Wireless Pers Commun
DOI 10.1007/s11277-010-0113-6

A Study of MIMO Gaussian Channels Based on Synergetics

Hai-Lin Xiao · Shan Ouyang · Cheng-Xiang Wang · Feng Zhao

Abstract By interpolating between information theory and synergetics, we provide a bridge to connect the two kinds of subjects. As an application, the capacity formula of multiple-input multiple-output Gaussian channels based on the Fokker-Planck Equation of the synergetics is derived. It is in accordance with Telatar's capacity formula in information theory and gives a physical explanation (order parameters) of the observed channel characteristics. Moreover, the master equation of the information theory is also derived to obtain error exponents. Error exponents provide a partial solution to how to get close to channel capacity by giving an upper bound to the probability of error. These results demonstrate that the notion of synergetics introduced here can serve as an intuitive tool in information theory.

Keywords Synergetics · MIMO · Gaussian channel · Capacity analysis · Error exponents

1 Introduction

Information theoretic analyses during the mid 1990s [1,2] have demonstrated a potentially huge gain in capacity of wireless systems by the use of multiple antennas at both the transmitter and receiver ends. The capacity grows linearly with $\min(M, N)$, when employ-

H.-L. Xiao (✉) · S. Ouyang · F. Zhao
School of Information and Communication, Guilin University of Electronic Technology, Guilin 541004, China
e-mail: xhl_xiaohailin@163.com

S. Ouyang
e-mail: hmoysh@guet.edu.cn

F. zhao
e-mail: ZhaoFeng@guet.edu.cn

C.-X. Wang
Joint Research Institute for Signal and Image Processing, School of Engineering and Physical Sciences, Heriot-Watt University, Edinburgh EH14 4AS, UK
e-mail: cheng-xiang.wang@hw.ac.uk

Published online: 28 August 2010

ing M transmit antennas and N receive antennas. These initial results were based on simple multiple-input multiple-output (MIMO) channel models with independent flat fading among sub-channels [3–5]. In practice, MIMO channels are an abstract and have many different communication environments of diverse physical nature. The real capacity gain by MIMO system in particular environment strongly depends on its propagation characteristics. The channel parameters are evaluated by a set of measurements in studied environments, or by simulating propagation models [6,7]. The measurement approach requires MIMO experimental measurement platforms, and gives access to pertinent information about the radio channel for both indoor and outdoor wireless communication scenarios. However, this approach presents difficulties: such as the complicated calibration step and the high cost. Consequently, an approach based on simulations is sought. There are two families of models: the statistical type and the deterministic type [4,5]. The statistical type can normally be applied to several environmental configurations with reasonable model accuracy and complexity. A deterministic model is more complex, but also more accurate for a special MIMO environment or scenario. Unfortunately, the complexity of the environment description indicates that dynamic instabilities exist in MIMO communication systems.

In recent years much effort has been devoted to understanding the origin of dynamic instabilities [8], induced by time-varying channel, in MIMO communication systems. The corresponding channel model was used to generate channel matrices whose space-time characteristics closely match those of realistic scenarios, particularly when birth and death of multipath clusters are considered in the stochastic representation. Meanwhile, numerous experimental and theoretical studies mainly on channel propagation environment have clearly demonstrated that instabilities leading to a chaotic behavior can easily be induced in a broad class of nonlinear systems [9].

The concepts of synergetics can be applied to a general class of nonlinear systems. It is an interdisciplinary field of macroscopic spatial, temporal and spatio-temporal structures arising out of chaos [10,11]. Synergetics is a mathematical model representing self-organization dynamics in a complex system. The state dynamics in synergetics is described with differential equations including two kinds of parameters called attention parameter and order parameter. A method for stereo matching problem in computer vision using synergetics was presented in [12]. The method has the two features: one is flexibility produced by constructing the parameters, and the other is low computational cost because of the possibility of parallel computability. Moreover, synergetics was used to study information theory [13], it provides a powerful tool for probing the fundamental nature of the driving forces of self-organization with respect to information storage, data processing, and so on, in living and manmade systems. Synergetics is established on the foundation of many scientific subject relations [14] and has achieved important application fruits in many ways (see [15–19] and references therein). However, very few studies are available in information domain, especially MIMO mobile communication systems.

