### CODING WITH MINIMAL PROGRAMS

### CRISTIAN S. CALUDE

Department of Computer Science, University of Auckland Private Bag 92019, Auckland, New Zealand

### HAJIME ISHIHARA

School of Information Science, Japan Advanced Institute of Science and Technology Tatsunokuchi, Ishikawa 923-1292, Japan

### and

### TAKESHI YAMAGUCHI

Department of Information Sciences, Tokyo Denki University Hatoyama-Machi, Hiki-Gun, Saitama-Ken 350-0394, Japan

> Received 15 June 2000 Revised 20 August 2000 Communicated by Arto Salomaa

## ABSTRACT

According to the Algorithmic Coding Theorem, minimal programs of any universal machine are prefix-codes asymptotically optimal (i.e. optimal up to at most an additive, unknown constant) with respect to the machine algorithmic probabilities. A stronger version of this result will be proven for a class of machines, not necessarily universal, and any semi-distribution. Furthermore, minimal programs with respect to universal machines will be shown to be almost optimal (i.e. optimal up to an additive constant less than or equal to 2) for any semi-computable semi-distribution. Finally, a complete characterization of all machines satisfying the Algorithmic Coding Theorem is given.

## 1. Introduction

Algorithmic information theory, mainly through the Algorithmic Coding Theorem ([4, 9]), has been successfully applied to a variety of physical problems (mainly in conjunction with Landauer's principle  $[10]^a$ ): the Maxwell demon paradox ([1, 17]), the irreversibility in classical Hamiltonian chaotic systems ([12]), the characterization of quantum chaos within the framework of statistical physics ([13, 14]). The program-size complexity (algorithmic information) with respect to two different universal machines differs at most by an unknown, additive, computer-dependent, constant. This type of uncertainty is a serious issue of concern for a

<sup>&</sup>lt;sup>a</sup>Which specifies the cost of energy dissipation for the erasure a bit of information.

physical theory, so various attempts have been made to eliminate it (see, for example, [11]). It is our aim to obtain sharper versions of the Algorithmic Coding Theorem in which the uncertainty is reduced to a minimum or no assumption is made on the computability of the semi-distribution.

Let C be a prefix-code with one code string per source string, that is, an oneone function from binary strings to binary strings whose range is a prefix-free set. Let P(x) be the probability of the source string x and let |C(x)| be the length of the code string of x. Shannon's Noiseless Coding Theorem says that the minimal average code string length is about equal to the entropy of the source string set. The strategy is to choose a prefix-code that matches best the probability distribution of the source codes.

In what follows we will study infinite prefix-codes, that is, prefix-codes naming all binary strings. We will work with semi-distributions, i.e. functions P from strings to reals such that  $\sum_x P(x) \leq 1$ . A Shannon type result is valid for semi-distributions. We will be interested in finding prefix-free codes which are almost optimal for a given semi-distribution, and also for a class of semi-distributions (in case the semi-distribution may be unknown, or uncomputable).

Algorithmic Information Theory (see [4, 5, 2, 6]) provides a natural class of prefix-free codes, namely the set of minimal (canonical) programs of a machine. According to Algorithmic Coding Theorem, minimal programs of any universal machine (a machine capable of simulating any other machine) are asymptotically optimal (i.e. optimal up to at most an additive, unknown constant) with respect to the machine algorithmic probabilities. A stronger version of this result is proven here for a class of machines, not necessarily universal, and any semi-distribution. Minimal programs with respect to universal machines are proven almost optimal (i.e. optimal up to an additive constant less than or equal to 2) for any semi-computable semi-distribution. Finally, a complete characterization of all machines satisfying the Algorithmic Coding Theorem is given.

## 2. Notation, Definitions and Basic Results

By  $\mathbf{N}, \mathbf{Q}$ , and  $\Sigma^*$  we denote the sets of nonnegative integers, rationals, and (finite) binary strings, respectively. The length of a string s is denoted by |s|. A string s is a prefix of a string t ( $s \subseteq t$ ) if there is a string  $t \in \Sigma^*$  such that t = t. A subset  $t \in \Sigma^*$  is prefix-free if whenever  $t \in \Sigma^*$  and  $t \in \Sigma^*$  inequality states that for every prefix-free set  $t \in \Sigma^*$ ,  $t \in \Sigma^*$  is prefix-free. Kraft's inequality states that for every prefix-free set  $t \in \Sigma^*$ ,  $t \in \Sigma^*$  is prefix-free.

