

1. A.A. Faisal, L.P.J. Selen, D.M. Wolpert, Nature Review Neuroscience **9**, 292 (2008)
2. R. Benzi, A. Sutera, A. Vulpiani, J. Phys. A **14**, L453 (1981)
3. L. Gammaitoni, P. Hänggi, P. Jung, F. Marchesoni, Rev. Mod. Phys. **70**, 223 (1998)
4. A. Priplata, J. Niemi, M. Salen, J. Harry, L.A. Lipsitz, J.J. Collins, Phys. Rev. Lett. **89**, 238101 (2002)
5. I. Hidaka, D. Nozaki, Y. Yamamoto, Phys. Rev. Lett. **85**, 3740 (2000)
6. J.J. Collins, T.T. Imhoff, P. Grigg, Nature **383**, 770 (1996)
7. J.J. Collins, T.T. Imhoff, P. Grigg, Phys. Rev. E **56**, 923 (1997)
8. Y. Gong, N. Matthews, N. Qian, Phys. Rev. E **65**, 031904 (2002)
9. D.M. Green, J.A. Swets, *Signal Detection Theory and Psychophysics* (Wiley, New York, 1966)
10. R.M. Siegel, H.L. Read, J. Stat. Phys. **70**, 297 (1993)
11. E. Simonotto, M. Riani, C. Seife, M. Roberts, J. Twitty, F. Moss, Phys. Rev. Lett. **78**, 1186 (1997)
12. E. Simonotto, F. Spano, M. Riani, A. Ferrari, F. Levrero, A. Pilot, P. Renzetti, R.C. Parodi, F. Sardanelli, P. Vitali, J. Twitty, F. Chiou-Tan, F. Moss, Neurocomputing **26**, 511 (1999)
13. H. Sasaki, M. Todorokihara, T. Ishida, J. Miyachi, T. Kitamura, R. Aoki, Neurosci. Lett. **408**, 94 (2006)
14. H. Sasaki, S. Sakane T. Ishida, M. Todorokihara, T. Kitamura, R. Aoki, Neurosci. Lett. **436**, 255 (2008)
15. E. Manjarrez, I. Mendez, L. Martinez, A. Flores, C.R. Mirasso, Neurosci. Lett. **415**, 231 (2007)
16. F. Moss, L.M. Ward, W.G. Sannita, Clinical Neurophysiology **115**, 267 (2004)
17. F. Jaramillo, K. Wiesenfeld, Nat. Neurosci. **1**, 384 (1998)
18. F. Zeng, Q.J. Fu, R. Morse, Brain Res. **869**, 251 (2000)
19. L. Faes, G. Nollo, F. Ravelli, L. Ricci, M. Vescovi, M. Turatto, F. Pavani, R. Antolini, Perception & Psychophysics **69**, 254 (2007)
20. Z.C. Long, F. Shao, Y.P. Zhang, Y.G. Qin, Phys. Lett. A **323**, 434 (2004)
21. D.T. Ries, Hearing Research **228**, 136 (2007)
22. L.A. Lesmes, S.T. Jeon, Z.–L. Lu, B.A. Dosher, Vision Research **46**, 3160 (2006)
23. W.H. Press, S.A. Teukolsky, W.T. Vetterling, B.P. Flannery, *Numerical Recipes in C++* (Cambridge University Press, 2003)