In this paper, we provide a bridge to connect the information theory and synergetics. As an application, the capacity formula of MIMO Gaussian channels based on the Fokker-Planck Equation of the synergetics is derived. It is in accordance with Telatar's capacity formula in view of information theory and gives a physical explanation of the observed channel characteristics. Moreover, the master equation of the information theory is also derived to obtain error exponents. Error exponents provide a partial solution to how to get close to channel capacity by giving an upper bound to the probability of error. These results demonstrate that the notion of synergetics introduced here can serve as an intuitive tool in information theory.

The rest of the paper is organized as follows. In Sect. 2, the capacity formula of MIMO Gaussian channels based on the Fokker-Planck Equation of the synergetics is derived. In Sect. 3 , the master equation of the information theory is derived to obtain error exponents and numerical results of error exponents are presented. The paper is finally summarized in Sect. 4.

Notation: Boldface upper case letters denote matrices, boldface lower case letters denote column vectors, and italics denote variable quantities. The superscripts$(\cdot)^*$and$(\cdot)^+$ denote complex conjugate and Hermitian operations, respectively. $\det(\cdot)$and$E[\cdot]$ denote determinant and expectation of a matrix, respectively.

2 MIMO Gaussian Channel Capacity

For a MIMO system with n_T transmit antennas and n_R receive antennas over a general linear vector MIMO Gaussian channel, the received signal vector $\mathbf{y}$ can be expressed by [1,20]

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \tag{1}$$

where all quantities are complex-valued, $\mathbf{x}$ is the transmitted signal vector, $\mathbf{H}$ is the $n_R \times n_T$ matrix, and $\mathbf{n}$ is an n_R-dimensional zero-mean complex Gaussian noise vector with independent, equal variance real and imaginary parts. The noise covariance matrix is

$$\sum_{\mathbf{n}} = E[(\mathbf{n} - E[\mathbf{n}])(\mathbf{n} - E[\mathbf{n}])^+] \tag{2}$$

It is assumed that $\sum_{\mathbf{n}} = \mathbf{I}_{n_R}$, that is, the noises corrupting the different receivers are independent. The transmitter is constrained in its total power to$P$, i.e.,

$$E[\mathbf{x}^+\mathbf{x}] \leq P. \tag{3}$$

A complex random vector $\mathbf{x}$ is said to be Gaussian if the real part of an Hermitian matrix is symmetric and imaginary part of an Hermitian matrix is anti-symmetric. In this case, a complex Gaussian random vector $\mathbf{x}$ is circularly symmetric complex Gaussian random vector. Its mean value and covariance are given by

$$E[\mathbf{x}] = \mu \tag{4}$$

$$\sum_{\mathbf{x}} = E[(\mathbf{x} - E[\mathbf{x}])(\mathbf{x} - E[\mathbf{x}])^+] = Q. \tag{5}$$

The input probability density function of a circularly symmetric complex Gaussian with μ and covariance Q is given by

$$P(\mathbf{x}) = \det(\pi Q)^{-1} \exp[-(\mathbf{x} - \mu)^+ Q^{-1} (\mathbf{x} - \mu)]. \tag{6}$$

The output conditional probability density function corresponding to the linear vector Gaussian model is written as

$$P_{\mathbf{y}|\mathbf{x}}(\mathbf{y}) = \frac{1}{\det\left(\pi \sum_{\mathbf{n}}\right)} \exp\left[-(\mathbf{y} - \mathbf{H}\mathbf{x})^+ \sum_{\mathbf{n}}^{-1} (\mathbf{y} - \mathbf{H}\mathbf{x})\right] \tag{7}$$

To find a proper tool for the evaluation of the corresponding probability, we make use of the equation that it has established in synergetics. The equation is capable of describing both deterministic and random processes in the motion of the particle and can be expressed as

$$\frac{dP}{dt} = \frac{d}{dq}(\gamma q P) + \frac{1}{2}\xi \frac{d^2}{dq^2} P. \tag{8}$$