By log we denote the base 2 logarithm. For every real  $\alpha > 0$ , put  $\lg \alpha = \lceil \log \alpha \rceil - 1$ . Note that if  $\alpha > 0$ , then  $2^{\lg \alpha} < \alpha, \lg \alpha < \log \alpha \le \lg \alpha + 1$ , and if m is an integer, then  $\lg \alpha \ge m$  iff  $\log \alpha > m$ .

We assume familiarity with Turing machines, computable sets and functions, computably enumerable (c.e.) sets, e.g. from [16]. We shall employ a special model of deterministic Turing machine computation, namely self-delimiting Turing machines or (Chaitin) machines: these are Turing machines (transforming binary

 $<sup>{}^{</sup>b}$ The base 10 logarithm will not be used in this paper.

strings into binary strings) having prefix-free domains. More precisely, for every Chaitin machine M the program set  $PROG_M = \{x \in \Sigma^* \mid M(x) \text{ halts}\}$  is prefix-free. Note that, conversely, every prefix-free c.e. set of strings is the domain of some Chaitin machine. In what follows we will operate only with Chaitin machines, which will be simply referred to as machines.

The following result will be frequently used (see [3] for a simple proof):

**Theorem 1 (Kraft–Chaitin)** Given a computable list of "requirements"  $(n_i, s_i)$   $(i \geq 0, s_i \in \Sigma^*, n_i \in \mathbb{N})$  such that  $\sum_i 2^{-n_i} \leq 1$ , we can effectively construct a machine M and a computable one-to-one enumeration  $x_0, x_1, x_2, \ldots$  of strings  $x_i$  of length  $n_i$  such that  $M(x_i) = s_i$  for all i, and M(x) is undefined if  $x \notin \{x_i \mid i \in \mathbb{N}\}$ .

The program-size complexity induced by the machine M is

$$H_M(x) = \min\{|z| \mid M(z) = x\},\$$

with the convention that the minimum of the empty set is undefined.

The algorithmic probability of the machine M to produce the output x is

$$P_M(x) = \sum_{M(u)=x} 2^{-|u|},$$

and the halting probability of M is

$$\Omega_M = \sum_{x \in \Sigma^*} P_M(x) = \sum_{x \in PROG_M} 2^{-|x|}.$$

It follows by Kraft's inequality that, for every machine M and any string  $x \in \Sigma^*$ ,

$$0 < P_M(x) < \Omega_M < 1.$$

For every machine M and string x such that  $P_M(x) > 0$ , we denote by

$$x_M^* = \min\{u \mid M(u) = x\},\$$

where the minimum is taken according to the quasi-lexicographical ordering of strings (the empty string  $< 0 < 1 < 00 < 01 < 10 < 11 < 000 < \cdots$ );  $x_M^*$  is called the *minimal (canonical) program* of x with respect to M.

A machine U is universal if for every machine M, there is a constant  $c_M$  (depending upon M) with the following property: if M(x) halts, then there is an  $x' \in \Sigma^*$  such that U(x') = M(x) and  $|x'| \leq |x| + c_M$ ;  $c_M$  is the simulation constant of M on U. Universal machines can be effectively constructed. If U is universal, then  $x_U^*$  exists for every string x. See more in [2]. For universal machines the following important result holds true:

Theorem 2 (Algorithmic Coding Theorem; Chaitin-Gács) There exists a constant  $c \ge 0$  such that for all strings x,

$$|H_U(x) + \log P_U(x)| \le 1 + c.$$

See [4, 5, 9, 2, 6].

## 3. Noiseless Coding Theorem

A function  $P: \Sigma^* \to [0,1]$  such that  $\sum_x P(x) \leq 1$  is called a *semi-distribution* over the strings. In case  $\sum_x P(x) = 1$ , P is a *distribution*. A semi-distribution P is semi-computable from below (above) in case the set  $\{(x,r) \mid x \in \Sigma^*, \ r \in \mathbf{Q}, \ P(x) > r\}$  ( $\{(x,r) \mid x \in \Sigma^*, \ r \in \mathbf{Q}, \ P(x) < r\}$ ) is c.e. A semi-distribution P is computable if it is semi-computable from below and from above. For example,  $P_M$  is a semi-distribution semi-computable from below. The function  $P(x) = 2^{-2|x|-1}$  is a computable distribution.