This equation is the so-called Fokker-Planck equation that it describes the change of the probability distribution P of a particle during the course of time t. $-\gamma q$ is called drift-coefficient, while ξ is known as diffusion coefficient. The same method can also be exactly applied to the general case of many variables. Next, our goal is to derive an equation for the output conditional probability density function of the linear vector Gaussian channel. We make use of (8) and obtain the corresponding Fokker-Plank equation of the MIMO Gaussian channels as

$$\frac{df}{dt} = \frac{d}{dq}(-\lambda f) + \frac{1}{2}\eta \frac{d^2}{dq^2} f \tag{9}$$

$$f = \ln P_{\mathbf{y}|\mathbf{x}}(\mathbf{y}) \tag{10}$$

where q, λ and η, and denote parameters of channel, conditional coefficient and transfer coefficient, respectively. In MIMO Gaussian channels, the logarithm of conditional probability density function is time independent and $df/dt = 0$ holds. Therefore, the (9) can be rewritten as

$$\frac{d}{dq}(-\lambda f) + \frac{1}{2}\eta \frac{d^2}{dq^2} f = 0. \tag{11}$$

Without loss of generality, (11) can be integrated with respect to the conditional probability density function $P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})$ and is given by

$$\lambda \frac{d}{dq} \int_R (-P_{\mathbf{y}|\mathbf{x}}(\mathbf{y}) \ln P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})\mathbf{dy} - \frac{1}{2}\eta \int_R -\left[\frac{d}{dq} \ln P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})\right]^2 P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})\mathbf{dy} = 0. \tag{12}$$

Let $I(P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})) := -\int_R (-P_{\mathbf{y}|\mathbf{x}}(\mathbf{y}) \ln P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})\mathbf{dy}$ be the Shannon entropy of the conditional probability density function, where ":=" denotes definition. Now, we generate the mathematical definition of Fisher information [21,22].The Fisher information is a way of measuring the amount of information that an observable random variable x carries about an unknown parameter θ upon the likelihood function of θ, $L(\theta) = f(x; \theta)$, depends. Let $\{P_q : q \in R\}$ be a family of conditional probability densities (or more generally, likelihood functions) parameterized by a parameter q. The Fisher information of P_q (with respect to the parameter q) is defined as

$$J[P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})] := \int_R \left[\frac{d}{dq} \ln P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})\right]^2 P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})\mathbf{dy}. \tag{13}$$

From (12) and (13), a remarkable relation can be obtained if the valued of the normalized order parameters equals one, i.e.,

$$\frac{d}{dq} I[P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})] = \frac{1}{2} J[P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})]. \tag{14}$$

This link between Fisher information and entropy is known as de Bruijn's identity [23,24]. The application of de Bruijn's identity to quantum systems is straightforward. The most direct application is to analyze and understand the sensitivity and robustness of a system to variations in certain parameters. In the following, we will discuss how to apply de Bruijn's identity to MIMO Gaussian channels. In information theory, the mutual information $I(\mathbf{x};\mathbf{y})$ is described by

$$I(\mathbf{x};\mathbf{y}) = H(\mathbf{y}) - H(\mathbf{y}|\mathbf{x}) = H(\mathbf{y}) - H(\mathbf{n}). \tag{15}$$

Channel capacity can be obtained by maximizing $I(\mathbf{x};\mathbf{y})$. The output conditional probability density function is given in (7), and the output unconditional probability density function can be written as $P(\mathbf{y}) = E_{\mathbf{x}}[P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})]$. The mutual information is given by

$$I(\mathbf{x};\mathbf{y}) = E\left[\log\frac{P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})}{P_{\mathbf{y}}(\mathbf{y})}\right] = -\log\det\left(\pi e\sum_{\mathbf{n}}\right) - \int P_{\mathbf{y}}(\mathbf{y})\log P_{\mathbf{y}}(\mathbf{y})\mathbf{dy}. \tag{16}$$

For MIMO Gaussian channels an extension of (14) to the gradients information measures with respect to $\mathbf{H}$ is given by

$$\frac{\partial}{\partial\mathbf{H}}I(\mathbf{x};\mathbf{Hx}+\mathbf{n}) = J(\mathbf{Hx}+\mathbf{n}) \tag{17}$$

where the definition $J(\mathbf{y}) := J(\mathbf{Hx}+\mathbf{n})$ is used in Refs. [24], and $\mathbf{H}$ is channel matrix with complex Gaussian distributed entries. For Fisher's information matrix, $J(\mathbf{y})$ is defined as

$$J(\mathbf{y}) := E_{\mathbf{y}}[\nabla_{\mathbf{y}}\log P_{\mathbf{y}}(\mathbf{y})\nabla_{\mathbf{y}}^{+}\log P_{\mathbf{y}}(\mathbf{y})]. \tag{18}$$

Now, using

$$\nabla_{\mathbf{y}}P_{\mathbf{y}}(\mathbf{y}) = \nabla_{\mathbf{y}}E_{\mathbf{x}}[P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})] = E_{\mathbf{x}}[\nabla_{\mathbf{y}}P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})] = -P_{\mathbf{y}}(\mathbf{y})(\mathbf{y}-\mathbf{H}E[\mathbf{x}|\mathbf{y}]) \tag{19}$$

and substituting (19) into (18), we get

$$\begin{aligned} J(\mathbf{y}) &= E[(\mathbf{y}-\mathbf{H}E[\mathbf{x}|\mathbf{y}])(\mathbf{y}-\mathbf{H}E[\mathbf{x}|\mathbf{y}])^{+}] = E[\mathbf{yx}^{+}] - E[\mathbf{H}E[\mathbf{x}|\mathbf{y}]E[\mathbf{x}^{+}|\mathbf{y}] \\ &= \mathbf{H}(E[\mathbf{xx}^{+}] - E[E[\mathbf{x}|\mathbf{y}]E[\mathbf{x}^{+}|\mathbf{y}]]) = \mathbf{H}(E[\mathbf{xx}^{+}] - E[E[\mathbf{x}|\mathbf{Hx}+\mathbf{n}]E[\mathbf{x}^{+}|\mathbf{Hx}+\mathbf{n}]]) \\ &= \mathbf{H}\sum_{\mathbf{x}}\left(\mathbf{I}_{n_R} + \mathbf{H}^{+}\mathbf{H}\sum_{\mathbf{x}}\right)^{-1}. \end{aligned} \tag{20}$$

Substituting (20) into (17), we obtain

$$\frac{\partial}{\partial\mathbf{H}}I(\mathbf{x};\mathbf{Hx}+\mathbf{n}) = \mathbf{H}\sum_{\mathbf{x}}\left(\mathbf{I}_{n_R} + \mathbf{H}^{+}\mathbf{H}\sum_{\mathbf{x}}\right)^{-1}. \tag{21}$$

Integrating (21), the maximum mutual information is given by

$$I(\mathbf{x};\mathbf{y})_{\max} = \log\det\left(\mathbf{I}_{n_R} + \mathbf{H}\sum_{\mathbf{x}}\mathrm{H}^{+}\right) = \log\det(\mathbf{I}_{n_R} + Q\mathbf{H}^{+}\mathbf{H}) \tag{22}$$

where $\mathbf{I}_{n_R}$ is the $n_R \times n_R$ identity matrix. The equation (22) is in accordance with Telatar's capacity formula of MIMO Gaussian Channels [2]. The behavior of MIMO Gaussian channels may be controlled from the outside by specific control parameters matrix $\mathbf{H}$. They are also called order parameters in synergetics theory, as the channels can no longer adjust its state smoothly and one or several collective variables may become unstable. These unstable configurations serve as order parameters. They describe the evolving order and simultaneously give orders to the subchannels on how to behave so that the ordered state is maintained. Hence, we are able to generalize the concept of order parameters in such a way that the Fokker-Planck Equation of the synergetics can systematically be applied to nonlinear system in MIMO Gaussian channel. By analyzing order parameters $\mathbf{H}$ for MIMO Gaussian

Channels, it is possible to determine whether a capacity can be obtained using a general purpose "generic" channel model or a more specific "high-level" channel. At critical values of the order parameters, the problem becomes unsolvable without the addition of extra prior knowledge.