A prefix-code for strings is an one-one function  $C: \Sigma^* \to \Sigma^*$  such that  $C(\Sigma^*)$  is prefix-free. For example, for every surjective machine M,  $C_M(x) = x_M^*$  is a prefix-code; universal machines are surjective. The average code-string length of a prefix-code C with respect to a semi-distribution P is

$$L_{C,P} = \sum_{x} P(x) \cdot |C(x)|.$$

The minimal average code-string length with respect to a semi-distribution P is

$$L_P = \inf \{ L_{C,P} \mid C \text{ prefix-code} \}.$$

The *entropy* of a semi-distribution P is

$$\mathcal{H}_P = -\sum_x P(x) \cdot \log P(x).$$

Shannon's classical argument [15] (see more in [8]) can be expressed for semidistributions as follows:

Theorem 3 (Noiseless Coding Theorem; Shannon) The following inequalities hold true for every semi-distribution P:

$$\mathcal{H}_P - 1 \le \mathcal{H}_P + \left(\sum_x P(x)\right) \log \left(\sum_x P(x)\right) \le L_P \le \mathcal{H}_P + 1.$$

If P is a distribution, then  $\log(\sum_x P(x)) = 0$ , so we get the classical inequality  $\mathcal{H}_P \geq L_P$ . However, this inequality is not true for every semi-distribution. For example, take  $P(x) = 2^{-2|x|-3}$  and  $C(x) = x_1x_1 \dots x_nx_n01$ . It follows that  $L_P \leq L_{C,P} = \mathcal{H}_P - \frac{1}{4}$ .

### 4. Main Result

We investigate conditions under which given a semi-distribution P, we can find a (universal) machine M such that  $H_M(x)$  is equal, up to an additive constant, to  $-\log P(x)$ . In what follows we will assume that P(x) > 0, for every x.

We start with the main technical result:

**Theorem 4** Assume that P is a semi-distribution and there exist a c.e. set  $S \subset \Sigma^* \times \mathbb{N}$  and a constant  $c \geq 0$  such that the following two conditions are satisfied for every  $x \in \Sigma^*$ :

- (i)  $\sum_{(x,n)\in S} 2^{-n} \le P(x)$ ,
- (ii) if  $P(x) > 2^{-n}$ , then  $(x, m) \in S$ , for some  $m \le n + c$ .

Then, there exists a machine M (depending upon S) such that for all x,

$$-\log P(x) \le H_M(x) \le (1+c) - \log P(x).$$
 (1)

**Proof.** In view of (i),

$$\sum_{(x,n)\in S} 2^{-n} \le \sum_{x} P(x) \le 1,$$

so using the Kraft-Chaitin Theorem we can construct a machine M such that for every  $(x,n) \in S$  there exists a string  $v_{x,n}$  of length n such that  $M(v_{x,n}) = x$ . If  $(x,m) \notin S$ , for all m, then P(x) = 0 and  $H_M(x) = \infty$ , so (1) is satisfied. If  $(x,m) \in S$ , for some m, then using (i) and (ii) we get:

$$H_{M}(x) = \min \{|v| \mid v \in \Sigma^{*}, M(v) = x\}$$

$$= \min \{n \mid n \in \mathbb{N}, (x, n) \in S\}$$

$$\leq \min \{m \mid m \in \mathbb{N}, P(x) > 2^{-m}\} + c$$

$$= \min \{m \mid m \in \mathbb{N}, m > -\log P(x)\} + c$$

$$= \min \{m \mid m \in \mathbb{N}, m \geq 1 - \lg P(x)\} + c$$

$$\leq (1 + c) - \log P(x).$$
(2)

If (x, n) is in S, then  $P(x) \geq 2^{-n}$ , hence  $-\log P(x) \leq H_M(x)$  because of (2).  $\square$ 

**Remark** Theorem 4 makes no direct computability assumptions on P.

**Lemma 1** Let M be a machine such that  $\Omega_M < 1$ . Then, there exists a universal machine U satisfying the inequality  $H_U(x) \leq H_M(x)$ , for all x.

**Proof.** By hypothesis,  $\Omega_M < 1$ , so there is a non-negative integer k such that  $\Omega_M + 2^{-k} \leq 1$ . Let V be a universal machine. The set

$$S = \{(M(x), |x|) \mid x \in PROG_M\} \cup \{(V(x), |x| + k) \mid x \in PROG_V\}$$

is c.e. and

$$\sum_{(y,n)\in S} 2^{-n} \le \Omega_M + 2^{-k} \le 1.$$

Consequently, in view of Kraft-Chaitin Theorem, there exists a machine U such that for  $(y, n) \in S$  there is a program  $z \in PROG_U$  of length n such that U(z) = y. Clearly, for every x,

$$H_U(x) \le \min\{|w| + k \mid V(w) = x\} = H_V(x) + k,$$

and

$$H_U(x) = \min\{|v| \mid U(v) = x\} \le H_M(x),$$

so U is universal and satisfies the required inequality.