3 Error Exponents

Usually, it is not always sufficient that we know the capacity formula of a channel. We must know how to get close to the channel capacity. Error Exponents provide a partial solution to the problem by giving an upper bound to the probability of error, it is achieved by block codes of a given length n and code rate$R$. The upper bound [2] is known as the random coding bound and is given by

$$\Psi(\text{error}) \leq \exp\left(-nE_r(R)\right) \tag{23}$$

where $\Psi(\text{error})$ is the probability of error. The random coding exponent $E_r(R)$ is given by

$$E_r(R) = \max_{0\leq\rho\leq 1} E_0(\rho) - \rho R \tag{24}$$

where ρ denotes modified coefficient $(0 \leq \rho \leq 1)$. In turn, $E_0(\rho)$ is given by the supremum over all input distribution q_x satisfying the energy constraint of

$$E_0(\rho, q_x) = -\log \int \left[\int q_x(x) P_{\mathbf{y}|\mathbf{x}}(\mathbf{y})^{1/(1+\rho)} dx\right]^{1+\rho}. \tag{25}$$

In MIMO Gaussian channels, we substitute (7) into (25) and obtain

$$E_r(R) = \rho \log\det\left(\mathbf{I}_{n_R} + (1+\rho)^{-1}\mathbf{H}Q\mathbf{H}^{+}\right) - \rho R. \tag{26}$$

In this subsequence section, in order to give the compact upper bound of error exponents, we derive the master equation of information theory to obtain the condition that the parameter $nE_r(R)$ is satisfied. The probability of signals m at a time t, $p(m,t)$, increases due to transition from other signals m' to the signals m under signals decision error. Therefore, we have the general relation

$$\frac{dp(m,t)}{dt} = \text{rate in-rate out}. \tag{27}$$

Since the "rate in" consists of all transitions from initial signals m' to m, it is composed of the sum over the initial signals. Each term of it is given by the probability at signals m', multiplied by the transition probability $w(m,m')$ per unit time to pass from m' to m. Thus, we obtain

$$\text{rate in} = \sum_{m'} w(m,m')p(m',t). \tag{28}$$

In a similar way, we find for the outgoing transitions the relation

$$\text{rate out} = p(m,t)\sum_{m'} w(m',m). \tag{29}$$

Putting (28) and (29) into (27), we obtain

$$\frac{dp(m,t)}{dt} = \sum_{m'} w(m,m')p(m',t) - p(m,t)\sum_{m'} w(m',m) \tag{30}$$

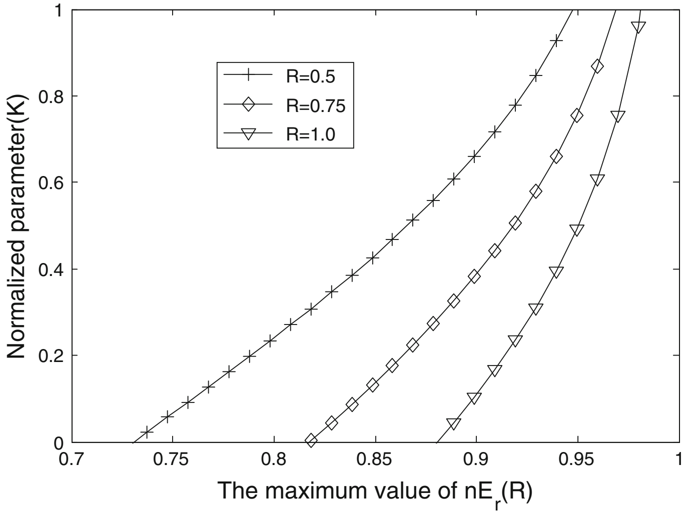

Fig. 1 The relation among normalized parameter k, the code rate R and the maximum value of $nE_r(R)$.

which is called the master equation of information theory. The crux to generate the master equation of information theory is to determine the transition probability $w(m, m')$and $w(m', m)$. In information theory, the signal transition probability is actually error probability, which is defined as

$$w(m, m') = \psi'(\text{error}) = e^{-kz} \tag{31}$$

where k denotes normalized parameter, and z is defined as $nE_r(R)$. The following relation holds

$$\sum_m p(m, t) = \varepsilon, \quad \sum_{m'} p(m', t) = 1 - \varepsilon. \tag{32}$$

substituting (31) and (32) into (30) and using the Stirling formula for approximation, we have

$$p_{st}[v(z)] = p_{st}(0) \exp[v(z)] \tag{33}$$

where $v(z) = -kz^2 + [z \ln z + (1 - z) \ln(1 - z)]$.

The extreme value is given by

$$\frac{\partial v(z)}{\partial z}|_{z=z_m} = -2kz_m + [\ln z_m - \ln(1 - z_m)] = 0. \tag{34}$$

Thus, $\ln \frac{z_m}{1-z_m} = 2kz_m$, and then $z_m = \tan kz_m$, where z_m denotes the maximum value of $nE_r(R)$. This means when $\psi'(\text{error})$ has the minimum value, and we obtain the compact upper bound of error exponents through not considering block codes of a given length n and rate R.

Fig. 1 illustrates the relation among normalized parameter k, the code rate R and the maximum value of $nE_r(R)$. It is shown that the maximum value of $nE_r(R)$ increases as the code rate R increases for the same normalized parameter k. This is because the code rate increases the length of signals n that they can bring a rather large probability of error.

4 Conclusions

A novel notion of synergetics with respect to information theory has introduced. As an application, the capacity formula of MIMO Gaussian channels based on the Fokker-Planck Equation has been derived. It is in accordance with Telatar's capacity formula in view of information theory and gives a physical explanation (order parameters) of the observed channel characteristics. Moreover, the master equation of the information theory is derived to obtain error exponents. Error exponents provide a partial solution to how to get close to channel capacity by giving an upper bound to the probability of error, and do not consider respectively block codes of a given length n and code rate R. These studies have demonstrated that the notion of synergetics introduced here could serve as an intuitive tool in information theory.

It should be emphasized that we have only worked on the MIMO Gaussian channels. Although the extension to the others channels, e.g., Rayleigh channels, Ricean channels, seems straightforward, it is out of the scope of this paper. However, we remark that this extension is more relevant in applications to information theory and will be our future work.

References

1. Foschini, G. J., & Gans, M. J. (1998). On limits of wireless communications in a fading environment when using multiple antennas. *Wireless Personal Communications, 6*, 311–317.
2. Telatar, I. E. (1999). Capacity of multi-antenna Gaussian channels. *European Transaction on Telecommunications, 10*, 585–595.
3. Xiao, H.-L, Ouyang, S., & Nie, Z. P. (2010). Design and performance analysis of compact planar inverted-L diversity antenna for handheld terminals. *Wireless Personal Communications, 52*, 709–718.
4. Wang, C.-X., Pätzold, M., & Yuan, D. (2007). Accurate and efficient simulation of multiple uncorrelated Rayleigh fading waveforms. *IEEE Transactions on Wireless Communications, 6*, 833–839.
5. Wang, C.-X., Yuan, D., Chen , H. H., & Xu, W. (2008). An improved deterministic SoS channel simulator for efficient simulation of multiple uncorrelated Rayleigh fading channels. *IEEE Transactions on Wireless Communications, 7*, 3307–3311.
6. Wang, C.-X., Hong, X., Ge, X., Cheng, X., Zhang, G., & Thompson, J. S. (2010). Cooperative MIMO channel models: A survey. *IEEE Communications Magazine, 48*, 80–87.
7. Wang, C.-X., Cheng, X., & Laurenson, D. I. (2009). Vehicle-to-vehicle channel modeling and measurements: Recent advances and future challenges. *IEEE Communications Magazine, 47*, 96–103.
8. Chen, C., & Jensen, M. A. (2009). A stochastic model of the time-variant MIMO channel based on experimental observations. *IEEE Transactions on Vehicular Technology, 58*, 2618–2625.
9. Czink, N., Yin , X. F., Ozcelik, H., & Herdin, M. (2007). Cluster characteristics in a MIMO indoor propagation environment. *IEEE Transactions on Wireless Communications, 6*, 1465–1475.
10. Haken, H. (1984). *Synergetic application in socioeconomic systems*. Beijing: Higher Education Press.
11. Haken, H. (1983). *Synergetics third revised and enlarged edition*. New York: Springer.
12. Irie, T., Katou, H., & Maeda, H. (2003). Object recognition from stereo images using synergetics and combinatorial optimization. *SICE Annual Conference in Fukui, 4*(6), 20.
13. Xiao, H.-L., & Nie , Z. P. (2007). A new method for the study of binary discrete channel average mutual information. *Acta Physics Sinica, 57*, 1948–1952.
14. Nakajima, C. H., & Hukushima, K. (2008). Phase transition of a spin-lattice-gas model with two timescales and two temperatures. *Physics Review Part E, 78*, 041132–041137.
15. Bannur, M. V. (2008). Self-consistent quasiparticle model for 2, 3, and (2+1) flavor QGP. *Physics Review C, 78*, 045206.
16. Torrieri, G., Jeon, S. Y., & Rafelski, J. (2006). Particle yield fluctuations and chemical nonequilibrium in Au-Au collisions. *Physics Review C, 74*, 024901–024908.
17. Yuan, J., Ren, Y., & Shan, X. (2000). Self-organized criticality in a computer network model. *Physics Review E, 61*, 1067–1071.
18. Betterncourt , L. M. A. (2007). Functional structure of cortical neuronal networks grown in vitro. *Physics Review E, 75*, 021910–021915.
19. Betterncourt, L. M. A., Vadas, G., & Michael, I.H. (2008). Identification of functional information subgraphs in complex networks. *Physics Review Letters, 100*, 238701–238704.