**Lemma 2** Let M be a machine. Then, there exists a machine M' such that  $\Omega_{M'} < 1$  and  $H_{M'}(x) = H_M(x) + 1$ , for all x.

**Proof.** Apply Kraft-Chaitin Theorem to the set  $\{(M(x), |x|+1) \mid x \in PROG_M\}$  to obtain the machine M'.

Corollary 1 Under the hypotheses of Theorem 4, a universal machine U can be constructed such that for all x,

$$H_U(x) \le (2+c) - \log P(x).$$
 (3)

**Proof.** Use Lemmas 2, 1 to get a universal machine U such that  $H_U(x) \leq H_M(x) + 1$ , for all x.

## 5. Coding with Minimal Programs

Specializing P in Theorem 4 we show that minimal programs are almost optimal for P. Minimal programs of universal machines are almost optimal for every semi-computable semi-distribution P.

Semi-distributions semi-computable from below (e.g. algorithmic probabilities of machines) are important in Algorithmic Information Theory (see for example [4, 5, 2, 7]).

**Proposition 1** Assume that P is a semi-distribution semi-computable from below. Then, there exists a machine M (depending upon P) such that for all x,

$$-\log P(x) \le H_M(x) \le 2 - \log P(x). \tag{4}$$

Consequently, minimal programs for M are almost optimal: the code  $C_M$  satisfies the inequalities:

$$0 \leq L_{C_M,P} - \mathcal{H}_P \leq 2.$$

**Proof.** Take  $S = \{(x, n+1) \mid P(x) > 2^{-n}\}$ . For every x we have:

$$\sum_{(x,n)\in S} 2^{-n} = \sum_{n>1-\log P(x)} 2^{-n} = \sum_{n\geq 1-\lg P(x)} 2^{-n} = 2^{\lg P(x)} < P(x),$$

so condition (i) in Theorem 4 is satisfied. Condition (ii) holds for c=1. Hence by (1) we get

$$0 \leq L_{C_M,P} - \mathcal{H}_P = \sum_x P(x) \cdot (H_M(x) + \log P(x)) \leq 2.$$

Corollary 2 Assume that  $f: \Sigma^* \to \mathbb{N}$  is a function such that the set  $\{(x,n) \mid f(x) < n\}$  is c.e. and  $\sum_x 2^{-f(x)} \le 1$ . Let  $P(x) = 2^{-f(x)}$ . Then P is a semi-distribution semi-computable from below, and there exists a machine M (depending upon f) such that for all x,

$$H_M(x) \le 1 + f(x). \tag{5}$$

Minimal programs for M are almost optimal: the code  $C_M$  satisfies the inequalities:

$$0 < L_{CM,P} - \mathcal{H}_P < 1.$$

One more bit is enough to guarantee universality of the constructed machine, that is, there exists a universal machine U (depending upon f) such that the code  $C_U$  satisfies the inequalities:

$$0 \leq L_{C_{U},P} - \mathcal{H}_{P} \leq 2.$$

**Proof.** Take  $S = \{(x,n) \mid n > f(x)\}$ . Clearly,  $S = \{(x,n) \mid P(x) > 2^{-n}\}$ . The first condition in Theorem 4 is satisfied as  $\sum_{n>f(x)} 2^{-n} = P(x)$ , for every x, and the second condition is satisfied for c = 0.

Remark When the semi-distribution P is given, an optimal prefix-code can be found for P. However, that code may be far from optimal for a different semi-distribution. For example, let C be a prefix-code such that  $|C(x)| = 2^{|x|+2}$ , for all x. Let  $\alpha > 0$  and consider the distribution

$$P_{\alpha}(x) = (1 - 2^{-\alpha}) 2^{-(\alpha+1)|x|}$$

Two radically different situations appear: if  $\alpha \leq 1$ , then

$$L_{C,P_{\alpha}} - \mathcal{H}_{P_{\alpha}} = \infty,$$

but if  $\alpha > 1$ , then

$$L_{C,P_{\alpha}} - \mathcal{H}_{P_{\alpha}} < \infty.$$

So, C is asymptotical optimal for every distribution  $P_{\alpha}$  with  $1 < \alpha$ , but C is far away from optimality if  $0 < \alpha \le 1$ . Note that  $P_{\alpha}$  is computable provided  $\alpha$  is computable.

The next result shows that minimal programs are asymptotical optimal for every semi-distribution semi-computable from below.

**Theorem 5** Let P be a semi-distribution semi-computable from below, and U a universal machine. Then, there exists a constant  $c_P$  (depending upon P) such that

$$0 \leq L_{C_{II},P} - \mathcal{H}_P \leq 1 + c_P.$$

**Proof.** Take M the machine constructed in Proposition 1 and let  $c_M$  be the simulation constant of M on U. Then,

$$0 \le L_{C_U,P} - \mathcal{H}_P \le L_{C_M,P} + c_M - \mathcal{H}_P \le 1 + c_M$$

so take  $c_P = c_M$ .

Remark Theorem 5 generalizes a result in [7] proven for computable distributions; see also [11]. The result is important only for semi-distributions for which the entropy is infinite. For example, the entropy of the semi-distribution

$$P(x) = \frac{2^{-|x|}}{(|x|+2)\log(|x|+2)}$$

is infinite.

Using Lemma 1 we can obtain sharper inequalities. For example, for every universal machine U, the code  $C_U$  is almost optimal with respect to  $P_U$ :

$$0 \leq L_{C_U, P_U} - \mathcal{H}_{P_U} \leq 2.$$

If f is a function as in Corollary 2 such that  $\sum_{x} 2^{-f(x)} < 1$ , then there exists a universal machine U such that

$$0 \leq L_{C_U,P} - \mathcal{H}_P \leq 1.$$

For example, take  $f(x) = H_U(x)$ , where U is a universal machine.

**Proposition 2** Let P be a computable semi-distribution. Then, there exists a machine M such that

$$-\log P(x) \le H_M(x) \le 1 - \log P(x).$$

**Proof.** Note that  $-\lg P(x) = \min\{n \mid n \in \mathbb{N}, P(x) > 2^{-n}\}$  and then apply Theorem 4 to the set  $S = \{(x, -\lg P(x)) \mid x \in \Sigma^*\}$  and constant c = 0.

**Corollary 3** Let P be a computable semi-distribution. Then, there exists a universal machine U such that

$$H_U(x) \leq 1 - \log P(x)$$
.

# 6. Algorithmic Coding Theorem Revisited

We characterize all machines satisfying the Algorithmic Coding Theorem and we construct a class of (universal) machines for which the inequality is satisfied with constant c = 0. This addresses the relevance of the theorem for statistical physics where the presence of an arbitrary constant is unsatisfactory (see [11]).

**Proposition 3** Let M be a machine and  $c \geq 0$ . The following statements are equivalent:

- (a) for all x,  $H_M(x) \le (1+c) \log P_M(x)$ ,
- (b) for all non-negative n, if  $P_M(x) > 2^{-n}$ , then  $H_M(x) \le n + c$ .

**Proof.** From  $H_M(x) \le (1+c) - \log P_M(x)$  and  $P_M(x) > 2^{-n}$  we deduce  $2^{-n} < P_M(x) < 2^{(1+c)-H_M(x)}$ .

Conversely, we have:

$$H_M(x) - c < \min\{n \mid n \in \mathbb{N}, P_M(x) > 2^{-n}\}.$$

**Remark** For any machine M satisfying one of the equivalent conditions in Proposition 3 the Algorithmic Coding Theorem holds:

$$|H_M(x) + \log P_M(x)| \le 1 + c.$$
 (6)

In fact, a machine M satisfies (6) if and only if condition (b) is satisfied. Every universal machine U satisfies condition (b), but not all machines satisfy this condition. To construct such an example, consider the following enumeration: for every string x enumerate  $2^{|x|}$  copies of the pair (x,3|x|+1). Use Kraft-Chaitin Theorem to construct a machine M such that for every string x there exist  $2^{|x|}$  different strings  $u_x^i$ , all of length 3|x|+1, such that

$$M(u_x^i) = x, i = 1, 2, \dots, 2^{|x|}.$$

It is seen that  $P_M(x) = 2^{-2|x|-1}$ , so taking  $n_x = 2|x| + 2$  we get  $P_M(x) > 2^{-n_x}$ , but there is no constant c such that  $H_M(x) \le n_x + c$ , for all strings x.

Some machines satisfy condition (b) with c=0, so their canonical programs are almost optimal. A class of (universal) such machines is provided in the next proposition.