20. Daniel, P. P., & Sergio, V. (2006). Gradient of mutual information in linear vector Gaussian channels. *IEEE Transactions on Informational Theory, 52*, 141–154.
21. Michael, J., & Hall, W. (2000). Quantum properties of classical Fisher information. *Physics Review A, 62*, 12106–12107.
22. Luo, S. L. (2002). Fisher information, kinetic energy and uncertainty relation inequalities. *Journal of Physics A: Mathematics General, 35*, 5181–5187.
23. Costa, M. H. M. (1985). A new entropy power inequality. *IEEE Transactions on Informational Theory, 31*(6), 751–760.
24. Poor, H. V. (1994). *An introduction to signal detection and estimation*. New York: Springer.

Author Biographies

Hai-Lin Xiao was born in 1976. He received the B.S. and M.S. degrees from Wuhan University and Guangxi Normal University in 1998 and 2004 respectively. He received Ph.D. degree from the University of Electronic Science and Technology of China (UESTC) in 2007. Now he is Associate Professor in the School of Information and Communications, Guilin University of Electronic Technology. His research interests include MIMO wireless communication and smart antenna techniques.

Shan Ouyang was born in 1960. He received the B.S. degree in electronic engineering from Guilin University of Electronic Technology, Guilin, China, in 1986 and the M.S. and Ph.D. degrees in electronic engineering from Xidian University, Xi'an, China, in 1992 and 2000, respectively. In 1986, he jointed Guilin University of Electronic Technology, where he is presently a Professor and the Dean of the School of Information and Communications. From June 2001 to May 2002, he was a Research Associate with the Department of Electronic Engineering, the Chinese University of Hong Kong. From January 2003 to January 2004, he was a Research Fellow with Department of Electronic Engineering, University of California at Riverside. His research interests are mainly in the areas of signal processing for communications and radar, adaptive filtering, and neural network learning theory and applications. Dr. Ouyang received the Outstanding Youth Award of the Ministry of Electronic Industry and Guangxi Province Outstanding Teacher Award, China, in 1995 and 1997, respectively. He received the National Excellent Doctoral Dissertation of China in 2002.

Cheng-Xiang Wang was born in 1975. He received the B.Sc. and M.Eng degrees in Communication and Information Systems from Shandong University, China, in 1997 and 2000, respectively, and the Ph.D. degree in Wireless Communications from Aalborg University, Denmark, in 2004. He has been with Heriot-Watt University, Edinburgh, UK since 2005, first as a Lecturer and then as a Reader in 2009. He is also an Honorary Fellow of the University of Edinburgh, UK. He was a Research Fellow at the University of Agder, Grimstad, Norway, from 2001–2005, a Visiting Researcher at Siemens AG-Mobile Phones, Munich, Germany, in 2004. His research interests include wireless channel modelling and simulation, cognitive radio networks, vehicular communication networks, green radio communications, cooperative (relay) communications, cross-layer design of wireless networks, MIMO, OFDM, UWB, and (beyond) 4G wireless communications.

Feng Zhao was born in 1974, He received the Ph.D. degree in Communication and Information System of Shandong University, China, in 2007. Now he is an associate professor in the School of Information and Communications of Guilin University of Electronic Technology. His research interests include wireless communication systems, information processing and information security.