**Proposition 4** Let M be a machine such that for all programs  $x \neq x'$  with M(x) = M(x') we have  $|x| \neq |x'|$ . Then, for all x,

$$H_M(x) \le 1 - \log P_M(x). \tag{7}$$

**Proof.** Consider the set  $S = \{(x, |y|) \mid M(y) = x\}$ , and notice that

$$P_M(x) = \sum_{(x,n)\in S} 2^{-n},$$

as programs producing the same output have different lengths. In view of the hypothesis,

$$P_U(x) > 2^{-n} \iff \exists (x, k_1) \in S [(k_1 < n) \lor (k_1 = n \land \exists k_2 (k_2 \neq k_1 \land (x, k_2) \in S))],$$

hence the second condition in Theorem 4 is satisfied with c=0. Using Theorem 4 we deduce the existence of a machine M' such that  $H_{M'}(x) \leq 1 - \log P_{M'}(x)$ , for all x. Inequality (7) follows from

$$H_M(x) = \min\{n \mid (x, n) \in S\} = H_{M'}(x).$$

Remark Not every universal machine satisfies the hypothesis of Proposition 4. However, if V is a universal machine, then one can effectively construct a universal machine U such that programs producing the same output via U have different lengths and  $H_U(x) = H_V(x)$ , for every x. (Of course,  $P_U(x) \leq P_V(x)$ , for all x.) Indeed, enumerate the graph of V and as soon as a pair (x, V(x)) appears in the list do not include in the list any pair (x', V(x')) with  $x \neq x'$  and V(x) = V(x'). The set enumerated in this way, which is a subset of the graph of V, is the graph of the universal machine U satisfying the required condition.

# Acknowledgements

Calude's work was done during his visit to the Japanese Advanced Institute of Science, and Technology as a Monbusho visiting professor. Ishihara was partly supported by a Grant-in-Aid for Scientific Research (C) No 09640253 of the Japanese Ministry of Education, Science, Sports and Culture. All authors wish to thank the anonymous referees for their useful comments.

## References

- 1. C. H. Bennett. The thermodynamics of computation. *International Journal of Theoretical Physics*, **21** (1982) 905-940.
- 2. C. Calude. Information and Randomness. An Algorithmic Perspective. (Springer-Verlag, Berlin, 1994).
- 3. C. Calude, C. Grozea. Kraft-Chaitin inequality revisited, *J. Univ. Comput. Sci.*, **5** (1996) 306–310.

- 4. G. J. Chaitin. Information, Randomness and Incompleteness, Papers on Algorithmic Information Theory (World Scientific, Singapore, 1987 (2nd ed., 1990)).
- 5. G. J. Chaitin. Algorithmic Information Theory (Cambridge University Press, Cambridge, 1987 (third printing 1990)).
- 6. G. J. Chaitin. The Unknowable (Springer-Verlag, Singapore, 1999).
- 7. T. M. Cover, P. Gács, R. M. Gray. "Kolmogorov's contributions to information theory and algorithmic complexity", The Annals of Probability, 17 (1989) 840–865.
- 8. T. M. Cover, J. A. Thomas. Elements of Information Theory (John Wiley, New York, 1991).
- 9. P. Gács. "On the symmetry of algorithmic information", Soviet Math. Dokl., 15 (1974) 1477-1480; correction, Ibidem 15 (1974) 1480.
- 10. R. Landauer. "Irreversibility and heat generation in the computing process", IBM J. Res. Develop., 5 (1961) 183–191.
- 11. R. Schack. "Algorithmic information and simplicity in statistical physics", Int. J. Theor. Physics, 36 (1997) 209–226.
- 12. R. Schack, C. M. Caves. "Information and entropy in the baker's map", Phys. Rev. Lett., 69 23 (1992) 3413-3416.
- 13. R. Schack, C. M. Caves. "Information-theoretic characterization of quantum chaos", Phys. Rev., E (3) (4) **53** (1996) 3257–3270.
- 14. R. Schack, C. M. Caves. "Chaos for Liouville probability densities", Phys. Rev., E (3) (4) **53** (1996) 3387–3401.
- 15. C. E. Shannon. "A mathematical theory of communication", Bell. Sys. Tech. Journal, 27 (1948) 379-423, 623-656.
- 16. R. I. Soare. Recursively Enumerable Sets and Degrees (Springer-Verlag, Berlin, 1987).
- 17. W. H. Zurek. "Algorithmic randomness, physical entropy, measurements, and the Demon of choice", in Feynman and Computation. Exploring the Limits of Computers, ed. J. G. Hey (Perseus Books, Reading, Massachusetts, 1999) pp. 393–410.